BUILDING MACHINE TRANSLATION SYSTEMS FOR THE NEXT THOUSAND LANGUAGES

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ABSTRACT

In this paper we share findings from our effort to build practical machine translation (MT) systems capable of translating across over one thousand languages. We describe results in three research domains: (i) Building clean, web-mined datasets for 1500+ languages by leveraging semi-supervised pre-training for language identification and developing data-driven filtering techniques; (ii) Developing practical MT models for under-served languages by leveraging massively multilingual models trained with supervised parallel data for over 100 high-resource languages and monolingual datasets for an additional 1000+ languages; and (iii) Studying the limitations of evaluation metrics for these languages and conducting qualitative analysis of the outputs from our MT models, highlighting several frequent error modes of these types of models. Using this approach, we add 24 new languages to Google Translate, the product's largest increase in language coverage to-date. We hope that our work provides useful insights to practitioners working towards building MT systems for currently understudied languages, and highlights research directions that can complement the weaknesses of massively multilingual models in data-sparse settings.

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1 AN OVERVIEW

The past decade has seen tremendous improvements in the quality of academic and commercial machine translation (MT) systems. These improvements have largely been driven by advances in machine learning and the availability of large-scale web-mined datasets (Resnik & Smith, 2003; Uszkoreit et al., 2010; Esplà-Gomis, 2009; Esplà et al., 2019; Bañón et al., 2020; Schwenk et al., 2021). The advent of deep learning and sequence-to-sequence models (Sutskever et al., 2014; Bahdanau et al., 2015; Luong et al., 2015; Vaswani et al., 2017), large parallel (and monolingual) datasets mined from the web, data augmentation approaches like back-translation (Sennrich et al., 2016; Edunov et al., 2018) and self-training (He et al., 2019) and massively multilingual modeling (Firat et al., 2016a; Johnson et al., 2017; Aharoni et al., 2019a; Arivazhagan et al., 2019; Tang et al., 2021; Fan et al., 2021) have enabled high quality machine translation systems that can support over 100 languages.

However, despite tremendous progress in low-resource MT, the number of languages for which widely-available, general-domain MT systems have been built has been limited to around 100, which is a small fraction of the over 7000+ languages that are spoken in the world today. Apart from the limited number of languages, the distribution of languages supported by current MT systems is highly skewed in favour of European languages. Despite high speaker populations, languages spoken in Africa, South and South-East Asia and indigenous languages of the Americas are relatively under-served. For example, Google Translate supports Frisian, Maltese, Icelandic, and Corsican, each with fewer than 1M L1 speakers, but not (up until this work) Bhojpuri (~51M speakers), Oromo (~24M speakers), Quechua (~9M speakers), or Tigrinya (~9M speakers) (van Esch et al., 2022). We will refer to these languages as *long-tail languages*, since the data scarcity requires the application of machine learning techniques that can generalize beyond the languages for which ample training data is available.

Web-crawled datasets for 1000 languages: The progress towards building machine translation systems in these languages has largely been limited by the lack of digitized and accessible datasets and NLP tools like language identification (LangID) models; such resources are ubiquitous for higher resource languages. The first stage of this paper describes our approach to building monolingual web text corpora in over 1500 languages, with a particular focus on dealing with common noise, data quality and scale challenges encountered when building a dataset from the web (Section 2).

Towards this goal, we first scale LangID models to 1500+ languages (2.1.1), both using traditional n-gram models and semi-supervised approaches. We next describe several practical approaches and filtering techniques that enable using these LangID models to identify long-tail language data on the web. To minimize recall loss during mining, we cluster languages by error rate (2.1.3). To reduce noise from LangID mis-predictions, we leverage document-level LangID consistency to filter our data (2.1.4), followed by percent-threshold wordlist filtering (2.1.5), TF-IIF filtering (2.1.7), and hand-designed filters to address specific noise issues with certain languages (2.1.8). We describe the resulting dataset in Section 2.2 and perform an audit of 72 language corpora (2.2.2), finding that the data is between 70% and 100% in-language, with a median score of 80%.

Machine Translation for long-tail languages: With monolingual data mined from the web, the next challenge is to build high quality, general-domain MT models from limited amounts of monolingual training data. We follow a practical approach, utilizing all the parallel data that is available for higher resource languages to boost the quality of long-tail languages where only monolingual data is available. We will refer to this setting as *zero-resource* since no direct supervision is available for our long-tail languages. We want to emphasize that this term is used only in the technical sense, meaning that the model itself is not able to see parallel text; in reality, there is a richness of resources for these languages, including tens of millions of native speakers, centuries (or in some cases millenia) of scholarship, and even large segments of text inaccessible to digital methods. See Bird (2020) for some more reflections on this term.

We leverage several techniques that have been developed for MT over the last few years in order to boost the quality of zero-resource translation for long-tail languages. These include self-supervised learning from monolingual data, massively multilingual supervised training, large-scale

¹Preliminary experiments indicated no quality improvements on our evaluation sets when incorporating widely available limited-domain parallel corpora in our models.

back-translation and self-training, and high capacity models. We utilize these tools to build MT models capable of translating across over 1000 languages, utilizing our existing parallel corpus spanning around 100 languages and the 1000-language monolingual dataset built from the web (Section 3).

We first highlight the importance of model capacity in highly multilingual models by comparing the performance of 1.5B and 6B parameter Transformers on zero-resource translation (3.2). We then scale up the number of self-supervised languages to 1000, demonstrating that the performance of most long-tail languages improves as more monolingual data from similar languages becomes available (3.3). While our 1000-language models demonstrate reasonable performance, in order to understand the strengths and limitations of the approach we incorporate large-scale data augmentation. For practical purposes we fine-tune the resulting model on a subset of 30 languages with large amounts of synthetic data via self-training and back-translation (3.4). We further describe practical approaches to filter synthetic data to increase the robustness of these fine-tuned models to hallucinations and wrong-language translations (3.5). We also describe our efforts to distill these models into smaller, more inference-friendly architectures using sequence level distillation, and highlight the performance gaps between the teacher and student models (3.6).

Evaluating MT for 1000 languages: Existing MT systems heavily rely on n-gram overlap based lexical metrics (BLEU) (Papineni et al., 2002) or the new and emerging model-based metrics like YISI (Lo, 2019), BLEURT (Sellam et al., 2020) or COMET (Rei et al., 2020) to evaluate translation quality. These metrics are usually computed on static evaluation sets with fixed references obtained from professional translators or crowd-workers.

To evaluate our MT models, we first build an evaluation set for 38 selected languages from the long-tail (4.1), by translating English sentences into these languages. We highlight the limitations of BLEU in the long-tail setting and make the case for evaluating these languages with CHRF (4.2). We also propose an approximate, round-trip translation based, reference-free metric to understand the quality of our models on languages where reference sets were unavailable, and report the quality of our models as measured on this metric (4.3). We conduct and report the findings from human evaluations of our models (on a subset of 28 languages), confirming that it is possible to build functioning MT systems by following the recipe described in this paper (4.4).

To understand the weaknesses of our massively-multilingual zero-resource models, we perform qualitative error analysis on several languages. We find that our models often confuse distributionally similar words and concepts, e.g. "tiger" becomes a "miniature crocodile" (4.5) and their ability to translate tokens deteriorates on less frequent tokens for lower-resource settings (4.6). We also find that these models often fail to adequately translate short, or single word inputs (4.7). A study of our distilled models also reveals that all models are more likely to magnify biases or noise present in the training data (4.8).

Other miscellaneous findings and experiments: We perform a few additional experiments on these models, demonstrating that they often perform better when translating directly between similar languages — rather than using English as a pivot (5.1) and that they can be utilized for zero-shot transliteration between different scripts (5.2). We describe a practical technique of appending terminal punctuation to any input, called the "period trick", that improves the quality of translation (5.3). Furthermore, we demonstrate that these models are robust to nonstandard Unicode glyph usage for some but not all languages (5.4), and we explore several non-Unicode fonts (5.5).

Throughout the course of this work, we rely extensively on native speakers of these languages to guide, evaluate and often contribute technically to the development of these systems. Section 6 highlights the important role they play — a role that researchers not familiar with the language and community could not have contributed.

As a result of the work outlined in this paper, we add support for 24 new languages to Google Translate. Adding a language to a user-facing product requires considerable effort and individual attention to evaluate each language thoroughly and consult members of affected communities; as a result we limited this effort to 30 languages, of which 24 met our launch bar. This set of languages was chosen to cover languages with large speaker populations in regions that are under-represented in technology, like the Americas, Africa, and South Asia.

2 Building a 1000-Language Web text Dataset

It is difficult to uncover large, clean, and highly multilingual corpora from the web. As explored in Caswell et al. (2020), the task of using LangID models for web-mining is exceedingly challenging for low-resource languages, with noise arising from domain mismatch between LangID training data and web text, idiosyncrasies of n-gram based LangID models, and the massive class imbalance between high- and low-resource languages. This is further borne out by Kreutzer et al. (2022), who demonstrate that a variety of public multilingual corpora, created using techniques that work for high-resource languages, are unusably noisy for many low-resource languages.

This problem is compounded by the size of the internet. For lower-resource languages, it is important to get as much data as possible to have any usable signal for a model to learn from. However, the sheer quantity of data online makes it infeasible to apply computationally intensive methods, like Transformer-based models; and even storing unfiltered data on disk can be challenging.

The following subsections explain in detail the approach we took to crawl a monolingual text dataset for 1500+ languages. Our approach focused on recovering high-precision data (high percentage clean, in-language text), so a large portion of the steps are various filtration approaches. The work in this section is an extension of and improvement over the methods presented in Caswell et al. (2020).

In summary, our approach is as follows:

- **2.1.2** Omit languages from the LangID model with poor quality training data and poor LangID performance; train both a 1,629-language CLD3 (n-gram) LangID model and Semi-supervised LangID (SSLID) model
- **2.1.3** Cluster languages by their error rate in the CLD3 model
- **2.1.4** Perform a first-pass webcrawl with the CLD3 model
- **2.1.4** Filter sentences with document-consistency filtering
- **2.1.5** Filter all corpora with percent-threshold wordlist filtering
- 2.1.6 Filter all corpora with Semi-Supervised LangID (SSLID) filtering
- **2.1.7** Detect outliers languages with Relative Recall Rate and filter them with Term-Frequency-Inverse-Internet-Frequency (**TF-IIF**) filtering
- 2.1.8 Detect outliers with Token-Frequency Anomalousness score and hand-design filters for them
- **2.1.9** De-duplicate all corpora at a sentence level

2.1 Steps necessary to create the dataset

2.1.1 LANGID MODELING

As described in Caswell et al. (2020), the task of reliably detecting what language a given portion of text is in, known as Language Identification or *LangID*, is surprisingly challenging for low-resource languages on the web.

There are two types of LangID models used in this work: CLD3 models (Bakalov et al., 2016) and Semi-Supervised LangID (SSLID) models (Caswell et al., 2020). The CLD3 models are a multi-layer perceptron on top of a bag of character ngrams, and are very efficient, but suffer from various error pathologies. The semi-supervised models use the MASS objective (Song et al., 2019) on noisy web text in addition to the LangID prediction task, and use the Transformer Big (Vaswani et al., 2017) architecture. They are generally more accurate and also more robust to web noise, but are much slower to run inference with.

Overall, three LangID models were used for this work: 1) a 1,745-language CLD3 model to measure the quality of the training data (Section 2.1.2); 2) a 1,629-language CLD3 model to cluster languages and label sentences when performing a deep crawl of the web (Sections 2.1.3 and 2.1.4); and 3) a 1,629-language semi-supervised LangID model for filtering (Section 2.1.6).

The training and evaluation data for our LangID models is identical to that described in Caswell et al. (2020); namely, we trained on an aggregation of proprietary and publicly available text corpora, with an average of 800K tokens per language. Some of the data came from sources with language tags

like Wikipedia or Corpus Crawler (Brawer, 2017), while another subset was created using a text elicitation task where we prompted native speakers to write sentences in their language (van Esch et al., 2019).

2.1.2 Paring down the set of languages

An important first step is determining what languages to crawl the web for. In an ideal world we would crawl all possible languages, but some of them may have poor-quality training data, or be very close to each other and be hard to distinguish.

We trained a CLD3 LangID model on 1,745 language varieties, and investigated languages that seemed to be having large quality losses. Our metrics for considering a language as possibly presenting difficulties were 1) LangID precision was under 33%; 2) language had over 50% confusion (False Negative Rate, FNR, or False Discovery Rate, FDR) with respect to another language; 3) a preliminary web-crawl with this model indicated severe overtriggering with a high-resource language; 4) LangID training data had under 2000 examples. Following this analysis we removed 116 languages from the model, primarily based on poor-quality training data. Among these most were regional dialects in Europe.

