

# Analyzing the Effect of Linguistic Similarity on Cross-Lingual Transfer: Tasks and Experimental Setups Matter

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## Abstract

Cross-lingual transfer is a popular approach to increase the amount of training data for NLP tasks in a low-resource context. However, the best strategy to decide which cross-lingual data to include is unclear. Prior research often focuses on a small set of languages from a few language families and/or a single task. It is still an open question how these findings extend to a wider variety of languages and tasks. In this work, we analyze cross-lingual transfer for 263 languages from a wide variety of language families. Moreover, we include three popular NLP tasks: POS tagging, dependency parsing, and topic classification. Our findings indicate that the effect of linguistic similarity on transfer performance depends on a range of factors: the NLP task, the (mono- or multilingual) input representations, and the definition of linguistic similarity.

## 1 Introduction

For many of the world’s languages, the available data to train natural language processing (NLP) models is scarce. If data is available, it is often only enough for an evaluation set, raising the question of how to select the training set. Two approaches are intuitive: (i) based on linguistic similarity measures: find the training data in a language that is linguistically as close as possible to the target language, where “linguistically close” is defined by one or multiple linguistic similarity measures, or (ii) based on dataset dependent measures: find a dataset in another language that is similar to the target dataset, e.g., in terms of high word or  $n$ -gram overlap. Naturally, these two types of approaches are not mutually exclusive.

However, it is unclear which of these measures are most important to select the source language

\*Work done while interning at Apple.

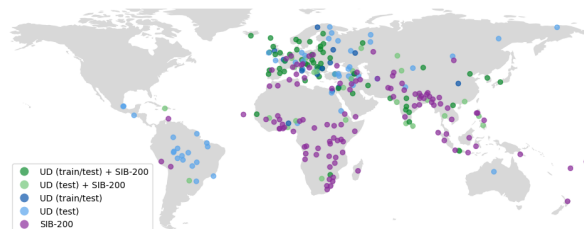


Figure 1: **Languages included in our experiments.** Green indicates languages included in all tasks, blue languages only used for POS tagging and parsing, and purple languages only used for topic classification. Base map via naturalearthdata.com (CC0).

for cross-lingual transfer, despite previous work focusing on this question (see §2): earlier studies often contradict each other, and therefore leave a number of important avenues for improvement. For example, prior work often lacks a large representation of languages and language families, as well as NLP tasks, and sometimes relies on synthetically constructed datasets. Furthermore, popular out-of-the-box measures for linguistic similarity are sometimes intransparent or faulty (Toossi et al., 2024; Khan et al., 2025; §3.3), and correlations between different similarity measures are often not taken into account. Summarizing, how findings from prior work generalize across a larger variety of languages and tasks, and how we should interpret different similarity scores, are open questions.

In this work, we contribute to these questions by analyzing transfer between 263 different languages from 33 language families (Figure 1) in three different tasks: (i) part-of-speech (POS) tagging, (ii) dependency parsing, and (iii) topic classification. In choosing our tasks, we are motivated by the following considerations: (i) availability of datasets: we select tasks for which we can find data for a multitude of languages from different language families, and (ii) types of tasks: we include two word-level grammatical tasks (i.e., POS tagging and dependency parsing) and one sentence-level topic iden-

tification task. To allow for a clean analysis, we opt for a zero-shot approach, in line with prior work (de Vries et al., 2022) – we train our models on the task in one particular source language, and evaluate on the target language without additional training or fine-tuning in the target language.

Our **key findings** can be summarized as:

1. For different tasks and input representations, different similarity measures are most predictive for cross-lingual transfer performance. For instance, syntactic similarity is most predictive for POS tagging and parsing, whereas trigram overlap is the most important predictor for  $n$ -gram-based topic classification (§5.1);
2. **Practical implication *within* studied tasks:** Choosing a source language based on a pertinent similarity measure leads to adequate transfer results (§5.2.1);
3. **Practical implication *across* studied tasks:** When no information about pertinent similarity measures is available for a given task, choosing a source language based on findings for a conceptually *similar* experiment is a relatively safe choice (§5.2.2).

## 2 Related Work

Table 1 provides an overview of related work, highlighting an apparent trade-off between including many languages or including multiple tasks. An important difference that distinguishes our work from prior work is the focus on both. We argue that including a large number of both source and target languages is important for ensuring a relatively balanced distribution of languages.<sup>1</sup> In comparison to the studies that come closest to our work in terms of number of included source and target languages (de Vries et al., 2022; Samardžić et al., 2022), we include a larger variety of tasks, allowing us to draw conclusions across task boundaries.

Philippy et al. (2023) survey contributing factors for cross-lingual transfer, including most of the works in Table 1. An important take-away from their work is that prior research presents contradicting findings. E.g., some studies find lexical overlap to correlate more strongly with token rather than sentence classification tasks (Srinivasan et al., 2021), whereas others find the opposite (Ahuja et al., 2022). Similar contradictory examples are

<sup>1</sup>I.e., such that there is not mainly one cluster of (European) languages that are similar to each other, and most other languages are both dissimilar to that cluster and to each other.

Work	# Tasks	# Langs per task (source×target)
de Vries et al. (2022)	1 (P)	65×105
Rice et al. (2025)	1 (P)	18×21
Samardžić et al. (2022)	1 (D)	47×62
Adelani et al. (2022)	1 (N)	42×42
Adelani et al. (2024)	1 (T)	4×197
Pires et al. (2019)	2 (NP)	{4–41}×{4–41}
Muller et al. (2023)	3 (FNQ)	{7–9}×{7–9}
Srinivasan et al. (2021)	3 (FNP)	{15–40}×{15–40}
Lin et al. (2024)	4 (INPT)	6×{44–130}
Lin et al. (2019)	4 (DEMP)	{30–60}×{9–54}
Xia et al. (2020)	4 (DEMP)	{30–60}×{9–54}
Lauscher et al. (2020)	5 (DFNPQ)	1×{8–14}
Ahujja et al. (2022)	6 (EFNPQS)	1×{7–48}
This work	3 (DPT)	70×153 (DP) 194×194 (T)

Table 1: **Related work** focusing on zero-shot transfer between many languages or on many tasks. Tasks: D=dependency parsing, E=entity linking, F=natural language inference, I=intent classification, M=machine translation, N=named entity recognition, P=part-of-speech tagging, Q=question answering, S=sentence retrieval, T=topic classification.

presented for different linguistic similarity metrics, pre-training dataset size, and model architecture.

Based on this insight, Philippy et al. make recommendations for follow-up work: (i) focus on real natural languages (instead of synthetic ones), (ii) examine the interaction between different contributing factors, (iii) focus on many languages, (iv) focus on linguistic features when selecting training languages, and (v) focus on generative tasks, given the success of generative models. We focus on the first four recommendations in this work. We include three classification tasks (POS tagging, dependency parsing, and topic classification), motivated by the availability of train and test data in a large number of languages for these tasks.

## 3 Methodology

We run transfer experiments on two word-level grammatical tasks with word-level annotations (§3.1) and a sentence-level topic classification task (§3.2). Of the 263 languages in our experiments, 55 training and 84 test languages are shared between all tasks. Appendix §A contains details on all languages and datasets in this study. Section §3.3 introduces our similarity measures.

### 3.1 Grammatical tasks

**Data** We use POS tags and syntactic dependencies from Universal Dependencies (UD; de Marneffe et al., 2021). The advantage of UD is the large number of languages (153) and language families (28) in which manually annotated datasets are available that both showcase a language’s specific syntactic structures and adhere to a shared set of annotation guidelines. UD also has its drawbacks in that the different treebanks are not necessarily from the same domains, most treebanks were annotated independently by different groups of researchers, and the size of the train and test splits is not identical across treebanks. To mitigate the latter, we evaluate the effect of training dataset size in §5.1. To account for differences in the test sets (e.g., differing complexities or sentence lengths), we focus on comparing the performance of different parsers/taggers on each test set (rather than comparing how well each parser/tagger does across test sets; §5.1).

We use the test splits of UD release (2.14; Zeman et al., 2024): 268 treebanks in 153 target languages, from 28 language families. We use pretrained models (see below), trained on 124 treebanks in 70 source languages from 12 language families. We exclude treebanks that are without text, particularly small, focus on code-switching, or have inconsistent train/test splits (§A.1).

**Models** We use the UDPipe 2 models (Straka, 2018, 2023) that were trained on UD 2.12 data. Each model is trained on a single treebank. The models have so far only been systematically evaluated on their within-treebank performance, but not cross-lingually. UDPipe 2 combines monolingual character and word embeddings with multilingual embeddings derived from mBERT (Devlin et al., 2019). The models are trained jointly for POS tagging, dependency parsing, lemmatization and morphological feature prediction. We only evaluate on the first two, as many treebanks do not have gold standard labels for the others. UDPipe 2 post-processes the predicted dependencies to ensure that each sentence includes a root dependency that all other nodes (in)directly depend on.

We evaluate POS tagging using accuracy, and dependency parsing using the labeled (LAS) and unlabeled attachment scores (UAS). For LAS, we follow UD’s evaluation scripts and ignore dependency label subtypes.

### 3.2 Topic classification

**Data** We use the SIB-200 dataset (Adelani et al., 2024), a subset of FLORES-200 (NLLB Team et al., 2022) with parallel sentences in 194 languages<sup>2</sup> (from 22 families) annotated with seven topic labels. Eight languages are represented twice, but with different writing systems. SIB-200 contains 701 training and 204 test sentences.

**Models** We use multi-layer perceptrons (MLPs) for topic identification, similar to the baseline models by Adelani et al. (2024). This lightweight architecture allows training and evaluating many models without prohibitive time or energy investments, and results in evaluation scores that are close to the performance of base-sized transformers like XLM-R (Conneau et al., 2020) (§D, Table 2). We use the scikit-learn implementation (Pedregosa et al., 2011) and conduct hyperparameter tuning on a subset of the languages (details in Appendix §C). We compare different ways of representing the input data:

1. **Character  $n$ -gram counts** (topics-base). We use character-level  $n$ -gram counts (1- to 4-grams) to represent the input. This ensures that we know exactly what training data were used, and it puts all languages on equal footing.
2. **Transliterated input** (topics-translit). To remove differences between writing systems, we use uroman (Hermjakob et al., 2018) to transliterate the dataset into Latin characters and remove diacritics, and otherwise repeat the previous set-up. We exclude three datasets that were not supported by uroman (§A.2).
3. **Multilingual representations** (topics-mbert). To allow for a more direct comparison with the grammatical experiments, which partially rely on multilingual mBERT representations, we follow UDPipe 2 by deriving embeddings from the mean-pooled last four layers of the frozen base-sized, uncased mBERT model (Devlin et al., 2019). We use the hidden representations of the [CLS] token as input to the MLP.

### 3.3 Similarity measures

We include a range of dataset-dependent and -independent similarity measures, which are similar to measures used in related work (§2).

**Structural similarities** Grambank (Skirgård et al., 2023) encodes grammatical information for

<sup>2</sup>This excludes three Arabic varieties whose sentences are nearly identical to the Standard Arabic sentences (§A.2).

several thousand languages. Its 195 grammatical features are chosen to allow almost no logical dependencies between the values of different features, i.e. the value of one feature does not logically entail the value of another.

We additionally use the `lang2vec` tool (Littell et al., 2017, 2019), which has also been used in many other studies on multilingual NLP (cf. Toossi et al., 2024). `Lang2vec` aggregates information on syntax, phonology, and phoneme inventories from multiple databases in the form of binary features. Since not all sources contain full information on all languages, we use language vectors that include information from multiple of the above sources (averaged values where sources disagree). Some grammatical features are covered by both Grambank and `lang2vec`, although sometimes with different value assignments (Baylor et al., 2023).

We use Gower’s (1971) coefficient to calculate similarities between language pairs by comparing their feature values. If information is missing for a feature in one or both languages, we ignore that feature. If two values are identical, their similarity is 1, otherwise it is 0. The overall distance between the two languages is the mean of the (attested) feature distances. We calculate similarity scores for Grambank’s entries (**gb**) and for `lang2vec`’s syntactic (**syn**), phonological (**pho**), and phonetic (**inv**) entries. We include only similarities for language pairs where at least half of all features could be included in the calculations. However, in practice, more features are compared in most cases. On average, 83% of the features are included in each similarity calculation for **gb**, 63% for **syn**, 100% for **inv**, and 84% for **pho**.

**Lexical similarity** As a proxy for how similar different languages’ vocabularies are, we compare multilingual word lists from the Automated Similarity Judgment Program (ASJP; Wichmann et al., 2016). Jäger (2018a,b) calculated language dissimilarity scores based on ASJP, taking into account cross-linguistic phonological patterns. Our lexical similarity score (**lex**) is 1 minus Jäger’s dissimilarity score. Since some languages have multiple ASJP entries, we use language-wise mean scores.

**Phylogenetic relatedness** We determine whether two languages are related (and how closely) with the help of Glottolog’s (Hammarström et al., 2024) phylogenetic trees. For each language, we retrieve the path from its family root node to the language node. The relatedness of two languages (**gen**) is

the ratio of shared nodes along these paths.<sup>3</sup>

**Geographic proximity** We use `lang2vec`’s location information (each language is represented as a vector of distances to a number of points on the Earth’s surface) and calculate the Euclidean distances between language vectors.<sup>4</sup> We define geographic proximity (**geo**) as 1 minus the distance.

**Character and word overlap** We measure the overlap between training and test datasets on the character level (**chr**) with the Jaccard similarity of the character sets. We repeat this on the word level (**wor**) for the UD datasets (where the data come with gold-standard word tokenization), and on the character trigram (**tri**) and mBERT subword token (**swt**) level for SIB-200.

**Amount of training data** We count the number of sentences in each training dataset (**size**). For the topic classification task, this is trivial as each language has the same number of training samples.

**Correlations between measures** Correlations between similarity measures can influence how importance is assigned to different measures in regression analyses. Table 8 in §B shows how the different similarity measures are correlated with each other. Lexical similarity and phylogenetic relatedness are highly correlated ( $r = 0.87$ ). Additionally, the two grammar-based similarity measures (**gb** and **syn**) are moderately strongly correlated ( $r = 0.61$ ), as are **gb** and lexical/phylogenetic similarity ( $r = 0.57, 0.56$ ), and word overlap in UD and lexical similarity ( $r = 0.59$ ).

## 4 Supporting Results

Here we present the results on which the main analyses in §5 build. In §4.1, we present the POS tagging, parsing and topic classification scores within and across languages. In §4.2, we compare how (dis)similar transfer patterns are across tasks and

<sup>3</sup>Because different trees/branches have different depths (owing to different family sizes and/or different levels of documentation), comparisons of scores can only serve as a proxy for the degree of phylogenetic relatedness. This is also noted in the metadata for `lang2vec`, which calculates genetic distances in a similar way: [http://www.cs.cmu.edu/~dmortens/projects/7\\_project/](http://www.cs.cmu.edu/~dmortens/projects/7_project/). For constructed languages, we ignore the top-most level (e.g., “artificial languages”) and instead retrieve phylogenetic information starting at the second level.

<sup>4</sup>We do not use `lang2vec`’s precomputed distances, as the package erroneously returns the maximum distance for some languages, regardless of the comparison.

experiments, which helps contextualize the importance of different similarity measures for different experiments and tasks in §5.1.

#### 4.1 Within-language vs. cross-lingual performance per task

As expected, the within-language performances are much higher than the cross-lingual performances. Table 2 shows the mean scores within and across languages and datasets. In the following analyses, we focus on the language-level results. For UD, which has nearly twice as many datasets as languages, we find that trends are very stable across datasets of the same language (§D.3).

All of our models achieve reasonable within-language results, indicating that cross-lingual transfer (to an appropriate target language) could be feasible for all models. For the two straightforward classification tasks (POS tagging and topic classification), we construct random baselines (§D.1) that are outperformed by all models in within-language evaluations. For our topic classification models, the within-dataset performance is comparable to the baselines in the dataset paper (Adelani et al., 2024), but we do not match the performance of their best model. Our POS tagging results are similar but not identical to the ones that de Vries et al. (2022) obtained on UD v2.8 with fine-tuned XLM-R models for 65 training and 105 test languages. If we consider our own POS tagging results but only select the subset of languages that was used in de Vries et al.’s experiments, the POS tagging accuracies are highly correlated with those that de Vries et al. obtained (Pearson’s  $r$  and Spearman’s  $\rho = 0.73$ ,  $p < 0.0001$ ). Thus while the model choice (UDPipe vs. XLM-R) matters for the resulting patterns, many transfer trends are similar.

For topic classification, we compare the different input representations. The *within-language* performance is higher for the monolingual  $n$ -gram-based models than the models with multilingual input representations from mBERT. We hypothesize that this due to high [UNK] token rates for some languages that were not in mBERT’s pre-training data.<sup>5</sup>

Although topics-base and topics-translit achieve the same within-language accuracy, topics-translit performs slightly better cross-lingually, having the advantage of higher  $n$ -gram

<sup>5</sup>Bagheri Nezhad and Agrawal (2024) similarly find that the performance of multilingual models that are monolingually trained and evaluated on SIB-200 relates to how well a language is represented in a model’s pre-training data.

	Dataset level		Language level	
	Within	Across	Within	Across
<i>Grammatical tasks</i>				
POS accuracy	96.4 <sub>3.1</sub>	43.6 <sub>20.8</sub>	93.4 <sub>6.8</sub>	43.0 <sub>20.2</sub>
POS acc. (de Vries et al.)	94.1 <sub>4.5</sub> *	57.4 <sub>22.4</sub> *	94.1 <sub>4.5</sub>	57.4 <sub>22.4</sub>
UAS	88.7 <sub>6.4</sub>	37.3 <sub>19.3</sub>	84.8 <sub>10.1</sub>	36.8 <sub>18.8</sub>
LAS	84.6 <sub>8.6</sub>	21.2 <sub>17.9</sub>	78.4 <sub>13.7</sub>	20.6 <sub>17.0</sub>
<i>Topic classification (accuracy)</i>				
topics-base	70.3 <sub>4.0</sub>	20.7 <sub>8.8</sub>	66.7 <sub>14.1</sub>	20.1 <sub>8.8</sub>
topics-translit	69.4 <sub>4.1</sub>	22.5 <sub>8.2</sub>	66.7 <sub>10.8</sub>	22.5 <sub>8.2</sub>
topics-mlp	60.1 <sub>18.7</sub>	42.6 <sub>20.4</sub>	58.2 <sub>19.9</sub>	42.6 <sub>20.4</sub>
MLP (Adelani et al.)	62.3	—	—	—
XLM-R <sub>B</sub> (Adelani et al.)	70.9	—	—	—
XLM-R <sub>L</sub> (Adelani et al.)	76.1	—	—	—

Table 2: Scores of models evaluation within vs. across datasets and languages, in this work and related work. Our analyses focus on the language-level scores. Scores are mean scores (in %), with standard deviations in subscripts. XLM-R<sub>B</sub> and <sub>L</sub> = XLM-R base/large. \*When multiple datasets were available for one language, de Vries et al. combined them into one.

overlap between datasets.<sup>6</sup> In cross-lingual evaluations, topics-mlp benefits from its multilingual input embeddings: its accuracy is about twice as high (42.6%) as for the monolingual models. Generally, transfer works well if both training and test languages are in mBERT’s pre-training data (or closely related to a language that is): The average accuracy is 68.3% if both languages were included in mBERT’s pre-training data, 46.5% if only the target language was included, 36.1% if only the source language was included, and 33.2% if neither was included. This is consistent with results by Adelani et al. (2024), who fine-tuned four XLM-R<sub>large</sub> models on one high-resource language each and found their transfer results to be very similar to each other.

#### 4.2 Comparing transfer patterns across tasks

In Figure 2, we plot heatmaps of the transfer results for the different experiments. Darker colours correspond to higher scores. To save space, we omit the language labels (which can be found in §D.2). We compute correlations between the results, which we summarize below (details in §E.1).

**The results of the grammatical tasks are highly correlated with each other, the correlations between other task results are weaker.**<sup>7</sup>

<sup>6</sup>We further analyze the effect of writing systems in §D.4. In our correlation analysis (§5.1), (lack of) character overlap serves as a proxy for writing system differences.

<sup>7</sup>Because of the very high correlation between the parsing measures LAS and UAS (Pearson’s  $r = 0.95$ ), we focus on

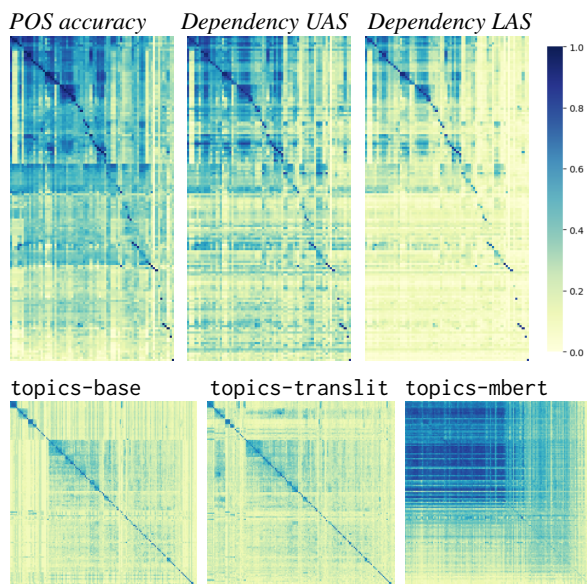


Figure 2: **Different experiments produce different transfer patterns.** NLP transfer results for all combinations of training (columns) and test languages (rows). The darker a cell, the higher the score. The three heatmaps for the grammatical tasks are sorted in the same order, and the three heatmaps with the topic classification results are sorted in the same order. The darker diagonal shows the within-language scores. Large, labelled heatmaps are in Appendix §D.2.

