Detecting Languages Unintelligible to Multilingual Models through Local Structure Probes

Louis Clouâtre¹,³ Prasanna Parthasarathi² Amal Zouaq¹ and Sarath Chandar¹,³,⁴
¹ Polytechnique Montréal
² Huawei Noah’s Ark Lab, Canada
³ Quebec Artificial Intelligence Institute (Mila)
⁴ Canada CIFAR AI Chair

Abstract

Providing better language tools for low-resource and endangered languages is imperative for equitable growth. Recent progress with massively multilingual pretrained models has proven surprisingly effective at performing zero-shot transfer to a wide variety of languages. However, this transfer is not universal, with many languages not currently understood by multilingual approaches. It is estimated that only 72 languages possess a “small set of labeled datasets” on which we could test a model’s performance, the vast majority of languages not having the resources available to simply evaluate performances on. In this work, we attempt to clarify which languages do and do not currently benefit from such transfer.

To that end, we develop a general approach that requires only unlabelled text to detect which languages are not well understood by a cross-lingual model. Our approach is derived from the hypothesis that if a model’s understanding is insensitive to perturbations to text in a language, it is likely to have a limited understanding of that language. We construct a cross-lingual sentence similarity task to evaluate our approach empirically on 350, primarily low-resource, languages.

1 Introduction

Natural Language Processing (NLP) boasts of significant recent successes, largely driven by the introduction of different flavors of pretrained models (Devlin et al., 2019; Lan et al., 2019; Liu et al., 2019; Radford and Narasimhan, 2018; Radford et al., 2019; Brown et al., 2020). However, the rewards of those successes have been mostly reaped by high-resource languages. The existence of high-quality benchmarks and metrics, the abundance of readily available high-quality corpora, or the number of researchers speaking the language themselves (Blasi et al., 2022) are significant contributors to the disproportionate advances in high-resource languages. Although recent improvements in NLP have been shown to extend to several different languages, such as the progress to language understanding by BERT-style models (Cui et al., 2019; Le et al., 2019; Martin et al., 2019; Antoun et al., 2020; Carmo et al., 2020; de Vries et al., 2019; Malmsen et al., 2020; Polignano et al., 2019; Nguyen and Tuan Nguyen, 2020), many of those extensions have been limited to relatively high-resource languages. Such improvements are often perceived to extend to low-resource languages, but the lack of appropriate benchmarking in those languages curtails our ability to verify such perceptions.

The World Atlas of Language Structures (Haspelmath et al., 2014; Dryer and Haspelmath, 2013) categorizes over 2600 languages, and Ethnologue (Eberhard et al., 2022) estimates that there are currently over 7000 living languages (Hammarström, 2015); the most popular cross-lingual benchmarks (Liang et al., 2020; Hu et al., 2020) together cover less than 50 languages and Joshi et al. (2020) estimates that only 72 languages worldwide pass the threshold of having “a small set of labeled datasets”, which could be used for evaluation. Towards contributing to an equitable society with the development of language technologies, it is imperative that we ensure that no living languages are left behind. Building automatic and cheap tools to provide better visibility into which languages are not currently well understood by cross-lingual NLP models then becomes essential.

To determine cheaply if a model understands text in a specific language or not, we first find behaviors that are consistently exhibited by models that do perform well on language understanding tasks. By finding when those behaviors are not exhibited, we can determine whether a model understands the text or not. Recent research trends have taken to evaluating
well-known natural language understanding (NLU) models on perturbed text (Sinha et al., 2020, 2021; Pham et al., 2021; Gupta et al., 2021; O'Connor and Andreas, 2021; Taktasheva et al., 2021; Clouatre et al., 2022). Such works attempt to distill which aspects of a text are not necessary and which aspects are necessary for language models to understand it by selectively perturbing the text, such as by shuffling the order of words. It may be possible to use the sensitivity of models to perturbations to properties of text that are found to be essential for NLU as a proxy for model understanding. As an extreme example, if a model develops the same understanding of a text and the same text with its characters shuffled, it can be hypothesized that its original understanding of the text was limited. The texts “I will eat an apple” and “ln i plla wat leaeap” contain the same characters. Yet, we would expect radically different representations of both from a model, assuming it correctly understood the unperturbed version.

We explore the following research questions and verify their corresponding hypotheses:

• **RQ1:** Is there an aspect of text that is universally used by language models that perform well on understanding tasks?

  **H1:** We hypothesize that the **local structure** (Clouatre et al., 2022) of text is one such aspect and that the performance of cross-lingual models on language understanding tasks in most languages should be highly sensitive to local structure perturbations. To verify this hypothesis, we use several cross-lingual tasks from popular benchmarks (Hu et al., 2020; Liang et al., 2020), on which we perform different local structure-altering perturbations and evaluate several cross-lingual models on said perturbed text.

• **RQ2:** If there is such a universally relied upon aspect of text, can a model’s performance sensitivity to that aspect be used as a proxy for understanding?

  **H2:** We hypothesize that if such an aspect of text exists, a model that is insensitive to perturbations to that aspect may be inferred to have a limited understanding of the original text. To verify this hypothesis, we construct a large-scale cross-lingual sentence representation task covering 350 languages which we use to measure the language understanding of several models in all the 350 languages. For each model and target language, we measure the sensitivity of perturbations to that aspect. We demonstrate that all languages for which our cross-lingual models are less sensitive to perturbations to the local structure of text are also not well understood by those models.

Our main contributions are:

• Across all tested languages, tasks, and models, we find that performance is directly correlated with the amount of local perturbations applied to the text.

• We develop the **monolingual local sensitivity** metric which measures the reliance of a model on the local structure to build text representations, only requiring unlabelled monolingual data.

• On a task covering 350 languages, we find that languages on which a model has low monolingual local sensitivity always has a poor representation of that language’s text.

2 Related Work

**Cross-Lingual Performance Prediction**

Predicting to what extent cross-lingual models’ performances transfer to different languages and tasks has seen a fair amount of interest (Birch et al., 2008; Xia et al., 2020; Lauscher et al., 2020; Dolicki and Spanakis, 2021; Srinivasan et al., 2021; Ye et al., 2021; Ahuja et al., 2022). These works formulate the zero-shot transfer to different languages and tasks as regression problems. Linguistic features and model-specific features such as the size of the pretraining data and the models’ performance in different languages and tasks serve as input. The performance of the model on a certain type of task and language is then used as the target of the regression.

All those approaches share a few limitations. They are evaluated on high-resource to medium-resource languages, as those languages all possess supervised learning datasets to be evaluated upon and generally rely upon linguistic features from the World Atlas of Language Structures (Haspelmath et al., 2014; Dryer and Haspelmath, 2013) which cover less than half of all estimated living languages (Hammarström, 2015). While
those approaches are tremendously valuable for optimizing transfer learning, they provide limited utility in predicting the performance of a model on a very low-resource language.

All cited studies (Birch et al., 2008; Xia et al., 2020; Lauscher et al., 2020; Dolicki and Spanakis, 2021; Srinivasan et al., 2021; Ye et al., 2021; Ahuja et al., 2022) predicting cross-lingual performance cover a total of 75 languages. It may seem like a large selection, but we observe that high-resource languages dominate these works. By counting the frequencies of appearances of every language used in those works, we find that most of the evaluations were made on some of the world’s highest resource languages, in terms of native speakers, as illustrated in Table 1. Taking an average of the number of native speakers in all languages surveyed, weighted by their appearances in the cited literature, we observe that evaluations were made on languages with, on average, 127 million native speakers.