We additionally did not try to crawl data for the highest-resource 83 languages, in part because of storage space limitations, and in part as we already had monolingual data for these languages from a previous web crawl.

2.1.3 FALSE NEGATIVE RATE CLUSTERING

For the first-pass, we wanted to avoid lost recall between related dialects, of which many existed in the 1,629 languages. For instance, our training data contains many different varieties of Hindustani, e.g. Haryanvi, Garhwali, Magahi, and so on.

To mitigate this, we clustered languages based on their False Negative Rate (FNR), as measured on our LangID evaluation sets. Of the many error rates one could cluster on, we chose to cluster on FNR to minimize the loss in recall for related languages. We clustered using the Sklearn (Pedregosa et al., 2011) implementation of Hierarchical Agglomerative Clustering, using distance_threshold=None and affinity="precomputed", and linkage=average. These parameters were chosen largely because they seemed to produce the nicest distribution in cluster sizes. Since some of the clusters were still excessively large, we re-split the largest ones by hand such that no cluster had more than 20 languages. We split these clusters by hand since re-splitting using clustering algorithms still resulted in very uneven sizes, probably because these clusters have hubs with poor or noisy data.

To observe the effect of clustering predictions, we compare the size of a dataset for a language if document-consistency filtering (Section 2.1.4) were applied on the language-code level (which would result in lower recall) or on the cluster level. The median ratio between these sizes was 1.006, meaning that for most languages, clustering didn't significantly improve recall. However, for some languages it improved recall significantly, with 57 languages showing a dataset size increase of greater than 20x. The languages with large wins here were by-and-large to be expected, including Hindustani and Arabic varieties, and a variety of cases like Oromo (om) and Eastern Oromo (hae).

The higher-resource languages omitted in this crawl (Section 2.1.2) were all put in their own clusters.

2.1.4 DOCUMENT CONSISTENCY FILTERING AND FIRST-PASS LANGID

To start with, we performed LangID prediction on every sentence in every document with the 1,629-language CLD3 n-gram LangID model. Having obtained these predictions, we applied *document consistency filtering* (Caswell et al., 2020). This is one of the simplest and by far most effective filtering steps. We simply discarded any sentence whose sentence-level LangID cluster prediction did not match the document-level LangID cluster prediction. We defined the document-level LangID cluster prediction as the most-often predicted cluster among all sentences — e.g. if a document had 20 sentences in cluster A, 19 sentences in cluster B, and 18 in cluster C, we gave it a document-level ID of cluster A.

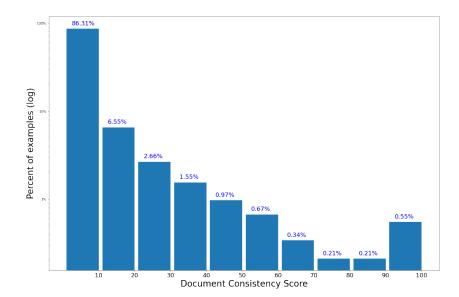


Figure 1: Histogram of document consistency scores, using a 1,745-language CLD3 LangID model, on web text. The large majority of sentence-level LangID predictions had a score of under 10%, indicating that they were likely noisy predictions on pages in other languages or non-linguistic content. Of the 0.55% with document consistency score over 90%, over half (0.3%) had a score of 100%.

To investigate the effectiveness of document consistency filtering, we looked at the *document consistency score*. For a given sentence in a document, the document consistency score is simply the percent of sentences in that document sharing the same LangID prediction as that sentence. (Therefore, if the document consistency score is over 50%, it will never be filtered out with document consistency filtering.) Figure 1 shows the deciles for document consistency score across all languages, for a sample web crawl with the initial, 1,745-language CLD3 LangID model. The distribution is heavily weighted towards the lower values, with a whole 83% of sentences having a score under 10%. The large mass of sentences with a low document consistency score indicates that there are many single, random sentences in larger documents, including non-linguistic content, whose language is mis-predicted. This suggests a more refined approach to document-consistency filtering. Using the method outlined above, a page with content in multiple languages could only yield data for one language; if instead any sentence were preserved with a document consistency score under a particular threshold (say, 0.3), documents with multilingual content would be handled much better, while preserving most of the benefits of filtering. This is left for future work.

2.1.5 HIGH-RECALL WORDLIST-FILTERING

Following Caswell et al. (2020), we apply percent-threshold wordlist filtering to all languages. A sentence was discarded if it had < 20% in-language words for any of the languages in the cluster, where the wordlists were the most frequent 800 words from the LangID training data.

2.1.6 FILTERING AND DECLUSTERING WITH SEMI-SUPERVISED LANGID

Once the first-pass, clustered filtering was completed, we classified each sentence with the more computationally expensive Semi-Supervised LangID model (SSLID), as described in Caswell et al. (2020), resulting in per-language corpora. If the SSLID model predicted any language outside of the cluster, we filtered that sentence. The CLD3 predictions were ignored.

2.1.7 TF-IIF FILTERING

Even after these three rounds of filtering — CLD3, percent-threshold, and SSLID – many languages still had extremely noisy data. The worst case was Tok Pisin (tpi), whose dataset consisted of 1.3B sentences, of which over 99.7% were in Standard English (mostly containing the word "long",

which is also a common function word in Tok Pisin). Therefore, as in Caswell et al. (2020), we applied percent-threshold filtering with **TF-IIF** (Term-Frequency Inverse-Internet-Frequency) lists ², meaning that we retained any sentence which contained at least 20% of its tokens in our TF-IIF wordlists. However, we optimize the approach used in Caswell et al. (2020), and furthermore develop a heuristic metric to determine whether to apply the filtering on a per-language basis.

$$TFIIF_{t,l} = TF_{t,l} * IIF_t = \frac{f(t, D_l)}{\max(f(t, internet), \alpha)}$$
 (1)

Note the clipping parameter α in the IIF term, which is introduced to account for OOV tokens (which are common) and noise near the tail of the distribution. For this work we set $\alpha=f(w_\kappa)$ — in other words, we only consider the top κ terms in the empirical frequency distribution, and give all less common terms the same weight as the κ^{th} most common token. A higher value of κ means that more words are covered by the frequency distribution — which seems good — but it also means that OOV words will have a higher weight, since the IIF term is an inverse. In the worst case this could mean that the resulting TF-IIF wordlist would contain too many rare words. An especially low value of α , e.g. $\alpha < 1.0$, would essentially guarantee this, pushing up only OOV words to the top of the list.

There is another parameter hidden in this formulation, namely τ . This parameter is simply how many words to include in the wordlist. For instance, $\tau=1000$ means that the wordlist used for filtering includes the top 1000 words by TF-IIF score.

In order to investigate the effect of these parameters, we define a heuristic measure of *distractibility* as a proxy for precision, which measures how much a given language's data is likely to be polluted by a common high-resource language. For a language l and a set of distractor languages \mathcal{D} , we define the distractibility δ_l :

$$\delta_l = \max_{d \in \mathcal{D}} (\text{FDR}(d, l)) \tag{2}$$

Where, for our purposes, we have chosen $\mathcal{D} = \{\text{en, de, es, hi, id, ar, ru}\}$, and the False Discovery Rate (FDR) of a distractor language d with regard to a language l is defined in the standard way, as (on a balanced eval set)

$$\text{FDR}(d,l) = \frac{\#\text{examples in language } d \text{ mis-predicted as } l}{\#\text{true examples in language } l}$$

Despite the concern that it would elevate rare and OOV words, we found that increasing the value of κ steadily decreased the distractibility with little loss in recall on the target languages. Increasing the size of the wordlists, τ , recouped the loss in recall, but increased distractibility to more dangerous levels. These results can be seen in Table 1.

Therefore, for our TF-IIF lists, we use values of $\kappa=80000$ and $\tau=1000$. For comparison, Caswell et al. (2020) use $\kappa=10000$, and the value of τ was set on a per-language basis from the recall on the dev set. Furthermore, Caswell et al. (2020) use an IIF list with only 980k unique tokens (7M webpages), whereas this work uses 41M unique tokens (250M web pages). The public GitHub repo has been updated to reflect these improvements.

Deciding when to apply TF-IIF filtering: Many languages do not need extra filtering, and it is important not to overfilter and decrease recall. Therefore we needed an outlier detection metric to determine whether filtering needed to be applied. We wanted to filter those corpora where the loss in recall was small, but the reduction in dataset size was large (indicating that many out-of-language sentences were removed).

 $^{^2}$ Open-sourced at https://github.com/google-research-datasets/TF-IDF-IIF-top100-wordlists/.

κ	au	mean recall	median recall	mean δ_l	median δ_l	$\delta_l > 10$
5000	1000	94.3	98.9	8.6	1.2	20
10000	1000	94.2	98.9	7.3	0.7	16
20000	1000	94.1	98.7	5.7	0.4	14
80000	1000	93.4	98.5	2.9	0.1	8
80000	2000	94.9	99.3	6.8	0.4	21

Table 1: Investigating the effect of varying the IIF-thresholding parameter κ on the recall and distractibility (δ_l) of TF-IIF filtering, over 1598 languages. As we increase κ , the distractibility steadily trends down, with only small losses in recall. Increasing τ recoups lost recall but increases distractibility.

We looked at the percent of our LangID eval sets that remained after filtering $(r_{\text{TFIIF}}(\text{gold}))$, aka the filtering recall), and compared it to the percent of our web-crawled corpora remaining after filtering $(r_{\text{TFIIF}}(\text{crawl}))$. We used these to define the heuristic Relative Recall Rate (RRR) as follows:

$$RRR_{TFIIF} = \frac{r_{TFIIF}(gold)^{\rho}}{r_{TFIIF}(crawl)}$$
 (3)

This quantity measures, approximately, how many true positives are kept by this method for every false positive filtered out. The exponent ρ is the trade-off between recall and percent filtered. A value of $\rho>1$ means that we weight a loss in recall (undesired outcome) more than an equivalently sized reduction in data size (desired outcome). One way of interpreting this is how much we trust the recall on our eval set. If $\rho=1$, we trust it perfectly. However, in practice, since we fear that the recall on our eval set overestimates the true recall on natural text on the web, we set $\rho>1$.

For our experiments we used a value of $\rho=2$. This flagged 895 out of 1503 languages. However since we were only concerned about datasets that were more severely polluted, we only filtered datasets where the filtering would remove 20% or more of the data $(r_{\text{TFIIF}}(\text{crawl}) \leq 80)$. We also decided not to filter any language where the recall $(r_{\text{TFIIF}}(\text{gold}))$ was less than 80%, in case we lost too much usable data. The result of this was that we applied TF-IIF filtering to 210 out of 1503 language corpora.

2.1.8 TOKEN DISTRIBUTION ANOMALY DETECTION AND NEGATIVE TOKEN FILTERS

Even after the filtering steps described in the previous sections, a variety of languages still had data-quality issues. One issue that was not easily filtered out by approaches like TF-IIF was templated content, which is technically in the right language, but is not useful for training data. To a lesser extent we also saw issues like the "unlucky n-gram" (Caswell et al., 2020) effect. Examples of the type of content we found were:

- Scottish Gaelic (gd) found 570M in-language sentences even after TF-IIF filtering. It turned out that this was mostly from one site, and the most common token was "Luchdaich a-nois" ("download")
- 2. Darija (ar-MA) came up with a dataset of over a billion sentences, but 94.9% contained some reference to "casinos", "gambling", etc.
- 3. Kurukh (kru-Mlym) was mainly A N T S P E A K. (And it later turned out that the training data was spurious.)
- 4. The Arabic-script Indo-Aryan languages of Kalami (gwc), Hindko (hnd), and Torwali (trw) had picked up masses of templates from unit conversion websites ("X lbs is Y ounces", "convert Euro to US American Dollar", etc.)
- 5. Many Latn-script Indic languages (hi-Latn, ml-Latn, etc.) had large amounts of content that were just download links or titles for videos, songs, and so on.
- 6. Cree (cr-Latn) was almost 100% "Lorem ipsum" sentences

While some of these are actually incorrect content, much of it is technically in-language, and therefore can't be filtered out by TF-IIF filtering or straightforward application of LangID. Therefore, we

decided to develop an approach to detect anomalous data and investigate datasets that looked like they had issues.

To detect these extreme domain shifts, we hypothesized that the token distribution would be severely skewed. Therefore, we compared the distribution of the tokens in the LangID train data (the *reference distribution*) to the token distribution in the crawled data (the *empirical distribution*). To compare these distributions we looked at several scores for the top N=40 tokens in the empirical distribution:

- **2n-overlap**: This is simply the percentage of the top N tokens that appear in the top 2N tokens of the reference distribution; this metric is very simple and highly interpretable.
- Euclidean: This is the Euclidean distance between the frequencies of the top N tokens and their corresponding frequencies from the reference distribution.

Different scores, like Jenson-Shannon divergence and Pearson R, were initially considered but found to be ineffective.