Even when using *exactly* the same underlying text data and models, evaluating on a related task results in transfer trends that are similar, but not entirely the same: The parsing (LAS) and POS tagging results by identical UDPipe models (except for the classification heads) are correlated with  $r = 0.86$ .

The preprocessing of the input data (e.g., transliteration) and especially the choice of input representation (mono- vs. multilingual) affects the transfer trends: The results of the two  $n$ -gram-based topic classifiers are highly correlated with each other ( $r = 0.68$ ), but not with the results of the mBERT-based set-up ( $r = 0.28$  and  $0.36$ ). Set-ups that involve multilingual representations are more highly correlated. For the languages that appear both in UD and SIB-200, the results of the grammatical tasks are most strongly correlated with those of the mBERT-based topic classification models ( $r = 0.64$  for POS tagging,  $r = 0.58$  for LAS).

## 5 Main Results and Analysis

Here, we investigate which factors correlate with overall transfer performance (§5.1). Then, we ex-

LAS in the remainder of the paper as the more extensive of the two: LAS not only measures whether the dependency arcs are correct, but also whether they were labelled correctly.

plore what this means for selecting a source language for cross-lingual transfer (§5.2).

### 5.1 How do the similarity measures correlate with the tasks and input representations?

We calculate the correlations between the similarity measures and the NLP task results. To account for differences between test sets, we calculate correlations (Pearson’s  $r$ ) between similarity measures and transfer results on a test language level. We compare the performance of different NLP systems on the same test language, but we do *not* compare the performance of a single system across multiple test sets. This decision is motivated especially by the challenges of comparing parsing performance across treebanks: Sentence length influences parsing difficulty as it determines the available search space (cf. McDonald and Nivre, 2011, Choi et al., 2015), and morphological differences between languages hamper the comparability of parsers (Nivre and Fang, 2017).

We analyze overall correlation scores by averaging across test languages. We treat correlation coefficients with  $p$ -values of at least 0.05 as 0, and exclude items where we could not calculate similarity scores due to missing linguistic information. We use language-level averages so that those languages with multiple training and test datasets do not have artificially high correlations, and languages with multiple test datasets do not have greater influence on the overall averages. However, if we instead consider treebank-level correlations, we observe that test sets that belong to the same language show very similar correlation patterns and scores (§D.3).

The correlations between task results and similarity measures vary across our experiments. Figure 3 shows the correlations, which we summarize below. Unaggregated correlations and 95% confidence intervals of the mean scores can be found in §E.3. These unaggregated correlations show that, while there are some outliers, the overall trends we report below accurately reflect the language-level trends.

We observe some **common trends across experiments**: Training dataset size does not matter much: it is the same across all topic classification experiments, and the correlations between training set size and performance in the grammatical tasks are close to zero. The phonological and phonetic similarity measures (pho, inv) also generally have low correlation scores.<sup>8</sup>

<sup>8</sup>The correlations with inv are comparatively high for the  $n$ -gram-based topic classification models. We assume that this

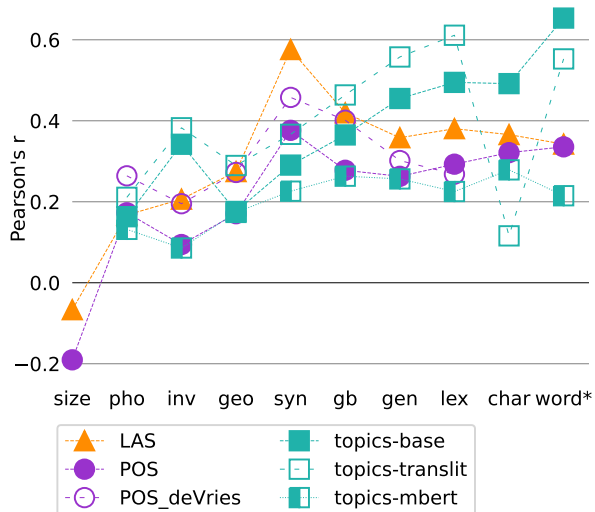


Figure 3: **Mean correlation scores between task results and similarity measures.** “Word\*” = overlap between words (wor; UD tasks) trigrams (tri; topics-base/translit), and subword tokens (swt; topics-mbert). Dotted lines are added for intelligibility.

**The strongest predictor for parsing performance is syntactic similarity (syn)** as determined by lang2vec ( $r_{avg\_syn} = 0.57$ ), **followed by the similarity of Grambank features (gb;  $r_{avg\_gb} = 0.42$ ).** These correlations are even stronger when we only consider the test languages that mBERT was pre-trained on ( $r_{avg\_syn} = 0.69$  and  $r_{avg\_gb} = 0.60$ , respectively; Appendix §E.3).

**The POS tagging outputs show correlation patterns similar to the ones for parsing, albeit weaker.** Although the correlation strengths are generally weaker for POS tagging, e.g., the strongest predictor is lang2vec’s **syntactic similarity (syn)** with  $r_{avg\_syn} = 0.37$ , **word overlap (wor)** is as good a predictor for POS accuracy as for LAS ( $r_{avg\_wor} = 0.33$  and  $r_{avg\_wor} = 0.34$ ). Again, the correlation strengths are higher when only considering test languages that were in mBERT’s pre-training data ( $r_{avg\_syn} = 0.46$ ).<sup>9</sup> The correlations we observe for the grammatical task’s transfer results partially align with prior research: Lauscher et al. (2020), Samardžić et al. (2022) and Pires et al. (2019) also find syntactic similarity to be important, and Lin et al. (2019) and Xia et al. (2020) also find word overlap to be a good predictor for

is due to inv being moderately correlated with string similarity measures like trigram overlap (§B), which is in turn strongly correlated with the topic classification results.

<sup>9</sup>The correlation strengths are also higher when we analyze de Vries et al.’s results ( $r_{avg\_syn} = 0.46$ ). We hypothesize that this is due to the smaller amount of test languages in their experiments, a higher proportion of which is in XLM-R’s pre-training data.

POS tagging. However, contrary to our results, the latter two find syntactic similarity to be relatively unimportant for both tasks. We hypothesize that such inconsistencies are due to differences in the language sets studied and other experimental differences (e.g., Lin et al. (2019) add data from the test language to the training set when possible).

**The results of the  $n$ -gram-based models are most highly correlated with measures of string similarity and lexical similarity.** This is expected based on their input representations. For topics-base, the **trigram overlap (tri)** between training and test data shows the highest correlation ( $r_{avg\_tri} = 0.65$ ), followed by **character overlap (chr;  $r_{avg\_chr} = 0.49$ )** and **lexical similarity (lex;  $r_{avg\_lex} = 0.49$ )**. Trigram overlap and lexical similarity (and the highly correlated genetic relatedness, gen) are also the strongest predictors for topics-translit ( $r_{avg\_tri} = 0.55$ ,  $r_{avg\_lex} = 0.61$ ,  $r_{avg\_gen} = 0.55$ ). However, for this model, character overlap only plays a very small role ( $r_{avg\_chr} = 0.11$ ), as all datasets use the same character inventory due to the transliteration.

**For the model using mBERT representations (topics-mbert), none of the correlations are strong.** The correlations peak at  $r_{avg\_chr} = 0.27$  for character overlap (chr). Model performance depends instead on the inclusion of the source and especially target languages in mBERT’s pre-training data (§4.1).

**The transfer results cannot be predicted by any one factor alone.** We fit a linear mixed effects model for each experiment, with the NLP score as the dependent variable and the source and target languages as random effects. The fixed effects are the similarity scores, whether the training and test data use the same writing systems, and whether the test language was included in mBERT’s pre-training data. We use R (R Core Team, 2024) and the lme4 package (Bates et al., 2015). This analysis involves a reduced set of languages, as for many language pairs in our data at least one similarity metric is not defined and we do not perform any data imputation. The analysis shows similar trends to the correlations described above. Additionally, for each experiment, most of the variables in our analyses are significant predictors of the transfer score (details in §E.2). This even sometimes applies to measures that capture similarity at the same linguistic level: e.g., both grammatical similarity measures (syn, gb) are independently among the highest predictors for parsing performance. The

	size	pho	inv	geo	syn	gb	gen	lex	chr	word*
<i>Top-1 source candidate (= most similar language)</i>										
POS deV	—	8 <sub>8</sub>	10 <sub>11</sub>	10 <sub>11</sub>	7 <sub>8</sub>	5 <sub>7</sub>	8 <sub>11</sub>	6 <sub>8</sub>	—	—
POS	29 <sub>12</sub>	15 <sub>13</sub>	14 <sub>12</sub>	15 <sub>15</sub>	10 <sub>12</sub>	12 <sub>12</sub>	9 <sub>11</sub>	10 <sub>10</sub>	15 <sub>14</sub>	12 <sub>13</sub>
LAS	21 <sub>14</sub>	13 <sub>12</sub>	13 <sub>13</sub>	13 <sub>16</sub>	7 <sub>10</sub>	10 <sub>9</sub>	8 <sub>10</sub>	8 <sub>9</sub>	16 <sub>16</sub>	11 <sub>13</sub>
UAS	27 <sub>12</sub>	16 <sub>13</sub>	15 <sub>12</sub>	16 <sub>15</sub>	8 <sub>9</sub>	13 <sub>11</sub>	9 <sub>10</sub>	10 <sub>11</sub>	17 <sub>14</sub>	14 <sub>15</sub>
top.-b.	—	17 <sub>12</sub>	17 <sub>14</sub>	13 <sub>14</sub>	15 <sub>12</sub>	14 <sub>13</sub>	9 <sub>12</sub>	9 <sub>11</sub>	13 <sub>11</sub>	4 <sub>5</sub>
top.-tr.	—	13 <sub>10</sub>	13 <sub>11</sub>	11 <sub>11</sub>	11 <sub>9</sub>	10 <sub>9</sub>	7 <sub>9</sub>	7 <sub>8</sub>	20 <sub>13</sub>	3 <sub>4</sub>
top.-m.	—	12 <sub>13</sub>	11 <sub>13</sub>	10 <sub>11</sub>	9 <sub>10</sub>	8 <sub>9</sub>	8 <sub>9</sub>	8 <sub>9</sub>	12 <sub>10</sub>	9 <sub>13</sub>
<i>Top-3 source candidates</i>										
POS deV	—	3 <sub>4</sub>	4 <sub>5</sub>	4 <sub>5</sub>	2 <sub>5</sub>	2 <sub>4</sub>	5 <sub>8</sub>	2 <sub>4</sub>	—	—
POS	25 <sub>13</sub>	7 <sub>8</sub>	7 <sub>8</sub>	5 <sub>7</sub>	3 <sub>4</sub>	4 <sub>6</sub>	5 <sub>7</sub>	4 <sub>6</sub>	7 <sub>8</sub>	5 <sub>7</sub>
LAS	18 <sub>14</sub>	8 <sub>9</sub>	7 <sub>9</sub>	5 <sub>8</sub>	3 <sub>4</sub>	4 <sub>6</sub>	4 <sub>6</sub>	3 <sub>5</sub>	8 <sub>11</sub>	6 <sub>9</sub>
UAS	24 <sub>13</sub>	8 <sub>8</sub>	7 <sub>8</sub>	6 <sub>8</sub>	3 <sub>5</sub>	5 <sub>6</sub>	5 <sub>7</sub>	5 <sub>7</sub>	9 <sub>10</sub>	7 <sub>9</sub>
top.-b.	—	10 <sub>10</sub>	9 <sub>11</sub>	5 <sub>9</sub>	6 <sub>7</sub>	6 <sub>9</sub>	5 <sub>7</sub>	3 <sub>6</sub>	8 <sub>9</sub>	2 <sub>4</sub>
top.-tr.	—	8 <sub>8</sub>	7 <sub>9</sub>	4 <sub>8</sub>	5 <sub>6</sub>	5 <sub>6</sub>	3 <sub>5</sub>	3 <sub>5</sub>	14 <sub>11</sub>	1 <sub>3</sub>
top.-m.	—	6 <sub>7</sub>	5 <sub>5</sub>	4 <sub>5</sub>	4 <sub>4</sub>	4 <sub>5</sub>	4 <sub>4</sub>	4 <sub>5</sub>	5 <sub>4</sub>	6 <sub>11</sub>

Table 3: **Mean performance loss if picking source languages based solely on a given metric** (or based on training dataset size). Performance loss in percentage points. Subscripts = standard deviations; “word\*” = wor, tri, swt; deV = de Vries et al. (2022).

finding that multiple measures contribute to predicting the transfer score confirms previous work (Lin et al., 2019; de Vries et al., 2022).

## 5.2 Practical implications

So far we have investigated correlations on a global level. In this section we investigate how these findings can be used in practice: Do the overall correlation patterns also apply when picking a source language for a given target language according to simple heuristics derived from the global patterns?

We intentionally pick very simple heuristics, as we believe them to be more realistic to how practitioners choose source language candidates in practice. Additionally, we choose them to be easily generalizable and not be constrained to the languages in our experiments.<sup>10</sup>

### 5.2.1 Should I pick the most similar language according to one similarity measure?

For each target language and each similarity measure, we calculate the difference between the best score obtained by any source language and the score obtained by the most similar language per the measure. We only consider the source language candidates for which we can compute a similarity

<sup>10</sup>For instance, while LangRank (Lin et al., 2019) is an easy-to-use tool for transfer recommendations, it is limited to the tasks and languages it was trained on and thus recommends one of 30 possible source languages for dependency parsing or one of 60 for POS tagging.

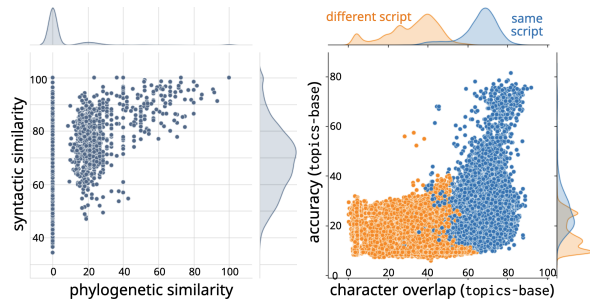


Figure 4: **Left:** Relationship between phylogenetic and syntactic similarity – unrelated or distantly related languages can be syntactically similar or dissimilar, but all closely related languages are syntactically similar. **Right:** Relationship between character overlap (between training and test sets) and the classification scores of the topics-base model – transfer between languages with low character overlap works poorly, but high overlap does not guarantee good transfer.

score for the target. For size, we select the language with the most training data. The patterns for the most strongly correlated similarity measures are similar – **choosing a source language based on the pertinent similarity measure incurs relatively small losses.** E.g., parsing performance is most strongly correlated with syntactic similarity, and picking the syntactically most similar language as the source also results in the lowest performance loss for parsing (Table 3, top). Our findings suggest choosing a syntactically similar language for POS tagging and dependency parsing, and a dataset with high trigram overlap for the  $n$ -gram-based topic classification experiments.

However, some of the less strong predictors in the global correlations are nearly as good for picking a source language, e.g., genetic and lexical similarity for parsing. We hypothesize that this is due some linguistic measures being more correlated when similarity is high.<sup>11</sup> Conversely, character overlap is a worse measure for selecting a source language than the overall correlations would suggest. This is likely due to transfer between languages with low character overlap generally working poorly, while high overlap does not guarantee good transfer (e.g., Figure 4, right).

We additionally simulate a setup where a researcher has data in multiple source language can-

<sup>11</sup>E.g., very closely related languages tend to be syntactically similar, even if the overall correlation between genetic and syntactic similarity is only moderately high due the existence of languages that are unrelated but share syntactic similarities or that are (more distantly) related and syntactically dissimilar (Figure 4, left).



	POS deV	POS	LAS	UAS	to.-b.	to.-t.	to.-m.
<i>Top-1 source candidate (= best src in another experiment)</i>							
POS deV	—	3 <sub>4</sub>	4 <sub>6</sub>	5 <sub>6</sub>	6 <sub>10</sub>	7 <sub>12</sub>	6 <sub>6</sub>
POS	6 <sub>9</sub>	—	2 <sub>5</sub>	3 <sub>5</sub>	9 <sub>11</sub>	10 <sub>12</sub>	16 <sub>14</sub>
LAS	7 <sub>9</sub>	1 <sub>2</sub>	—	1 <sub>2</sub>	11 <sub>14</sub>	10 <sub>13</sub>	18 <sub>14</sub>
UAS	8 <sub>10</sub>	3 <sub>5</sub>	1 <sub>2</sub>	—	12 <sub>15</sub>	10 <sub>12</sub>	17 <sub>14</sub>
top.-b.	12 <sub>11</sub>	10 <sub>11</sub>	11 <sub>12</sub>	13 <sub>13</sub>	—	3 <sub>7</sub>	19 <sub>15</sub>
top.-tr.	10 <sub>9</sub>	8 <sub>8</sub>	8 <sub>8</sub>	9 <sub>9</sub>	3 <sub>6</sub>	—	18 <sub>13</sub>
top.-m.	5 <sub>6</sub>	4 <sub>3</sub>	5 <sub>5</sub>	5 <sub>5</sub>	7 <sub>7</sub>	6 <sub>7</sub>	—
<i>Top-3 source candidates</i>							
POS deV	—	1 <sub>3</sub>	2 <sub>4</sub>	3 <sub>4</sub>	3 <sub>5</sub>	2 <sub>3</sub>	4 <sub>4</sub>
POS	3 <sub>6</sub>	—	1 <sub>2</sub>	1 <sub>3</sub>	4 <sub>6</sub>	4 <sub>6</sub>	7 <sub>7</sub>
LAS	3 <sub>5</sub>	0 <sub>1</sub>	—	—	5 <sub>8</sub>	5 <sub>8</sub>	9 <sub>10</sub>
UAS	4 <sub>6</sub>	1 <sub>3</sub>	0 <sub>1</sub>	—	5 <sub>8</sub>	5 <sub>7</sub>	8 <sub>9</sub>
top.-b.	6 <sub>8</sub>	5 <sub>7</sub>	5 <sub>8</sub>	5 <sub>8</sub>	—	1 <sub>3</sub>	12 <sub>11</sub>
top.-tr.	5 <sub>6</sub>	5 <sub>6</sub>	4 <sub>5</sub>	5 <sub>6</sub>	2 <sub>5</sub>	—	12 <sub>10</sub>
top.-m.	2 <sub>2</sub>	2 <sub>2</sub>	2 <sub>2</sub>	2 <sub>2</sub>	3 <sub>3</sub>	3 <sub>4</sub>	—

Table 4: **Mean performance loss if picking source languages based solely on performance on the task in the column.** Performance loss in percentage points. Subscripts = standard deviations; “word\*” = wor, tri, swt; deV = de Vries et al. (2022).

didates at their disposal and can afford training and comparing a small selection of models. We select the top three most similar languages according to each measure and take the highest transfer score produced by any of them (Table 3, bottom). The same trends still hold as when picking only one candidate. However, the overall results are much better, and the gaps between the performance losses between the different measures become smaller. **Comparing the results of multiple top source language candidates often yields better results than only considering the most similar one.**

### 5.2.2 Should I choose a source language based on another experiment?

We repeat these analyses but select source languages based on how well they served as source languages for the target language in other experiments (Table 4).

**For the tasks included in our experiments, choosing a source language based on the results for a similar task with similar input representations leads to only small losses:** POS tagging results serve as a good predictor for parsing and vice versa, but not for topic classification. Similarly, the results for some topic classification settings are good predictors for each other, but not for POS tagging and parsing. These losses are often even smaller than when selecting source languages

based on similarity measures (cf. Tables 3 and 4).

However, using other input representations weakens the predictive effect somewhat: e.g., for picking source languages for POS tagging with UDPipe, it is worse to choose based on de Vries et al.’s XLM-R results than to choose based on UDPipe’s parsing results. Topics-mbert is an especially poor predictor – this method likely suggests a fairly arbitrary mBERT language, which might or might not be similar to the target.

## 6 Conclusion

We investigated how linguistic and dataset level similarities impact cross-lingual transfer, and find that the most predictive similarity measures differ across tasks and input representations. For practitioners working on the tasks included in our study, we recommend choosing a source language based on a pertinent similarity measure, or, if results for an extensive transfer experiment involving a similar task and similar input representations are available, based on the transfer results in that experiment. Future work should investigate to what extent these patterns hold across even more languages, tasks, and NLP models.

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## Limitations

Throughout our study we have made a number of pragmatically motivated decisions. Although well motivated, these decisions come with some limitations that we address below.

**Data** Despite the fact that our study includes more languages than any prior work, we were able to include only 263 of the world’s ~7000 languages. Moreover, the usual high-resource languages are also over-represented in our work. We encourage data collection in more languages, especially those that are currently extremely low-resource or not available at all.

Despite our best efforts to mitigate any confounding effects, it is impossible to entirely avoid these. For instance, while the parallel nature of the SIB-200 datasets avoids some of the confounders related to UD (datasets containing texts from many

different sources, genres, and domains), parallel datasets can also show translation artifacts (Artetxe et al., 2020).

**Models** We investigate one model type per task. Our model choices are motivated by practical considerations. We use UDPipe in part because of its state-of-the-art status for many languages and its wide coverage of languages, making it a likely out-of-the-box tool to be used for (morpho)syntactic annotations. An important motivation for us to choose MLPs for our topic classification experiments is the lightweight architecture that allows us to quickly train and compare many models, and we show that the performance is not far off from larger, more resource-intensive models (Table 2). We include  $n$ -gram-based MLPs in order to be able to have full control over the language model training data. Despite these models not having access to word order or syntactic information of the input data (and being more affected by exact word choices than a model with (sub)word embeddings would be), we include them because of their computational cheapness, and because there are no (comparable) monolingual embeddings for all  $\sim 200$  languages in the topic classification data.