### Text Perturbations and Structure Probing
Several text perturbation schemes have been explored in the context of probing model performances. Sankar et al. (2019) shuffles and reverses utterances and words in a generative dialogue setting, highlighting insensitivity to the order of conversational history. Pham et al. (2021) shuffles n-grams for different values of n, highlighting the insensitivity of pretrained Transformer models. Sinha et al. (2020) performs perturbations on the position of the words on textual entailment tasks, with the added criterion that all words’ positions must have changed. Taktasheva et al. (2021) extend perturbation studies to Swedish and Russian and performs perturbations by shuffling syntactic phrases, rotating sub-trees around the root of the syntactic tree of a sentence, or simply shuffling the words of the text.

These approaches work well to provide insight into many languages with automatic parsing tools or well-developed tokenizers. However, low-resource languages cannot be assumed to possess those automatic linguistic tools that permit grammatical perturbations. Language-agnostic tools and measures will need to be prioritized to evaluate the importance of the different aspects of text in low-resource languages. Priors regarding the form of the text, such as the presence of whitespace delimited words, will have to be kept to a minimum.

Clouatre et al. (2022) proposes a suite of controllable perturbations on characters, which should be compatible with almost any written language, as well as a metric quantifying perturbations to the local structure that measures perturbations on a character-level. The findings of Clouatre et al. (2022) in regards to the ubiquitous nature of local sensitivity as it relates to language understanding and the compatibility of both the metric and perturbations with any text make their work particularly well suited to a massively multilingual setting.

### Canine and General Tokenization
Some of the language scripts used in this work, such as Inuktitut Syllabics, are not covered by the tokenization scheme of most pretrained cross-lingual models such as XLM-R (Lample and Conneau, 2019) and multilingual-BERT (Devlin et al., 2019), which rely on a learned vocabulary of subwords (Sennrich et al., 2015; Wu et al., 2016). The Canine model (Clark et al., 2021) offers a tokenization scheme that covers every Unicode character, allowing it to have representations for scripts that were not part of the pretraining dataset. This permits us to evaluate low-resource languages in previously unseen scripts that would otherwise have to be ignored. Has evidence exists that transfer can occur even in languages written in different scripts (Pires et al., 2019), the use of universal tokenization will be necessary to evaluate cross-lingual transfer properly. Canine also uses character-level tokenization instead of explicitly modeling subwords, which should be more resilient to perturbations to the order of

| Languages | German | Chinese | Spanish | Turkish | Vietnamese | Arabic | Russian | Hindi |
|-----------|--------|---------|---------|---------|------------|--------|---------|-------|
| Appearances | 20 | 20 | 19 | 18 | 17 | 17 | 17 | 16 |
| Native Speaker (Millions) | 95 | 1300 | 493 | 80 | 76 | 400 | 150 | 260 |

| Languages | French | Greek | Thai | Bulgarian | Japanese | Korean | Indonesian | Italian |
|-----------|--------|-------|------|-----------|----------|-------|------------|--------|
| Appearances | 16 | 16 | 15 | 13 | 12 | 12 | 12 | 12 |
| Native Speaker (Millions) (Eberhard et al., 2022) | 77 | 13 | 28 | 8 | 128 | 80 | 43 | 67 |

Table 1: Statistics on languages making the most appearances in the cited cross-lingual performance prediction work.
characters and control for the confounder of vocabulary destruction.

Cross-Lingual Sentence Similarity Cross-lingual sentence retrieval tasks, such as Tatoeba (Artetxe and Schwenk, 2018), rely on the presence of language-agnostic sentence embeddings. By comparing the cosine distance between the embeddings of a text in a target language with the same text in English or another high-resource language, we can obtain a relative idea of the quality of the representations of said target language when compared to its understanding of English. As models evaluated on English NLU tasks obtain, at times, superhuman performances (Wang et al., 2019b,a), a model having a similar representation to English sentences in a low-resource language would imply at least some level of understanding of that text. Cross-lingual sentence retrieval is also particularly interesting as, compared to other NLU tasks, obtaining a broad coverage of languages is relatively simple.

3 Multilingual Local Sensitivity

To answer RQ1, we borrow some of the perturbation schemes and metrics from Clouatre et al. (2022) and apply them to a multilingual setting. We aim to demonstrate empirically that neural models generally make some use of local structure to perform understanding tasks, irrespective of language. This can be demonstrated by progressively removing local structure from text through order altering perturbations and observing a similar decline in understanding (as measured by performance metrics) of that text from models. Such results will motivate using low local structure sensitivity as a proxy for lack of ability to perform language understanding tasks. We perform those experiments on seven popular cross-lingual tasks covering 44 unique languages.

3.1 Metric and Perturbations

The CHRF-2 (chrF) (Popović, 2015) metric measures the amount of character bi-gram overlap between a perturbed text and the original text and is used to represent the amount of local structure that has not been perturbed in a text.

We perform perturbations by altering the order of characters present in the text. This is done by using the neighbor flipping (Clouatre et al., 2022) perturbations, which, with a controllable probability ρ, flips a character with its neighbor, thus providing an arbitrary amount of local perturbations. This perturbation is illustrated in 1.

3.2 Experimental Details

All experiments are conducted with the pretrained cross-lingual models Canine-S (Clark et al., 2021), XLM-RoBERTa-base (XLM-R) (Lample and Conneau, 2019) and multilingual-BERT-based-cased (mBERT) (Devlin et al., 2019).

A total of 7 cross-lingual tasks selected from the most popular cross-lingual benchmarks (Hu et al., 2020; Liang et al., 2020) covering 44 languages are used for evaluation (see Table 2).

![Figure 1: From top to bottom: Unperturbed Text, Neighbor Flipping with ρ = 0.5](image)

![Table 2: Summary information of the different tasks used.](table)

The zero-shot cross-lingual setting (Hu et al., 2020) is used for all experiments, meaning that the cross-lingual model is finetuned on the English version of the dataset and evaluated without further tuning on all target languages. 3

No finetuning is performed on the cross-lingual sentence retrieval tasks, defaulting to simple cosine similarity of the mean of the final hidden representations of the model for every input token, as described in Hu et al. (2020).

The English version on which the model is finetuned is kept unperturbed, while the target

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1 Pseudocode of the perturbation is present in the Appendix D
2 Extractive tasks such as extractive QA are not compatible with our perturbations, as the answer would also be perturbed and were not considered.
3 Detailed training and testing hyperparameters and process are present in the Appendix A.

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language text on which the model is evaluated goes through several perturbations. We perform a total of 12 different perturbations on every task and language and obtain their performance, thus evaluating the sensitivity of the target languages to the perturbations. All models are finetuned on five different random seeds, and all perturbations are performed on five different random seeds, for a total of 25 evaluations for every model on every task, every language present in the tasks, and every perturbation setting.

3.3 Results and Discussion

We observe that, in an aggregate, local structure perturbations almost perfectly correlate with the degradation of the ability of a model to perform language understanding tasks in a cross-lingual setting. A Pearson’s r of 0.99 is found between our measure of the perturbations and the performance obtained. We call this correlation between degradation in performance and the amount of local perturbation the local sensitivity. Figure 2 shows the results averaged across all tasks, all random seeds, and all languages. We can observe an almost perfect linear relationship between the amount of local structure remaining in the text on which a model is evaluated, as measured by the character bigram F-score, and the average score of our models when evaluated on that text.

![Figure 2](image.png)

Figure 2: Plotted is the relation between local structure perturbations and average performance on all tested datasets and languages, averaged across all models. The local sensitivity, measured by the correlation between local perturbations and performance degradations, is reported at the top of the figure.