We then combined these two scores together with the harmonic mean, yielding the *Harmonic Token Anomalousness Score*. This is a very approximate measure, but still gives a useful score for outlier detection. Based on some qualitative analysis, we determined that a score of < 0.70 is a sign of a questionable dataset quality. Interestingly enough, however, datasets with scores that were too high also had issues: a score of > 0.97 often indicated that the web crawl had merely recovered the training data, which in these cases was often religious material.

After computing this score for all datasets, we manually observed samples of the data for all languages with Harmonic Token Anomalousness Score < 0.7 and more than 20,000 sentences. There were 179 languages flagged as suspicious in this way. It was relatively straightforward to make filters for 62 of these, for instance excluding sentences containing "casino" in Arabic dialects. For some of the others, we made notes that they were the wrong language. For many others, there was no clear or obvious solution, so we left them as-is. These filters removed on median 21% of the data for these 62 languages.

We acknowledge that this measure of quality is very approximate, so it should be used judiciously.

2.1.9 DEDUPLICATION

The last step was simply to remove duplicate sentences in all datasources. This reduced the median dataset size by a factor of 1.8x, and the average dataset by a factor of 1.4x.

2.2 DESCRIPTION OF RESULTANT DATASET

2.2.1 Monolingual Data

The result of the process described in section 2.1 was a dataset with corpora for 1503 low-resource languages, ranging in size from one sentence (Mape) to 83 million sentences (Sabah Malay). For our experiments we chose to experiment only on those 1057 languages where we recovered more than 25,000 monolingual sentences (before deduplication). We combined this with our existing monolingual datasources for the 83 high-resource languages. Table 2 shows statistics for these three datasets — the full low-resource dataset ("LRL-full"), the portion of the full low-resource dataset used for model training ("LRL-train"), and the full training dataset ("all-train"), which combines in the 83 higher-resource languages.

2.2.2 Monolingual Data Quality Audit

We conducted an audit of our data as in Kreutzer et al. (2022) with a variety of volunteers, comprising native speakers and non-speakers willing to do detective work. From the sample of 72 languages we audited, the median data score was 80%. The "score" is a simple heuristic to estimate the percent usable data given the different error codes, and is defined as 1.0 * cc + 0.5 * cb + 0.3 * ca + 0.2 * wd, where cc is the percent of the sample labeled as "Correct", cb is the percent labeled as "correct, Low quality", ca is the percent labeled as "Correct, ambiguous dialect", and wd is the percent labeled as "Correct, wrong dialect" (See Appendix Section B for details).

dataset	N	total	median	> 1M	> 100K
LRL-full	1503	1.7B	25k	122	322
LRL-train	1057	1.7B	38k	122	321
all-train	1140	28B	43k	205	404

Table 2: Summary statistics about monolingual data for 1) the full dataset of low-resource languages; 2) the portion thereof used to train our model; and 3) the full training set including high resource languages. Columns are the number of languages covered, the total number of sentences across all languages, the median number of sentences per language, the number of languages with more than 1 million sentences, and the number of languages with more than 100,000 sentences.

The largest error category tended to be Wrong Language, with an average value of 16%, followed by Low Quality/Boilerplate, with an average of 10%. Languages with the poorest quality tended to be close dialects of major languages, especially varieties of Arabic (Sa'idi, Moroccan, Mesopotamian, Latinized, Algerian: aec, ar-MA, acm, ar-Latn, arq), but also varieties of French (Saint Lucian Creole: acf) and English (Nigerian Pidgin: pcm). There were also some close varieties that had higher quality, including varieties of French (Seychellois Creole: crs), Hindi (Bhojpuri: bho) and English (Krio: kri). Of these three, kri and crs use quite different orthographies than their high-resource relatives. In addition to close varieties, some African languages (Ndebele, Anaang, Kwanyama, Wolof: nd, anw, kj, wo) also had very poor quality. Less common languages with extremely high quality, e.g. Northeastern Dinka (dip), Zarma (dje), and Dombe (dov), each with a score of 100, may also be viewed with suspicion, as this may mean that a very narrow domain has been recovered (usually religious text). Details on the per-language performance and the set of error codes we used can be seen in Appendix Section B.

2.2.3 PARALLEL DATA

In addition to the monolingual data described above, we also utilize the web-crawled parallel corpora available to us. This corpus is a slightly extended version of the corpus described in Arivazhagan et al. (2019), containing approximately 25 billion sentence pairs spanning 112 languages, to and from English.

3 BUILDING MACHINE TRANSLATION MODELS FOR LONG-TAIL LANGUAGES

Next, we utilize the datasets described in Section 2.2 to build our MT models. As we see from the monolingual data statistics in Table 2, while there are over 1M sentences per language present in our corpus for the highest-resource 205 languages, the median number of sentences in our full training corpus is only around 43K sentences per language. This is a relatively small amount of data, given that traditional MT systems often require a few hundred thousand to a few million **parallel** sentences to reach good quality, while we are limited to around 43K **monolingual** sentences per language.

Given the highly data sparse setting, it is clear that the approaches that work for high resource languages cannot apply directly in our setting. In order to build high quality models for long-tail languages, we build on the approach developed previously in Siddhant et al. (2022) to enable zero-resource translation, by leveraging (i) Self-supervised training on in-language monolingual data, (ii) Massively multilingual supervised translation on out-of-language data, (iii) Large-scale data augmentation via back-translation and self-training and (iv) Model scaling. In this section we describe our recipe for training MT models for long-tail languages, starting with massive massively multilingual models and concluding with smaller, inference-friendly models trained on a selected subset of languages.

We start by highlighting the role of capacity in our highly multilingual setting by comparing the performance of 1.5B and 6B parameter models in Section 3.2. These experiments were conducted on an earlier version of our dataset, spanning 112 supervised and 94 zero-resource languages. In Section 3.3 we scale up our models to cover over 1000 languages and highlight the effect of increasing multilinguality in the long-tail setting. To further increase performance, we incorporate large-scale back-translation and self-training. In Section 3.4, We evaluate these approaches on a subset of 30 languages for practical considerations. In Section 3.5, we further highlight the role of filtering synthetic data and its effect on model quality for close dialects. Finally we describe our distillation approach and compare the resulting student models against the fine-tuned teachers, in Section 3.6.

Of the languages we evaluate on in this work, only Sorani Kurdish (ckb) uses any in-language supervised data; all other languages are evaluated under a zero-resource setting. While small amounts of parallel resources weren't difficult to obtain for many of these languages, preliminary experiments did not result in any quality improvements with including limited amounts of (often religious-domain) parallel text.

3.1 EXPERIMENTAL SETUP

We utilize the 1000-language monolingual corpus available to us, together with large amounts of massively multilingual parallel data in 112 languages (including English), to build zero-resource MT models for 1000 languages following the approach described in Siddhant et al. (2022). To elaborate, we train Transformer-based MT models on the translation task on 112 languages, simultaneously with the MASS masked denoising task (Song et al., 2019) to first build zero-resource models capable of translating from $xx\rightarrow$ en with reasonable quality. These models follow a two-stage training procedure, where the first stage consists of training on just the MASS and supervised translation tasks, and the second stage also incorporates data generated using online translation from the model's latest checkpoints (in the $xx\rightarrow$ en direction). This data is used as back-translated and self-training (aka forward-translated) data simultaneously.

All our models are based on the standard Transformer architecture, with 32 layer encoders and decoders. We use two variants of the Transformer; a smaller model, with approximately 1.5B parameters, and a larger one with 2x larger model dimension and 2x wider hidden dimension, with approximately 6B parameters. Our models utilize the vocabulary from a 64K-token SentencePiece model (SPM) (Kudo & Richardson, 2018) trained on monolingual data from the entire set of languages covered by the model. Data is upsampled with a temperature of T=5 (Arivazhagan et al., 2019) before creation of the SPM. An analysis of the vocabulary suggests that our vocabulary is close to character-level for all but the highest resource languages. We use GPipe pipeline parallelism (Huang et al., 2019) and the Tensorflow-Lingvo (Shen et al., 2019) framework for all our MT experiments.

Different from Siddhant et al. (2022), in addition to the <2xx> token that was prepended to the source sequence to signify the target language for both translation and MASS tasks, we add a <2task> token (<2translation> for the translation task, and <2mass> for the MASS task) that specifies

the task to be performed by the model. We find this to be critical for zero-resource performance, especially when model sizes are scaled up. In the absence of this task token, our models learnt to 'infer' the task from the source languages instead of relying on the <2xx> token, resulting in copying sentences when provided zero-resource language sentences with the <2en> token.

All our models are evaluated with CHRF on standard evaluation sets built by translating 1200 English sentences into the target language, for 38 languages. Details of our evaluation metrics and datasets are provided in Section 4.

3.2 EXPERIMENTS COMPARING EFFECT OF MODEL CAPACITY

We first compare the effect of model capacity on zero-resource performance. In this experiment we train our 1.5B and 6B Transformer variants on supervised data from 112 languages, to and from English, and monolingual data from 206 languages (including the above 112 languages). These models are first trained with MASS and translation, and as a second stage, additionally trained on online-translated monolingual sentences as back-translation and self-training data. The results of these experiments are listed in Table 3. We demonstrate results for 38 languages, of which we didn't include any monolingual data for 6 languages (which weren't present in our initial scrape). We find that increasing the capacity of the model from 1.5B to 6B has a significant effect on the quality of translation, improving by an average of 2.7 CHRF on the xx→en translation direction. On the other hand, the en→xx direction regresses in quality with an average loss of -1.0 CHRF. This degradation was associated with the same issue that required us to append extra <2task> tokens to the source input (models learning to infer the task from the input language, resulting in copying instead of translation).

Looking at the overall results, we notice that the performance of these models reaches above 40 CHRF in the $xx\rightarrow$ en direction for a majority of the languages. Performance is especially high for languages which either have similar languages in our parallel corpus (including South-Asian languages and Pidgins like Bhojpuri (bho), Dogri (doi), and Nigerian Pidgin (pcm)), while CHRF scores are relatively low for lower-resource and those with no related languages in the model (including Native American languages like Quechua (qu), K'iche' (quc), Aymara (ay), and Kalaallisut (kl)). We observe that our model learns to translate Goan Konkani (gom) into English with surprisingly high quality despite the lack of gom monolingual data seen by the model, perhaps owing to its similarity with Marathi (mr), which is present in our supervised data.

3.3 CONTINUAL LEARNING, EXTENDING MODELS FROM 200 TO 1000 LANGUAGES

We next compare our 6B model trained on monolingual data from 200 languages against one trained on our entire monolingual set, spanning 1000 languages. To train the 1000-language translation model we utilize the continual learning technique described in Garcia et al. (2021a). To elaborate, we replace the vocabulary used by our 200-language MT model with one trained on monolingual data from all 1000 languages. To be able to reuse the model learnt on 200 languages to initialize the newer, 1000 language model, we align the SPM tokens shared across the two vocabularies and assign them the same IDs. The tokens in the new vocabulary that do not map to any token in the original vocabulary are assigned random IDs not assigned to the aligned tokens. This allows to continue training our 1000-language model from the model trained on 200-language subset.