We cannot guarantee that our findings hold for other models that could be used for the task, which is an avenue for investigation in future work. We also do not consider model- or tokenization-specific biases that may have different effects based on the word order (White and Cotterell, 2021), morphology (Park et al., 2021), or writing system and orthography (Sprout and Gutkin, 2021).

**Similarity measures** Within linguistics, there is a rich literature on defining similarity measures (cf. Borin, 2013). We chose to include similarity measures that are commonly used in NLP studies, and we adapt them where necessary. However, we acknowledge that there are many other similarity measures that are interesting to investigate.

Recent work has focused on extending lang2vec (Khan et al., 2025; Amirzadeh et al., 2025) – we do not include these extensions in this paper as they were released concurrently to our work.

**Tasks** We included POS tagging, dependency parsing, and topic classification in our study. An important motivation for this choice was the availability of data in a significant number of languages for these tasks. However, many more NLP tasks exist that are important to investigate. We

echo Philippy et al. (2023): it is especially important to extend this work to more generative tasks, such as language modeling.

**Analysis** The transfer results are overall rather symmetric (i.e., the scores when training on language  $A$  and evaluating on language  $B$  tend to be similar to when training on  $B$  and testing on  $A$ ; compare the upper right and lower left triangles of the result heatmaps in Figure 2). However, these trends are not perfectly symmetrical. Transfer asymmetries have also been observed by other researchers (Malkin et al., 2022; Protasov et al., 2024). However, we do not assume that these asymmetries mean that certain languages are intrinsically well-suited as source or target languages, but rather that they reflect peculiarities of the data sets (cf. Bjerva, 2024). We encourage further research on the (a)symmetries of cross-lingual transfer patterns.

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## A Languages and Resources

Table 5 lists the versions of the datasets, models, and software we use. Lang2vec (Littell et al., 2017) contains information on syntax, phonology, and phoneme inventories from WALS (Dryer and Haspelmath, 2013), SSWL (Collins and Kayne, 2011), Ethnologue (Lewis et al., 2015), and PHOIBLE (Moran et al., 2014). SIB-200 (Adelani et al., 2024) is an annotated subset of FLORES-200 (NLLB Team et al., 2022), which in turn builds on previous versions and extensions of FLORES (Goyal et al., 2022; Guzmán et al., 2019; Doumbouya et al., 2023; AI4Bharat et al., 2023). UD-Pipe 2 (Straka, 2023) was trained on Universal Dependencies 2.12.<sup>12</sup> Its input representations include the last four layers of base-size uncased mBERT (Devlin et al., 2019). This project uses the universal romanizer software ‘uroman’ written by Ulf Hermjakob, USC Information Sciences Institute (2015-2020).

Tables 6 and 7 show the languages and datasets included in our experiments. Their geographic distribution is pictured in Figure 1.

### A.1 Excluded UD treebanks

We exclude treebanks with code-switched language data (qaf\_arabizi, qfn\_fame, qtd\_sagt, qte\_tect), without text (ar\_nyuad, en\_gumreddit, gun\_dooley, ja\_bccwj, ja\_bccwjluw), with glossed language (swl\_sslc), and where the division into training and test split changed between releases 2.12 and 2.14 (tr\_imst). We also exclude test sets with fewer than 20 sentences (kfm\_aha, nap\_rb, nyq\_aha, soj\_aha) and training sets with less than 100 sentences (bxr\_bdt, hsb\_ufal, kk\_ktb, kmr\_mg, lij\_glt, olo\_kkpp). We additionally exclude other training datasets that were not included in UDPipe 2 (ky\_ktmu, de\_lit, de\_pud). Finally, we exclude the Czech UDPipe-2 models, as they use embeddings from a pretrained Czech model rather than mBERT.

<sup>12</sup><http://hdl.handle.net/11234/1-5150>

### A.2 Excluded SIB-200 languages

We exclude three Arabic dialects whose sentences in SIB-200 are almost identical to the Modern Standard Arabic (arb\_Arab) sentences: ars\_Arab, acm\_Arab, acq\_Arab. This is a known issue for FLORES-200, from which SIB-200 is derived.<sup>13</sup>

For the transliteration experiment, we exclude Japanese (jpn\_Jpan) since uroman is not able to properly transliterate kanji as of version 1.3.1.1. We also exclude Mandarin with traditional characters (zho\_Hant) and Cantonese (yue\_Hant) since uroman crashes when trying to transliterate the corresponding datasets.

## B Correlations between similarity measures

Table 8 shows how the different dataset-independent similarity measures are correlated with each other (top) and with the dataset-dependent similarity measures (bottom).

## C Hyperparameters and Standard Deviations of Topic Classification Models

Table 9 shows which hyperparameter values we included in the grid search for the topic classification models (the  $n$ -gram model trained and evaluated on the non-transliterated data, and the model using mBERT-based representations). We used the average development set scores for models (monolingually) evaluated on the following languages for hyperparameter tuning: arb\_Arab, ayr\_Latn, eng\_Latn, eus\_Latn, grn\_Latn, kan\_Knda, kat\_Geor, kor\_Hang, quy\_Latn, vie\_Latn, zho\_Hans.

We calculate standard deviations for the final hyperparameter selection and the above-mentioned languages (evaluated monolingually on their development sets) over five random seeds. For the  $n$ -gram model, the standard deviations are between 0.0088 (ayr\_Latn) and 0.0286 (kat\_Geor), with a mean of 0.0181. For the mBERT-based model, the standard deviations are between 0.0081 (eng\_Latn) and 0.0244 (grn\_Latn), with a mean of 0.0160.

## D NLP Task Results

### D.1 Random baselines

For POS tagging and topic classification, we consider random baselines that randomly predict one

<sup>13</sup>[github.com/openlanguageata/flores/issues/8](https://github.com/openlanguageata/flores/issues/8)

Resource	Resource URL
Universal Dependencies 2.14 (Zeman et al., 2024)	hdl.handle.net/11234/1-5502
SIB-200 (Adelani et al., 2024)	huggingface.co/datasets/Davlan/sib200
Grambank v1.0.3 (Skirgård et al., 2023)	zenodo.org/records/7844558
Glottolog v5.0 (Hammarström et al., 2024)	zenodo.org/records/10804582
ASJP v17 (Wichmann et al., 2016)	asjp.clld.org
Jäger (2018a)	osf.io/cufv7
lang2vec v1.1.6 (Littell et al., 2019)	github.com/antonisa/lang2vec
UDPipe 2 (2.12) (Straka, 2023)	https://ufal.mff.cuni.cz/udpipe/2/models
mBERT base uncased (Devlin et al., 2019)	huggingface.co/google-bert/bert-base-multilingual-uncased
lme4 (Bates et al., 2015)	github.com/lme4/lme4
scikit-learn 1.5 (Pedregosa et al., 2011)	scikit-learn.org
uroman 1.3.1.1 (Hermjakob et al., 2018)	github.com/isi-nlp/uroman
GlotScript (Kargaran et al., 2024)	github.com/cisnlp/GlotScript
SciPy (Virtanen et al., 2020)	scipy.org

Table 5: Details about the data, model, and software resources used in this paper.

of the 17 POS tags (or one of the seven topics) and are thus correct 5.9 % (or 14.3 %) of the time.

For each setup, all within-language performances (the diagonals in Figure 2) are above this threshold. Thus, all models learned something about the task, regardless of the training language and could be expected to be able to transfer some of that knowledge to a well-suited test language.

For some of the train–test language combinations, we see performances that are worse than random chance. This is the case for 3.1 % of the POS tagging results, 26.6 % of topics–base’s results, 14.5 % of topics–translit’s results, and 6.8 % of the results by topics–mbert. These worse-than-random transfer results are also meaningful: a POS tagger (or parser) trained on one language might learn grammatical patterns that run counter to how another language works, or a topic classification model might be misled by superficial string overlaps between datasets that are false friends.

## D.2 Heatmaps of transfer results

We include large, labelled versions of the heatmaps in Figure 2. We order the languages in each heatmap by clustering its rows (target languages) produced using Ward’s (1963) method, and applying the same order to the source languages. Because the heatmaps take up a lot of space, they are placed at the end of the appendix.

Figure 7 shows the POS tagging accuracies for all language pairs. Figures 8 (LAS) and 9 (UAS) present the parsing scores. Figure 10 shows the topic classification accuracies for topics–base, and Figure 11 for topics–translit. Finally, Figure 12 shows the results for the mBERT-based topic

classification model.

## D.3 Robustness across datasets of the same language

In UD, many languages have multiple training and/or test datasets: there are 124 training datasets in 70 languages and 268 test datasets in 153 languages. These datasets differ in the sentences that are annotated (oftentimes, they are from different sources and text genres) and often they are annotated by different people. Treebanks in the same language use the same writing system, with the exception of Sanskrit (and Mandarin Chinese if distinguishing between traditional and simplified characters). In SIB-200, there are eight languages that have two datasets each, which differ in their writing system.

We compare how robust the transfer patterns are across datasets of the same language. For test datasets, we calculate the correlation between the different models’ scores on a pair of datasets. For training datasets, we calculate the correlation between the evaluation scores produced by each pair of models trained on datasets of the same language.

**Parsing** For parsing (LAS), most datasets of the same language produce very similar transfer patterns. Pearson’s  $r$  and Spearman’s  $\rho$  tend to produce very similar correlation numbers. Most correlations (both from the training and testing side) are above 0.9, and most correlations below that are still above 0.8.<sup>14</sup>

<sup>14</sup>For the training datasets, we see exceptions ( $r < 0.8$ ) for two of the five Latin training sets (llct & proiel:  $r = 0.79$ ) and the two German training sets (hdt & gsd:  $r = 0.78$ ). For the test datasets, the following treebank pairs show correlations with  $r < 0.8$ : two of the four Old East Slavic treebanks

ISO	Name	Family	UD	SIB-200	ISO	Name	Family	UD	SIB-200
abk	Abkhazian	Abkhaz-Adyge	ab_abnc	-	hbo	Ancient Hebrew	Afro-Asiatic	hbo_ptnk	-
abq	Abaza	Abkhaz-Adyge	abq_atb	-	heb	Hebrew	Afro-Asiatic	he_{hth, iahltwiki}	heb_Hebr
ace	Acehnese	Austronesian	-	ace_{Arab, Latn}	hin	Hindi	Indo-European	hi_{hdtb, pud}	hin_Deva
aeb (ara)	Tunisian Arabic	Afro-Asiatic	-	aeb_Arab	hit	Hittite	Indo-European	hit_hittb	-
afr	Afrikaans	Indo-European	af_afribooms	afr_Latn	hne	Chhattisgarhi	Indo-European	-	hne_Deva
aii	Assyrian Neo-Aramaic	Afro-Asiatic	aii_as	-	hrv	Croatian	Indo-European	hr_set	hrv_Latn
ajp (apc, ara)	South Levantine Arabic	Afro-Asiatic	ajp_madar	ajp_Arab	hsb	Upper Sorbian	Indo-European	hsb_ufal	-
aka	Akan	Atlantic-Congo	-	aka_Latn	hun	Hungarian	Uralic	hu_szeged	hun_Latn
akk	Akkadian	Afro-Asiatic	akk_{pisdub, riao}	-	hye	Armenian	Indo-European	hy_{armtdp, bsut}	hye_Armm
aln	Gheg Albanian	Indo-European	aln_gps	-	hyw	Western Armenian	Indo-European	hyw_armtdp	-
als	Tosk Albanian	Indo-European	sq_tsa	als_Latn	ibo	Igbo	Atlantic-Congo	-	ibo_Latn
amh	Amharic	Afro-Asiatic	am_att	amh_Ethi	ilo	Iloko	Austronesian	-	ilo_Latn
apc (ara)	North Levantine Arabic	Afro-Asiatic	-	apc_Arab	ind	Indonesian	Austronesian	id_{csui, gsd, pud}	ind_Latn
apu	Apurina	Arawakan	apu_ufpa	-	isl	Icelandic	Indo-European	is_{gc, icepahc, modern, pud}	isl_Latn
aqz	Akuntsu	Tupian	aqz_tudet	-	ita	Italian	Indo-European	it_{isdrt, markit, old, parlamint, partut, postwita, pud, twittiro, valico, vit}	ita_Latn
arb (ara)	Standard Arabic	Afro-Asiatic	ar_{padt, pud}	arb_{Arab, Latn}	jaa	Madî	Arawan	jaa_jarawara	-
arr	Karo	Tupian	arr_tudet	-	jav	Javanese	Austronesian	jav_csui	jav_Latn
ary (ara)	Moroccan Arabic	Afro-Asiatic	-	ary_Arab	jpn	Japanese	Japonic	ja_{gsd, gsdluw, pud, pudluw}	jpn_Jpan
arz (ara)	Egyptian Arabic	Afro-Asiatic	-	arz_Arab	kab	Kabyle	Afro-Asiatic	-	kab_Latn
asm	Assamese	Indo-European	-	asm_Beng	kac	Jingpho	Sino-Tibetan	-	kac_Latn
ast	Asturian	Indo-European	-	ast_Latn	kam	Kamba	Atlantic-Congo	-	kam_Latn
awa	Awadhi	Indo-European	-	awa_Deva	kan	Kannada	Dravidian	-	kan_Knda
ayr	Central Aymara	Aymaran	-	ayr_Latn	kas	Kashmiri	Indo-European	-	kas_{Arab, Deva}
azb (aze)	South Azerbaijani	Turkic	-	azb_Arab	kat	Georgian	Kartvelian	ka_glc	kat_Geor
aze	Azerbaijani	Turkic	az_tuecl	-	kaz	Kazakh	Turkic	kk_ktb	kaz_Cyrl
azj (aze)	North Azerbaijani	Turkic	-	azj_Latn	kbp	Kabiyè	Atlantic-Congo	-	kbp_Latn
azz	Highland Puebla Nahuatl	Uto-Aztecan	azz_itml	-	kea	Kabuverdianu	Indo-European	-	kea_Latn
bak	Bashkir	Turkic	-	bak_Cyrl	khh	Halh Mongolian	Mongolic-Khitani	-	khh_Cyrl
bam	Bambara	Mande	bm_crb	bam_Latn	khm	Central Khmer	Austroasiatic	-	khm_Khmr
ban	Balinese	Austronesian	-	ban_Latn	kik	Gikuyu	Atlantic-Congo	-	kik_Latn
bar	Bavarian	Indo-European	bar_maibaam	-	kin	Kinyarwanda	Atlantic-Congo	-	kin_Latn
bej	Bedawiyet	Afro-Asiatic	bej_nsc	-	kir	Kyrgyz	Turkic	ky_{ktmu, tuecl}	kir_Cyrl
bel	Belarusian	Indo-European	be_hse	bel_Cyrl	kmb	Kimbundu	Atlantic-Congo	-	kmb_Latn
bem	Bemba	Atlantic-Congo	-	bem_Latn	kmr	Kurmanji	Indo-European	kmr_mg	kmr_Latn
ben	Bengali	Indo-European	bn_bru	ben_Beng	knc	Central Kanuri	Saharan	-	knc_{Arab, Latn}
bho	Bhojpuri	Indo-European	bho_bhtb	bho_Deva	koi	Komi-Permyak	Uralic	koi_uh	-
bjn	Banjar	Austronesian	-	bjn_{Arab, Latn}	kon	Kongo	Atlantic-Congo	-	kon_Latn
bod	Tibetan	Sino-Tibetan	bod_tibt	-	kor	Korean	Koreanic	ko_{gsd, kaist, pud}	kor_Hang
bor	Bororo	Bororoan	bor_bdt	-	kpz	Komi-Zyrian	Uralic	kpz_{ikdp, lattice}	-
bos	Bosnian	Indo-European	-	bos_Latn	krl	Karelian	Uralic	krl_kkpp	-
bre	Breton	Indo-European	br_keb	-	lao	Lao	Tai-Kadai	-	lao_Laoo
bug	Buginese	Austronesian	-	bug_Latn	lat	Latin	Indo-European	la_{cirsce, ith, llct, perseus, proiel, udante}	-
bul	Bulgarian	Indo-European	bg_btb	bul_Cyrl	lij	Ligurian	Indo-European	lij_glt	lij_Latn
bxr (bua)	Russia Buriat	Mongolic-Khitani	bxr_bdt	-	lim	Limburgan	Indo-European	-	lim_Latn
cat	Catalan	Indo-European	ca_ancora	cat_Latn	lin	Lingala	Atlantic-Congo	-	lin_Latn
ceb	Cebuano	Austronesian	ceb_gja	ceb_Latn	lit	Lithuanian	Indo-European	lt_{alksnis, hse}	lit_Latn
ces	Czech	Indo-European	cs_{cac, cltt, fctree, pdt, poetry, pud}	ces_Latn	lmo	Lombard	Indo-European	-	lmo_Latn
chu	Old Church Slavonic	Indo-European	cu_proiel	-	ltg	Latgalian	Indo-European	ltg_cairo	ltg_Latn
cjk	Chokwe	Atlantic-Congo	-	cjk_Latn	ltz	Luxembourgish	Indo-European	lb_luxbank	ltz_Latn
ckb	Central Kurdish	Indo-European	-	ckb_Arab	lua	Luba-Lulua	Atlantic-Congo	-	lua_Latn
ckt	Chukot	Ch.-Kamchatkan	ckt_hse	-	lug	Ganda	Atlantic-Congo	-	lug_Latn
cmn (zho)	Mandarin Chinese	Sino-Tibetan	zh_{beginner, cfl, gsd, gsdimp, hk, patentchar, pud}	zho_{Hans, Hant}	luo	Dholuo	Nilotic	-	luo_Latn
cop	Coptic	Afro-Asiatic	cop_scriptorium	-	lus	Lushai	Sino-Tibetan	-	lus_Latn
cpq	Cappadocian Greek	Indo-European	cpq_tuecl	-	lv	Standard Latvian	Indo-European	lv_{cairo, lvtb}	lv_Latn
crh	Crimean Tatar	Turkic	-	crh_Latn	lzh	Classical Chinese	Sino-Tibetan	lzh_{kyoto, tuecl}	-
cym	Welsh	Indo-European	cy_ccg	cym_Latn	mag	Magahi	Indo-European	-	mag_Deva
dan	Danish	Indo-European	da_ddt	dan_Latn	dik	Dinka	Indo-European	-	dik_Deva
deu	German	Indo-European	de_{gsd, hdt, lit, pud}	deu_Latn	dik_Latn	Dinka	Indo-European	-	dik_Deva
dik	Southwestern Dinka	Nilotic	-	dik_Latn	dya	Dyula	Mande	-	dya_Mymr
dyu	Dyula	Mande	-	dya_Latn	dzo	Dzongkha	Sino-Tibetan	-	dzo_Deva
dzo	Dzongkha	Sino-Tibetan	-	dzo_Tibt	egy_uaen	Ancient Egyptian	Afro-Asiatic	-	egy_Deva
egy	Ancient Egyptian	Afro-Asiatic	egy_uaen	-	est_Latn	Standard Estonian	Uralic	et_{edt, ewt}	est_Latn
ekk (est)	Standard Estonian	Uralic	et_{edt, ewt}	est_Latn	ell_Grek	Modern Greek	Indo-European	el_{gdt, gud}	ell_Grek
ell	Modern Greek	Indo-European	el_{gdt, gud}	ell_Grek	eme_tudet	Emerillon	Tupian	-	eme_Latn
eme	Emerillon	Tupian	eme_tudet	-	eng_Latn	English	Indo-European	en_{atis, ctetec, eslspek, ewt, gentle, gum, lines, partut, pronouns, pud}	eng_Latn
eng	English	Indo-European	en_{atis, ctetec, eslspek, ewt, gentle, gum, lines, partut, pronouns, pud}	eng_Latn	epo_Latn	Esperanto	(Constructed)	-	epo_Latn
epo	Esperanto	(Constructed)	-	epo_Latn	ess_sli	Central Siberian Yupik	Eskimo-Aleut	-	ess_sli
ess	Central Siberian Yupik	Eskimo-Aleut	ess_sli	-	eu_bdt	Basque	(Isolate)	-	eu_bdt
eus	Basque	(Isolate)	eu_bdt	-	eus_Latn	Ewe	Atlantic-Congo	-	eus_Latn
ewe	Ewe	Atlantic-Congo	-	eus_Latn	ewe_Latn	Erzya	Uralic	myv_tudet	ewe_Latn
fao	Farøese	Indo-European	fo_{farpahc, ofi}	fao_Latn	myv	Erzya	Uralic	myv_jr	fao_Latn
fij	Fijian	Austronesian	-	fij_Latn	nds	Low Saxon	Indo-European	nds_lsdsc	fij_Latn
fin	Finnish	Uralic	fi_{fth, ood, pud, tdt}	fin_Latn	nhi	W. S. Puebla Nahuatl	Uto-Aztecan	nhi_itml	fin_Latn
fon	Fon	Atlantic-Congo	-	fon_Latn	nld	Dutch	Indo-European	nld_{alpino, lassysmall}	fon_Latn
fra	French	Indo-European	fr_{fqb, gsd, parisstories, partut, pud, rhapsodie, sequoia}	fra_Latn	nno	Norwegian Nynorsk	Indo-European	no_nynorsk	fra_Latn
frm	Middle French	Indo-European	frm_profiterole	-	nob	Norwegian Bokmål	Indo-European	no_bokmaal	frm_Latn
fro	Old French	Indo-European	fro_profiterole	-	npi	Nepali	Indo-European	-	npi_Deva
fur	Friulian	Indo-European	-	fur_Latn	nqo	N'Ko	(Constructed)	-	nqo_Nkoo
fuv	Nigerian Fulfulde	Atlantic-Congo	-	fuv_Latn	nso	Northern Sotho	Atlantic-Congo	-	nso_Latn
gaz	West Central Oromo	Afro-Asiatic	-	gaz_Latn	nus	Nuer	Nilotic	-	nus_Latn
gla	Gaelic	Indo-European	gd_arcoag	gla_Latn	nya	Chewa	Atlantic-Congo	-	nya_Latn
gle	Irish	Indo-European	ga_{cadhan, idt, twittirish}	gle_Latn	oci	Occitan	Indo-European	-	oci_Latn
glg	Galician	Indo-European	gl_{ctg, pud, treegal}	glg_Latn	olo	Livvi	Uralic	olo_kkpp	glg_Latn
glv	Manx	Indo-European	gv_cadhan	-	orv	Old East Slavic	Indo-European	orv_{birchbark, rnc, ruthenian, torot}	glv_Latn
got	Gothic	Indo-European	got_proiel	-	ory	Odia	Indo-European	-	ory_Orya
grc	Ancient Greek	Indo-European	grc_{perseus, proiel, ptnk}	-	ota	Ottoman Turkish	Turkic	ota_{boun, dudu}	grc_Latn
grn	Guarani	Tupian	gn_oldtudet	grn_Latn	otk	Old Turkish	Turkic	otk_clausal	grn_Latn
grs	Swiss German	Indo-European	grs_uzh	-	pad	Paumari	Arawan	pad_tuecl	grs_Latn
gub	Guajará	Tupian	gub_tudet	-	pag	Pangasinan	Austronesian	-	pag_Latn
guj	Gujarati	Indo-European	guj_gujb	guj_Gujr	pan	Panjabi	Indo-European	-	pan_Guru
gun	Mbyá Guaraní	Tupian	gun_thomas	-	pap	Papiamentu	Indo-European	-	pap_Latn
hat	Haitian	Indo-European	ht_autogramm	hat_Latn	pbt	Southern Pashto	Indo-European	-	pbt_Arab
hau	Hausa	Afro-Asiatic	ha_{northernautogramm, southernautogramm}	hau_Latn	pcm	Nigerian Pidgin	Indo-European	pcm_nsc	hau_Latn
					pes (fas)	Iranian Persian	Indo-European	fa_{perdt, seraji}	pes_Arab

Table 6: Languages and datasets used in our experiments. Continued and explained in next table.