The local sensitivities of the different models on the various tasks are also very consistent, performances being either perfectly or highly correlated to the amount of local structure remaining, as pictured in Figure 3. This is consistent across all models, including the tokenization-free Canine, which lets us control for the vocabulary destruction brought by perturbing the order of characters.

Finally, we can observe whether or not languages with lower local sensitivity tend to underperform their locally sensitive counterparts. In Figure 4, we observe that while high local sensitivity does not guarantee good performance, none of the languages that posses low local sensitivity do much better then chance on the task of Natural Language Inference. Those results are consistent across all tasks and present in Appendix B.

![Figure 4](image.png)

Figure 4: Plotted are the individual language’s local sensitivity plotted against their performance on the unperturbed text on the XNLI task, averaged across all models.

From our results, we cannot find a dimension in which a model’s performance is not extremely sensitive to local structure perturbations, lending credence that local structure is an aspect of text that is always, at least, relied upon to
perform understanding tasks. Those results support H1, demonstrating that it is likely that language models universally make some use of local structure to perform understanding tasks, irrespective of language, task, or the specific pretrained model. Further, in our tested tasks, languages on which a model has low local sensitivity tend to underperform those with high local sensitivity.

4 Low Monolingual Local Sensitivity as a Proxy for Lack of Understanding

This section explores using an insensitivity to local perturbations as a proxy for lack of understanding to address RQ2. To find a proxy for understanding that will provide greater visibility in the performance of very low-resource languages where evaluation is not possible, we cannot measure the local sensitivity by evaluating a language on a labeled task. Therefore, we will explore monolingual local sensitivity as a proxy for lack of language understanding, with unlabelled monolingual data in the target language as its only requirement.

4.1 Monolingual Local Sensitivity

We previously defined local sensitivity as the correlation between the degradation of performance of a model on a task and the local perturbations applied to its text. To calculate the local sensitivity of a model on a specific task, we evaluate the model’s performance on that task with all 12 of our perturbations and calculate the Pearson’s r between the performance on the perturbed text and the local structure as measured by CHRF-2. However, this process has the limitation of requiring a labeled dataset on which to evaluate performance.

To obtain a measure of local sensitivity while bypassing the requirement for a supervised learning dataset, we turn to the monolingual local sensitivity. First, we build a corpus in the target language containing 1000 unique texts. We then formulate the problem as a sentence similarity between two copies of the same corpus, initially resulting in a perfect similarity between sentence pairs. We apply our perturbations to one copy of the corpus while keeping the other copy unperturbed. As more of the local structure is destroyed, the representation of the different pieces of text should also drift apart, assuming that the model considers local structure. We can then obtain a measure of local sensitivity based on the task of sentence retrieval between the same corpus, one of which is perturbed. A toy example comparing cross-lingual sentence similarity and monolingual sentence similarity is pictured in Figure 8.

4.2 MTData Sentence Retrieval

We first require a simple task covering many low-resource languages to evaluate low monolingual local sensitivity as an indicator of lack of understanding in a meaningful way. From the MTData (Gowda et al., 2021) dataset, which is composed of millions of sentence pairs between English and over 500 target languages, we build an English-to-language cross-lingual sentence similarity task covering 350 different language-to-English pairs containing 1000 text pairs per language. The dataset is built using the same process and filtering as was used to construct the Tatoeba cross-lingual sentence similarity dataset (Artetxe and Schwenk, 2018). We will use the normalized cosine similarity between the sentence representation and its target representation to evaluate performance. We normalize by removing the mean and scaling it by the standard deviation of cosine similarity between the text and all other potential texts. This evaluation metric should control for the different models’ behaviors, the different quality of corpora for the different languages, and the diversity of examples for every language, making comparisons more uniform than a simple cosine distance and less sparse than an absolute hit rate. Under this scoring system, a score of 1.0 would mean that the representation of a text with its counterpart would be 1.0 standard deviation closer than its distance to all other texts, as measured by the cosine distance. We will refer to this metric as the similarity Z-Score.

4.3 Results and Discussion

From our MTData cross-lingual sentence similarity task, we can obtain and compare two measures for the 350 languages.

The first is the model’s performance on the task of cross-lingual similarity between an English representation, which is assumed to be of reasonable quality as the model performs well on English understanding tasks, and a target language

5Specific details, dataset statistics, and evaluation methods are expanded upon in the Appendix C.
representation, as measured by the similarity Z-Score. The closer the representation target language’s text to its English representation, the closer the abilities of the model to represent that language are to the ability of the model to represent English.

The second is the monolingual local sensitivity, which we obtain by performing sentence retrieval using two copies of the target language side of the MTData cross-lingual sentence retrieval dataset, as illustrated in the left side of Figure 5.

We compare the performance of our pretrained models against the monolingual local sensitivity of all 350 tested languages, pictured in Figure 5. Languages with high local sensitivity may often have poor unperturbed performance, meaning that relying on local structure does not imply good language understanding. The opposite, however, seems broadly true. Specifically, languages with low monolingual local sensitivity have universally poor unperturbed performance. To build representations roughly in line with the quality of an English representation, a model must rely, at least somewhat, on that text’s local structure.

All languages that obtained a monolingual local sensitivity of under 0.99 did not have representations that were very close to their English counterparts. Assuming normality, a similarity Z-Score of 0.8 implies that over 21% of representations outputted by the model for that language were closer to the representation of the English counterpart than the target text pair. None of the languages with monolingual local sensitivity under 0.99 clear that hurdle. Surprisingly, from the 350 languages surveyed, only a few could truly be said not to be understood by the models. The probability of having an average score of even 0.10 on this task through a random process is vanishingly small, and only 23 of the 350 languages do not cross that threshold, an encouraging result for the current multilingual pretraining approaches.

To provide greater context on those results, we have plotted all 350 surveyed languages on their estimated geographical centers (Haspelmath et al., 2014; Dryer and Haspelmath, 2013), in Figure 12. We can observe several languages that both underperform, as indicated by the color, and are predicted to underperform, as indicated by the size of the circle. Further analysis of our results is provided in the Appendix B.

From our results, we find that a low monolingual...
sensitivity is indicative of a limited ability to represent text. Those results support H2, demonstrating that it is likely that a model’s inability to properly represent a certain language can be detected through monolingual local structure probes.

5 Limitations and Ethical Considerations

There are several limitations to our approach that may have an ethical impact.

The first one is the poor recall. While languages with low monolingual local sensitivity, from our experiments, always are poor performers, many poor performers are also sensitive to local perturbations. Our approach can successfully find some languages that do require additional attention but will miss many other languages. If we rely on automatic tools to detect where to put efforts, there is a possibility that no efforts are put on languages that are not detected by those tools.

The second one is the data requirement. Obtaining a sufficient sample of text to calculate monolingual local sensitivity for some low-resource languages may still be too high of a hurdle. Some living languages, especially those from oral traditions, may have a limited pool of written text available.

It is crucial that if we use automatic tools to detect which languages requires further efforts, we do not forget of the languages that might not be detected or are incompatible with those tools.

6 Conclusion

Regardless of the language, task, or model used, the use of local structure seems to be relied upon by neural models to build an understanding of text. Local structure sensitivity does not seem to be an artifact of the English language and broadly applies to written text in most languages.