We compare the performance of our 200-language model against the 1000 language MT model in Table 4. Unsurprisingly, languages that were not covered by our 200-language model but are now covered by our new monolingual data, including Goan Konkani (gom), Isoko (iso), Kalaallisut (k1) and Tsonga (ts), see large quality improvements. However, we also observe quality improvements almost for all languages in our evaluation set, including both, the xx \rightarrow en and en \rightarrow xx translation directions with average improvements of +2.5 and +5.3 CHRF points respectively. This is counterintuitive since we are increasing the number of self-supervised languages, which should presumably increase the amount of interference and worsen capacity contention within this model, similar to what was observed in Siddhant et al. (2022). What is different from earlier studies is the extent of multilinguality in the model; any new added language in our model is likely to be very similar to one of the existing languages, resulting in stronger transfer between those languages. This transfer effect is strengthened by the low quantity of monolingual data for long-tail languages; in the massively multilingual and resource constrained setting the cross-lingual transfer effect dominates the

Mono Size		mfa 'k		-ff 6k		mni 16k		kri 9k		nad 8k
Direction	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow
1.5B 6B	57.8 62.1	26.0 17.9	33.7 34.3	31.1 25.0	54.8 55.1	35.7 31.9	48.7 54.8	32.7 28.2	44.9 52.0	29.8 25.9
Mono Size Direction		doi 9k →		bm 7k →		ban 8k →	en 25 ←	quc 0k →	en-a 29 ←	
1.5B 6B	57.4 60.4	29.9 24.4	27.6 33.4	28.7 28.5	32.2 35.5	31.8 29.4	24.4 27.5	22.8 22.2	53.7 56.0	21.8 21.4
Mono Size		-av 01k →		om* 1k →		iso* 9k →	en- 41 ←	yua 9k →	en-ı 53	
1.5B 6B	48.1 50.5	26.1 27.3	50.7 53.3	1.1 0.9	17.9 19.3	16.5 16.8	34.6 39.3	30.6 31.3	58.8 62.6	51.8 54.1
Mono Size Direction		bho 4k →		kl* 1k →		-qu -2k →	en- 86 ←	-gn 1k →	en-¹ 92 ←	
1.5B 6B	54.8 56.9	38.9 38.8	18.4 20.0	12.5 13.0	29.9 32.7	29.8 30.2	26.7 35.6	24.3 28.8	40.9 43.9	34.9 35.6
Mono Size Direction	en-skr 974k ← →		en-ak 1.29m ← →			-ts* 3m →	en-1 1.3 ←	mai 5m →	en- 1.3∙ ←	-ce 6m →
1.5B 6B	44.4 46.1	32.8 28.5	31.7 34.6	32.1 32.8	25.5 28.3	17.4 17.5	57.8 59.9	34.1 32.5	44.6 48.1	23.5 24.4
Mono Size Direction		pcm 9m →		nso 7m →		-ilo 6m →	en- 2.9 ←	-cv 9m →	en 3.9 ←	
1.5B										
6B	54.9 52.5	54.7 52.4	45.8 49.1	45 46.9	50.8 39.9	49.7 47.8	39.9 44.4	28.1 27.5	37.9 40.9	19.9 20.0
	52.5 en-		49.1 en		39.9 en-	49.7		27.5 us*		20.0 -as
6B Mono Size	52.5 en- 5.0	52.4 om 6m	49.1 en 6.2	46.9 -sa 2m	39.9 en- 7.9	49.7 47.8 -dv 9m	en-l 8.3	27.5 lus* 8m	40.9 en-9.3	20.0 -as 8m
Mono Size Direction 1.5B	52.5 en- 5.0 4 32.1 37.0 en-1	52.4 com com com com com com com com	49.1 en 6.2 43.5 45.8 en-	46.9 -sa 2m → 26.9	39.9 en- 7.9 ← 37 35.8 en-c	49.7 47.8 -dv 9m → 43.2	en-l 8.3 ← 22.6	27.5 dus* 8m → 16.9	40.9 en- 9.3 ← 52.9	$ \begin{array}{c} 20.0 \\ \hline -as \\ 8m \\ \rightarrow \\ \hline 36.3 \\ 36.2 \end{array} $

Table 3: Comparison of our 206-language 1.5B and 6B models trained on supervised data from 112 languages to and from English and monolingual data from 206 languages. Languages marked with * weren't included in the set of 206 languages, so monolingual data was not used for these languages in this experiment.

interference observed in massively multitask models. This is also supported by the fact that languages that benefit the least from increased multilinguality are Native American languages like Quechua (qu), K'iche' (quc), Aymara (ay), Yucatec Maya (yua), and Kalaallisut (k1), which tend to have few or no similar languages in the training data.

Mono Size		mfa 'k		-ff 6k		mni 6k		-kri 9k		nad 8k
Direction	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow
200L 1000L	62.1 65.4	17.9 27.5	34.3 41.2	25.0 32.3	55.1 56.4	31.9 38.2	54.8 56.5	28.2 34.9	52.0 50.5	25.9 30.2
Mono Size Direction		doi 9k →		-bm 57k →		ban 8k →		quc 0k →		ady 6k →
200L 1000L	60.4 63.1	24.4 25.5	33.4 36.3	28.5 34.3	35.5 35.4	29.4 33.1	27.5 26.7	22.2 22.9	56.0 54.8	21.4 28.2
Mono Size Direction		-av 01k →		gom* 1k →		iso* 9k →		yua 9k →	en-1 53 ←	min 3k →
200L 1000L	50.5 48.1	27.3 28.1	53.3 55.5	0.9 39.1	19.3 29.4	16.8 30.5	39.3 40.7	31.3 31.6	62.6 62.4	54.1 56.1
Mono Size Direction		bho 4k →		-kl* -1k →		-qu -2k →		-gn 51k →	en- 92 ←	$ \begin{array}{c} \text{bbc} \\ 3k \\ \rightarrow \end{array} $
200L 1000L	56.9 58.3	38.8 40.6	20.0 29.7	13.0 23.1	32.7 32.5	30.2 33.1	35.6 38.9	28.8 32.2	43.9 44.0	35.6 35.4
Mono Size Direction	en-skr 974k ← →		en-ak 1.29m ← →			ts* 3m →		mai 5m →		-ce 6m →
200L 1000L	46.1 48.4	28.5 31.3	34.6 36.3	32.8 34.3	28.3 43.0	17.5 45.5	59.9 61.6	32.5 37.6	48.1 44.9	24.4 23.7
Mono Size Direction	1.5	pcm 9m	1.8	nso 7m	2.0	-ilo 6m	2.9	-cv 9m	3.9	-ti Om
200L 1000L	52.5 51.2	→ 52.4 53.5	← 49.1 51.3	→ 46.9 41.6		→ 47.8 52.4	<i>←</i> 44.4 46.3	$ \begin{array}{c} \rightarrow \\ \hline 27.5\\ 32.1 \end{array} $	← 40.9 44.2	$ \begin{array}{c} $
Mono Size Direction		om 6m →		-sa 2m →		-dv 9m →		-lus 3m →	en 9.3 ←	-as Bm →
200L 1000L	37.0 38.1	36.7 39.1	45.8 46.3	24.7 28.4	35.8 45.2	39.2 43.7	33.0 34.5	19.1 39.3	49.6 58.6	36.2 36.7
Mono Size Direction		mzn 6m →		bew 3m →		ckb* 1m →			Ave	rage →
200L 1000L	53.3 55.2	40.2 41.4	51.6 51.8	44.0 46.0	51.7 54.4	41.6 41.6			+2.5	+5.3

Table 4: Comparison of our 206-language 6B and 1000-language 6B models trained on monolingual data from 206 languages and 1000 languages respectively, while sharing supervised data from 112 languages. Languages marked with * weren't included in the set of 206 languages, so monolingual data was not used for these languages in the baseline model, and the 1000-language model consequently sees larger performance improvements.

While our evaluation sets are limited to 38 languages, we provide RTTLANGIDCHRF as a highly approximate measure of the quality of the model on all 1000 languages in Appendix Table 24. More details of the metric and the performance of the model on all languages are described in Section 4.3.

Mono Size Direction		-ff 6k →		mni 6k →		-kri 9k →		doi 9k →	en- 18 ←	$ \begin{array}{c} \text{bm} \\ 7k \\ \rightarrow \end{array} $
1000L	41.2	32.3	56.4	38.2	56.5	34.9	63.1	25.5	36.3	34.3
Finetuned	44.5	35.7	60.5	40.8	62.2	36.8	64.6	37.2	37.9	34.7
Mono Size Direction		quc 0k →	•	gom 1k →		yua 9k →		bho 4k →	en 74 ←	-kl 1k →
1000L	26.7	22.9	55.5	39.1	40.7	31.6	58.3	40.6	29.7	23.1
Finetuned	29.2	23.5	57.5	40.0	43.0	31.8	60.5	41.4	39.1	27.8
Mono Size Direction		-qu -2k →		-gn 1k →		-ak 9m →		-ts 3m →	en-: 1.3 ←	mai 5m →
1000L	32.5	33.1	38.9	32.2	36.3	34.3	43.0	45.5	61.6	37.6
Finetuned	35.3	36.1	42.7	32.3	38.6	34.1	46.2	46.5	64.3	39.2
Mono Size Direction		pcm 9m →		nso 7m →	en- 2.0 ←	-ilo 6m →		-ti 9m →	en- 5.6 ←	om 6m →
1000L	51.2	53.5	51.3	41.6	43.4	52.4	44.2	21.1	38.1	39.1
Finetuned	59.3	54.5	52.2	45.4	61.7	53.4	46.0	21.0	41.2	39.9
Mono Size Direction		-sa 2m →		-dv Om →		·lus 3m →		-as 3m →	←	ckb 1m →
1000L	46.3	28.4	45.2	43.7	34.5	39.3	58.6	36.7	54.4	41.6
Finetuned	49.0	30.9	47.3	43.8	40.0	40.3	59.8	39.0	54.7	42.7

Table 5: Comparison of our 1000-language 6B models against the 30-language version fine-tuned from this model. Scores are shown for the languages that were fine-tuned on.

3.4 EFFECTS OF LARGE SCALE DATA AUGMENTATION

In order to understand the limits of quality with our zero-resource approach, we select a subset of 30-languages for large-scale data augmentation. We continue training our 1000-language model on this subset of 30-languages with the MASS, translation and online back-translation objectives. To leverage the full power of data augmentation, we translate all the available monolingual data (up to 10 million sentences) for these languages into English, and sample around 10 million English web sentences which are translated into each of these languages. The model is then continued training with MASS, translation and offline back-translation and self-training with this synthetic data. This process is repeated twice since quality improvements with subsequent stages were observed to be incremental. This model is then compared against our vanilla 1000-language model that wasn't trained with large-scale augmented data.

The results of this comparison are depicted in Table 5. We notice that fine-tuning with augmented data shows substantial quality improvements across the board, with especially large improvements for en—xx translation for several languages. Excepting our Native American subset, most languages reach greater than 40 CHRF on xx—en translation and greater than 35 CHRF in the reverse direction.

3.5 EFFECT OF FILTERING SYNTHETIC DATA

One challenge with using the model's own predictions for improving model quality is the presence of positive feedback loops which can magnify any problems with the model outputs, as elaborated in Section 4.8. To reduce these effects we compare our fine-tuned model against a version that was fine-tuned with a round-trip translation and LangID filtered version of our synthetic data for training.

Mono Size		ı-ff 6k		en-mni 106k		en-kri 129k		doi 9k		bm 7k
Direction	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow
Finetuned	44.5	35.7	60.5	40.8	62.2	36.8	64.6	37.2	37.9	34.7
Filtered	45.3	35.3	62.1	40.8	64.2	35.4	65.5	36.9	38.4	34.7
		quc	en-	gom	en-	yua		bho	en	-kl
Mono Size	25	0k	31	1k	41	9k	73	4k	74	1k
Direction	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow
Finetuned	29.2	23.5	57.5	40	43	31.8	60.5	41.4	39.1	27.8
Filtered	29.8	23.5	57.9	40.8	43.7	32.0	60.9	41.2	39.0	35.8
	en-	-qu	en	-gn	en	-ak	en	-ts	en-	mai
Mono Size	84	2k	86	1k	1.2	9m	1.3	3m	1.3	5m
Direction	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow
Finetuned	35.3	36.1	42.7	32.3	38.6	34.1	46.2	46.5	64.3	39.2
Filtered	35.3	35.7	43.0	32.1	38.6	34.3	47.5	46.5	65.5	39.2
	en-	pcm	en-	nso	en-	-ilo	en-ti		en-om	
Mono Size	1.5	9m	1.8	7m	2.0	5m	3.9	9m	5.0	óm
Direction	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow	\leftarrow	\rightarrow
Finetuned	59.3	54.5	52.2	45.4	61.7	53.4	46.0	21.0	41.2	39.9
Filtered	64.6	57.2	52.5	47.1	62.7	54.1	46.1	21.5	40.7	40.0
	en	-sa	en	-dv	en-	-lus	en	-as	en-	ckb
Mono Size	6.2	2m	7.9	9m	8.3	3m	9.3	3m	25.	1m
Finetuned	49.0	30.9	47.3	43.8	40.0	40.3	59.8	39.0	54.7	42.7
Filtered	49.2	31.0	48.4	45.0	42.1	39.7	60.6	39.6	55.3	42.6

Table 6: Comparison of our 30-language fine-tuned model against one fine-tuned with RTT and LangID filtered data.

The results of this comparison are depicted in Table 6. For most languages this additional filtering has no major impact on model performance, often performing within 0.5 CHRF of the non-filtered model. However, for certain languages like Nigerian Pidgin (pcm) and Kalaallisut (k1) we observe large improvements in quality. Closer inspection reveals that our pcm data suffered from mixing with African-American Vernacular English (AAVE), which gets magnified as the model trained on its own outputs. Similarly, our k1 monolingual set was polluted with a small fraction of Danish (da) data, which gets magnified with self-training. Filtering with round-trip-translation and LangID reduces the instances of data pollution improving the correctness of the model outputs. Section 4.8 explores this in greater depth.

3.6 DISTILLATION

We next describe our approach for distilling our best 6B parameter Transformer model fine-tuned on 30 languages into smaller, more efficient, architectures. This process also yields further quality gains.