ISO	Name	Family	UD	SIB-200	ISO	Name	Family	UD	SIB-200
plt	Plateau Malagasy	Austronesian	–	plt_Latn	taq	Tamasheq	Afro-Asiatic	–	taq_(Latn, TIng)
pol	Polish	Indo-European	pl_{lfg, pdb, pud}	pol_Latn	tat	Tatar	Turkic	tt_nmctt	tat_Cyrl
por	Portuguese	Indo-European	pt_{bosque, cintil, gsd, petrogold, portinari, pud}	por_Latn	tel	Telugu	Dravidian	te_mtg	tel_Telu
prs (fas)	Dari	Indo-European	–	prs_Arab	tgk	Tajik	Indo-European	–	tgk_Cyrl
qpm (bul)	Pomak	Indo-European	qpm_philotis	–	tgl	Tagalog	Austronesian	tl_{trg, ugnayan}	tgl_Latn
quc	K'iche'	Mayan	quc_iu	–	tha	Thai	Tai-Kadai	th_pud	tha_Thai
quy	Ayacucho Quechua	Quechuan	–	quy_Latn	tir	Tigrinya	Afro-Asiatic	–	tir_Ethi
ron	Romanian	Indo-European	ro_{art, nonstandard, rrt, simonero, tuecl}	ron_Latn	tpi	Tok Pisin	Indo-European	–	tpi_Latn
run	Rundi	Atlantic-Congo	–	run_Latn	tpn	Tupinambá	Tupian	tpn_tudet	–
rus	Russian	Indo-European	ru_{gsd, poetry, pud, syntagrus, taiga}	rus_Cyrl	tsn	Tswana	Atlantic-Congo	tn_popapolelo	tsn_Latn
sag	Sango	Atlantic-Congo	–	sag_Latn	tso	Tsonga	Atlantic-Congo	–	tso_Latn
sah	Yakut	Turkic	sah_yktdt	–	tuk	Turkmen	Turkic	–	tuk_Latn
san	Sanskrit	Indo-European	sa_{ufal, vedic}	san_Deva	tum	Tumbuka	Atlantic-Congo	–	tum_Latn
sat	Santali	Austroasiatic	–	sat_Olck	tur	Turkish	Turkic	tr_{atis, boun, framenet, gb, kenet, penn, pud, tourism}	tur_Latn
say	Saya	Afro-Asiatic	say_autogramm	–	twi	Twi	Atlantic-Congo	–	twi_Latn
scn	Sicilian	Indo-European	–	scn_Latn	tzm	C. Atlas Tamazight	Afro-Asiatic	–	tzm_TIng
sga	Old Irish	Indo-European	sga_{dipsgg, dipwbg}	–	uig	Uyghur	Turkic	ug_udt	uig_Arab
shn	Shan	Tai-Kadai	–	shn_Mymr	ukr	Ukrainian	Indo-European	uk_iu	ukr_Cyrl
sin	Sinhala	Indo-European	si_stb	sin_Sinh	umb	Umbundu	Atlantic-Congo	–	umb_Latn
sjo	Xibe	Tungusic	sjo_xdt	–	urb	Kaapor	Tupian	urb_tudet	–
slk	Slovak	Indo-European	sk_snk	slk_Latn	urd	Urdu	Indo-European	ur_udtb	urd_Arab
slv	Slovenian	Indo-European	sl_{ssj, sst}	slv_Latn	uzn	Northern Uzbek	Turkic	–	uzn_Latn
sme	Northern Sami	Uralic	sme_giella	–	vec	Venetian	Indo-European	–	vec_Latn
smo	Samoan	Austronesian	–	smo_Latn	vep	Veps	Uralic	vep_vwt	–
sms	Skolt Sami	Uralic	sms_giellagas	–	vie	Vietnamese	Austroasiatic	vi_{tuecl, vtB}	vie_Latn
sna	Shona	Atlantic-Congo	–	sna_Latn	war	Waray	Austronesian	–	war_Latn
snd	Sindhi	Indo-European	–	snd_Arab	wbp	Warlpiri	Pama-Nyungan	wbp_ufal	–
som	Somali	Afro-Asiatic	–	som_Latn	wol	Wolof	Atlantic-Congo	wo_wtb	wol_Latn
sot	Southern Sotho	Atlantic-Congo	–	sot_Latn	xav	Xavante	Nuclear-Macro-Je	xav_xdt	–
spa	Castilian	Indo-European	es_{ancora, coser, gsd, pud}	spa_Latn	xcl	Classical Armenian	Indo-European	xcl_caval	–
srd	Sardinian	Indo-European	–	srd_Latn	xho	Xhosa	Atlantic-Congo	–	xho_Latn
srp	Serbian	Indo-European	sr_set	srp_Cyrl	xnr	Kangri	Indo-European	xnr_kdtb	–
ssw	Swati	Atlantic-Congo	–	ssw_Latn	xum	Umbrian	Indo-European	xum_ikuvina	–
sun	Sundanese	Austronesian	–	sun_Latn	ydd (yid)	Eastern Yiddish	Indo-European	–	ydd_Hebr
swe	Swedish	Indo-European	sv_{lines, pud, talbanken}	swe_Latn	yor	Yoruba	Atlantic-Congo	yo_ytb	yor_Latn
swh	Swahili	Atlantic-Congo	–	swh_Latn	yrl	Nhengatu	Tupian	yrl_complin	–
szl	Silesian	Indo-European	–	szl_Latn	yue	Yue Chinese	Sino-Tibetan	yue_hk	yue_Hant
tam	Tamil	Dravidian	ta_{mwtt, ttb}	tam_Tam1	zsm	(zlm, msa) Std. Malay	Austronesian	–	zsm_Latn
					zul	Zulu	Atlantic-Congo	–	zul_Latn

Table 7: **Languages and datasets used in our experiments, continued.** ISO 639-3 codes in parentheses denote macrolanguage codes. Language family information is sourced from Glottolog (Hammarström et al., 2024).

	gb	syn	pho	inv	lex	gen	geo
syn	<b>0.61</b>						
pho	0.28	0.30					
inv	0.22	0.16	0.30				
lex	<b>0.57</b>	<b>0.45</b>	0.30	0.29			
gen	<b>0.56</b>	<b>0.47</b>	0.31	0.25	<b>0.87</b>		
geo	<b>0.42</b>	<b>0.35</b>	<b>0.39</b>	0.10	<b>0.36</b>	<b>0.40</b>	
wor (UD)	0.44	0.35	0.24	0.39	<b>0.59</b>	<b>0.47</b>	0.17
swt (topics)	0.30	0.28	0.15	0.42	0.39	0.38	0.10
tri (topics)	0.16	0.24	0.12	0.37	0.24	0.24	-0.01
tri (top. tr.)	0.29	0.25	0.20	0.38	0.33	0.34	0.05
chr (UD)	0.26	<b>0.38</b>	<b>0.35</b>	0.28	0.29	0.28	<b>0.23</b>
chr (topics)	0.10	0.17	0.12	0.27	0.14	0.16	–
chr (top. tr.)	0.06	0.10	-0.03	0.16	0.04	0.06	–

Table 8: **Correlations (Pearson’s  $r$ ) between linguistic similarity measures (top) and between dataset similarity and linguistic similarity measures (bottom).** Correlations with  $p$ -values  $\geq 0.05$  are replaced with —. Correlations between linguistic similarity measures are for the full set of languages included in our study. Key: gb=Grambank similarity, syn=syntactic similarity (lang2vec), pho=phonological similarity, inv=similarity of phoneme inventories, lex=lexical similarity, gen=phylogenetic relatedness, geo=geographic proximity, wor=word overlap, tri=character trigram overlap, chr=character overlap, top. tr.=transliterated topic classification data.

Parameter	MLP ( $n$ -grams)	MLP (mBERT)
<i>N</i> -grams		
Min. length	<b>1</b>	–
Max. length	2, 3, <b>4</b>	–
Type	char, <b>char_wb</b>	–
Max. features	5000, <b>unlimited</b>	–
Max. epochs	5, 10, <b>20</b> , 200, 300, 400	5, 10, <b>20</b> , 30, 50, 200
Learning rate	0.0005, <b>0.001</b> , 0.002	0.0005, <b>0.001</b> , 0.002
Optimizer	<b>adam</b>	<b>adam</b>

Table 9: **Hyperparameters used in the grid search for the topic classification models.** Values in **bold** are the ones used in the final models.

**POS tagging** Most treebank pairs of the same language also show very similar transfer patterns. Again, most correlations are close to 1.<sup>15</sup>

(birchbark & rnc:  $r = 0.79$ ), several of the seven Mandarin Chinese treebanks (hk & patentchar:  $r = 0.63$ , beginner & patentchar:  $r = 0.63$ , beginner & gsd:  $r = 0.69$ , cfl & patentchar:  $r = 0.71$ , gsdsimp & hk:  $r = 0.72$ , beginner & gsdsimp:  $r = 0.72$ , gsd & hk:  $r = 0.72$ , cfl & gsd:  $r = 0.76$ , beginner & pud:  $r = 0.79$ , cfl & gsdsimp:  $r = 0.79$ ), the two Akkadian treebanks (pisandub & riao:  $r = 0.79$ ), the two Tamil treebanks (mwtt & ttb:  $r = 0.76$ ), and the two Sanskrit treebanks (ufal & vedic:  $r = 0.24$ ).

<sup>15</sup>For the training treebanks, we see correlations ( $r$ ) below 0.8 only for the following pairs: the two German training

**topics-base** The writing system matters, and datasets in different writing systems (but the same language) show different transfer patterns. The two Mandarin Chinese datasets (traditional vs. simplified characters) show similar patterns (correlation as training sets:  $r = 0.96$ , as test sets:  $r = 0.96$ ). For the test datasets, nearly all other correlations are insignificant, except for the Arabic and Devanagari Kashmiri datasets ( $r = 0.43$ ). For the training datasets, all correlations other than for the Mandarin datasets are either close to zero or negative. The strongest negative correlation is for Arabic- vs. Latin-script Modern Standard Arabic ( $r = -0.58$ ).

**topics-translit** For the transliterated version, all correlations are positive and/or close to zero, but not very high (the highest correlations are for the transliterated versions of the Tifinagh and Latin-script Tamasheq datasets: test  $r = 0.63$ , train  $r = 0.34$ ). Note that we only have one transliterated version of the Mandarin Chinese datasets, as the transliteration tool did not work for the traditional script version. We hypothesize that the correlations for the transliterated data are fairly low since they do not necessarily have many  $n$ -grams in common. For instance, many of the languages with two datasets have one Arabic-script version and one Latin-script version. The latter contains vowels, while the automatically produced transliteration of the former only includes consonants.

**topics-mbert** For topics-*mbert*, the correlations tend to be higher than for the  $n$ -gram-based models. For the training data, all correlations are above 0.6 except for Achinese (which shows no significant correlation). For the test data, the results are more split, with mostly positive correlations, but also some negative ones (Minangkabau,  $-0.24$ ; Banjar,  $r = -0.32$ ). We hypothesize that the test data shows less coherent correlation patterns due to the inclusion of a language (in a given script) in mBERT’s test data having a stronger effect on

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sets (hdt & gsd:  $r = 0.75$ ), the two Persian ones (perft & seraji:  $r = 0.73$ ), and the two Korean ones (gsd & kaist:  $r = 0.72$ ). For the test datasets this applies to some of the six Latin treebanks (circse & udante:  $r = 0.79$ , circse & ittb:  $r = 0.79$ ), several of the eight Turkish datasets (atis & tourism:  $r = 0.55$ , pud & tourism:  $r = 0.73$ , penn & tourism:  $r = 0.74$ , boun & tourism:  $r = 0.74$ , gb & tourism:  $r = 0.78$ , kenet & tourism:  $r = 0.79$ ), several of the seven Mandarin Chinese treebanks (hk & patentchar:  $r = 0.77$ , beginner & patentchar:  $r = 0.78$ , patentchar & pud:  $r = 0.79$ , cfl & patentchar:  $r = 0.79$ , gsd & patentchar:  $r = 0.79$ ), two of the four Old East Slavic treebanks (birchbark & rnc:  $r = 0.75$ ), the two Akkadian treebanks (pisandub & riao:  $r = 0.75$ ), and both Sanskrit treebanks (ufal & vedic:  $r = 0.57$ ).

the classification results than the inclusion of the training dataset’s language.

#### D.4 Effect of writing system

We compare transfer between languages using the same writing system to transfer across writing systems. For UD, we use GlotScript (Kargaran et al., 2024) to determine the scripts; for SIB-200, writing system information is included as metadata.

**Transfer between datasets with the same writing systems generally works better than between different scripts, however this is in part due to the language selection rather than the scripts themselves.** Two-sample Kolmogorov–Smirnov tests indicate that the results within vs. across scripts come from different distributions ( $p$ -values all  $< 0.0001$ ; statistics: 0.51 for topics-base, 0.26 for topics-*mbert*, 0.16 for POS accuracy, 0.18 for LAS). However, the results of topics-*translit* for datasets that were in the same vs. different scripts before transliteration also come from different distributions ( $p < 0.0001$ , statistic: 0.37), indicating that at least for SIB-200, the combinations of languages usually associated with the scripts alone already make an important difference.

Nonetheless, writing systems still play a role, especially for the  $n$ -gram-based models. Although topics-base and topics-*translit* achieve the same within-language accuracy (Table 2), topics-*translit* performs slightly better cross-lingually. Its within-dataset performance is slightly lower than for topics-base (69.4% vs. 70.3%), likely due to some language-specific information being lost when diacritics are removed. This would be compensated in the within-language performance by improved transfer between datasets of languages that originally had different scripts.

##### D.4.1 Effects of transliteration

**Transliterated UD treebanks** Thirty-five UD test treebanks (in 25 languages) come with token-level Latin transliterations. We compare performance on the original data with performance on transliterated data. Figure 5 shows the performance differences of the POS taggers and parsers when evaluated on transliterated instead of original-script data. Performance is worse on most transliterated test treebanks, even when the models were trained on Latin-script treebanks.<sup>16</sup> This is in line

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<sup>16</sup>The exceptions are three languages whose scripts appear neither in any training treebanks nor in mBERT’s pretraining data (Amharic, Xibe, Sinhala), and one language that is usually

with results from Pires et al. (2019), who observe that mBERT performs worse on transliterated than original-script data.

**Topic classification** We compare the results of topics-base and topics-translit. Figure 6 shows the topic classification performance difference between the  $n$ -gram model trained and evaluated on the original data and the one trained and evaluated on transliterated data. For topics-translit, transfer between many original Cyrillic and Latin-script language pairs is improved.

Eight of the languages in SIB-200 come in two script versions each. The writing systems are completely distinct, except for Mandarin Chinese, which has versions in traditional and simplified characters. For topics-base, transfer between the two scripts of a language is unsurprisingly always much lower than the performance on the same script (with accuracies between 8.3% and 25.9% for in-language cross-script transfer – excluding the Mandarin Chinese entries, for which cross-script accuracy is up to 64.7% – vs. within-language, within-script accuracies between 60.8% and 75.9% for the same languages). Although transfer between the transliterated versions of the datasets works better (between 14.2% and 50.5%), the accuracies are still much lower than the within-language, within-original-script accuracies (between 58.3% and 74.0%). This is likely due to different transliteration conventions for different writing systems (and due to missing vowels in the transliterated versions of abjads).

The patterns are also similar for topics-mbert, with within-language, cross-script scores between 8.3% and 45.6%, compared to within-language, within-script accuracies between 42.2% and 79.9%.

## E Correlations

### E.1 Correlations between task results

Table 10 shows the correlations between task results. It is described in §4.2. The correlations across different task types only involve the 55 training and 84 test languages that appear both in UD and in SIB-200 (54 and 82 in the comparisons with the transliterated SIB-200 data).

### E.2 Mixed effects models

As described at the end of §5.1, we fit one linear mixed effects model per experiment. We model the

written in Arabic, but unrelated to other languages using this writing system (Uyghur).

	POS	LAS	UAS	topics	
				base	trans
LAS	0.86				
UAS	0.83	0.95			
topics-base	0.39	0.43	0.40		
topics-translit	0.40	0.53	0.48	0.68	
topics-mbert	0.64	0.58	0.56	0.28	0.36

Table 10: **Correlations between task results** (Pearson’s  $r$ , all  $p$ -values are below 0.0001). Where possible, correlations are on a dataset level, otherwise on a language level.

NLP results (POS accuracy, parsing scores, topic classification accuracy) as the dependent variable, and the training and test languages as random effects. The fixed effects are the similarity measures, as well as binary variables (dummy-coded) indicating whether the training and test datasets have the same writing system and whether the test language is among mBERT’s pretraining languages. Because the models can only be fit for entries where no data points are missing (i.e., geo, lex, syn, pho, inv, and gb are all defined for the language pair at hand), the number of language pairs included in each mixed effects analysis is much smaller than for the correlations calculated independently per effect in §5.1.

Collinearity was observed between several fixed effects in all models (with correlation coefficients between  $-0.769$  and  $-0.819$  for phylogenetic relatedness and lexical similarity, between  $-0.442$  and  $-0.496$  for character overlap and sharing the same writing system, and between  $-0.447$  and  $-0.509$  for gb and syn). We mark them as such in Table 11, which shows the estimates and their significance values. We report the significance values based on model comparison (i.e., by comparing the full model and a model with one predictor taken out) and thus significance values are robust to collinearity.

The values for these related effects should be interpreted with these correlations in mind, as this can impact the estimates for these variables.

### E.3 Correlations between NLP results and similarity measures

Tables 12 and 13 show the correlations between POS/parsing scores and the similarity measures for each test language. Tables 14, 15, and 16 show the same for the topic classification experiments. Because these tables take up a lot of space, they are placed at the very end of the appendix.