We explore monolingual local sensitivity to automatically detect unintelligible languages to cross-lingual models, the only requirement being access to monolingual unlabelled text. If local structure is essential to building understanding, not relying on the local structure would imply a limited understanding. We demonstrate a high correlation between monolingual local sensitivity and the ability of a model to perform cross-lingual sentence similarity in 350 diverse languages. Specifically, all languages with low monolingual local sensitivity performed poorly on that task. Those results indicate that with the measure of monolingual local sensitivity alone, it is possible to estimate the performance of a certain language on a certain model without access to any supervised learning datasets.

Our contribution will be useful to direct further efforts, such as unlabelled data gathering for pretraining, to expand the coverage of cross-lingual models in the most efficient way.
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A  Experiment Details

Model Hyperparameters and Training  We finetune each pretrained models on the English version of each dataset for a total of 10 epochs, checkpointing the model after each epoch. The English version is never perturbed, the finetuning is done on unperturbed data. This finetuning is done 5 times with different random seeds for each model and each datasets. For 7 datasets and 3 models we have a total of \(3 \times 7 \times 5 = 105\) finetuning and 1050 checkpoints, one for each epoch. A learning rate of \(2e-5\), a batch size of 32 and a weight decay of 0.01 is used in all finetuning. All experiments used a warmup ratio of 0.06, as described in Liu et al. (2019). A maximum sequence length of 512 for the mBERT and XLM-R model and a maximum sequence length of 2048 for the Canine model are used.

For the evaluation, we perform the same perturbations on the validation and testing data of the different target languages. We evaluate the perturbed validation data on each of the 10 checkpoints, chose the best checkpoint on the perturbed validation data, and evaluate that checkpoint on the perturbed test data. This process is repeated for each perturbations, each of the 5 random seed and 5 times with different perturbation random seeds for each finetuned models. In total, for each language in each task on each model for each perturbation setup we average results over 25 random seeds.

For the sentence retrieval tasks, such as Tatoeba and BUCC, we do not perform any finetuning. We obtain the representation by averaging the output of the final hidden layer of the model. (Hu et al., 2020) First, we obtain the representation of the unperturbed English side of the dataset. This is done by feeding the English text through the model and averaging the final layers hidden representation of the text. We then perform our perturbations on the target language text, feed those perturbed text through the same pretrained cross-lingual model and obtain it’s representation through the same process. We now have a set of English representation and a set of target language representation, on which we can obtain the cosine distances. We can either find the nearest neighbours (Tatoeba, BUCC) or use the Z-Score of those representations (MTData). If the nearest neighbour is the sentence that was to be retrieved, we consider this an hit, else it is a miss. The reported results are over the average of 5 random seeds of those perturbations.

Monolingual Local Sensitivity  The monolingual sentence retrieval task is performed in the exact same process as for the sentence retrieval task described in Appendix A. The only difference is that the unperturbed English text is replaced by the target language corpus. Pictured in Figure 8 is a toy example representing the monolingual sentence retrieval tasks compared to the crosslingual one. We calculate monolingual local sensitivity by taking the correlation of the degradation in performance on the monolingual sentence retrieval task with the amount of local perturbations applied to the right side of the dataset.

Figure 8: Toy example of sentence retrieval and monolingual sentence retrieval with and without perturbations.

Perturbations  A total of 13 evaluations, containing 12 perturbations are used for all experiments. The first one is the Benchmark, which is simply the unperturbed text. On a character-level perturbations we
perform neighbour-flip shuffling with $\rho$ values of: $[0.025, 0.05, 0.075, 0.1, 0.125, 0.15, 0.175, 0.2, 0.25, 0.3, 0.35, 0.45]$. No neighbor-flip with $\rho$ over 0.5 or over are performed, as they would ultimately shuffle the text less. Unlike Clouatre et al. (2022), we focus purely on local structure perturbations, as we are not interested in the relative importance of local structure compared to other structures, but simply that local structure is important at all.
B Additional Results

Cross-Lingual Local Sensitivity Additional Results In this section we present additional results on the first set of experiments on the cross-lingual zero-shot local sensitivity tasks.

The trend of extremely high correlation between performance and perturbations also holds when grouping results by script and language family, as shown in Figure 9 and Figure 10.

![Table 1](image1.png)

Figure 9: Local sensitivity matrix between the different languages families with at least 3 tested languages in our tasks, averaged across all tasks and models.

![Table 2](image2.png)

Figure 10: Local sensitivity matrix between the different scripts with at least 3 tested languages in our tasks, averaged across all tasks and models.

Further, using low local sensitivity to predict low performance on a particular language seem to be consistent across tested tasks, as seen in Figure 11.
Figure 11: Plotted are the individual language’s local sensitivity plotted against their performance on the unperturbed text on all tasks, averaged across all models. We can observe that with the exception of QAM, which only contains two language with very high local sensitivity, all language and tasks exhibit the same overall behaviour. Languages with low local sensitivity invariably have low performance.

| Languages   | Sensitivity | Native Speaker (Millions) |
|-------------|-------------|---------------------------|
| Coptic      | 0.973       | 0.05                      |
| Northwestern Ojibwa | 0.978       | 0.02                      |
| Inuktitut   | 0.979       | 0.04                      |
| Lao         | 0.980       | 30.34                     |
| Dhivehi     | 0.981       | 3                         |
| S’gaw Karen | 0.982       | 16                        |
| Yoruba      | 0.983       | 0.34                      |
| Khmer       | 0.984       | 60                        |

Table 3: Statistics on the language containing the lowest monolingual local sensitivity of all 350 languages.

Low-Performance Languages In Figure 12, we have plotted the monolingual local sensitivity of all 350 languages on a world map at their geographical centers (Haspelmath et al., 2014; Dryer and Haspelmath, 2013), with their size scaled by amount of native speakers in those specific languages. Many statements can be made about low-performance languages from this study.

It seems that languages that are geographically close to Europe or South-East Asia are generally well understood by our cross-lingual models. The majority of poorly understood languages seem to either be concentrated in Sub-Saharan Africa or Central America, as well as island-specific languages across the Pacific ocean.

The languages that have the lowest monolingual local sensitivity are reported in Table 3. Some of those languages, like Coptic, a now long-dead language in an unseen script, are fairly obvious low-performers. Our approach, however, seems able to detect low-performance in languages that would not be that obvious and would be quite important to detect, like Lao with its over 30 million native speakers.
Figure 12: Monolingual local sensitivity of 350 languages on the task of cross-lingual similarity on our MTData cross-lingual sentence similarity dataset, scaled by the estimated amount of native speakers.

C MTData Sentence Similarity Task

From the MTData dataset (Gowda et al., 2021) we build a sentence similarity dataset covering a total of 350 languages. We use and adapt the approach used to build the Tatoeba sentence retrieval dataset (Artetxe and Schwenk, 2018). Specifically, from the MTData dataset containing english aligned sentences in over 500 languages, we remove all sentences containing either "@", "http" or "%", remove any English sentence containing less than 3 words, and remove any duplicate. We randomly sample 1000 sentence pairs per language, removing languages with less then 1000 sentence pair present after filtering. We also remove text of sign languages, as their written form is almost exactly the same as the original language. In total, 350 languages remain after that point. Table 4 to Table 9 contains statistics on every single language present in our MTData Sentence Retrieval Task.