3.6.1 Data Generation for Distillation

We follow the sequence-distillation approach (Kim & Rush, 2016) to distill our teacher model into smaller students. To this end, we generate large amounts of synthetic forward- and backward-translated data with the teacher model, which is then used to train a smaller student model. We start with the 30-language fine-tuned model and translate roughly 15-25 million English sentences into each of the 30 languages. We translate our entire corpus in these 30 languages (up to a maximum of 20 million sentences) into English. This synthetic data is then filtered using the same round-trip and LangID filtering approach described in Section 3.5. We also applied a few manual regex-based

filters for specific languages where we observed particular data pollution and noise issues, as further elaborated in Section 4.8.

3.6.2 DISTILLATION APPROACH AND HYPER-PARAMETERS

We looked at two candidate student architectures with increasing encoder depth; we refer to them as *shallow encoder* (330M parameters) and *deep encoder* (850M parameters). All our models are sequence-to-sequence models with attention (Bahdanau et al., 2015), using Transformer encoders and LSTM (Hochreiter & Schmidhuber, 1997) decoders, as described in Chen et al. (2018). All our student models are multilingual, with separate models for $xx \rightarrow en$ and $en \rightarrow xx$ translation.

Effect of student model capacity: Although there are some quality improvements from optimizing hyperparameters, we found that most distilled models performed similarly, having little sensitivity to the hyperparameters we experimented with. Nonetheless, one important take-away is that trends that appeared to hold for the shallow encoder model, for instance the impact of increased amounts of back-translated data, were often erased when experimenting with the deeper model.

In all cases, the shallow encoder model was noticeably worse. For 30-language models, the deep encoder saw gains of about +0.3 and +1.0 CHRF in the en \rightarrow xx and xx \rightarrow en directions respectively. With respect to multilinguality, we found that increasing the multilinguality of the students from 6 languages to 30 yielded small quality losses of 0.1-0.3 median CHRF.

Effect of amounts of synthetic en \rightarrow xx data used for distillation: Another important hyperparameter was the amount of English-original synthetic data used for distillation (the non-English datasets were small enough that we could just translate the entire dataset). In the en \rightarrow xx direction, where English-original data is forward-translated data, we varied the number of forward-translated sentences from 1M to 8M, but found no significant differences in model performance. In the xx \rightarrow en direction, where English-original data is back-translated data, we saw consistent but small gains across all languages, with CHRF rising by about +0.6 when increasing from 1M to 2M synthetic sentences. Increasing past 2M back-translated sentences saw minimal gains. However, these experiments were carried out on the lower-capacity shallow encoder models (with 14 languages each), so more gains from higher quantities of back-translated data may be seen on a higher-capacity model.

Although the teacher model may be trained with back-translation (BT), sequence-level distillation is typically only conducted with forward-translated data (FT). However, in this case there are some interesting implications that arise from a) the very small data sizes, and b) the asymmetrical teacher model quality, where $xx\rightarrow$ en quality tends to be better than $en\rightarrow xx$ quality. For $en\rightarrow xx$, FT (aka English-original) data is more abundant, but also lower quality; for $xx\rightarrow$ en , the FT data is higher quality but rather scarce. Therefore, we experiment with using different proportions of FT and BT data for distillation.

For en \to xx , we saw very small differences in performance between different ratios, and preferred using 80% FT and 20% BT data.

For an initial experiment on a 7-language shallow encoder model in the xx→en direction, we saw noticeable losses with under 50% FT data, losing about 1.7 CHRF when going to 33% FT, and losing a further 3.7 CHRF when going to 20% FT. Values above 50% FT were not significantly different. However, when observing the CHRF curve over time, we saw that the models with more BT data were learning more slowly and probably underfitting. Replicating this experiment with the deep encoder model, the performance on all languages increases, and the aggregate differences between different ratios of synthetic data are minimal. However, there is a slight trend on a per-language basis, with higher-resource languages benefiting from more back-translated data, with a Kendall tau of 0.28 between the number of monolingual training sentences and the difference between the 70% FT and 20% model. Since the differences are very slight, we favor models with a smaller percentage of FT data (20%-50%), motivated by the intuition that the increased amount of natural target side English compared to the small number of natural source-side sentences may have benefits we can't measure on our eval sets and metrics.

3.6.3 Comparison against teacher model

A comparison of our best deep encoder student models against the teacher on all 30 languages can be seen in Table 7. The student outperforms the teacher on the en→xx direction, with an average gain of

Mono Size Direction		-ff 6k →		-kri 29k →		doi ′9k →		bm 7k →		en-ay 267k ← →	
Teacher Student Δ	45.3	35.3	64.2	35.4	65.5	36.9	38.4	34.7	39.8	28.6	
	45.5	37.2	64.6	36.1	65.7	40.5	38.6	36.4	40.1	34.2	
	+0.2	+1.9	+0.4	+0.7	+0.2	+3.6	+0.2	+1.7	+0.4	+5.6	
Mono Size Direction		gom 1k →		bho 64k →		-kl -1k →		-ee 6k →		-qu -2k →	
Teacher Student Δ	57.9	40.8	60.9	41.2	39.0	35.8	37.0	40.2	35.3	35.7	
	57.4	42	61.3	42.7	39.5	41.0	37.5	40.7	35.1	36.1	
	-0.4	+1.2	+0.4	+1.5	+0.5	+5.2	+0.5	+0.4	-0.1	+0.4	
Mono Size Direction	en-gn 861k ← →		en-ak 1.3m ← →			ı-ts 3m →		mai 3m →		-ln 4m →	
Teacher Student Δ	43.0	32.1	38.6	34.3	47.5	46.5	65.5	39.2	31.7	34.6	
	43.4	31.9	38.9	34.4	47.7	46.8	65.5	40.0	32.1	34.6	
	+0.4	-0.2	+0.4	+0.1	+0.2	+0.3	0.0	+0.8	+0.4	0.0	
Mono Size Direction		nso 9m →		-lg m →		-ilo 6m →		ı-ti 9m →		om 6m →	
Teacher Student Δ	52.5	47.1	40.5	39.3	62.7	54.1	46.1	21.5	40.7	40.0	
	52.8	48.2	41.0	39.8	62.9	54.8	46.0	21.9	41.5	40.1	
	+0.3	+1.1	+0.5	+0.5	+0.2	+0.8	0.0	+0.5	+0.8	+0.2	
Mono Size Direction		-sa 2m →		-dv 9m →		-lus 3m →		-as 3m →		ckb 1m →	
Teacher Student Δ	49.2	31.0	48.4	45.0	42.1	39.7	60.6	39.6	55.3	42.6	
	49.2	33.3	48.4	45.3	41.9	41.3	61.1	40.3	56.4	44.3	
	0.0	+2.3	0.0	+0.3	-0.1	+1.6	+0.6	+0.7	+1.1	+1.7	

Table 7: Performance of teacher model versus student model in CHRF.

+1.1 CHRF, and minor gains of +0.2 average CHRF on xx \rightarrow en . These gains are probably in part due to the filtering applied to the RTT data. However, for the most part the differences are likely an artifact of the fact that the eval sets are English-Original, meaning that the English sentences are natural sentences, and the non-English sentences were produced via translation. Since distilled models tend to produce more translationese than their teachers, reference-based metrics like CHRF will tend to overestimate their performance in the source-original direction (en \rightarrow xx), and underestimate it in the target-original direction (xx \rightarrow en). This phenomenon is investigated in depth in Freitag et al. (2019).

For the 30 languages in the distilled model, we looked for correlations between the amount of monolingual data, the number of speakers, the percentage of data removed by deduplication, the harmonic data quality score (Section 2.1.8), and the CHRF score and human-rated scores in en \rightarrow xx and xx \rightarrow en directions. The correlations were all quite low, with Kendell's Tau under 0.3. The only exception to this is that there was a larger correlation (τ = 0.59) between CHRF in the xx \rightarrow en direction and a heuristic measure of closeness to supervised languages (e.g. Bhojpuri/bho, being very close to Hindi, gets a score of 0.9; Aymara/ay, with some loanwords from Spanish but otherwise entirely unrelated, gets a score of 0.1).

4 EVALUATION

Traditional metrics like BLEU, which have enough problems with higher-resource languages (Freitag et al., 2019; 2020), have even more problems with the languages studied in the present work. Reference translations are hard to come by, and tail languages are often less standardized with respect to dialect, orthography, and even sometimes Unicode encoding. Furthermore, the frequent presence of close varieties complicates evaluation: automatic metrics like CHRF can give very high scores to outputs which are entirely in the wrong variety. Finally, as Marchisio et al. (2021) find, outputs of unsupervised NMT are less monotonic and more natural than outputs from supervised NMT, which, like the findings on paraphrased references from Freitag et al. (2020), produce BLEU scores that are much lower — although sometimes better correlated with human judgements of quality. Model-based metrics like Y1S1 (Lo, 2019), BLEURT (Sellam et al., 2020) or COMET (Rei et al., 2020) cannot be used for these languages due to a lack of human ratings and pretrained models in these languages.

The following sections analyze performance along a variety of axes. First we describe the evaluation sets we collected (Section 4.1). We analyze the models starting with more quantitative methods, including the performance of CHRF versus BLEU (4.2) and human evaluations (4.4). We explore RTTLANGIDCHRF, a reference-free metric supervised for very low-resource languages, which shows reasonable correlation with CHRF. We next perform qualitative analysis of our model outputs, and highlight several patterns of errors including confusing between distributionally similar words and concepts like "tiger" and "miniature crocodile" (4.5), errors on single word inputs (4.7), and investigation of magnification of error modes in distilled models (4.8).

4.1 EVALUATION SETS

In order to measure the quality of translation for development and experiments, we collected reference translations for 38 languages. For ease of comparison we collected a multi-way parallel data set, with the same English side for all languages. The xx \rightarrow en eval sets were made by reversing this dataset. Rather than opting for larger evaluation sets for a small number of languages, we decided to collect relatively small evaluation sets containing 1200 sentences in 38 linguistically and geographically diverse languages. 50% of the English sentences were drawn from a corpus of simpler and more colloquial language (average length: 12.0 tokens; $\sigma = 4.45$), and the remaining 50% from more technical web content (average length: 20.1 tokens; $\sigma = 11.6$). The resulting dataset was shuffled and then split into a 600-sentence development set and a 600-sentence test set. The tables in this paper report the score across the combined set except where otherwise mentioned. The average absolute difference between the CHRF scores on both sets was about 0.5.

4.2 EVALUATION METRICS

For this work we deem token-level metrics like BLEU unsuitable, and rely almost entirely on the character level CHRF ³ (Popović, 2015), reported on a scale from 0 to 100. This section explains this decision, and gives examples of where the two metrics differ on the languages we studied.

Many of the languages studied in this work have complex morphologies, including the agglutinating Bantu languages and the polysynthetic Native American languages. This means that they can inflect to form very long tokens. An extreme example can be seen in Table 9, which shows how full sentences in English translate to only a few tokens in Kalaallisut ($k \perp$). For such highly inflecting languages, it is to be expected that a character-based metric, like CHRF, would correlate better with quality than a token-based metric like BLEU. This expectation is borne out by our observations. These observations align with Mirzakhalov et al. (2021b), who observed similar trends for the agglutinating Turkic languages.

It is difficult to make any sort of direct comparison between BLEU and CHRF. Not only do they measure different quantities and have different score distributions (e.g. CHRF = 0 is exceedingly unlikely), but they also are influenced by different artifacts. The BLEU score will be affected by infection, and a slightly wrong infection will nullify all affected n-grams. On the other hand, CHRF is affected by the writing system – for languages with abugidas or abjads, for instance, it will

³sacrebleu signature nrefs:1|case:mixed|eff:yes|nc:6|nw:0|space:no|version:2.0.0

lp	BLEU	CHRF	ratio	lp	BLEU	CHRF	ratio
en→om	3.8	40.1	4.0	en→ts	12.8	46.7	1.6
en→lg	3.7	39.8	4.0	en→gom	10.8	42.3	1.6
en→dv	5.4	45.5	3.5	en→ee	11.9	40.5	1.3
en→sa	2.8	33.1	3.5	en→ff	9.9	37.2	1.3
en→qu	3.6	36.2	3.4	en→bm	9.5	36.4	1.3
en→ln	3.5	34.9	3.2	en→lus	13.2	41.5	1.2
en→kl	5.3	40.6	2.9	en→kri	10.6	36.2	1.1
en→ay	4.6	34.3	2.4	en→ilo	24.2	54.9	1.1
en→ckb	9.4	44.2	1.9	en→ak	10.4	34.6	1.0
en→gn	5.2	32.1	1.7	en→nso	20.3	47.6	1.0
en→mai	8.6	39.8	1.7	en→bho	16.7	42.7	1.0
en→as	9.6	40.6	1.6	en→doi	15.3	40.7	1.0
en→mni-Mtei	12.9	47.1	1.6	en→ti	3.7	22.1	0.4

Table 8: CHRF versus BLEU scores on en→xx language pairs in the distilled model. Although it is almost impossible to compare these scores directly, as explained for a variety of reasons in the text, it is still clear that they give a very different picture of the performance on the languages. In order to make an approximate comparison between the two, we have included the ratio of the SCALEDCHRF score to the BLEU score. Language pairs in this table are sorted from the highest ratio (where BLEU underestimates performance) on the top to the lowest ratio on the bottom. As expected, polysynthetic and agglutinative languages are misjudged my BLEU.

source	translation
I can't sing so well so I don't want to be a singer.	Erinangippallaannginnama erinarsortartunngorusunngilanga.
Without my car, I wouldn't be able to get to work.	Biileqanngikkuma suliartorsinnaanavianngilanga.
I would like to raise a dog instead of a cat	Qimmiuteqarusunnerussangaluarpunga qitsuuteqarnissannit.
I have a cat who is lazy.	Qitsuuteqarpunga eqiasuttuuvoq.