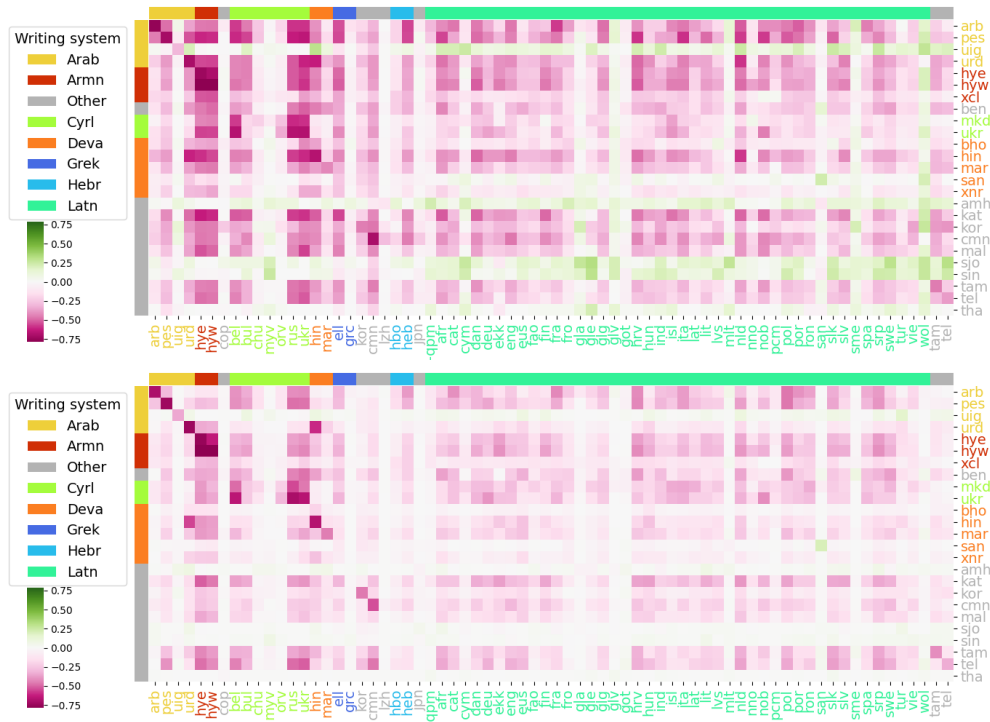


Figure 5: Differences between the performance on the original test treebanks and their transliterated counterparts for POS tagging (top) and parsing (LAS, bottom). Rows are for test sets, columns for training sets. Pink cells mark configurations where scores are better on the original data; green where scores are better on the transliterated treebank. Original writing systems are colour-coded. Writing systems in grey appear only for one language.

Fixed effect	Est.	POS		LAS		UAS			topics-base			topics-translit			topics-mbert		
		Est.	$\chi^2$ p	Est.	$\chi^2$ p	Est.	$\chi^2$ p	Est.	$\chi^2$ p	Est.	$\chi^2$ p	Est.	$\chi^2$ p	Est.	$\chi^2$ p		
(Intercept)	-0.30	-4.09		-0.60	-9.75	-0.41	-5.58	0.05	0.91	-0.12	-2.28	-0.13	-1.45				
corr {	gb	0.15	10.92 ***	0.27	43.08 ***	0.27	30.25 ***	-0.06	2.84 .	0.04	1.42	0.07	1.51				
	syn	0.21	67.5 ***	0.53	503.28 ***	0.56	415.29 ***	0.00	0.00	-0.01	0.26	0.07	6.38 *				
	pho	-0.07	4.19 *	-0.03	0.77	0.02	2.28	0.02	0.87	-0.02	1.07	0.14	12.12 ***				
inv	0.30	20.17 ***	0.07	1.14	0.00	0	-0.01	0.01	0.12	6.04 *	0.10	1.04					
corr {	lex	-0.07	3.66 .	-0.13	16.71 ***	-0.19	23.58 ***	0.07	3.65 .	0.24	64.27 ***	-0.16	7.64 **				
	gen	0.28	95.21 ***	0.36	194.29 ***	0.32	110.28 ***	0.19	54.13 ***	0.06	5.65 *	0.21	21.86 ***				
	geo	0.15	22.92 ***	0.18	39.61 ***	0.19	32.08 ***	0.04	54.13 ***	0.07	16.15 ***	0.06	3.31 .				
wor/tri/swt	-0.03	0.14	0.36	21.00 ***	0.05	0.26	0.52	125.83 ***	0.75	477.22 ***	-0.12	3.00 .					
corr {	chr	0.01	0.273	-0.07	24.14 ***	-0.04	4.90 *	0.25	136.93 ***	-0.08	2.83 .	0.26	7.37 ***				
	same_scriptTrue	0.13	311.95 ***	0.06	67.62 ***	0.10	142.68 ***	-0.03	9.16 **			-0.04	-3.17 ***				
	mbert_testTrue	0.22	20.81 ***	0.12	16.75 ***	0.14	13.98 ***					0.26	8.76 ***				
size	0.00	26.34 ***	0.00	4.90 *	0.00	6.52 *											
# Train langs	19		19		19		42		40		42		42				
# Test langs	31		31		31		42		40		42		42				

Table 11: Linear mixed effects model results for each experiment.  $P$ -values are based on model comparison: \*\*\* =  $< 0.001$ , \*\* =  $< 0.01$ , \* =  $< 0.05$ , . =  $< 0.1$ . Entries with  $p$ -values of  $\geq 0.05$  are in grey. The last two rows show the number of training and test languages included in the analysis (i.e., the language pairs for which no fixed effects had missing information). “Corr” indicates pairs of strongly correlated fixed effects (see text, §E.2). “Same\_script” is True iff the training and test datasets use the same writing system; “mbert\_test” is True iff the test language is one of mBERT’s pretraining languages.

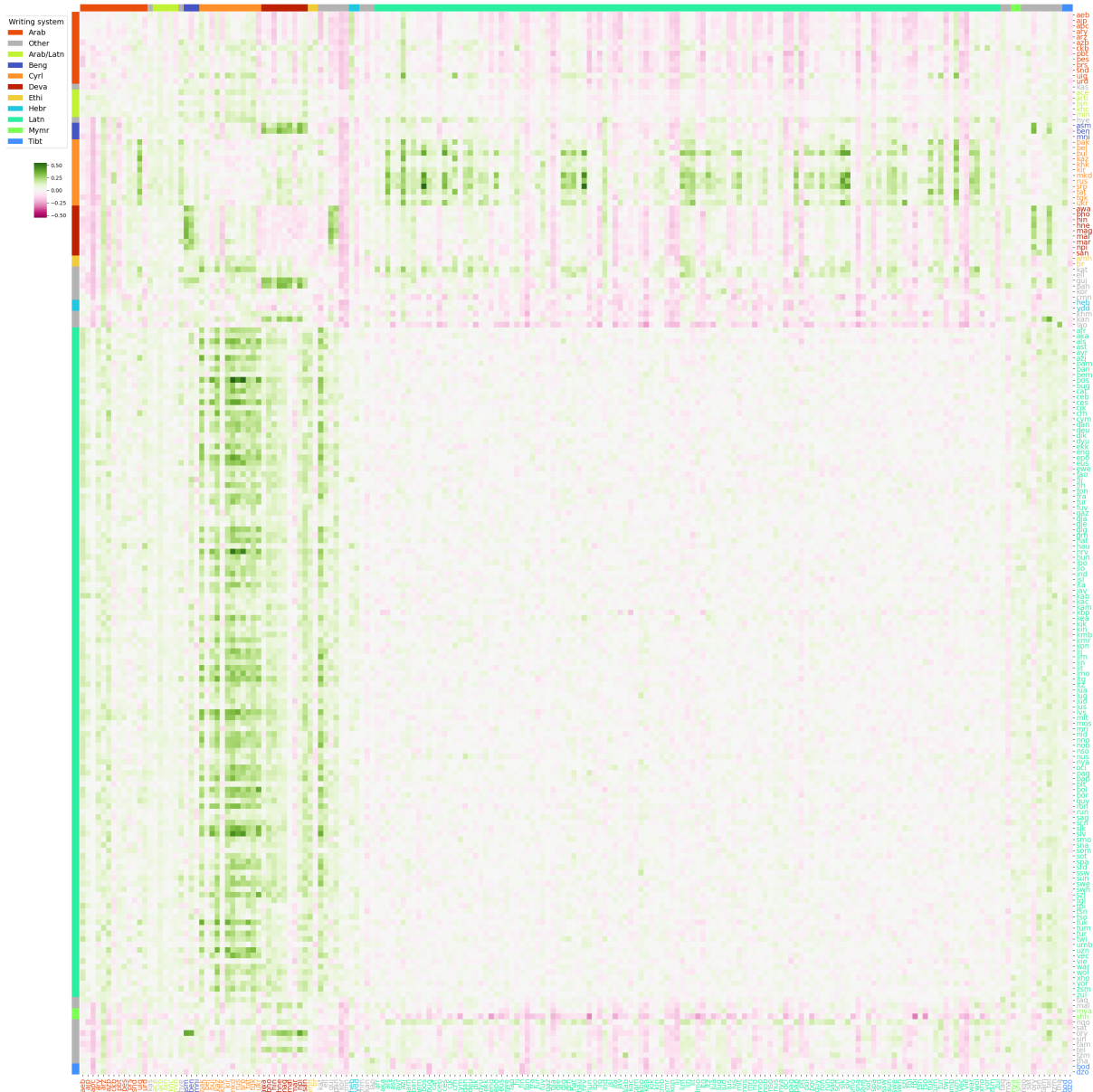


Figure 6: **Differences between the n-gram-based topic classification performance on the original test languages and their transliterated counterparts.** Rows are for test sets, columns for training sets. Pink cells mark configurations where scores are better on the original data; green where scores are better on the transliterated data. Original writing systems are colour-coded. Writing systems in grey appear only in one language.

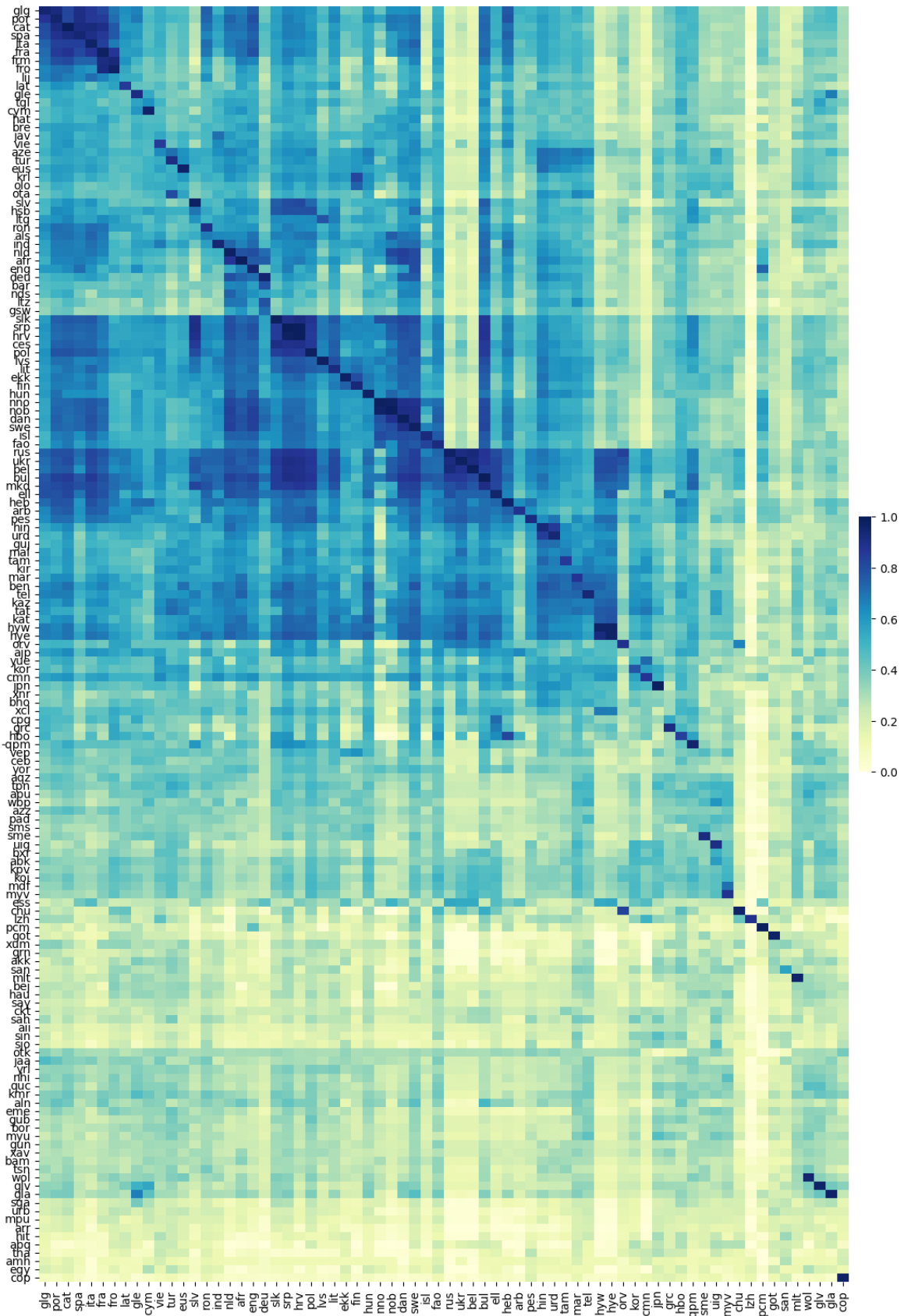


Figure 7: **POS tagging accuracy scores** for all combinations of source (columns) and target languages (rows), ordered by target language clusters (Ward's method). The darker a cell, the better the score.

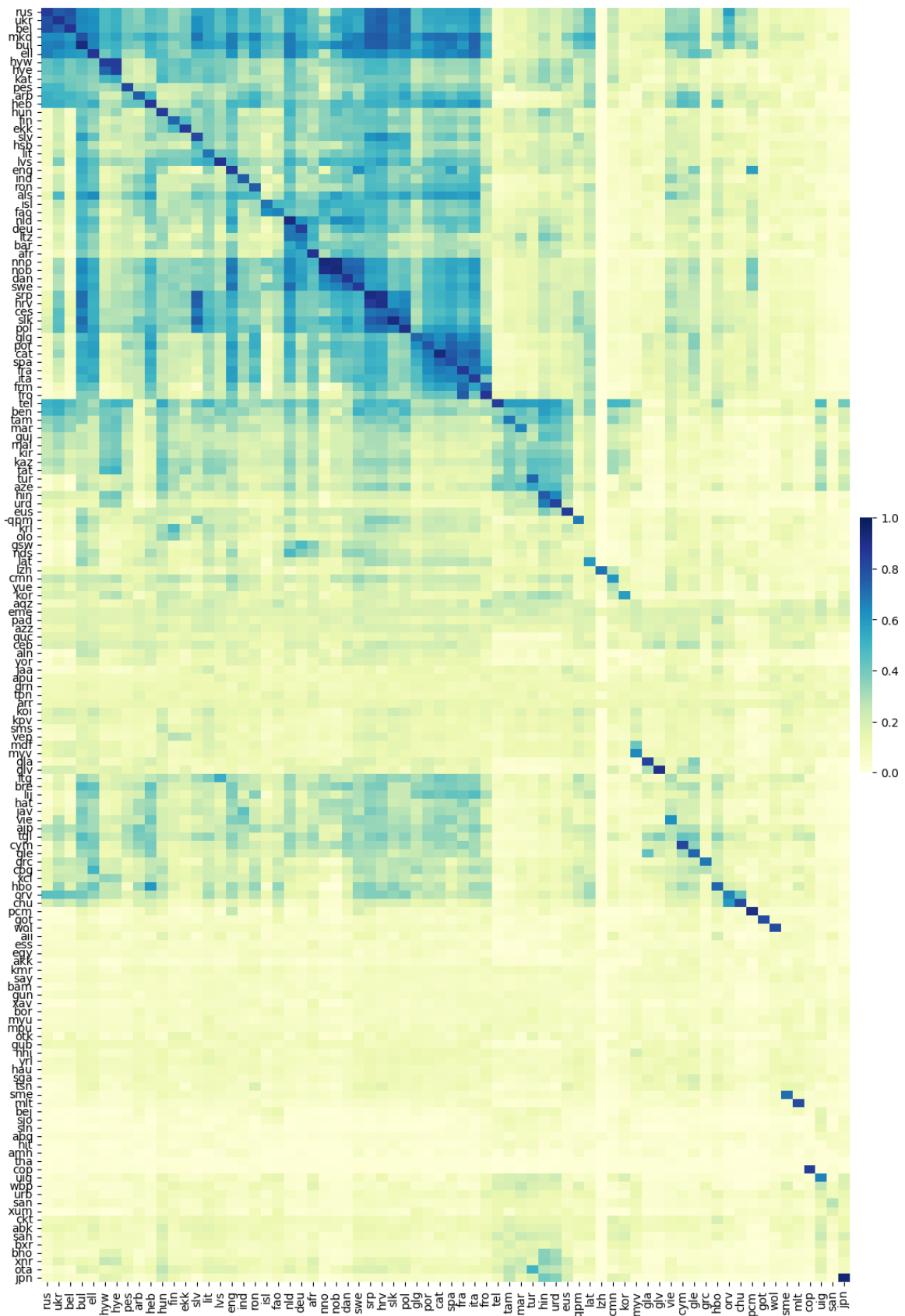


Figure 8: **Labelled attachment scores** for all combinations of source (columns) and target languages (rows), ordered by target language clusters (Ward's method). The darker a cell, the better the score.





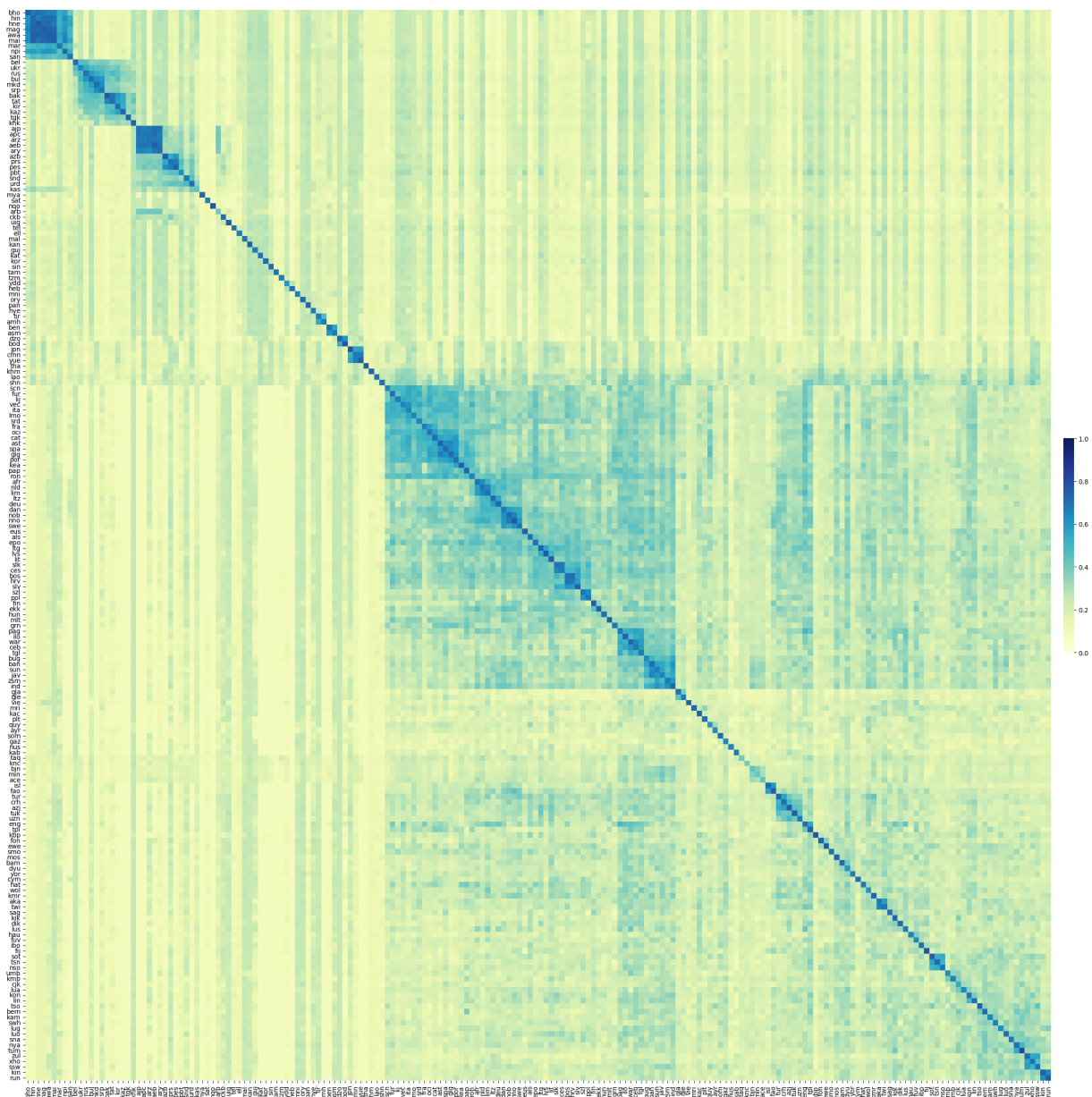


Figure 10: **Topic classification accuracy scores (MLP with n-grams, original writing systems)** for all combinations of source (columns) and target languages (rows), ordered by target language clusters (Ward's method). The darker a cell, the better the score.