D Pseudocode for Perturbation

```
Function NeighborFlip(ρ ← 0.5, text←list):
    perturbed_tokens ← list();
    held_token ← list(text[0])
    for token in text[1:] do
        p ~ Unif([0, 1]);
        if p < ρ then
            perturbed_tokens.append(held_token);
            held_token ← list(token)
        else
            perturbed_tokens ← [perturbed_tokens, token];
        end
    end
    perturbed_tokens.append(held_token);
    perturbed_text ← ''.join(perturbed_tokens)
    return perturbed_text
```

Algorithm 1: Pseudocode for NeighborFlip.
| Language | ISO-639-3 | Language Family | Language Script | Num Native Speakers |
|----------|-----------|-----------------|-----------------|---------------------|
| Chinese  | zho       | Sino-Tibetan    | Chinese characters and derivatives | 1300000000 |
| Mandarin Chinese | cmn | Sino-Tibetan    | Chinese characters and derivatives | 9200000000 |
| Spanish  | spa       | IE: Italic      | Latin           | 4930000000 |
| Arabic   | ara       | Afro-Asiatic    | Arabic          | 4000000000 |
| Bengali  | ben       | IE: Indo-Iranian| Brahmic         | 3000000000 |
| Hmong    | hun       | IE: Indo-Iranian| Brahmic         | 2600000000 |
| Portuguese | por     | IE: Italic      | Latin           | 2500000000 |
| Russian  | rus       | IE: Balto-Slavic| Cyrillic        | 1500000000 |
| Japanese | jpn       | Japanese        | Kana            | 1280000000 |
| Panjabi  | pan       | IE: Indo-Iranian| Arabic          | 1130000000 |
| German   | deu       | IE: Germanic    | Latin           | 9500000000 |
| Yue Chinese | yue | Sino-Tibetan    | Chinese characters and derivatives | 8400000000 |
| Egyptian Arabic | arz | Afro-Asiatic    | Arabic          | 8300000000 |
| Javanese | jav       | Austronesian    | Brahmic         | 8200000000 |
| Korean   | kor       | Koreanic        | Hangul          | 8040000000 |
| Turkish  | tur       | Turkish         | Latin           | 8000000000 |
| Wu Chinese | wuu | Sino-Tibetan    | Chinese characters and derivatives | 8000000000 |
| Malay (individual language) | zlm | Autronesian    | Arabic          | 8000000000 |
| Malay (macrolanguage) | msa | Austronesian    | Latin           | 7700000000 |
| Standard Malay | zsm | Austronesian    | Arabic          | 7700000000 |
| French   | fra       | IE: Italic      | Latin           | 7680000000 |
| Vietnamese | vie | Austroasiatic   | Latin           | 7600000000 |
| Telugu   | tel       | Dravidian       | Brahmic         | 7500000000 |
| Marathi  | mar       | IE: Indo-Iranian| Brahmic         | 7000000000 |
| Persian  | pas       | IE: Indo-Iranian| Arabic          | 7000000000 |
| Tamil    | tam       | Dravidian       | Brahmic         | 7000000000 |
| Urdu     | urd       | IE: Indo-Iranian| Arabic          | 7000000000 |
| Italian  | ita       | IE: Italic      | Latin           | 6700000000 |
| Iranian Persian | pes | IE: Indo-Iranian| Arabic          | 5500000000 |
| Gujarati | guj       | IE: Indo-Iranian| Brahmic         | 5000000000 |
| Hausa    | hau       | Afro-Asiatic    | Latin           | 5000000000 |
| Pushito  | pus       | IE: Indo-Iranian| Arabic          | 5000000000 |
| Tagalog  | tgl       | Austronesian    | Latin           | 4500000000 |
| Polish   | pol       | IE: Balto-Slavic| Latin           | 4500000000 |
| Filipino | fil       | Austronesian    | Latin           | 4500000000 |
| Uzbek    | uzb       | Turkic          | Latin           | 4400000000 |
| Indonesian | ind | Austronesian    | Latin           | 4300000000 |
| Yoruba   | yor       | Niger-Congo     | Latin           | 4300000000 |
| Kannada  | kan       | Dravidian       | Brahmic         | 4300000000 |
| Sundanese | sun | Austronesian    | Latin           | 4200000000 |
| Ukrainian | ukr | IE: Balto-Slavic| Cyrillic        | 4000000000 |
| Nigerian Pidgin | pcm | English Creole  | Latin           | 4000000000 |
| Oromo    | orm       | Afro-Asiatic    | Latin           | 3740000000 |
| Orinya (macrolanguage) | orl | IE: Indo-Iranian| Brahmic         | 3500000000 |
| Malayalam | mal | Dravidian      | Brahmic         | 3500000000 |
| Maithili | mni       | IE: Indo-Iranian| Brahmic         | 3390000000 |
| Burmese  | mya       | Sino-Tibetan    | Brahmic         | 3300000000 |
| Amharic  | amh       | Afro-Asiatic    | Ge’ez           | 3200000000 |
| Azerbaijani | aze | Turkic       | Arabic          | 3000000000 |
| Lao      | lao       | Kha-Dai         | Brahmic         | 3000000000 |
| Igbo     | ibo       | Niger-Congo     | Latin           | 3000000000 |
| Thai     | tha       | Kha-Dai         | Brahmic         | 2800000000 |
| Sindhi   | snd       | IE: Indo-Iranian| Arabic          | 2500000000 |
| Malay | mlg | Austronesian | Latin | 2500000000 |
| Plateau Malagasy | plm | Austronesian | Latin | 2500000000 |
| Dutch    | ndl       | IE: Germanic    | Latin           | 2500000000 |
| Kurdish  | kur       | IE: Indo-Iranian| Arabic          | 2500000000 |
| Romanian | rom       | IE: Italic      | Latin           | 2380000000 |
| Cebuano  | ceb       | Austronesian    | Latin           | 2200000000 |
| Somali   | som       | Afro-Asiatic    | Latin           | 218077350 |
| Croatian | cro       | IE: Balto-Slavic| Cyrillic        | 2100000000 |
| Ganda    | gnd       | Niger-Congo     | Latin           | 2000000000 |
| Ewe      | ewe       | Niger-Congo     | Latin           | 2000000000 |
| Swahili (macrolanguage) | swa | Niger-Congo | Latin | 1800000000 |
| Chhattisgarhi | hme | IE: Indo-Iranian| Brahmic         | 1800000000 |
| Kazakh   | kaz       | Turkic          | Cyrillic        | 1780000000 |
| Lingala  | lin       | Niger-Congo     | Latin           | 1750000000 |
| Sinhala  | sinh      | IE: Indo-Iranian| Brahmic         | 1700000000 |
| Nepali (macrolanguage) | nep | IE: Indo-Iranian| Brahmic         | 1600000000 |