Table 9: Example translations from English to Kalaallisut from our evaluation set. A token-based metric like BLEU is unsuitable for such a highly inflecting language, as exact match is very unlikely. Character-based metrics, like CHRF, are more appropriate.

behave differently than for languages with alphabets, as there will be fewer characters to match. (On languages with writing systems like Chinese or Japanese, it will function very similarly to BLEU.)

Nonetheless, in order to make some attempt to demonstrate how and where the two metrics differ, we have defined a very simplistic conversion metric based on performance of the less-inflecting low-resourced languages we studied: SCALEDCHRF = 0.75*CHRF - 0.15. The purpose of this metric is solely to have some way of flagging which languages lead to very different performance under the two metrics. Table 8 shows the language pairs in our distilled models, along with their BLEU score, their CHRF score (unscaled) and the ratio between SCALEDCHRF and BLEU. The results correspond with intuitions: The languages with the highest ratio tend to be polysynthetic (Quechua/qu, Aymara/ay, Kalaallisut/kl), agglutinative (Luganda/lg, Lingala/ln), or otherwise highly fusional (Sanskrit/sa). Oromo (om) is worth a special mention, as its orthography seems to have higher character usage per morpheme (because of the many doubled letters), which may inflate CHRF. It is not clear why Dhivehi (dv) has such a high ratio. The performance of both metrics on Tigrinya (ti) is also something of a mystery, given that the model translations were rated very highly by humans, and native speakers validated that the reference translations were also high quality.

4.3 RTT LANGID CHRF

Because of the infeasibility of collecting reference translations for 1000+ languages, some sort of reference-free evaluation is increasingly important. Round-trip translations have been utilized as a metric for MT Quality Evaluation several times over the last few decades (Huang, 1990; Aiken & Park, 2010; Moon et al., 2020). We experimented with a simple modification we call RTTLANGIDCHRF. To compute this score, we simply round-trip-translate a corpus of English sentences through some language, and compute the CHRF score of these translations with respect to the original sentences. However, since this metric is trivially fooled by error modes like copying or translating into the wrong language, we omit any round-trip translation where the intermediate translation is not in the correct language according to our SSLID model. If fewer than 10% of the intermediate translations receive

the correct LangID score, we consider the score invalid, as this may also be a result of errors in the LangID model.

We computed correlation between CHRF and RTTLANGIDCHRF over 30 languages, and found it to correlate moderately well both in the en \rightarrow xx direction ($\rho=0.46, \tau=0.34$) and the xx \rightarrow en direction ($\rho=0.30, \tau=0.28$). When we recalculated only on the scores from the distilled models, the correlations were much better in the xx \rightarrow en direction ($\rho=0.80, \tau=0.69$), but similar in the en \rightarrow xx direction ($\rho=0.36, \tau=0.22$).

In addition to this, we computed this score over all languages in the 1000-language model, of which 630 passed the LangID > 10% threshold. Figure 2 shows these scores as a function of log data size. There is a relatively clear trend ($\rho=0.80, \tau=0.63$), and the large majority of languages with over 100,000 monolingual sentences have relatively high scores. In general, the languages above the trend line are close dialects to high-resource languages, most notably variants of English written in different scripts. Languages below the trend line tend to be unrelated to high-resource languages or have poor-quality data according to our data audit.

Of the 630 languages with valid RTTLANGIDCHRF scores, 268 have a RTTLANGIDCHRF score of over 30.0, which we tentatively deem of "hopeful quality", and 147 have RTTLANGIDCHRF ≥ 50 , which is the minimum score from any of our supervised languages. Interestingly enough there is actually fairly low correlation between RTTLANGIDCHRF and the percent of intermediate translations that were assigned the correct LangID score ($\rho=0.18, \tau=0.10$). One possible explanation is that frequent error modes are outputs in the wrong language and copying, phenomena that we observed in Section 4.8.

We include RTTLANGIDCHRF for all 630 languages in Appendix Table 24, as an approximate measure of translation quality of the model. However, since we have done only cursory analysis of how effective this score is at measuring quality, we advise readers to view it with appropriate skepticism. While a low RTTLANGIDCHRF probably means low translation quality, a high value may well mean something other than high quality.

The version of this score described above we call the *loose* version of RTTLANGIDCHRF, since it does not penalize the model for intermediate sentences in the wrong language. To get the *strict* RTTLANGIDCHRF, we multiply the loose RTTLANGIDCHRF by the percent of intermediate translations assigned the correct LangID score, thereby penalizing wrong-language translations. This version does not correlate well with CHRF on the 30 languages where we have evaluation sets, and in fact has negative correlation in the xx \rightarrow en direction ($\rho=-0.28, \tau=-0.20$), and only a weak correlation in the en \rightarrow xx direction ($\rho=0.12, \tau=0.09$), likely due to noise from the LangID model. It also has weaker correlation with the size of the monolingual dataset over all 630 applicable languages ($\rho=0.43, \tau=0.55$), and is noticeably messed up by close dialects, e.g. assigning Bosnian (bs) a low score because intermediate translations were frequently LangID'd as Croatian (hr), a mistake that should not be penalized as the two languages are frequently indistinguishable. Despite these failings, it has the attractive property that it penalizes the common error mode of wrong-language outputs; and furthermore, the supervised and zero-shot languages appear more clearly separated when plotting them versus monolingual data size. The graph is therefore included in Appendix B.1.

4.4 Human evaluations

Any decision on translation quality ultimately cannot by made with automatic metrics like CHRF alone. In order to understand the quality of our distilled models, we asked human raters to rate the quality of the translations from our test set on a scale from 0 (nonsense or wrong language) to 6 (perfect). Full results may be seen in Appendix Table 20.

Although we made an attempt to calibrate raters and explain each point in the scale very clearly, each rater will naturally have a different understanding of "a good translation". For this reason, it is very difficult to interpret these results in any sort of holistic way. However, with some diving into the results together with native speakers, a few things stood out.

The biggest takeaway is that automatic metrics overestimate performance on related dialects. Nigerian Pidgin (pcm), a dialect of English, had very high BLEU and CHRF scores, of around 35 and 60 respectively. However, humans rated the translations very harshly, with a full 20% judged as

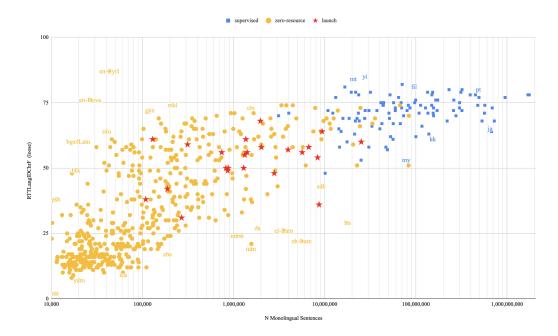


Figure 2: Plot of RTTLANGIDCHRF scores (loose) for languages as a function of log monolingual data size. With over 100,000 sentences, almost any language does reasonably well. Outliers are labeled with their language code. The largest outliers are English in Cyrillic script (en-Cyrl), which has excellent RTTLANGIDCHRF score but very little monolingual data, and Tibetan (bo), which has plenty monolingual text but very poor performance. In general, the languages above the trend line are close to high-resource languages (where the metric may also be fooled), and the languages below the trend line are linguistically distant from other languages in the model or have poor-quality data. Languages added to Google Translate as part of this effort (all unsupervised except Sorani Kurdish (ckb)) are marked with stars.

"Nonsense/Wrong Language", with trusted native speakers confirming that the translations were unusable. Krio (kri-close to English), Maithili (mai-close to Hindi), and Bhojpuri (bho-close to Hindi) were in a similar boat, though trusted native speakers agreed that the translation quality, though borderline, was usable. What's happening here that the model translates into (a corrupted version of) the wrong dialect, but it is close enough on a character n-gram level that the CHRF is still high. In our cases, this is the result of a data pollution problem. Since these languages are so close to other much more common languages on the web – in this case, English and Hindi – the training data is much more likely to be mixed with either corrupted versions of the higher-resource language, or other varieties. As a result, many model outputs that were supposed to be in Dogri (doi) were actually in misspelled or ungrammatical Hindi (hi), outputs supposed to be in Nigerian Pidgin (pcm) were sometimes in other English dialects like AAVE, and so on.

4.5 MISTAKES ON DISTRIBUTIONALLY SIMILAR WORDS

We observe that our zero-resource models exhibit some characteristic error modes. The most common one relates to translating nouns that occur in distributionally similar contexts in the training data. This occurs even for relatively common nouns like "tiger" – which is often translated as another kind of animal, showing that the model learned the distributional context in which this noun occurs, but was unable to acquire the exact mappings from one language to another with enough detail within this category. This may be related to the relatively small amounts of training data that were used, alongside the unsupervised nature of training. Common nouns suffering from these mistakes include animal names, colors, and times of day. This was also an issue with adjectives, but we observed few such errors with verbs. Sometimes, words were translated into sentences that might be considered culturally analogous concepts – for example, translating "cheese and butter" into "curd and yogurt" when translating from Sanskrit (sa). Surprisingly, the model hypotheses were often strings that would probably yield a high perplexity under most language models. Table 10 provides a variety of

sl	reference	translation
ak	I believe a lion is stronger than a tiger .	I think the hyena's hotter than the elephant.
dv	I believe a lion is stronger than a tiger .	I believe a lion would be stronger than a miniature crocodile .
mni	I believe a lion is stronger than a tiger .	I believe a snake is stronger than a crocodile.
doi	I believe a lion is stronger than a tiger .	I believe seizures are more severe than epilepsy.
ff	I believe a lion is stronger than a tiger .	I think a rabbit is stronger than a squirrel.
mni	The first three colors are red, orange, and yellow.	The first three colors are red, yellow, and blue.
qu	The first three colors are red, orange, and yellow.	The first three colors are red, fire red, and yellow.
sa	The first three colors are red, orange, and yellow.	The first three colors are red, yellow and saffron.
ts	The first three colors are red, orange, and yellow.	the first three colors are red, purple and pink
yua	The first three colors are red, orange, and yellow.	the first colors are red, red and yellow.
sa	In this I use capsicum, tomatoes, onions, garlic, green chilies,	Here I deal with greater marjoram, blood fruit, plantain,
	olives, etc. and do not use cheese and butter in it.	lassi, green marjoram, jujube, etc., but I do not deal with curd
		and yogurt.
ak	I would want to be a dog for a day.	I want to be a crocodile just one day.
ak	I would ask my cat some questions about what he's always try-	I will ask my friend some questions about why she is crying.
	ing to tell him by meowing .	
ak	my dog keeps me moving and enjoying life. he is man's best	my pet cat teaches me how to live a healthy lifestyle and enjoy
	friend.	being with people.
ak	I went to a carnival yesterday that was located in the middle of	I went to a place of pleasure in a desolate place, unknown to
	nowhere under a huge red and white circular striped tent	me, where there was a parrot that had a golden-yellow coat
ak	John was working in the lighthouse and went for a walk on the	John was working in the synagogue and he was sound asleep
	beach one night .	one afternoon.
ak	this is why hair turns grey with age.	this is the reason why ticks change into worms after a certain
		period of time.
sa	my bad habit is that I eat too much.	My bad behaviour is that I eat poison.
sa	Dogs are very intelligent animals, they understand very much	Cockroaches are extremely sharp minded animals, they know
	about humans.	about humans correctly
sa	Susy loved her space book and would ask her parents to read it	Susie loved her newspaper, and she asked her parents to read it
	to her every night .	to her in the morning.

Table 10: Examples of correct translations (**blue**) and mistranslations (**orange**), illustrating the model's tendency to make mistakes on distributionally similar nouns.

examples of mistakes from these models. These examples are from the 6B parameter 1000-language Transformer model, described in Section 3.3.

A good example of what it means for words to have different meanings but to be distributionally similar given the usage of the language is the translation of the string "English Language". Around 25% of the languages translated the string "English Language" into the name of their *own* language, e.g. into Tsonga as *ririmi ra xitsonga* or into Oromo as *Afaan Oromoo*.