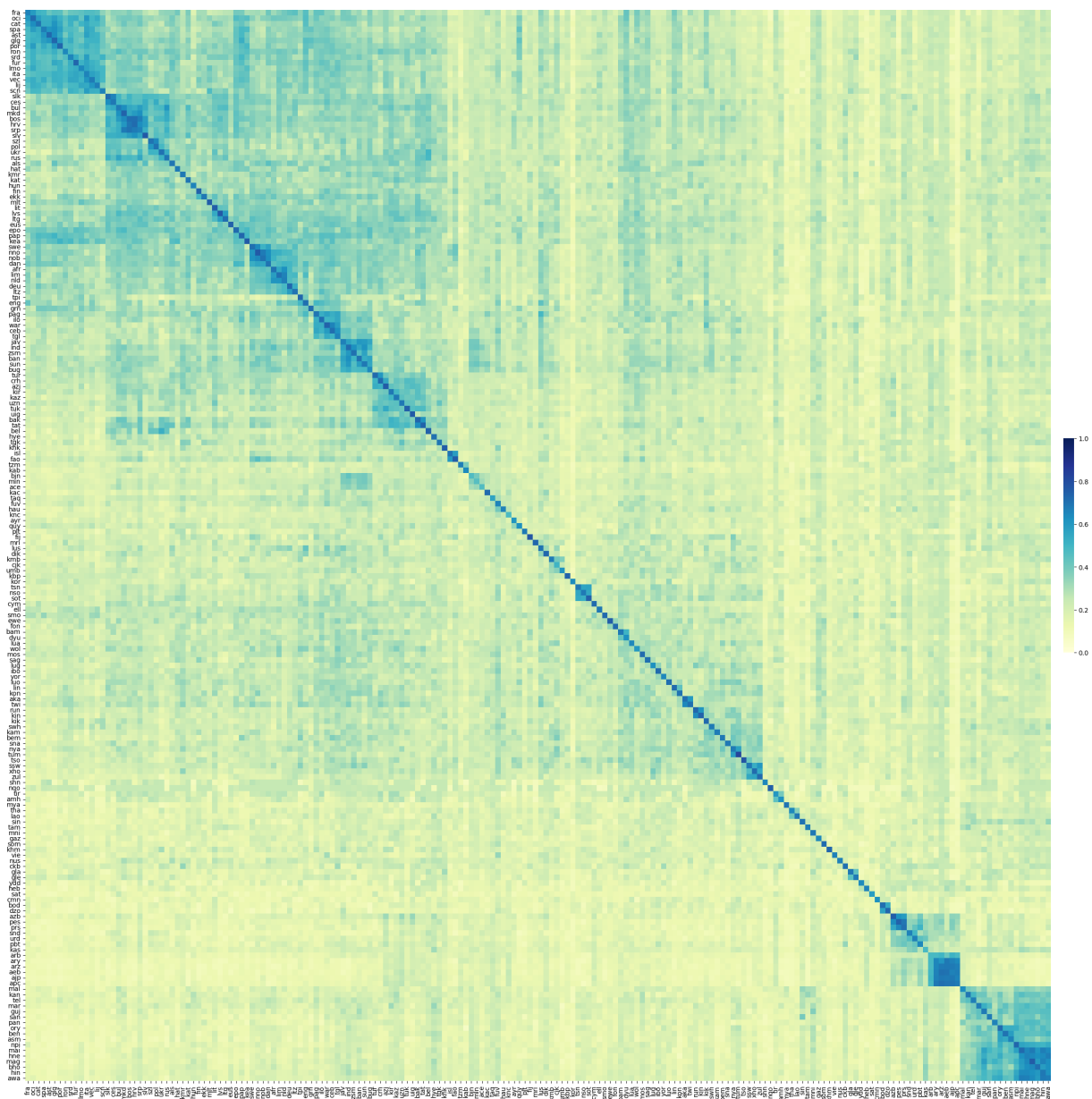


Figure 11: **Topic classification accuracy scores (MLP with n-grams, transliterated data)** for all combinations of source (columns) and target languages (rows), ordered by target language clusters (Ward's method). The darker a cell, the better the score.

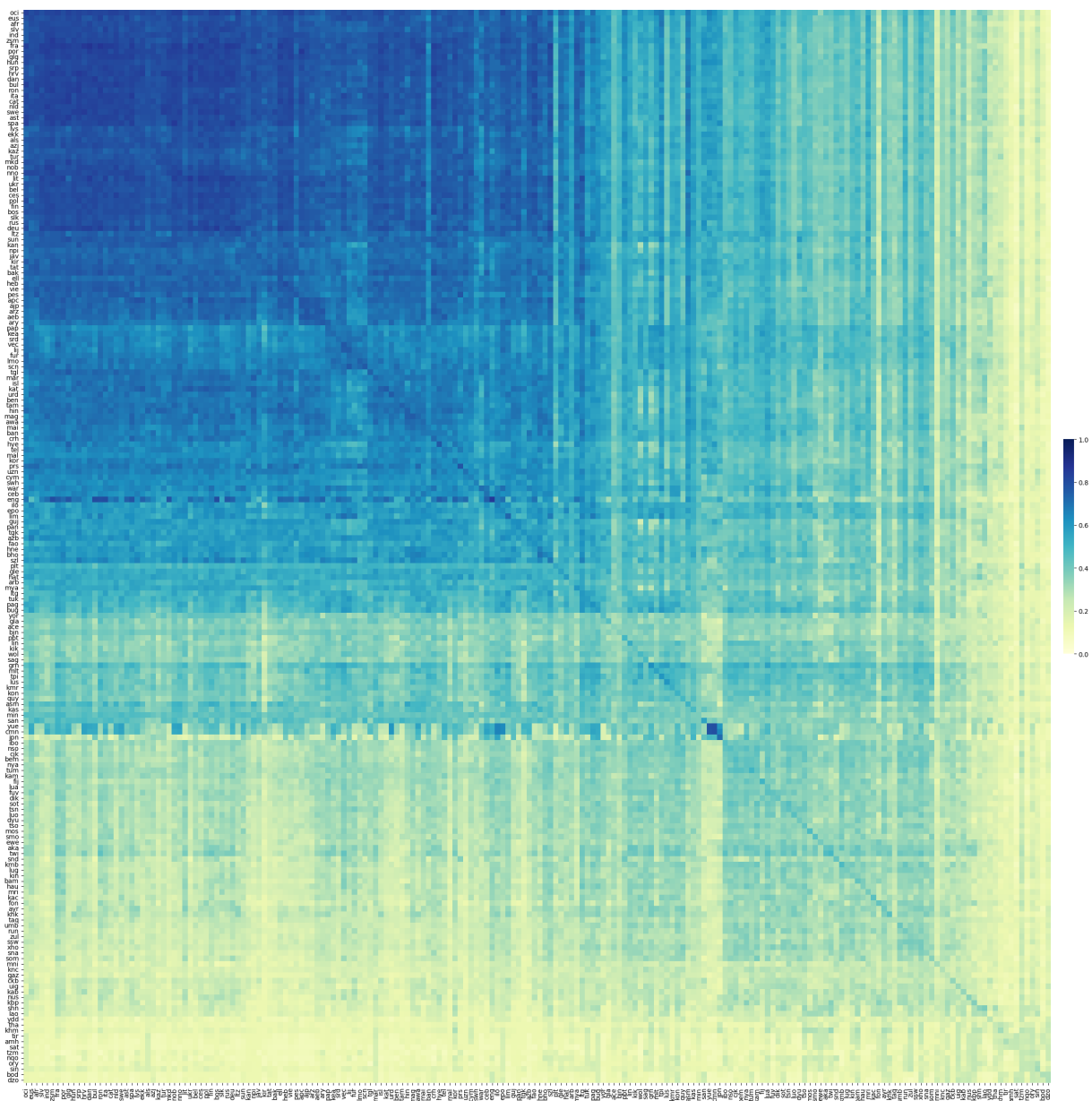


Figure 12: **Topic classification accuracy scores (MLP with mBERT representations)** for all combinations of source (columns) and target languages (rows), ordered by target language clusters (Ward's method). The darker a cell, the better the score.

Test language		POS										LAS											
lang	script	mBERT	size	pho	inv	geo	syn	gb	gen	lex	chr	wor	size	pho	inv	geo	syn	gb	gen	lex	chr	wor	
abk	Cyrl		-36	—	N/A	—	29	—	—	—	—	30	-30	—	N/A	—	54	—	—	—	—	—	30
abq	Cyrl		—	N/A	N/A	—	N/A	N/A	—	—	24	—	—	N/A	N/A	—	N/A	N/A	—	—	—	—	—
afr	Latn	x	—	N/A	—	31*	N/A	N/A	52*	59*	46*	36*	—	N/A	45*	37*	N/A	N/A	71*	78*	46*	56*	
aii	Syrc		-32	N/A	N/A	—	N/A	N/A	—	—	29	—	-23	N/A	N/A	—	N/A	N/A	—	—	—	—	—
ajp	Arab		-25	N/A	N/A	30	N/A	[36]	—	—	—	—	—	N/A	N/A	30	N/A	[51]	—	—	—	—	
akk	Latn		-25	N/A	N/A	—	N/A	—	—	—	—	—	-25	N/A	N/A	—	N/A	—	—	—	—	24	
aln	Latn		-37	N/A	N/A	—	N/A	—	—	—	—	32*	23	—	N/A	40*	N/A	54*	—	—	—	31*	
als	Latn		—	—	—	32*	50*	46*	—	25	48*	29	—	—	—	41*	81	66*	27	37*	41*	—	
amh	Ethi		—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	
apu	Latn		-40	—	—	—	—	—	—	—	—	—	-33*	—	—	28	—	—	—	—	—	23	
aqz	Latn		-40	N/A	—	—	N/A	—	—	—	—	—	-37*	N/A	—	—	N/A	—	—	—	—	—	
arb	Arab	x	—	N/A	N/A	27	53*	42*	—	—	29	28	—	N/A	N/A	—	77*	53*	—	25	35*	33*	
arr	Latn		-33	N/A	36	—	—	N/A	—	—	—	27	—	N/A	—	40*	-60	N/A	—	—	—	30	
aze	Latn	x	-31*	—	—	—	N/A	—	N/A	—	34*	31*	—	—	—	61	N/A	35*	N/A	—	—	—	
azz	Latn		-39*	N/A	N/A	31*	N/A	—	—	—	37*	37*	-27	N/A	N/A	45*	N/A	—	—	—	49*	37*	
bam	Latn		-40*	45	—	—	—	—	—	—	37*	30	-37*	—	—	26	—	—	—	—	—	39*	
bar	Latn	x	—	N/A	N/A	24	N/A	N/A	48*	N/A	37*	37*	—	N/A	N/A	40*	N/A	N/A	58*	N/A	49*	42*	
bej	Latn		-34	—	—	—	—	—	—	25	—	—	—	—	—	—	54	—	—	—	—	—	
bel	Cyrl	x	—	N/A	N/A	37*	N/A	64*	58*	56*	50*	34*	—	N/A	N/A	51*	N/A	66*	65*	66*	63*	38*	
ben	Beng	x	-24	—	—	—	N/A	—	—	—	26	39*	—	—	—	—	N/A	35*	38*	32*	—	—	
bho	Deva		-40	N/A	N/A	25	47*	—	29	33*	32*	33*	—	N/A	N/A	48*	81*	57*	43*	58*	54*	60	
bor	Latn		-42*	40	—	—	N/A	—	—	—	29	36*	—	—	—	—	N/A	30	—	—	—	—	
bre	Latn	x	-31*	—	—	37*	51*	38*	—	27	53*	46*	—	—	31	48*	76	64*	—	39*	52*	36*	
bul	Cyrl		—	—	39*	36*	71	34	51*	47*	40*	25	—	—	47*	48*	84	N/A	54*	54*	47*	29	
bxr	Cyrl		-35	N/A	N/A	28	N/A	34	—	—	—	—	-24	N/A	N/A	34*	N/A	70	—	—	—	—	
cat	Latn	x	—	—	—	44*	72*	61*	64*	67*	53*	48*	—	—	41*	52*	83*	77*	70*	74*	51*	56*	
ceb	Latn	x	-35	N/A	—	-34*	N/A	N/A	—	—	38*	27	—	N/A	—	-48*	N/A	N/A	—	—	—	32*	
ces	Latn	x	—	N/A	—	40*	36	30	35*	33*	52*	52*	—	N/A	39*	51*	54	50*	51*	54*	51*	56*	
chu	Cyrl		—	N/A	N/A	26	N/A	N/A	49*	46*	62*	63*	—	N/A	N/A	38*	N/A	N/A	60*	62*	73*	79*	
ckt	Cyrl		-32	—	—	—	—	—	—	—	—	—	-38*	—	-33	—	—	—	—	—	-29	—	
cmn	Hans, Hant	x	—	44	—	—	54*	51*	—	40*	29	29	—	62	33	—	64	52*	38*	55*	32*	39*	
cop	Copt		—	N/A	N/A	—	35	69	87	91*	90	92*	—	N/A	N/A	25	46*	73*	93	98*	98	99*	
cpj	Grek		-38	N/A	N/A	26	N/A	N/A	36*	N/A	42*	43*	—	N/A	N/A	43*	N/A	N/A	53*	N/A	59*	43*	
cym	Latn	x	-30	N/A	N/A	34*	42*	41*	39*	54*	50*	48*	—	N/A	N/A	49*	71	73*	51*	66	53*	58*	
dan	Latn	x	—	N/A	N/A	33*	49*	59*	45*	56*	57*	48*	—	N/A	N/A	45*	71*	77*	55*	63*	57*	55*	
deu	Latn	x	—	—	34	—	50*	N/A	50*	55*	35*	50*	—	—	50*	50*	36*	70*	N/A	60*	65*	48*	
egy	Latn		—	N/A	N/A	—	N/A	N/A	—	N/A	—	—	—	N/A	N/A	—	N/A	N/A	—	N/A	41*	27	
ekk	Latn	x	—	N/A	N/A	25	N/A	32	36*	37*	58*	43*	—	N/A	N/A	42*	N/A	52*	53*	55*	56*	61	
ell	Grek	x	—	47	32	34*	62*	63*	43*	37*	45*	24	—	48	42*	49*	82*	76*	48*	39*	55*	27	
eme	Latn		-39	N/A	—	23	—	N/A	—	—	33*	37*	-34*	N/A	—	—	N/A	—	—	—	—	—	
eng	Latn	x	—	44	33	—	29	37	39*	38*	33*	42*	—	50*	42*	32*	57*	64*	52*	51*	42*	52*	
ess	Latn		—	—	36	—	N/A	N/A	—	—	—	—	—	—	—	-28	N/A	—	—	—	—	35*	
eus	Latn	x	—	—	—	—	53*	44	N/A	41*	52*	43*	—	—	42*	—	75	72	N/A	71	43*	73	
fao	Latn		—	N/A	N/A	45*	N/A	52*	52*	58*	61	37*	—	N/A	N/A	46*	N/A	66	62	68	53*	39*	
fin	Latn	x	—	42	—	25	37	—	34*	36*	59*	41*	—	47	31	39*	61	36	44*	46*	56*	52*	
fra	Latn	x	—	—	—	37*	51*	50*	63*	59*	42*	39*	—	—	34	46*	69*	69*	70*	67*	42*	46*	
frm	Latn		-23	N/A	N/A	33*	N/A	N/A	63*	N/A	26	35*	—	N/A	N/A	44*	N/A	N/A	72*	N/A	28	40*	
frf	Latn		-24	N/A	N/A	36*	N/A	N/A	66	N/A	24	45*	—	N/A	N/A	42*	N/A	N/A	72*	N/A	—	46*	
gla	Latn		-32	N/A	N/A	26	41*	N/A	54*	74*	41*	68*	—	N/A	N/A	41*	64	N/A	67*	85*	46*	86*	
gle	Latn	x	-30	N/A	50*	38*	50*	51*	43*	55*	51*	57*	—	N/A	56*	52*	76*	73*	57*	62	50*	65*	
glg	Latn	x	—	N/A	—	43*	N/A	56*	62	66	45*	46*	—	N/A	37	53*	N/A	75*	70	72	47	51	
glv	Latn		-34	N/A	N/A	28	N/A	N/A	55*	75*	34*	68*	—	N/A	N/A	39*	N/A	N/A	71*	84*	36*	81*	
got	Latn		-25	N/A	N/A	—	N/A	N/A	29	42*	45*	74*	—	N/A	N/A	24	N/A	N/A	49*	62	47*	96*	
grc	Grek		-28	N/A	N/A	27	N/A	45*	45*	57*	51*	48*	—	N/A	N/A	48*	N/A	68*	64*	71*	66*	62	
grn	Latn		-33*	—	—	47*	N/A	—	N/A	40*	37*	—	—	41	41*	—	—	N/A	N/A	—	—	—	
gsw	Latn		—	N/A	N/A	—	N/A	N/A	45*	49*	32*	—	—	N/A	N/A	25	N/A	N/A	56*	62	36*	—	
gub	Latn		-41*	N/A	—	—	—	N/A	—	N/A	—	—	—	N/A	—	38*	—	N/A	—	N/A	43*	—	
guj	Gujr	x	—	N/A	—	—	N/A	N/A	31*	29	29	—	—	N/A	—	28	N/A	N/A	40*	40	28	—	
gun	Latn		-43*	N/A	—	—	N/A	—	—	—	—	27	-24	N/A	—	—	N/A	—	—	—	—	—	
hat	Latn	x	-26	N/A	N/A	29	N/A	—	31*	N/A	48*	37*	—	N/A	N/A	38*	N/A	38*	39*	N/A	48*	27	
hau	Latn		-43*	50*	—	—	N/A	—	—	—	—	—	-39*	43	—	—	N/A	—	—	—	26	—	
hbo	Hebr		-37*	N/A	N/A	36*	N/A	50*	46*	49*	41*	33*	—	N/A	N/A	49*	N/A	70*	55*	56*	55*	46*	
heb	Hebr	x	—	N/A	—	26	61	41*	—	27	47*	33*	—	N/A	35	33*	83	54*	23	32*	53*	37*	
hin	Deva	x	—	51*	34	—	67*	50*	41*	43*	41*	33*	—	—	59*	36*	74*	73*	63	64	53*	58*	
hit	Latn		-24	N/A	N/A	—	N/A	N/A	—	—	—	—	-28	N/A	N/A	—	N/A	N/A	—	—	—	—	
hrv	Latn	x	—	N/A	—	39*	N/A	N/A	37*	31	60	46*	—	N/A	44*	49*	N/A	N/A	54*	52*	55*	56*	
hsb	Latn		-27	N/A	N/A	36*	N/A	N/A	31*	29	50*	53*	—	N/A	N/A	48*	N/A	N/A	49*	52*	58*	51*	
hun	Latn	x	—	42	—	25	31	33	28	31	58*	40*	—	49	—	40*	59*	53*	42*	47*	53*	53*	
hye	Armn	x	—	45	—	—	60*	51*	38*	43*	51*	34*	—	58*	43*	36*	58*	56*	55*	61*	68*	51*	
hyw	Armn		—	N/A	N/A	N/A	N/A	N/A	42*	46*	55*	38*	—	N/A	N/A	N/A	N/A	N/A	58*	63*	70*	55*	
ind	Latn	x	—	46	—	—	41*	N/A	31*	29	58*	42*	—	40	—	—	62	N/A	39*	43*	52*	49*	
isl	Latn	x	—	N/A	30	41*	46*	45*	54*	59*	60	40*	—	N/A	42*	46*	66	59*	61	64	56*	45*	
ita	Latn	x	—	N/A	—	35*	59*	58*	58*	61*	44*	42*	—	N/A	36	44*	79*	73*	64*	67*	45*	48*	
jaa	Latn		-36	N/A	—	—	—	—	—	—	27	23	-37*	N/A	—	—	N/A	—	—	—	—	—	
jap	Latn	x	-24	—	—	—	N/A	N/A	25	—	58*	44*	—	—	—	-26	N/A	N/A	29	25	54*	47*	
jpn	Hira	x	-24	53*	—	32*	38*	41*	48*	48*	41*	46*	—	65*	45*	51*	65	77*	81*	77*	71*	78*	
kat	Geor	x	—	—	—	—	75*	34	—	-28	30*	—	—	—	—	27	71*	31	—	-31	37*	—	
kaz	Cyrl		-27	N/A	N/A	—	N/A	N/A	—	—	—	36*	—	N/A	N/A	25	N/A	N/A	—	—	—	—	
kir	Cyrl	x	-27	—	—	—	N/A	N/A	—	—	—	—	—	—	—	31*	—	—	—	—	—	—	
kmr	Latn		-43*	—	—	—	N/A	—	—	—	29	32*	-39*	—</									