Table 4: Statistics on all 350 languages present in the MTData sentence retrieval dataset. (1 of 6)
| Language         | ISO-639-3 | Language Family       | Language Script | Num Native Speakers |
|------------------|-----------|-----------------------|-----------------|---------------------|
| Khmer            | khm       | Austroasiatic         | Brahmic         | 16000000            |
| Assamese         | asm       | IE: Indo-Iranian      | Brahmic         | 13311351            |
| Northern Kurdish | kmr       | IE: Indo-Iranian      | Arabic          | 15000000            |
| Bavarian         | bar       | IE: Germanic          | Latin           | 14000000            |
| Modern Greek (1453-) | ell   | IE: Hellenic         | Greek           | 13400000            |
| Hungarian        | hun       | Uralic                | Latin           | 13000000            |
| Umbundu          | umb       | Niger-Congo           | Latin           | 12740000            |
| Haitian          | hat       | IE: Italic            | Latin           | 12000000            |
| Shona            | sna       | Niger-Congo           | Latin           | 12000000            |
| Zulu             | zul       | Niger-Congo           | Latin           | 12000000            |
| Serbian          | srp       | IE: Balto-Slavic      | Cyrillic        | 12000000            |
| Nyamwezi         | nya       | Niger-Congo           | Latin           | 12000000            |
| Kandi            | run       | Niger-Congo           | Latin           | 11244750            |
| Turkmen          | tuk       | Turkic                | Latin           | 11000000            |
| Czech            | ces       | IE: Balto-Slavic      | Latin           | 10700000            |
| Swedish          | swe       | IE: Germanic          | Latin           | 10000000            |
| Uighur           | uig       | Turkic                | Arabic          | 10000000            |
| Tigrinya         | tir       | Afro-Asiatic          | Ge'ez            | 9850000             |
| Kinyarwanda      | kin       | Niger-Congo           | Latin           | 9800000             |
| Congo Swahili    | swc       | Niger-Congo           | Latin           | 9000000             |
| Xhosa            | xho       | Niger-Congo           | Latin           | 8700000             |
| Ga               | gaa       | Niger-Congo           | Latin           | 8500000             |
| Iloko            | ilo       | Austronesian          | Latin           | 8100000             |
| Tajik            | tjk       | IE: Indo-Iranian      | Cyrillic        | 8100000             |
| Bulgarian        | bul       | IE: Balto-Slavic      | Cyrillic        | 8000000             |
| Quechua          | que       | Quechuan              | Latin           | 8000000             |
| Mossi            | mos       | Niger-Congo           | Latin           | 7830000             |
| Hiligaynon       | hil       | Austronesian          | Latin           | 7800000             |
| Makhuwa          | vmw       | Niger-Congo           | Latin           | 7400000             |
| Afrikaans        | afr       | IE: Germanic          | Arabic          | 7200000             |
| Dyula            | dyu       | Mande                 | Latin           | 6852620             |
| Kikuyu           | kik       | Niger-Congo           | Latin           | 6600000             |
| Paraguayan Guaraní | gug    | Tupian                | Latin           | 6500000             |
| San Salvador Kongo | kwy   | Niger-Congo           | Latin           | 6300000             |
| Luba-Lulua       | lwa       | Niger-Congo           | Latin           | 6300000             |
| Low German       | nds       | IE: Germanic          | Latin           | 6000000             |
| Armenian         | hye       | IE: Armenian          | Armenian        | 6000000             |
| Albanian         | sqi       | IE: Albanian          | Latin           | 6000000             |
| Danish           | dan       | IE: Germanic          | Latin           | 6000000             |
| Kabyle           | kab       | Afro-Asiatic          | Arabic          | 6000000             |
| Finnish          | fin       | Uralic                | Latin           | 5800000             |
| Wolof            | wol       | Niger-Congo           | Latin           | 5454000             |
| Norwegian        | nor       | IE: Germanic          | Latin           | 5320000             |
| Slovak           | slk       | IE: Balto-Slavic      | Latin           | 5200000             |
| Tatar            | tat       | Turkic                | Cyrillic        | 5200000             |
| Tswana           | tsn       | Niger-Congo           | Latin           | 5200000             |
| Mongolian        | mon       | Mongolic              | Cyrillic        | 5200000             |
| Belarusian       | bel       | IE: Balto-Slavic      | Cyrillic        | 5100000             |
| Tiv              | tv        | Niger-Congo           | Latin           | 5000000             |
| Hebrew           | heb       | Afro-Asiatic          | Aramaic         | 5000000             |
| Pedi             | nso       | Niger-Congo           | Latin           | 4700000             |
| Baoan            | bci       | Niger-Congo           | Latin           | 4700000             |
| Kirghiz          | kir       | Turkic                | Cyrillic        | 4500000             |
| Luo (Kenya and Tanzania) | luo  | Nilo-Saharan          | Latin           | 4300000             |
| Bemba (Zambia)   | bem       | Niger-Congo           | Latin           | 9100000             |
| Kamba (Kenya)    | kam       | Niger-Congo           | Latin           | 3900000             |
| Tachelhit        | shi       | Afro-Asiatic          | Arabic          | 3900000             |

Table 5: Statistics on all 350 languages present in the MTData sentence retrieval dataset. (2 of 6)
| Language                | ISO-639-3 | Language Family    | Language Script | Num Native Speakers |
|------------------------|-----------|--------------------|----------------|--------------------|
| Lombard                | lmo       | IE: Italic         | Latin          | 3800000            |
| Georgian               | kat       | Kartvelian         | Georgian        | 3700000            |
| Hmong                  | hmn       | Hmong–Mien         | Latin          | 3700000            |
| Tsonga                 | tso       | Niger-Congo        | Latin          | 3700000            |
| Waray (Philippines)    | war       | Autronesian        | Latin          | 3600000            |
| Zarma                  | dje       | Nilo-Saharan       | Latin          | 3600000            |
| Tumbuka                | tum       | Niger-Congo        | Latin          | 3546000            |
| Romany                 | rom       | IE: Indo-Iranian   | Latin          | 3500000            |
| Nyankole               | nyn       | Niger-Congo        | Latin          | 3400000            |
| Yao                    | yao       | Niger-Congo        | Latin          | 3100000            |
| Lithuanian             | lit       | IE: Balto-Slavic   | Latin          | 3000000            |
| S’gaw Karen            | ksw       | Sino-Tibetan       | Brahmic        | 3000000            |
| Sidamo                 | sid       | Afro-Asiatic       | Latin          | 3000000            |
| Pampanga               | pam       | Autronesian        | Brahmic        | 2800000            |
| Slovenian              | slv       | IE: Balto-Slavic   | Latin          | 2500000            |
| Macedonian             | mkd       | IE: Balto-Slavic   | Cyrillic       | 2500000            |
| Bosnian                | bos       | IE: Balto-Slavic   | Cyrillic       | 2500000            |
| Central Bikol          | bcl       | Austronesian       | Latin          | 2500000            |
| Galician               | glg       | IE: Italic         | Latin          | 2400000            |
| Ndau                   | ndc       | Niger-Congo        | Latin          | 2400000            |
| Iban                   | iba       | Autronesian        | Latin          | 2300000            |
| Swati                  | ssw       | Niger-Congo        | Latin          | 2300000            |
| Fon                    | ton       | Niger-Congo        | Latin          | 2200000            |
| Kimbundu               | kmb       | Niger-Congo        | Latin          | 2100000            |
| Acoli                  | ach       | Nilo-Saharan       | Latin          | 2100000            |
| Cameroon Pidgin         | wes       | English Creole     | Latin          | 2000000            |
| Urhobo                 | urh       | Niger-Congo        | Latin          | 2000000            |
| Lomwe                  | ngl       | Niger-Congo        | Latin          | 1850000            |
| Pangasinan             | pag       | Austronesian       | Latin          | 1800000            |
| Latvian                | lav       | IE: Balto-Slavic   | Latin          | 1750000            |
| Alur                   | alz       | Nilo-Saharan       | Latin          | 1700000            |
| Aymara                 | aym       | Aymaran            | Latin          | 1700000            |
| Batak Toba             | bbc       | Austronesian       | Latin          | 1610000            |
| Wolaytta               | wal       | Afro-Asiatic       | Latin          | 1600000            |
| Sena                   | seh       | Niger-Congo        | Latin          | 1600000            |
| Bini                   | bin       | Niger-Congo        | Latin          | 1600000            |
| Luba-Katanga           | lub       | Niger-Congo        | Latin          | 1505000            |
| Mende (Sierra Leone)   | men       | Mande              | Latin          | 1500000            |
| Yiddish                | yid       | IE: Germanic       | Aramaic        | 1500000            |
| Cusco Quechua          | quz       | Quechuan           | Latin          | 1500000            |
| Tonga (Zambia)         | loi       | Niger-Congo        | Latin          | 1500000            |
| Kuanyama               | kua       | Niger-Congo        | Latin          | 1441000            |
| Bashkir                | bak       | Turkic             | Cyrillic       | 1400000            |
| Limburgan              | lim       | IE: Germanic       | Latin          | 1300000            |
| Southwestern Dinka     | dik       | Nilo-Saharan       | Latin          | 1300000            |
| Venda                  | ven       | Niger-Congo        | Latin          | 1300000            |
| Manipuri               | mini      | Sino-Tibetan       | Brahmic        | 1250000            |
| Tswana                 | tsc       | Niger-Congo        | Latin          | 1200000            |
| Batak Simalungun       | bts       | Austronesian       | Latin          | 1200000            |
| Sardinian              | srd       | IE: Italic         | Latin          | 1175000            |