Another interesting phenomenon evident from Table 10 is that models seem to be good at translating "red", mediocre at translating "yellow", and poor at translating "orange". This observation is consistent with cross-lingual hierarchy of color terms described in Berlin & Kay (1969); Saunders & Brakel (2002), which find that terms for color generally arise in specific orders across the world's cultures, with words for "red" occurring in stage II of color development, "yellow" in stage III/IV, and "orange" in stage VII.

An interesting parallel can be found between this problem and an issue of "unsupervised" translation in the real world – the case of the words for *four* and *six* in Etruscan, a language that went extinct about 2,000 years ago (Freeman, 1999). There does not currently exist any surviving parallel text with Etruscan, excepting a single 37-word tablet, but there do exist some 13,000 monolingual inscriptions. Etruscan does not seem obviously related to any living languages, so meanings usually cannot be discovered by their similarity to cognates. As a result, modern scholars have to use a sort of "unsupervied translation" called the *Combinatorial Method*, a first-principles approach to discovering word sense and grammar. And in the case of Etruscan, there are some words whose meaning cannot be teased apart with existing context. As an example, the words for all numerals from one to ten have been established with some certainty – with the exception of *four* and *six*. For these two there is no clear contextual clue to separate them, and there is no academic consensus of which of $hu\theta$ and śa mean four and six (Artioli et al., 2011).

4.6 PERFORMANCE ON TOKENS BY TOKEN FREQUENCY

In order to quantitatively measure the distributional token errors from Section 4.5, we decided to look at the accuracy of our model at translating particular tokens as a function of their frequency in an open-domain English web corpus.

First, we collected a list of the 8000 most common tokens in a large, web-crawled, monolingual English corpus. Then, we separated these into exponentially-spaced bins, based on the exponential distribution of token frequencies in natural text (Zipf, 1935). Therefore, each bin corresponds to a set of English tokens in a certain frequency band. Then, for each of these bins, we made a evaluation set for this bin composed of all sentences in our standard $xx\rightarrow$ en evaluation set containing these target tokens at least once in their references.

To score a model on a bin-specific evaluation set, we looked at a simple hit-rate metric. For a given reference sentence containing k tokens in the set of target sentence, the model got one point for each token it produced in its output that was among these k tokens (a "hit"), for a maximum of k points. The hit-rate score for that eval set is then simply the number of hits the model got divided by the total number of possible hits. Formally, for a given set of tokens \mathcal{B} (in our case a frequency bin), a list of reference translations $r_i \in R$ and a corresponding list of model hypotheses $h_i \in H$, the hit-rate $\Xi(H,R,\mathcal{B})$ is defined as follows:

$$\Xi(H, R, \mathcal{B}) = \frac{\sum_{i} \sum_{t \in r_i} \mathbb{1}\{t \in h_i, t \in \mathcal{B}\}}{\sum_{i} \sum_{t \in r_i} \mathbb{1}\{t \in r_i, t \in \mathcal{B}\}}$$

Table 11 shows the result of this analysis, sorted by the number of monolingual sentences seen by the model. Hit-rate is reported on five bins, starting on the most frequent tokens (tokens #0 - #125) and ending with the most infrequent tokens (tokens #8000 - #12800). For each bin the number of sentences in this eval set is included in the column labeled sents. The most frequent bin includes 1191 of the 1197 sentences in the full eval set; the lest frequent bin includes only 958 of them. For each bin the total number of possible points (i.e. hits) is also reported in the column labeled pts. Whereas the first bin has a total of 9682 possible points – averaging eight per sentence, and constituting mostly function words – the least frequent bin had only 2420 possible points, so slightly above two per sentence. It is also worth mentioning that the least frequent bin had 6,000 possible tokens in it, so only about 30% of them actually occurred in our eval set.

For many languages, higher CHRF means higher hit-rate across the board, and for others, like K'iche' (quc) low CHRF corresponds with generally lower hit-rate. Things get more interesting for languages that have higher hit-rates for the first several bins of higher frequency tokens, but lower hit-rates for less common tokens. These are the ones that have higher CHRF scores, corresponding to the ability to translate the top 500 tokens or so very well, but that also make frequent mistakes on less common tokens. Perhaps the best example of this is Fulfulde (ff), which had the relatively high CHRF of 40.7, but sees a large drop-off in hit-rate from 41% on bin 2 (token #125 - #500) to 26% on bin 4 (token #2000 - #8000). This is also the language where, anecdotally, we observed several of these sorts of mistakes. Mizo (lus) and Bambara (bm) exhibit similar patterns.

sl	tl	source	translation
en	ff	devices	kaßird'e (dispositifs)
en	lus	fragile	hring hring (fragile)
en	pcm	removes	dey remove
en	pcm	blame	blame wetin?
en	lus	four	pali a awm a
en	lus	freedom	zalenna a awm
en	quc	solved	xsol rij ri
en	quc	dam	ri k'o pa ri cho
en	kri	juvenile	pikin we no rich 18 ia yet
en	kri	notorious	pipul den we get badnem

Table 12: Our models frequently displayed exceeding verbosity with single-word inputs. In some cases they would add extra definitions for words in parentheses or commas afterwards (top half of table). In other instances they added function words from that language after the translation (**boldface**), or gave whole definitions, as with Krio.

sents	pts	lb	ub	metric	bew	mzn	as	lus	dv	sa	om	ti	cv	ilo
				N mono	33M	12M	9M	8M	8M	6M	6M	4M	3M	3M
				CHRF	51.5	54.6	59.1	34.5	45.1	46.6	38	43.8	46.6	43.5
1191	9682	0	125	Ξ	64	65	73	43	58	64	55	60	62	41
994	2537	125	500	Ξ	56	60	65	32	49	51	42	52	51	39
1034	3102	500	2k	Ξ	55	61	66	31	48	50	39	45	49	42
958	2420	2k	8k	Ξ	51	56	56	27	44	42	28	38	43	41
metric	nso	pcm	ce	mai	ts	ak	skr	bbc	gn	qu	min	yua	iso	gom
N mono	2M	2M	1M	1M	1M	1M	974k	932k	861k	842k	533k	419k	409k	311k
CHRF	51.1	52.3	45.2	61.4	43.6	36.1	47.8	44.2	38.2	32.2	62.2	40.8	29.1	54.9
Ξ	73	61	55	68	61	57	64	56	57	40	72	58	45	69
Ξ	57	53	47	66	45	34	53	47	35	28	66	40	23	59
Ξ	51	54	45	67	42	30	53	46	32	30	67	39	20	59
Ξ	41	53	43	62	38	24	47	39	28	29	63	31	17	52
metric	av	ady	quc	ban	bm	doi	mad	kri	mni	ff	mfa			
N mono	301k	296k	250k	188k	187k	179k	138k	129k	106k	86k	7k			
CHRF	48.4	55.2	27	35.4	35.8	62.8	50.1	56.1	56.2	40.7	65.1			
Ξ	55	56	42	48	57	77	61	65	71	66	77			
Ξ	53	63	20	33	34	68	50	58	61	41	71			
Ξ	57	67	19	33	30	69	49	59	59	33	69			
Ξ	55	65	16	29	22	62	45	50	51	26	62			

Table 11: Token hit-rate (Ξ) for different sets of tokens, binned by frequency. The lower and upper bound of the token frequency rank per bin are given in the 1b and ub columns; thus, the top row is the hit-rate on the 125 most frequent tokens, and the bottom row is on the 6,000 least frequent tokens. Columns sents and pts give the number of sentences in each bin-specific eval set and the number of tokens in that bin occurring in those references, respectively. The CHRF score and number of monolingual training sentences is also given. The interesting results are on the languages, like Fulfulde (ff), that have a high hit-rate on more frequent tokens and a lower hit-rate on rarer tokens. All results are only in the xx \rightarrow en direction.

4.7 Errors on short inputs

Another category of errors we encountered was with single word inputs to the model. The translations tended to be longer, and the model would frequently give alternate translations or append frequent tokens (Table 12). Outputs also frequently had duplicates among the other outputs, suggesting hallucination, or copied inputs. A breakdown of types of errors can be found in Table 13.

This was an issue we observed mainly for lower-resource languages. For higher-resource languages, like Ilocano, the model tended to provide a succinct and correct single-word translation. Ensuring that the MASS training data covers the lower end of the length distribution would likely remedy these issues. However, this is also an inherently difficult problem since we do not provide the model any source language information. For the $xx\rightarrow$ en direction, the translation task needs to solve LangID and translation simultaneously, which could often be ambiguous and quite challenging for short queries. This can potentially be addressed by providing the model source language information along with the input, and is left to future work.

direction	model	copies	multi-word	duplicate	repeats	other
en→xx	teacher	1.28	66.23	26.48	5.55	17.43
$en \rightarrow xx$	teacher.	0.85	71.71	31.66	2.79	13.87
en→xx	student	1.15	48.21	37.16	1.43	27.38
$en \rightarrow xx$	student.	8.28	45.53	36.18	2.05	22.73
xx→en	teacher	61.87	6.19	21.11	0.74	14.74
$xx\rightarrow en$	teacher.	47.3	17.02	24.8	0.47	18.21
xx→en _	student	18.33	28.54	43.23	2.65	22.65
xx→en	student.	20.1	35.14	40.41	0.27	21.70

Table 13: Statistics for single-token translation on the top ten thousand most common tokens from the monolingual datasets, compared for 48 language pairs, for the fine-tuned teacher model. Metrics shown are 1) percent of outputs that copy the source; 2) percent of input that is multi-word; 3) percent of outputs that are identical to other outputs, suggesting incorrect translation; 4) percent of outputs with low character diversity, suggesting repeats; and 5) percent of outputs with none of those features. The entries with full-stops (.) after them use the "period trick" (Section 5.3). Single word translation is a particularly tricky task as the model needs to solve translation and LangID simultaneously, which can be undefined for short queries.

language	% mono	% synth (clean)	% synth (noisy)
pcm	8%	20%	-
kl	14%	18%	30%
sa	13%	16%	37%
ja	0.0004%	-	1%

Table 14: Percent of each data set removed after applying specialized filters. mono refers to the monolingual data from the corpus mined in Section 2.2. synth(clean) refers to synthetic data generated by forward translating a clean English monolingual corpus and synth (noisy) refers to synthetic data generated from a noisy web-scraped English corpus. We see that the synthetic text generated by the teacher model exhibited these problems to a greater degree than the monolingual web-sourced data, and that these problems intensified on noisier data.

LP	this method	M2M-100	LP	this method	M2M-100
en→as	29.1	1.22	as→en	34.5	3.76
en→ckb	28.5	0.23	ckb→en	37.5	7.65
$en \rightarrow ff$	2.5	0.68	ff→en	11.2	2.4
en→lg	17.3	0.61	lg→en	29.3	4.45
en→ln	24.7	1.03	ln→en	30.2	4.57
en→nso	32.5	1.54	nso→en	45.0	6.76
en→om	17.2	0.4	om→en	30.8	3.33

Table 15: Flores dev-test: comparing SPBLEU between this method and Goyal et al. (2021).

4.8 Magnification of error modes in student models

After training distilled models, we noticed a variety of unexpected error modes when analyzing the output translations:

- The translations to Nigerian Pidgin (pcm) frequently instead translated to (often offensive) US slang. For instance, the English sentence "She said to herself" was translated to the unacceptable string "da b***** say ta da b*****self."
- Many of the translations to Kalaallisut (kl) were actually Danish (da)
- Many translations to Sanskrit (asa) were actually Hindi (hi)

We developed filters to remove this content from the forward translated data and distilled the models again. We observed that these problems were more prevalent in the synthetic data used for distillation (generated by the teacher model) than in the monolingual data that had originally been used to train these models, and that the issues were more severe for synthetic text produced by translating a noisier source corpus. The changes in noise level are illustrated in Table 14. We hypothesize that this error magnification could either be an artifact of a positive feedback loop arising from training the model on its own prediction (self-training), or due to a difference in domains between the training and distillation datasets.

This table also includes one entry about distillation from Japanese to English. In this case, we found that one particular Amharic string was often hallucinated. This string occurred occasionally in the target side of the original training data, and then occurred much more often in the distilled data.

4.9 Comparison on Flores Benchmark

Since these models are not trained on the same data as public benchmarks, a comparison on public benchmarks is not necessarily very meaningful. Nonetheless, in Table 15 we provide a comparison between the SPBLEU results from our method (on distilled models) versus the Flores-101 benchmark scores (Goyal et al., 2021) reported for the massively multilingual M2M-124 (Fan et al., 2021) for overlapping languages. Given the higher language coverage in our monolingual dataset, our models yield higher SPBLEU for all language pairs.

5 ADDITIONAL EXPERIMENTS AND NOTES

5.1 Non-English-Centric Bridging

There is nothing inherently English-centric about the approach to zero-resource translation put forth in this paper. Nonetheless, the model has only seen translated text between English and other languages, so it would be a reasonable hypothesis that it is just inherently better at translating to and from English, even in the zero-shot scenario.