Test language		POS										LAS											
lang	script	size	pho	inv	geo	syn	gb	gen	lex	chr	wor	size	pho	inv	geo	syn	gb	gen	lex	chr	wor		
kor	Hang	x	—	—	—	32*	55*	52*	35*	40*	34*	37*	—	46	31	36*	79*	73*	57*	59*	58*	58*	
kpv	Cyrl	x	-38*	—	—	24	N/A	—	—	—	—	36*	-28	42	—	36	N/A	—	—	—	31*	37*	
krl	Latn	x	-27	N/A	N/A	—	N/A	N/A	34*	36*	53*	50*	—	N/A	N/A	35*	N/A	N/A	41*	41*	54*	41*	
lat	Latn	x	-28	N/A	N/A	26	N/A	—	41*	51*	33*	41*	—	N/A	N/A	44*	N/A	43*	56*	65*	37*	58*	
lij	Latn	x	-29	N/A	N/A	42*	N/A	N/A	60	63	43*	44*	—	N/A	N/A	52*	N/A	N/A	64	66	45*	41*	
lit	Latn	x	-24	50	—	28	—	35	—	36*	57*	32*	—	40	47	48*	47	52*	42*	52*	56*	40*	
ltg	Latn	x	-23	N/A	N/A	28	N/A	N/A	—	N/A	46*	23	—	N/A	N/A	41	N/A	N/A	32*	N/A	43	—	
ltz	Latn	x	—	N/A	N/A	—	N/A	N/A	39*	50*	—	—	—	N/A	N/A	—	N/A	N/A	46*	58*	28	—	
lvs	Latn	x	—	N/A	N/A	28	N/A	[—]	27	35*	55*	37*	—	N/A	N/A	46*	N/A	[36]	44*	52*	56*	46*	
lzh	Hant	x	26	N/A	N/A	47*	N/A	N/A	65*	N/A	57*	65	47*	N/A	N/A	44*	N/A	N/A	85*	N/A	60*	87*	
mal	Mlym	x	—	N/A	—	—	N/A	—	—	35*	—	—	—	N/A	—	—	N/A	48*	23	28	35*	—	
mar	Deva	x	—	N/A	—	—	64	53*	29	36*	33*	27	—	N/A	—	32*	69*	65*	43*	49*	47*	42*	
mdf	Cyrl	x	-35*	N/A	N/A	29	N/A	30	33*	40*	35*	44*	—	N/A	N/A	43*	N/A	44*	59*	62*	62*	71*	
mkd	Cyrl	x	—	N/A	36	37*	—	69*	49*	48*	—	—	—	N/A	46	51*	N/A	72	50*	50*	—	—	
mlt	Latn	x	-32*	N/A	34	—	N/A	31	47*	60	27	76	—	N/A	49*	27	N/A	59*	69	82	29	97	
mpu	Latn	x	-36*	N/A	—	—	N/A	N/A	—	—	—	—	—	N/A	—	—	N/A	N/A	—	—	—	—	
myu	Latn	x	-39*	N/A	—	—	N/A	—	—	—	—	32*	-39*	N/A	—	—	N/A	—	—	—	—	31*	
myv	Cyrl	x	-33*	N/A	N/A	29	N/A	45*	51*	61	46*	57*	—	N/A	N/A	38*	N/A	60	81	85*	71	88*	
nds	Latn	x	—	N/A	—	28	N/A	N/A	40*	53*	39*	48*	—	N/A	—	39*	N/A	N/A	50*	63*	42*	47*	
nhi	Latn	x	-44*	N/A	N/A	24	N/A	—	—	—	29	41*	-37*	N/A	N/A	29	N/A	—	—	—	30	42*	
nld	Latn	x	—	N/A	36	31*	56	59*	48*	58*	53*	48*	—	N/A	49*	41*	77	76	61	68*	55*	56*	
nno	Latn	x	—	N/A	N/A	32*	N/A	N/A	52*	62	59*	56*	—	N/A	N/A	43*	N/A	N/A	61*	68*	57*	64*	
nob	Latn	x	—	—	—	32*	49*	N/A	50*	59*	60*	55*	—	—	—	42*	73	N/A	58*	65*	59*	62*	
olo	Latn	x	-36*	N/A	N/A	—	N/A	—	34	N/A	46*	41*	—	N/A	N/A	35*	N/A	35	48*	N/A	46*	—	
orv	Cyrl	x	—	N/A	N/A	30	N/A	N/A	59*	N/A	44*	51*	—	N/A	N/A	47*	N/A	N/A	72	N/A	53*	59*	
ota	Latn	x	-35*	N/A	N/A	—	N/A	N/A	34*	N/A	32*	42*	—	N/A	N/A	—	N/A	N/A	57*	N/A	—	54*	
otk	Orkh	x	—	N/A	N/A	—	N/A	N/A	N/A	68	32*	—	—	N/A	N/A	—	N/A	N/A	N/A	N/A	29	—	
pad	Latn	x	-41*	—	—	—	N/A	—	—	—	—	37*	-39*	—	—	—	N/A	—	—	—	—	—	
pcm	Latn	x	—	N/A	—	38*	N/A	N/A	63	N/A	31*	77*	—	N/A	37	40*	N/A	N/A	67*	N/A	37*	91*	
pes	Arab	x	—	48	—	25	39*	—	44*	40*	26	28	—	67	45*	—	53*	46*	57*	55*	43*	45*	
pol	Latn	x	—	44	—	37*	44*	48*	34*	29	54*	39*	—	—	34	49*	69*	62*	49*	67*	52*	45*	
por	Latn	x	—	N/A	31	43*	53*	51*	59*	59*	51*	50*	—	N/A	42	52*	78*	71*	66	64*	52*	54*	
qpm	Latn	x	-33*	[54]	[—]	[35]	[40]	N/A	42	[27]	52*	51*	—	[47]	[43]	[49]	[68]	N/A	59*	[48]	50*	59*	
quc	Latn	x	-42*	N/A	—	—	N/A	—	—	—	—	25	—	N/A	32	52*	N/A	—	—	—	—	42*	27*
ron	Latn	x	-26	45	—	32*	44*	N/A	55*	59*	50*	48*	—	—	33	44*	76	N/A	63*	65*	49*	53*	
rus	Cyrl	x	—	—	42*	—	61	52*	56*	54*	43*	35*	—	40	53*	—	77	54*	65*	64*	55*	40*	
sah	Cyrl	x	-36*	—	—	—	50*	37	32*	27	—	25	-28	—	—	24	81*	54*	40*	38*	—	—	
san	Deva, Latn	x	-41*	N/A	47*	25	N/A	N/A	—	—	30*	39*	-25	N/A	62	56*	N/A	N/A	27	56*	48*	66*	
say	Latn	x	-42*	N/A	—	—	N/A	—	—	—	—	—	-39*	N/A	—	—	N/A	—	—	—	30	—	
sga	Latn	x	-38*	N/A	N/A	—	N/A	N/A	31*	45*	27	37*	-34*	N/A	N/A	47*	N/A	N/A	48*	60*	33*	39*	
sin	Sinh	x	-25	—	—	32*	N/A	N/A	—	—	—	-46*	—	—	33	42*	N/A	N/A	—	—	—	—	
sjd	Mong	x	—	N/A	N/A	34*	N/A	N/A	—	—	—	-35*	—	—	N/A	N/A	34*	N/A	—	—	—	—	
slk	Latn	x	—	N/A	N/A	39*	N/A	N/A	32*	28	65	41*	—	N/A	N/A	49*	N/A	N/A	51*	51*	59*	48*	
slv	Latn	x	—	N/A	39*	39*	47*	40*	43*	40*	48*	52*	—	N/A	49*	49*	69	56*	53*	53*	47*	58*	
sme	Latn	x	-34*	N/A	N/A	25	N/A	40*	64	66	44*	62	—	N/A	N/A	28	N/A	58*	91*	93*	41*	96*	
sms	Latn	x	-43*	N/A	N/A	24	N/A	30	36*	34*	34*	39*	-27	N/A	N/A	38*	N/A	—	47*	37*	35*	—	
spa	Latn	x	—	—	—	43*	60	N/A	63	64	44*	52*	—	39	—	51*	78	N/A	70*	70*	44*	56*	
srp	Latn	x	—	N/A	N/A	35*	N/A	N/A	36*	N/A	61	43*	—	N/A	N/A	47	N/A	N/A	53*	N/A	55*	53*	
swe	Latn	x	—	N/A	43*	27	59*	65	48*	57	57*	43*	—	N/A	47	39*	78	79	57*	62	57*	48*	
tam	TamI	x	—	N/A	—	23	50*	48*	33*	36*	38*	31*	—	N/A	—	37*	70	65*	39*	41*	40*	37*	
tat	Cyrl	x	-26	N/A	N/A	—	—	40	36	—	—	—	—	N/A	N/A	—	65*	55*	—	—	—	—	
tel	Telu	x	—	—	—	50*	43*	29	34*	31*	28	—	—	35	39*	81*	65*	38*	43*	36*	35*		
tgl	Latn	x	-32*	48	—	-37*	33	—	—	—	37*	25	—	—	—	-46*	74*	—	—	—	31*	—	
tha	Thai	x	—	—	—	44*	—	—	—	—	-52*	-29	-30*	—	—	60*	—	—	—	—	30*	28	
tpn	Latn	x	-39*	N/A	—	—	N/A	—	—	—	23	29	-36*	N/A	—	—	N/A	—	—	—	26	—	
tsn	Latn	x	-33*	N/A	N/A	—	—	—	—	—	36*	31*	-27	N/A	N/A	—	N/A	—	—	30	33*	—	
tur	Latn	x	-28*	—	—	—	36	38*	34*	31	43*	42*	—	—	—	—	76	71	55*	53*	—	52*	
uig	Arab	x	-35*	N/A	N/A	34*	63	N/A	60	61	38*	58*	—	N/A	N/A	42*	76	N/A	79	78*	61	77*	
ukr	Cyrl	x	—	N/A	41*	37*	68*	52*	57*	54*	48*	30	—	N/A	51*	51*	82*	60*	65*	65*	61	36*	
urb	Latn	x	-27	—	—	—	N/A	—	—	—	—	29	-30	—	—	53*	N/A	—	—	26	—	—	
urd	Arab	x	—	N/A	43*	29	71	N/A	47*	51*	28	37*	—	N/A	62	48*	74	N/A	70*	77*	39*	64*	
vep	Latn	x	-35*	N/A	N/A	—	N/A	—	40*	44*	44*	41*	—	N/A	N/A	41	N/A	34	61*	64*	44*	—	
vie	Latn	x	-31*	40	39*	—	31	—	35*	34*	54*	37*	—	51*	50*	—	59*	32	42*	39*	58*	43*	
wbp	Latn	x	-38*	N/A	N/A	—	—	—	—	—	—	29	—	N/A	N/A	34*	70*	—	—	—	—	32*	
wol	Latn	x	-31*	43	55*	35*	34	71	72*	76	43*	73	—	—	65	43*	50*	82*	96*	95*	36*	96*	
xav	Latn	x	-46*	N/A	—	—	N/A	—	—	—	—	28	-36*	N/A	—	—	N/A	—	—	—	—	—	
xcl	Armn	x	-36*	N/A	N/A	31*	—	—	32*	46*	39*	37*	—	N/A	N/A	42*	N/A	—	42*	43*	39*	37*	
xnr	Deva	x	-36*	N/A	—	28	N/A	N/A	—	N/A	38*	38*	—	N/A	—	41*	N/A	N/A	30	N/A	50*	47*	
xum	Latn	x	-28	N/A	N/A	—	N/A	N/A	—	N/A	32*	28	-25	N/A	N/A	—	N/A	N/A	—	N/A	24	—	
yor	Latn	x	-36*	40	—	—	N/A	—	—	—	47*	—	—	—	26	61*	N/A	—	—	—	47*	—	
yrl	Latn	x	-42*	N/A	—	—	N/A	—	—	—	31*	42*	-34*	N/A	—	38*	N/A	—	—	—	47*	44*	
yue	Hant	x	—	—	—	36	30	—	36*	—	—	—	—	—	—	53*	—	—	—	28	—	—	
mean (all)			-19	17	9	17	37	28	26	29	32	33	-7	17	20	27	57	42	35	38	36	34	
mean (mBERT)			-21;-15	11;23	5;12	13;19	31;42	22;32	22;29	24;33	28;35	30;36	-8;-4	10;22	15;25	23;30	50;63	35;47	30;40	32;43	32;39	29;38	
mean (~mBERT)			-8	23	11	20	46	40	34	38	43	35	0	24	28	31	69	60	46	49	44	40	
			-11;-4	14;30	6;15	15;24	41;51	34;46	28;38	32;42	38;46	31;38	0;0	14;32	22;34	25;36	64;72	55;64	40;50	43;54	40;48	35;45	
			-27	8	7	14	20	14	20	21	23	32	-12	6	9	24	36	23	27	27	30	29	
			-30;-23	0;15	2;12	10;17	10;29	7;20	14;25	14;27	17;28	26;36	-15;-8	0;12	2;15	19;28	20;50	13;31	20;34	19;35	24;34		

Test language		Original										Transliterated										mBERT									
lang	script	pho	inv	geo	syn	gb	gen	lex	chr	tri	pho	inv	geo	syn	gb	gen	lex	chr	tri	pho	inv	geo	syn	gb	gen	lex	chr	swt			
ace Arab, Latn		N/A	33*	—	—	38*	52*	49*	41*	60	N/A	26*	28*	—	—	44*	56*	53*	—	40*	N/A	—	-25*	33*	—	—	—	53*	28*		
aeb Arab		N/A	N/A	—	N/A	N/A	60*	68*	55*	81*	N/A	N/A	16	N/A	N/A	75*	80*	32*	90*	N/A	N/A	24*	N/A	N/A	—	—	—	20*	—		
afz Arab	x	N/A	36*	—	N/A	N/A	43*	51*	55*	69*	N/A	34*	-14	N/A	N/A	48*	54*	14	54*	N/A	—	-33*	N/A	N/A	39*	31*	—	—	—		
ajp Arab		N/A	N/A	17	N/A	[37]	61*	66*	49*	78*	N/A	N/A	29*	N/A	[57]	79*	82*	35*	89*	N/A	N/A	25*	N/A	[20]	—	—	—	18*	—		
aka Latn		—	44*	22*	44*	N/A	53*	45*	61*	72*	—	36*	22*	38*	N/A	57*	59*	23*	46*	—	34*	33*	—	N/A	40*	14*	52*	58*			
als Latn		29	39*	—	26*	18	22*	34*	62*	76*	42*	43*	28*	39*	41*	36*	43*	—	56*	44*	—	32*	48*	47*	46*	28*	—	—	—		
amhEthi		28	—	—	29*	47*	39*	49*	49*	55*	29	22	22*	40*	55*	40*	50*	—	33*	—	—	—	—	—	—	15	25*	40*			
apc Arab		N/A	N/A	19*	—	38*	61*	66*	55*	80*	N/A	N/A	28*	32*	58*	78*	82*	41*	89*	N/A	N/A	27*	—	20	—	—	—	17	—		
arb Arab, Latn x		N/A	N/A	16	—	26*	56*	59*	22*	43*	N/A	N/A	31*	27	53*	77*	80*	19*	81*	N/A	N/A	14	27	31*	—	—	—	20*	—		
ary Arab		N/A	23*	—	24	N/A	59*	66*	54*	79*	N/A	37*	—	40*	N/A	77*	81*	32*	89*	N/A	N/A	22*	29	N/A	—	—	15	22*	—		
arz Arab		30	26*	18	24	35*	61*	70*	53*	81*	37*	38*	26*	35*	64	78*	84*	21*	90*	35*	—	23*	—	23	—	—	—	19*	—		
ast Beng		N/A	—	26*	34	N/A	36*	52*	36*	61	N/A	—	50*	52*	N/A	66*	76*	—	63*	N/A	—	—	—	N/A	31*	21*	19*	—			
asn Latn	x	N/A	N/A	32*	N/A	N/A	65*	68*	56*	73*	N/A	N/A	43*	N/A	N/A	70*	73*	16	64*	N/A	N/A	31*	N/A	N/A	43*	37*	—	—	—		
awa Deva		N/A	34*	42*	N/A	49*	64*	N/A	77*	86*	N/A	51*	51*	—	56*	72*	N/A	23*	75*	N/A	—	—	N/A	40*	33*	N/A	25*	17			
ayr Latn		—	39*	39*	—	34*	53*	49*	52*	64	29	30*	25*	—	46*	61*	57*	—	38*	—	30*	40*	—	20	14	17	46*	46*			
azb Arab	x	—	—	22*	48*	N/A	16	22*	54*	71*	—	34*	32*	—	N/A	42*	50*	41*	78*	36*	—	23*	—	N/A	14	—	—	18*	—		
azj Latn		N/A	35*	—	N/A	28*	37*	32*	53*	68*	N/A	56*	31*	N/A	42*	63*	67	17	54*	N/A	21	34*	N/A	21	—	—	15	—	—		
bak Cyrll	x	39	30*	30*	42	31*	52*	49*	60	80*	52	34*	37*	61	53*	64	65*	26*	57*	48*	—	41*	41*	25*	16	18	23*	14	—		
bamLatn		27	41*	17	80*	35*	47*	51*	54*	64	—	29*	17	87*	30*	61*	59*	—	39*	—	40*	34*	—	—	16	24*	55*	60*			
ban Latn		N/A	45*	—	N/A	46*	59*	55*	60	74*	N/A	42*	22*	N/A	43*	60	58*	—	56*	N/A	-18	—	N/A	-19	—	—	—	17	—		
bel Cyrll	x	N/A	N/A	22*	N/A	35*	36*	41*	52*	71*	N/A	N/A	23*	N/A	42*	54*	63*	26*	63*	N/A	N/A	41*	N/A	55*	44*	35*	23*	—	—		
bemLatn		N/A	45*	29*	N/A	51*	55*	58*	52*	63*	N/A	33*	31*	N/A	57*	55*	61*	—	47*	N/A	39*	38*	N/A	54*	59*	53*	50*	62*			
ben Beng	x	—	34*	27*	81*	N/A	37*	49*	39*	64*	31*	56*	53*	77*	N/A	69*	78*	36*	63*	—	—	—	—	N/A	29*	22*	—	—			
bho Deva		N/A	N/A	40*	45*	54*	65*	58*	67*	83*	N/A	N/A	50*	45*	59*	72*	73*	—	71*	N/A	N/A	—	45*	30*	34*	26*	36*	22*			
bjn Arab, Latn		N/A	N/A	24*	N/A	N/A	61*	63	35*	55*	N/A	N/A	42	N/A	N/A	69*	67	—	56*	N/A	N/A	-18*	N/A	N/A	—	—	—	43*	15		
bod Tibt		24	23*	—	43	34*	62*	56*	34*	65*	—	32*	17	60*	47*	76*	71*	—	72*	—	—	—	58*	33*	35*	36*	20*	48*			
bos Latn	x	N/A	N/A	21*	29	N/A	31*	40*	64*	79*	N/A	N/A	36*	61*	N/A	66*	73*	28*	72*	N/A	N/A	36*	63*	N/A	44*	35*	14	—	—		
bug Latn		N/A	47*	—	N/A	46*	52*	49*	64*	77*	N/A	40*	—	N/A	44*	55*	53*	14	55*	N/A	—	-19*	N/A	—	15	16	47*	38*			
bui Cyrll		—	33*	19*	22	N/A	39*	40*	51*	75*	30	59*	41*	51*	N/A	61*	67*	34*	66*	27	—	39*	49*	N/A	46*	38*	24*	16	—		
cat Latn	x	—	48*	29*	49*	44*	60*	62*	59*	72*	24	43*	42*	57*	58*	69*	70*	—	65*	27	—	33*	34	49*	43*	39*	—	—	—		
ceb Latn	x	N/A	44*	—	N/A	N/A	62*	62*	60	74*	N/A	42*	24*	N/A	N/A	66*	68*	—	60*	N/A	—	—	N/A	N/A	14	—	—	20*	—		
ces Latn	x	N/A	40*	18*	24	—	29*	37*	67*	82*	N/A	50*	37*	57*	43*	59*	66	20*	72	N/A	—	—	41*	52*	54	46*	36*	17	—		
cjk Latn		N/A	N/A	29*	N/A	N/A	50*	57*	49*	61*	N/A	N/A	24*	N/A	N/A	44*	55*	—	46*	N/A	N/A	36*	N/A	N/A	51*	43*	59*	64*			
ckb Arab		N/A	N/A	18*	N/A	N/A	31*	50*	30*	60*	N/A	N/A	27*	N/A	N/A	43*	54*	15	54*	N/A	N/A	—	N/A	N/A	19*	18	29*	—	—		
cmnHans, Hant x		—	27*	15	30*	30*	56*	56*	69*	—	24	41*	17	—	28*	67*	68	—	27*	25	26*	15	36*	25*	30*	34*	42*	37*			
crh Latn		N/A	N/A	—	N/A	29*	24*	28*	59*	70*	N/A	N/A	29*	N/A	49*	66*	70*	25*	54*	N/A	N/A	33*	N/A	—	—	15	19*	—	—		
cymLatn	x	N/A	N/A	—	24	25*	28*	45*	45*	57*	N/A	N/A	22*	22	36*	35*	51*	19*	40*	N/A	N/A	35*	—	41*	37*	31*	21*	—	—		
dan Latn	x	N/A	N/A	26*	38*	37*	39*	51*	59*	73*	N/A	N/A	38*	58*	50*	48*	56*	21*	62	N/A	N/A	43*	61*	54*	44*	33*	14	—	—		
deu Latn	x	30*	36*	24*	35*	N/A	45*	52*	53*	66*	52*	45*	37*	56*	N/A	48*	53*	15	55*	47*	—	41*	57*	N/A	41*	32*	—	—	—		
dik Latn		N/A	N/A	—	N/A	N/A	40*	45*	49*	62*	N/A	—	N/A	N/A	49*	50*	—	26*	N/A	N/A	—	N/A	N/A	—	—	18	53*	48*			
dyu Latn		N/A	43*	—	N/A	34*	40*	49*	54*	64*	N/A	31*	15	N/A	36*	54*	57*	—	49*	N/A	24*	23*	N/A	—	20*	26*	58*	55*			
dko Tibt		N/A	N/A	21*	N/A	40*	64*	60*	63*	66*	N/A	N/A	14	N/A	38*	78*	75*	56*	72*	N/A	N/A	—	N/A	30*	29*	32*	30*	32*			
ekk Latn	x	N/A	N/A	—	N/A	—	37*	38*	62*	74*	N/A	N/A	29*	N/A	38*	43*	45*	17	52*	N/A	N/A	45*	N/A	44*	—	16	—	—	—		
ell Grek	x	—	19	—	—	21	29*	43*	15	47*	31*	41*	18	43*	42*	46*	57*	21*	54*	36*	—	34*	52*	49*	44*	29*	18	—	—		
eng Latn	x	23	32*	—	25*	19	35*	35*	47*	61*	—	34	17	30*	31*	38*	35*	—	49*	35*	—	41*	45*	45*	34*	31*	—	—	—		
epo Latn		N/A	N/A	28*	N/A	N/A	22*	N/A	60	74*	N/A	N/A	38*	N/A	N/A	25*	N/A	16	64	N/A	N/A	28*	N/A	N/A	—	N/A	30*	23*			
eus Latn	x	—	36*	18*	—	27*	N/A	28*	62*	77*	—	45*	29*	21	40*	N/A	36*	—	59*	—	—	32*	—	—	N/A	—	—	—	—		
ewi Latn		33*	51*	20*	43*	50*	48*	N/A	59*	70*	25	44*	21*	33*	51*	50*	N/A	17	51*	—	40*	29*	24	21	43*	N/A	55*	61*			
fao Latn		N/A	N/A	22*	N/A	39*	45*	52*	53*	66*	N/A	N/A	30*	N/A	48*	56*	61	17	51*	N/A	N/A	34*	N/A	37*	36*	27*	24*	—	—		
fij Latn		25	41*	17	32*	49*	44*	45*	47*	56*	—	27	21*	26	45*	45*	48*	20*	26*	—	28*	—	25	—	23*	22*	56*	55*			
fin Latn	x	—	49*	—	22	27*	42*	40*	55*	69*	33*	51*	24*	48*	41*	49*	48*	19*	49*	33*	—	48*	59*	43*	—	—	17	—	—		
fon Latn		N/A	40*	20*	53	38*	53*	54*	43*	55*	N/A	25*	16	52	33*	48*	64	—	34*	N/A	31*	32*	—	25*	43*						