Table 6: Statistics on all 350 languages present in the MTData sentence retrieval dataset. (3 of 6)
| Language                        | ISO-639-3 | Language Family | Language Script | Num Native Speakers |
|--------------------------------|-----------|-----------------|-----------------|---------------------|
| Gun                            | guw       | Niger-Congo     | Latin           | 1162000             |
| Kekchi                         | kek       | Mayan           | Latin           | 1100000             |
| Estonian                       | est       | Uralic          | Latin           | 1100000             |
| Zande (individual language)    | zne       | Niger-Congo     | Latin           | 1100000             |
| K'iche'                        | quc       | Mayan           | Latin           | 1100000             |
| Morisyen                       | mfe       | French Creole   | Latin           | 1090000             |
| Chuvash                        | chv       | Turkic          | Cyrillic        | 1042989             |
| Kabiye                         | kbp       | Niger-Congo     | Latin           | 1000000             |
| Songe                          | sop       | Niger-Congo     | Latin           | 1000000             |
| Central Huasteca Nahuatl       | nch       | Uto-Aztecan     | Latin           | 1000000             |
| Chokwe                         | cjk       | Niger-Congo     | Latin           | 9800000             |
| Chuwabu                        | chw       | Niger-Congo     | Latin           | 9700000             |
| Kachin                         | kac       | Sino-Tibetan    | Latin           | 9400000             |
| Ayacucho Quechua               | quy       | Quechuan        | Latin           | 9182000             |
| Welsh                          | cym       | IE: Celtic      | Latin           | 8922000             |
| Ngaui                          | njj       | Austronesian    | Latin           | 8900000             |
| Kabuverdianu                   | kea       | English Creole  | Latin           | 8710000             |
| Balu (Cameroon)                | bml       | Niger-Congo     | Latin           | 8600000             |
| Lushai                         | lus       | Sino-Tibetan    | Brahmic         | 843750              |
| Ndonga                         | ndo       | Niger-Congo     | Latin           | 8100000             |
| Adangme                        | ada       | Niger-Congo     | Latin           | 8000000             |
| Yucateco                       | yua       | Mayan           | Latin           | 7700000             |
| Nias                           | nia       | Austronesian    | Latin           | 7700000             |
| Chopi                          | cce       | Niger-Congo     | Latin           | 7600000             |
| Tetela                         | tll       | Niger-Congo     | Latin           | 7600000             |
| Basque                         | eus       | Basque          | Latin           | 7500000             |
| Nyaneka                        | nyk       | Niger-Congo     | Latin           | 7500000             |
| Lozi                           | loz       | Niger-Congo     | Latin           | 7250000             |
| Chavacano                      | cbk       | IE: Italic      | Latin           | 7000000             |
| Luvale                         | lue       | Niger-Congo     | Latin           | 6400000             |
| Konzo                          | koo       | Niger-Congo     | Latin           | 6100000             |
| Walloon                        | win       | IE: Italic      | Latin           | 6000000             |
| Mami                           | mam       | Mayan           | Latin           | 6000000             |
| Batak Karo                     | btx       | Austronesian    | Latin           | 6000000             |
| Luxembourgish                  | ltx       | IE: Germanic    | Latin           | 6000000             |
| Ossetian                       | oss       | IE: Indo-Iranian| Cyrillic        | 597450              |
| Tzeltal                        | tzh       | Mayan           | Latin           | 5900000             |
| Balkan Romani                  | rmm       | IE: Indo-Iranian| Latin           | 563670              |
| Udmurt                         | udm       | Uralic          | Cyrillic        | 5540000             |
| Tzotzil                        | tzo       | Mayan           | Latin           | 5500000             |
| Norwegian Nynorsk              | nno       | IE: Germanic    | Latin           | 5320000             |
| Southern Kisi                  | kss       | Niger-Congo     | Latin           | 5300000             |
| Maltese                        | mlt       | Afro-Asiatic    | Latin           | 5200000             |
| Samoan                         | smo       | Austronesian    | Latin           | 5100000             |
| Mambwe-Lungu                   | mgr       | Niger-Congo     | Latin           | 5000000             |
| Tamashke                        | tmh       | Afro-Asiatic    | Latin           | 5000000             |
| Krio                           | kri       | English Creole  | Latin           | 5000000             |
| Imbubara Highland Quechua      | qvi       | Quechuan        | Latin           | 5000000             |
| Tooro                          | ttj       | Niger-Congo     | Latin           | 4900000             |