Test language	lang	script	mB	Original										Transliterated										mBERT									
				pho	inv	geo	syn	gb	gen	lex	chr	tri	pho	inv	geo	syn	gb	gen	lex	chr	tri	pho	inv	geo	syn	gb	gen	lex	chr	swt			
kmb	Latn	N/A	N/A	32*	N/A	N/A	52*	60*	51*	65*	N/A	N/A	25*	N/A	N/A	47*	66*	—	48*	N/A	N/A	42*	N/A	N/A	59*	41*	53*	67*					
kmr	Latn	—	24*	—	—	N/A	—	20*	56*	68*	34*	41*	15	28	N/A	23*	31*	—	43*	—	—	—	N/A	15	16	50*	38*						
knc	Arab, Latn	24	34*	—	—	34*	30*	27*	31*	48*	—	26*	14	38*	39*	52*	52*	—	35*	—	27*	17	—	22	14	17	46*	50*					
kon	Latn	N/A	N/A	24*	48*	N/A	49*	N/A	58*	68*	N/A	N/A	23*	45*	N/A	48*	N/A	—	45*	N/A	N/A	—	36*	N/A	29*	N/A	53*	40*					
kor	Hang	32*	17	20*	—	23	53*	55*	49*	43*	—	33*	17	—	27*	57*	58*	—	41*	—	—	16	23	—	—	—	—	—					
lao	Laoo	N/A	30*	—	26	50	22*	30*	42*	62*	N/A	29*	27*	—	69*	59*	59*	—	47*	N/A	20	-24*	—	47	18*	22*	22*	23*					
lij	Latn	N/A	N/A	30*	N/A	N/A	59*	58*	60*	72*	N/A	N/A	39*	N/A	N/A	65*	62*	—	66*	N/A	N/A	31*	N/A	N/A	44*	38*	31*	25*					
lim	Latn	N/A	N/A	21*	N/A	N/A	40*	48*	57*	70*	N/A	N/A	33*	N/A	N/A	47*	56*	—	56*	N/A	N/A	31*	N/A	N/A	34*	29*	38*	30*					
lin	Latn	N/A	45*	20*	N/A	N/A	46*	51*	55*	65*	N/A	39*	20*	N/A	N/A	46*	53*	17	45*	N/A	28*	20*	N/A	N/A	44*	42*	55*	54*					
lit	Latn	32*	35*	15	—	21	29*	42*	63*	77*	—	46*	34*	54*	43*	48*	57*	32*	65*	—	—	46*	54*	54*	47*	37*	14	—					
lmo	Latn	N/A	N/A	28*	N/A	44*	57*	56*	62*	75*	N/A	N/A	39*	N/A	57*	66*	65*	—	63*	N/A	N/A	34*	N/A	50*	42*	39*	23*	19*					
ltg	Latn	N/A	N/A	15	N/A	N/A	30*	N/A	65*	80*	N/A	N/A	37*	N/A	N/A	48*	N/A	18*	65*	N/A	N/A	28*	N/A	N/A	37*	N/A	31*	23*					
ltz	Latn	N/A	N/A	24*	N/A	N/A	39*	46*	56*	67*	N/A	N/A	34*	N/A	N/A	43*	49*	15	54*	N/A	N/A	36*	N/A	N/A	37*	28*	22*	—					
lua	Latn	—	N/A	25*	N/A	N/A	46*	48*	55*	68*	—	N/A	21*	N/A	N/A	41*	45*	—	50*	—	N/A	26*	N/A	N/A	40*	39*	57*	55*					
lug	Latn	N/A	49*	25*	53*	60*	51*	55*	57*	70*	N/A	35*	25*	49*	53*	49*	55*	20*	50*	N/A	37*	27*	34*	50*	53*	44*	54*	64*					
luo	Latn	—	48*	18	34*	60	39*	32*	56*	66*	—	35*	17	37*	58*	49*	43*	14	47*	—	23*	—	20	40*	—	—	55*	55*					
lus	Latn	N/A	37*	—	—	35*	37*	42*	47*	59*	N/A	25*	—	—	33*	45*	48*	—	40*	N/A	20	-29*	—	—	—	—	51*	42*					
lvs	Latn	N/A	N/A	20*	N/A	[—]	31*	45*	65*	80*	N/A	N/A	44*	N/A	[47]	55*	66*	25*	62*	N/A	N/A	44*	N/A	[53]	45*	34*	17	—					
mag	Deva	N/A	N/A	41*	N/A	45*	64	N/A	78*	86*	N/A	N/A	52*	N/A	51*	72	N/A	23*	74	N/A	N/A	—	N/A	—	33*	N/A	26*	17					
mai	Deva	N/A	35*	41*	64	56*	65*	61*	74*	87*	N/A	55*	53*	50*	57*	73	74	16	74*	N/A	N/A	—	43	—	32*	27*	28*	16					
mal	Mlym	N/A	24*	17	N/A	27*	37*	38*	21*	51*	N/A	49*	50*	N/A	53*	52*	61*	37*	59*	N/A	—	—	N/A	21	—	20*	15	—					
mar	Deva	N/A	34*	37*	39*	46*	54*	56*	61*	75*	N/A	50*	52*	46*	59*	62*	70*	21*	70*	N/A	—	—	22	29*	32*	24*	23*	—					
min	Arab, Latn	N/A	35*	—	—	46*	56*	56*	41*	60*	N/A	33*	22*	—	42*	64*	60*	—	53*	N/A	—	-18*	—	-23	—	—	34*	—					
mkd	Cyrl	N/A	—	15	N/A	22	38*	35*	46*	73*	N/A	55*	41*	N/A	56*	64*	69*	23*	70*	N/A	—	35*	N/A	46*	45*	38*	22*	15					
mli	Latn	N/A	37*	14	N/A	19	—	—	59*	72*	N/A	26*	28*	N/A	35*	—	16	—	48*	N/A	17	—	N/A	22	—	—	43*	40*					
mni	Beng	—	—	22*	24	N/A	46*	49*	—	48*	28	35*	23*	32*	N/A	55*	59*	—	50*	—	19*	-20*	—	N/A	15	22*	31*	—					
mos	Latn	N/A	43*	18	56*	N/A	48*	49*	60*	71*	N/A	39*	17	52*	N/A	49*	58*	—	48*	N/A	30*	23*	—	N/A	36*	30*	55*	55*					
mri	Latn	40*	39*	26*	40*	40*	47*	46*	44*	58*	N/A	35*	32*	29*	34*	42*	53*	53*	—	36*	—	29*	—	21	20	17	16	56*	54*				
mya	Mymr	—	24*	15	29*	40*	56*	55*	27*	56*	27	36*	28*	30*	45*	63*	61*	—	57*	—	—	—	—	—	—	—	—	—	—				
nld	Latn	N/A	40*	22*	34*	34*	43*	50*	56*	69*	N/A	38*	26*	44*	41*	45*	51*	—	54*	N/A	—	41*	45*	55*	41*	33*	—	—					
nno	Latn	N/A	N/A	26*	N/A	N/A	45*	56*	57*	73*	N/A	N/A	40*	N/A	N/A	54*	62*	—	61*	N/A	N/A	46*	N/A	N/A	43*	32*	—	—					
nob	Latn	—	—	28*	41*	N/A	45*	54*	58*	72*	—	—	40*	57*	N/A	52*	57*	27*	63*	—	—	46*	63*	N/A	44*	34*	—	—					
npi	Deva	N/A	N/A	39*	N/A	40*	58*	61*	53*	79*	N/A	N/A	52*	N/A	44*	68*	79*	—	71*	N/A	N/A	—	N/A	45*	32*	20*	22*	—					
nqo	Nkoo	N/A	N/A	—	N/A	N/A	52*	N/A	22*	57*	N/A	N/A	15	N/A	N/A	50*	N/A	15	54*	N/A	N/A	—	N/A	N/A	—	N/A	—	16	—				
nso	Latn	N/A	N/A	38*	N/A	N/A	56*	62*	49*	64*	N/A	N/A	38*	N/A	N/A	55*	67*	—	45*	N/A	N/A	32*	N/A	N/A	46*	38*	57*	61*					
nus	Latn	N/A	35*	—	33*	47*	52*	52*	25*	41*	N/A	21	—	25	51*	54*	56*	—	21*	N/A	25*	17	—	21	19*	15	42*	47*					
nya	Latn	N/A	N/A	36*	40*	N/A	57*	61*	57*	69*	N/A	N/A	40*	41*	N/A	61*	66*	21*	51*	N/A	N/A	28*	28*	N/A	49*	47*	55*	58*					
oci	Latn	N/A	N/A	27*	N/A	43*	59*	60*	60*	74*	N/A	N/A	42*	N/A	57*	67*	67*	—	66*	N/A	N/A	35*	N/A	48*	41*	35*	16	—					
ory	Orya	N/A	N/A	20*	N/A	36*	25*	36*	14	53*	N/A	N/A	54*	N/A	59*	65*	73*	20*	65*	N/A	N/A	—	N/A	—	—	—	17	26*					
pag	Latn	N/A	42*	—	N/A	37*	46*	51*	63*	78*	N/A	36	—	N/A	30*	52*	58*	—	55*	N/A	—	-15	N/A	—	16	18	39*	28*					
pan	Guru	N/A	23*	17	19	36*	24*	39*	—	53*	N/A	56*	54*	42*	64*	58*	65*	—	64*	N/A	—	—	33*	33*	29*	27*	14	—					
pap	Latn	N/A	N/A	39*	N/A	46*	N/A	62*	73*	N/A	N/A	39*	N/A	N/A	52*	N/A	23*	58*	—	64*	N/A	23*	N/A	N/A	40*	N/A	35*	27*					
pbt	Arab	N/A	N/A	—	N/A	—	21*	37*	40*	58*	N/A	N/A	31*	N/A	29*	29*	51*	15	68*	N/A	N/A	—	N/A	26*	26*	25*	40*	—					
pes	Arab	26	—	24*	19	33*	33*	47*	49*	75*	34*	—	43*	42*	50*	42*	60*	23*	83*	34*	—	18	22	34*	38*	29*	15	—					
plt	Latn	—	36*	—	24	N/A	54*	46*	32*	41*	—	31*	—	—	N/A	53*	48*	—	33*	—	—	-17	—	N/A	—	16	34*	16	—				
pol	Latn	28	50*	—	—	22	30*	29*	59*	74*	24	43*	31*	33*	38*	56*	59*	21*	62*	27	—	43*	54*	43*	46*	35*	15	—					
por	Latn	N/A	47*	31*	35*	46*	62*	59*	60*	74*	N/A	42*	40*	49*	59*	66*	63*	—	66*	N/A	—	31*	40*	49*	39*	34*	—	—					
prs	Arab	N/A	N/A	28*	N/A	N/A	34*	43*	48*	76*	N/A	N/A	39*	N/A	N/A	42*	54*	16	83*	N/A	N/A	17	N/A	N/A	37*	28*	15	—	—				
quy	Latn	N/A	36*	42*	N/A	19	46*	53*	55*	62*	N/A	29*	30*	N/A	38*	54*	57*	—	36*	N/A	—	29*	N/A	—	—	—	48*	37*					
ron	Latn	28	31*	19*	32*	N/A	49*	48*	61*	76*	26	31*	37*	50*	N/A	58*	54*	25*	65*	24	—	39*	46*	N/A	44*	38*	—	—					
run	Latn	N/A	43*	32*	N/A	N/A	57*	67*	50*	64*	N/A	32*	33*	N/A	N/A	56*	68*	20*	58*	N/A	37*	35*	N/A	N/A	62*	56*	54*	68*					
rus	Cyrl	—	29*	29*	33*	36*	33*	38*	56*	77*	35*	48*	21*	50*	47*	59*	65*	27*	74*	32	—	38*	57*	53*	46*	38*	24*	16					
sag	Latn	35*	43*	19*	37*	N/A	52*	51*	51*	59*	33*	38*	22*	32*	N/A	54*	55*	—	41*	25	28*	17	23	N/A	26*	18	50*	40*					
san	Deva	N/A	31*	37*	N/A	N/A	45*	52*	56*	73*	N/A	55*	53*	N/A	N/A	48*	63*	21*	71*	N/A	—	N/A	N/A	38*	36*	35*	23*	—					
sat	Olek	N/A	—	18*	35*	40*	50*	50*	28*	51*	N/A	—	24*	35*	57*	66*	66*	45*	71*	N/A	—	—	21	21	16	—	42*	—					
scn	Latn	N/A	N/A	23*	N/A	40*	58*	61*	61*	74*	N/A	N/A	35*	N/A	59*	67*	67*	—	61*	N/A	N/A	27*	N/A	47*	44*	38*	22*	17					
shn	Mymr	23	N/A	-20*	N/A	N/A	19*	24*	50*	70*	—	N/A	—	N/A	N/A	33*	34*	—	30*	—	N/A	-17	N/A	N/A	29*	36*	20*	31*	—				
sin	Sinh	—	20	16*	N/A	N/A	23*	48*	17	52*	—	55*	45*	N/A	N/A	40*	58*	19*	50*	—	—	—	N/A	N/A	—	17	23*	21*	—				
slk	Latn	N/A	N/A	21*	N/A	N/A	34*	39*	64*	78*	N/A	N/A	39*	N/A	N/A	63*	68*	23*	70*	N/A	N/A	38*	N/A	N/A	44*	34*	16	—	—				
slv	Latn	N/A	47*	25*	30	27*	34*	44*	58*	74*	N/A	50*	42*	56*	55*	65*	73*	22*	66*	N/A	—	36*	57*	53*	45*	36*	15	—					
smo	Latn	N/A	N/A	14	31*	34*	41*	45*	57*	68*	N/A	N/A	15	32*	28*	44*	48*	—	46*	N/A	N/A	—	23	—	19*	24*	59*	56*					

Test language			Original													Transliterated													mBERT												
lang	script	mB.	pho	inv	geo	syn	gb	gen	lex	chr	tri	pho	inv	geo	syn	gb	gen	lex	chr	tri	pho	inv	geo	syn	gb	gen	lex	chr	swt												
tum	Latn		N/A	N/A	42*	N/A	N/A	67	74	48*	64	N/A	N/A	42*	N/A	N/A	63	76	—	53*	N/A	N/A	25*	N/A	N/A	47*	45*	56*	58*												
tur	Latn	x	25	42*	—	—	—	27	23*	61	72	36	56	21*	24	31*	54*	58*	16	52*	N/A	N/A	33*	20	18	14	19	—	—												
twi	Latn		N/A	N/A	17	N/A	N/A	53*	N/A	55*	65*	N/A	N/A	21*	N/A	N/A	53*	N/A	22*	42*	N/A	N/A	30*	N/A	N/A	40*	N/A	52*	57*												
tzm	Tfng		26	18	—	—	N/A	39*	38*	—	50*	32*	33*	25*	46*	N/A	68*	62*	—	57*	—	—	—	—	N/A	—	—	—	24*												
uig	Arab		N/A	N/A	24*	37*	N/A	25*	23*	16	58*	N/A	N/A	22*	44*	N/A	74*	74*	17	49*	N/A	N/A	-29*	—	N/A	—	—	29*	—												
ukr	Cyrl	x	N/A	17	21*	29*	29*	37*	41*	57*	74*	N/A	33*	28*	40*	37*	57*	61*	27*	68*	N/A	—	40*	58*	57*	44*	35*	22*	15												
umb	Latn		40*	46*	26*	N/A	48*	50*	57*	48*	60*	32*	46*	30*	N/A	47*	50*	61*	15	49*	29	46*	44*	N/A	47*	59*	51*	57*	69*												
urd	Arab	x	N/A	30*	30*	29*	N/A	23*	35*	50*	69*	N/A	41*	42*	29	N/A	36*	41*	28*	80*	N/A	—	—	36*	N/A	32*	30*	—	—												
uzn	Latn	x	N/A	33*	—	—	22	31*	28*	50*	62*	N/A	39*	32*	34*	45*	69*	71*	16	61*	N/A	—	33*	—	25*	—	20*	—	—												
vec	Latn		N/A	N/A	29*	N/A	N/A	61	N/A	58*	71*	N/A	N/A	41*	N/A	N/A	70*	N/A	—	64*	N/A	N/A	33*	N/A	N/A	44*	N/A	31*	26*												
vie	Latn	x	30	45*	—	23	33*	53*	59*	39*	50*	—	43*	—	23	34*	59*	66*	—	27*	—	—	—	—	-20	—	—	14	-20*												
war	Latn	x	N/A	N/A	—	N/A	42*	63*	64*	58*	71*	N/A	N/A	24*	N/A	48*	67*	69*	—	54*	N/A	N/A	—	N/A	—	15	—	24*	—												
wol	Latn		—	44*	16	21	43*	37*	33*	58*	66*	—	34*	—	—	42*	36*	42*	—	40*	—	23*	16	—	23	20*	—	52*	42*												
xho	Latn		N/A	46*	50*	51*	34*	66*	72*	47*	61*	N/A	38*	48*	48*	30*	63*	74*	—	51*	N/A	32*	48*	28	26*	55*	49*	49*	63*												
ydd	Hebr		N/A	—	—	N/A	N/A	17	19	—	42*	N/A	24*	17	N/A	N/A	30*	30*	16	63*	N/A	—	-25*	N/A	N/A	—	—	27*	—												
yor	Latn	x	32*	42*	—	36*	N/A	42*	44*	53*	65*	31*	32*	17	26*	N/A	44*	48*	19*	44*	—	—	—	—	N/A	—	—	37*	17												
yue	Hant		—	—	—	43*	42*	56*	55*	69*	30*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	—	—	—	44*	38*	28*	32*	39*	35*												
zsm	Latn		N/A	43*	—	N/A	40*	53*	[44]	56*	71*	N/A	41*	21*	N/A	36*	61	[49]	—	52*	N/A	—	—	N/A	-19	—	[—]	—	—												
zul	Latn		43*	44*	47*	49	N/A	67	77	35*	53*	37*	34*	49*	49*	N/A	67	79*	—	49*	26	35*	42*	34*	N/A	54*	52	52*	65*												
<i>mean (all)</i>			16	34	17	29	36	45	49	49	65	21	38	29	36	46	55	61	11	55	13	8	17	22	26	25	22	27	21												
<i>mean (mbert)</i>			12:19	31:36	15:19	25:32	33:38	43:46	47:50	46:50	63:66	16:25	35:39	26:30	32:39	43:47	53:57	58:62	9:13	52:56	9:16	6:10	14:20	18:26	22:29	22:27	19:24	24:30	17:24												
<i>mean (~mBERT)</i>			16	33	17	26	32	44	48	49	66	25	40	32	38	46	57	61	14	59	20	0	24	31	32	27	22	13	3												
<i>mean (~mBERT)</i>			11:21	29:36	14:19	21:30	28:35	41:46	45:50	45:53	63:69	18:30	37:43	29:34	33:42	43:48	54:59	59:63	11:16	56:61	13:25	-1:1	19:27	24:36	24:36	22:30	19:25	10:15	0:4												
<i>mean (~mBERT)</i>			16	35	18	32	40	46	50	48	64	17	36	26	34	46	54	60	9	52	6	15	13	14	20	24	22	38	34												
<i>mean (~mBERT)</i>			10:21	31:37	14:20	26:37	37:43	43:48	47:52	45:50	61:66	10:22	32:38	23:28	28:39	43:48	51:56	57:62	7:11	48:54	1:10	11:18	8:16	8:18	16:25	20:28	18:25	34:41	30:38												

Table 16: **Correlations (Pearson’s  $r \times 100$ , to save space) between topic classification results and similarity measures for each test language, continued.** Where a training or test language has multiple datasets (one per writing system), we use language-wise score averages for calculating the correlations. The asterisk\* denotes correlations with a  $p$ -value below 0.01. Grey cells with a bar (—) denote correlations with a  $p$ -value of 0.05 or above. Square brackets [ ] mean that no entry for this ISO code was found in the linguistic databases, so the entry for its macrolanguage code was used instead (aze for azb and azj, apc for ajp, lav for lvs, zlm for zsm). ‘N/A’ means that no correlation score could be calculated due to missing entries in the linguistic databases (or due to missing transliterations in the case of the transliteration experiment). The bottom rows show the mean scores across test languages (‘—’ entries are treated as zeros, ‘N/A’ entries are ignored). Below each row of mean scores are the corresponding 95% confidence intervals (numbers separated by semicolons). ‘avg mBERT’ (‘avg ~mBERT’) is for the test languages that are (are not) in mBERT’s pretraining data.