Table 7: Statistics on all 350 languages present in the MTData sentence retrieval dataset. (4 of 6)
| Language               | ISO-639-3 | Language Family | Language Script | Num Native Speakers |
|------------------------|-----------|-----------------|-----------------|---------------------|
| Western Frisian        | fry       | IE: Germanic    | Latin           | 470000              |
| Sango                  | sag       | French Creole   | Latin           | 450000              |
| Plattdeitsch           | pdt       | IE: Germanic    | Latin           | 450000              |
| Occitan (post 1500)    | oci       | IE: Italic      | Latin           | 450000              |
| Chimbaborazo Highland Quichua | qug    | Quechuan       | Latin           | 450000              |
| Hakha Chin             | cnh       | Sino-Tibetian   | Latin           | 446264              |
| Nyungwe                | nyu       | Niger-Congo     | Latin           | 440000              |
| Friulian               | fur       | IE: Italic      | Latin           | 420000              |
| Isoko                  | iso       | Niger-Congo     | Latin           | 420000              |
| Nzima                  | nzi       | Niger-Congo     | Latin           | 412000              |
| Catalán                | cat       | IE: Italic      | Latin           | 410000              |
| Kaqchikel              | cak       | Mayan           | Latin           | 410000              |
| Etik                   | efi       | Niger-Congo     | Latin           | 400000              |
| Ibanag                 | ibg       | Austronesian    | Latin           | 400000              |
| Lunda                  | lun       | Niger-Congo     | Latin           | 400000              |
| Tetun Dili             | tdt       | Austronesian    | Latin           | 390000              |
| Gitonga                | toh       | Niger-Congo     | Latin           | 380000              |
| Mingrelian             | xmf       | Kartvelian      | Georgian        | 344000              |
| Papamiento             | pap       | IE: Italic      | Latin           | 341300              |
| Dhrveli                | div       | IE: Indo-Iranian| Thana           | 340000              |
| Fijian                 | fj        | Austronesian    | Latin           | 339210              |
| Kaonde                 | kqn       | Niger-Congo     | Latin           | 290000              |
| Icelandic              | isl       | IE: Germanic    | Latin           | 314000              |
| Wayuu                  | gcu       | Arawakan        | Latin           | 305000              |
| Esan                   | sh        | Niger-Congo     | Latin           | 300000              |
| Basa (Cameroon)        | bas       | Niger-Congo     | Latin           | 300000              |
| Tuvinian               | tyn       | Turkic          | Cyrillic        | 280000              |
| Mapudungun             | arn       | Araucanian      | Latin           | 260000              |
| Kuund                  | ndt       | Niger-Congo     | Latin           | 250000              |
| Syriac                 | syr       | Afro-Asiatic    | Aramaic         | 240000              |
| Fijian                 | fj        | Austronesian    | Latin           | 239210              |
| Huaulal Mazatec        | mao       | Oto-Manguean    | Latin           | 230000              |
| Nyemba                 | nba       | Niger-Congo     | Latin           | 225000              |
| Herero                 | her       | Niger-Congo     | Latin           | 211700              |
| Breton                 | bre       | IE: Celtic      | Latin           | 210000              |
| Ams                    | ami       | Austronesian    | Latin           | 200000              |
| Garifuna               | cab       | Arawakan        | Latin           | 200000              |
| Sango                  | sxn       | Austronesian    | Latin           | 200000              |
| Northern Puebla Nahuatl | ncj     | Uto-Aztecan     | Latin           | 200000              |
| Lamba                  | lam       | Niger-Congo     | Latin           | 200000              |
| Abkhazian              | abk       | North Caucasus  | Cyrillic        | 190000              |
| Tonga (Tonga Islands)  | ton       | Austronesian    | Latin           | 187000              |
| Tahitian               | tah       | Austronesian    | Latin           | 185000              |
| Navajo                 | nav       | Dene-Yenisean   | Latin           | 170000              |
| Ngabere                | gym       | Chibchan        | Latin           | 170000              |
| Irish                  | gle       | IE: Celtic      | Latin           | 170000              |
| Tonga (Nyasa)          | tog       | Niger-Congo     | Latin           | 170000              |
| Kwangali               | kwn       | Niger-Congo     | Latin           | 152000              |
| Malinaltepec Me phaa   | tcl       | Oto-Manguean    | Latin           | 150000              |
| Belize Kriol English   | bj        | English Creole  | Latin           | 130000              |
| Metlachic Mixtec       | msv       | Oto-Manguean    | Latin           | 150000              |
| Guerrerico Nahualet    | ngu       | Uto-Aztecan     | Latin           | 150000              |
| Purepecha              | tsz       | Purepecha       | Latin           | 140000              |
| Kadazan Dusun          | dtp       | Austronesian    | Latin           | 140000              |
| Sranan Tongo           | srr       | English Creole  | Latin           | 130000              |
| Tok Pisin              | tpi       | English Creole  | Latin           | 120000              |
| Gilbertese             | gil       | Austronesian    | Latin           | 120000              |

Table 8: Statistics on all 350 languages present in the MTData sentence retrieval dataset. (5 of 6)
| Language       | ISO-639-3 | Language Family | Language Script | Num Native Speakers |
|---------------|-----------|-----------------|-----------------|---------------------|
| Paite Chin    | pck       | Sino-Tibetan    | Latin           | 100000              |
| Saramaccan    | smn       | English Creole  | Latin           | 90000               |
| Duala         | dsu       | Niger-Congo     | Latin           | 87700               |
| Ishmus Zapotec| zai       | Oto-Manguean    | Latin           | 85000               |
| Galela        | ghs       | West Papuan     | Latin           | 80000               |
| Papantla Totonac | top     | Mayan           | Latin           | 80000               |
| Seselwa Creole| crs       | French Creole   | Latin           | 75000               |
| Faroese       | fao       | IE: Germanic    | Latin           | 72000               |
| Lokpa         | dep       | Ngor-Congo      | Latin           | 70000               |
| Itak           | bhw       | Austro-Brisian  | Latin           | 70000               |
| Topobal        | toj       | Mayan           | Latin           | 67000               |
| Eastern Maroon| djk       | English Creole  | Latin           | 67000               |
| Guerrero Amargo| arus     | Oto-Manguean    | Latin           | 66000               |
| Chiamoro      | cha       | Austro-Brisian  | Latin           | 38000               |
| Scottish Gaelic| gla       | IE: Celtic      | Latin           | 37000               |
| Kalatalait   | kal       | Eskimo–Aleut    | Latin           | 56000               |
| Southern Altai| alt       | Turkic          | Cyrillic        | 56780               |
| Marshallese   | nath      | Austro-Brisian  | Latin           | 30000               |
| Papuan        | pgu       | Austro-Brisian  | Latin           | 25000               |
| Northern Satt | sine      | Uralic          | Latin           | 25000               |
| Okpe (Southwestern Edou)| oke| Ngor-Congo | Latin | 25000 |
| Pijm          | prz       | English Creole  | Latin           | 24000               |
| Wuna          | rsk       | Austro-Brisian  | Latin           | 20000               |
| Northernwestern Ojbo| cbg| Algic         | Latin           | 20000               |
| Tena Lowland Quichua| qew| Quechuan     | Latin           | 17855               |
| Central Peeble Nahuatl | ncu| Uto-Aztecian | Latin           | 16000               |
| Mirandese     | nwl       | IE: Italian     | Latin           | 15000               |
| Delu          | uhv       | Austro-Brisian  | Latin           | 13000               |
| Wallisian     | wls       | Austro-Brisian  | Latin           | 10000               |
| Hsibama       | bsl       | IE: Germanic    | Latin           | 10000               |
| Akawao        | ake       | Cariban         | Latin           | 10000               |
| Quilepo CHEMATEC | chq     | Oto-Manguean    | Latin           | 10000               |
| Cabecar       | cip       | Chibchan        | Latin           | 8000                |
| Yvese         | yip       | Austro-Brisian  | Latin           | 5130                |
| Uspaneco      | usp       | Mayan           | Latin           | 5100                |
| Camsa         | kbb       | Oto-Manguean    | Cambo           | 4000                |
| Achuar-Shiwaar| acu       | Chicham         | Latin           | 4000                |
| Yecuicxacu Nahuat| nhg| Uto-Aztecian | Latin           | 35000               |
| Cherokee      | chr       | Iroquoian       | Latin           | 2100                |
| Asturian      | ast       | IE: Italian     | Latin           | 2000                |
| Nunean        | nnu       | Austro-Brisian  | Latin           | 2000                |
| Bassana Edurna| bsn       | Tuscanan        | Latin           | 1900                |
| Interlingua   | ina       | International Auxiliary Language Association | Constructed | Latin | 1500 |
| Esperanto     | epo       | Constructed     | Latin           | 1000                |
| Cornish       | cor       | IE: Celtic      | Latin           | 357                 |
| Karotongan    | rar       | Austro-Brisian  | Latin           | 450                 |
| Hirr Motu     | hmo       | Austro-Brisian  | Latin           | 100                 |
| Potawatomi    | pot       | Algic           | Latin           | 100                 |
| Manx          | gav       | IE: Celtic      | Latin           | 92                  |
| Klingon       | khan      | Constructed     | Latin           | 23                  |
| Ido           | ido       | Constructed     | Latin           | 20                  |
| Volapik       | vol       | Constructed     | Latin           | 7                   |
| Latin         | lat       | IE: Italian     | Latin           | 1                   |
| Interlingue   | ile       | Constructed     | Latin           | 1                   |
| Coptic        | cop       | Afro-Asiatic    | Coptic          | 1                   |
| Logban        | jbo       | Constructed     | Latin           | 1                   |
| Lingua Franca Nova | lfn | Constructed | Latin | 1 |

Table 9: Statistics on all 350 languages present in the MTData sentence retrieval dataset. (6 of 6)