We test this hypothesis by evaluating the model on bridged translations. We first translate the English source sentences to other languages using bilingual supervised models on these language pairs. Then we use the model proposed in this paper to translate these translations directly into the desired target language. For each desired target language we pick 1) the closest mid- or high-resource language (HRL) that we expect our bilingual models to do well on; and 2) if applicable, a lower-resource language (LRL) that may be closer to the desired target language, but have lower quality supervised models. Please note that the definition of close is somewhat approximate. For instance, for Native American languages we choose colonial languages as the "close" languages, because they may share a certain amount of vocabulary, even if the grammar is entirely divergent. Furthermore, for some of these languages the "close" languages are in fact not very close at all, as with the Sino-Tibetan languages of North-East India (Bodo (brx), Meiteilon (mni-Mtei), Mizo (lus)), which are only somewhat related to the "closer LRL" of Myanmar/Burmese (my).

lang.	direct	clos	se HRL	clos	er LRL	lang.	direct	clos	e HRL	close	er LRL
	Native American Languages					Indian Languages (Not Indo-European)					an)
ay	33.1	es	34.2	-	-	brx-Beng	4.6	hi	11.5	my	3.4
gn	31.5	es	28.9	-	-	lus	38.6	hi	38.2	my	34.1
kl	35.5	da	27.5	-	-	mni	40.7	hi	35.5	my	29.4
qu	35.3	es	29.5	-	-	sat-Latn	20.9	hi	20.8	km	18.2
que	24.1	es	22.5	-	-			'			
yua	31.5	es	28.4	-	-	Bantu Languages					
-				1		lg	38.7	SW	34.1	rw	33.6
Ind	lian Lang	guage	s (Indo-I	Europe	ean)	ln	34.4	sw	31.9	fr	25.5
as	39.2	hi	39.8	bn	36.3	nso	45.7	sw	33.3	st	29.1
bho	42.0	hi	43.4	-	-	ts	46.2	sw	40.0	zu	44.0
doi	36.3	hi	39.5	pa	33.3					•	
dv	44.4	hi	42.0	si	39.7			Othe	r		
gom	40.2	hi	39.3	mr	39.7	bm	34.3	fr	26.6	-	-
ks	21.9	hi	25.7	ur	28.5	ff	34.7	SW	26.7	-	-
mai	38.1	hi	44.3	-	-	ilo	54.0	id	48.4	fil	51.2
sa	30.5	hi	27.3	-	-	om	39.2	-	-	so	30.2
	'			1		ti	21.4	-	-	am	22.6
						yue	20.3	zh	21.6	-	-

Table 16: Results for bridged translation from English (CHRF) on 1200 sentences/language. Bridging seems to improve quality only when the intermediate language is both higher-resource and close to the target language.

Table 16 shows the results of this investigation, along with which languages were chosen as "close high-resource languages" and "closer low-resource languages".

We find that in a substantial number of cases, bridged translation scores better on automatic metrics. This is true especially for the languages of India, with bridged translation drawing even or improving even for the non-Indo-European languages. Overall, the largest improvements are seen on close dialects, for instance Maithili (mai: +6.2 CHRF), Bhojpuri (bho: +1.4 CHRF), Kashmiri (ks: +7.4 CHRF), and Cantonese (yue: +1.5 CHRF). Aymara (ay) and Dogri (doi) also saw noticeable gains. However, most Native American languages, Bantu languages, and languages without close relatives saw large losses by bridging.

⁴For this experiment, we considered Swahili (sw) to be a high resource language. This is not precisely accurate, but it was the closest mid-resource language available.

Nonetheless, in 19 out of 28 cases, we find that direct translation from English produces the highest CHRF score. This may be due in part to the model being inherently better at translating from English, and in part from errors compounding from the two-step process. Evidence for the second hypothesis may be seen in the fact that only two languages (Kashmiri (ks) and Tigrinya (ti)) see any gain from bridging through a lower-resource language. Overall, it seems that bridging only improves quality when the intermediate model is already relatively high quality, and additionally when the intermediate language is close to the target language.

The fact that bridging appears to work relatively well is a good sign. In practice, translation to and from English is not the major use case for many low resource languages, and direct models to local languages (e.g. Hindi for India, Spanish for Latin America, etc.) would likely provide more utility to local communities.

5.2 Zero-shot transliteration

Many of the world's languages are written in multiple scripts, whether because of historical and national changes, informal online usage, non-standardized writing systems, or different ethnic or religious populations. For this reason, especially with under-resourced languages where this is more common, it is especially important to be able to support these languages in their many different writing systems.

For our data collection efforts, we crawled data in a variety of different scripts for several languages, e.g. both Malayalam in Malayalam script (ml) and Malayalam in Latin script (ml-Latn). We treated script-variants of the same language as separate languages, with their distinct <2xx> tags. To transliterate, we simply asked the model to provide "translations" from text in one script to the same language in another script.

We applied this approach to transliterate from Latinized variants of Indian languages to their native scripts, and found that it worked very well out of the box, appearing to be more robust than existing transliteration libraries to informal or nonstandard spellings. One example is the common abbreviation kr in Latinized Hindi (hi-Latn), as in kya kr rhe ho which our model correctly transliterated as "kar" (in Devanagari script), whereas the rule-based model incorrectly rendered as "ke". Similarly the model was able to do some spelling correction, e.g. on the the misspelled Konkani swpnatat, which the model correctly transliterated to "swapnaat". However, the model also had a tendency to change small parts of the input sentence, as well as occasionally hallucinating extra content. This also made it difficult to compare this model to rule-based approaches in a rigorous way, because the lack of guaranteed monotonic alignment made word error rate inapplicable.

One interesting example highlighting issues this approach has is the Konkani sentence *Xet-camot ani kneddeam- gauncho vaur vo dondo*. This was transliterated mostly correctly to Devanagari, but the the dialect was changed: the original text is Goan Roman Catholic Konkani, but the transliteration was in Goan or Maharashtrian Konkani, changing "camot" to "camat" and "vo dondo" to "vaa dando".

Future work is necessary to coax this technique into a form that does not take any liberties with the input. One promising direction is to separate the <2xx> tokens (Johnson et al., 2016) into a language subtag and a script subtag. For instance, <2ms> becomes <2ms> <2Latn>, and <2ms-Arab> becomes <2ms> <2Arab>. This enables 0-shot transliteration between any scripts supported by the model, simply by using the desired <2Script> tag at inference time. In order to prevent the model editorializing, it would also be advisable to consider adding synthetic transliterated parallel text with a <2transliteration> tag, to teach the model that this task only involves substituting letters/sounds.

5.3 THE "PERIOD TRICK"

Even after having been distilled on a mix of clean and noisy data, we observed that some of these languages still had lower performance on inputs that lacked terminal punctuations. To study this, we compared performance on the evaluation sets with and without terminal punctuation. Table 17 illustrates the results of this experiment on the distilled models, though we noticed similar trends in the teacher models. The gain is small but consistent, and in the xx→en direction, 100% of the language pairs benefit. We noticed that sentences without terminal punctuation sometimes triggered common error modes, e.g. decoding into Danish (da) instead of Kalaallisut (k1), or misspelled

direction	no TP.	TP	Δ	W/L
en→xx	39.32	39.56	+0.24	0.77
$xx\rightarrow en$	48.54	49.23	+0.69	1.0

Table 17: Comparing CHRF on versions of the evaluation sets with and without terminal punctuation (TP) on 26-language distilled models. The Win/Loss ratio is also reported, meaning the fraction of language pairs that saw an increase in CHRF by applying the terminal punctuation.

Hindi (hi) instead of Dogri (doi). We hypothesize that the presence of terminal punctuations might provide a "domain" signal to the model and trigger different translation qualities.

5.4 ROBUSTNESS TO NON-STANDARD GLYPH USAGE

There are many different ways to write certain letters, especially those where a Unicode standard was introduced after a population was already active online, or before keyboards using this standard were widely available. Common cases include the many Unicode points for the "open o" (3) and "open e" (8) used in many African languages; the Palochka (resembling the letter I), used in many Caucasian languages; the apostrophe or 'Okina, used around the world but especially in many American languages; and many other examples that can be found in the Unicode Confusables list (Davis & Suignard, 2021). Table 18 gives an example of this phenomenon in the wild, showing the variation of Unicode points used for the Chechen and Chuvash languages in our webcrawled data. We refer the reader to Prasad et al. (2018) for many more examples of this phenomenon.

We conducted a simple experiment to determine how robust our model was to these different usages. Looking at translations into English, we decoded our evaluation sets (with the non-finetuned, 1000-language teacher model) using each of a variety of different ways of representing each letter. We then compared the CHRF scores on the output. Results can be seen in Table 19. We found that in most cases, this made very little difference in CHRF, even when using rare glyphs like the capital Greek Iota in place of the Palochka in Caucasian languages, indicating that our models were quite robust to these variations. However, we did notice a relatively large change in CHRF for West African languages when using nonstandard glyphs, including the "chatspeak" ASCII characters used when texting or writing very informally – for instance, writing "aho)f3" for "ahoɔfɛ".

Unicode character name	Percent of Data
LATIN CAPITAL LETTER I	33.6%
DIGIT ONE	30.4%
CYRILLIC LETTER PALOCHKA	3.8%
CYRILLIC CAPITAL LETTER BYELORUSSIAN-UKRAINIAN I	4.2%
LATIN SMALL LETTER L	2.8%
GREEK CAPITAL LETTER IOTA	0.4%
LATIN SMALL LETTER A WITH BREVE	52.4%
LATIN SMALL LETTER E WITH BREVE	55.0%
LATIN SMALL LETTER C WITH CEDILLA	43.4%
CYRILLIC SMALL LETTER IE WITH BREVE	10.2%
CYRILLIC SMALL LETTER A WITH BREVE	9.4%
CYRILLIC SMALL LETTER ES WITH DESCENDER	8.8%

Table 18: Examples of the different Unicode points used to encode the Palochka character in the Chechen language (above) and letters with diacritics in the Chuvash language (below), along with their prevalence on web-crawled data. In both cases, the "correct" Unicode point (**bolded**) is much less common.

5.5 Non-Unicode fonts

Before easy access to keyboards using the correct Unicode points, or before the Unicode standard itself, it was often not clear how to represent alphabets or characters that were not in the ASCII range. We already saw one consequence of this in Section 5.4. A more difficult consequence is the existence of non-Unicode fonts. The way this often works is that one types in ASCII characters, but downloads a special font that provides glyphs for these the ASCII code points that give the desired visual rendering – for instance, one types "172is4wo", and it renders as the Ewe word ladjesowo.

Unicode point	name	avg. CHRF							
	gn, luo, quc, yua \rightarrow en								
U+2019	Right quote	25.7							
U+0060	Grave accent	25.5							
U+0027	Apostrophe	25.5							
U+02BB	'Okina	25.5							
U+00B4	Acute accent	25.4							
	None	24.5							
	ady, av, ce \rightarrow en								
	Palochka	49.6							
U+0031	ASCII 1	49.4							
U+0399	Greek Iota	49.4							
U+0406	Byelorusian/Ukrainian I	49.3							
ak.	bm, dyu, ee \rightarrow en								
Ū+025B, Ū+0254	Latin open e/o	33.6 -							
U+03B5, U+1D10	Greek epsilon; small capital O	25.8							
U+0033, U+0029	3 and) (chatspeak)	25.3							
	av. Lam								
- TI-07D7-II-04D1-II-07AD-	$cv \rightarrow en$								
U+04D7, U+04D1, U+04AB	Cyrillic codepoints	42.3							
U+0115, U+0103, U+00E7	Latin Codepoints	43.0							

Table 19: CHRF score where the source uses different versions of common Unicode points. The top line of each bloc represents the "correct" codepoints, whereas the lower lines are other ways of representing the same letter. In many cases there is very little difference in performance, but the African languages are affected by nonstandard $\mathfrak z$ and $\mathfrak e$. When the apostrophe is removed entirely, the performance also drops noticeably.

Other non-Unicode fonts even assign different values to code points beyond the ASCSII block; one well-known example is the Zawgyi encoding for Myanmar (Burmese) (Liao, 2017). In the course of this work, we discovered that a wide variety of languages still use non-Unicode fonts. We ran into such fonts for Ewe (ee), Kashmiri (ks), Meiteilon (mni-Mtei), Mooré (mos), Navajo (nv), and Tamazight (ber-Latn), usually in the case of deliveries from professional translators. It is likely that there exists a large, hidden portion of data for some languages using these or other fonts. Our attempted reconstruction of some of these fonts can be seen in Appendix Section D.

6 IMPORTANCE OF NATIVE SPEAKERS

Since the advent of statistical and then neural machine translation, large data sets and improved modeling techniques have driven progress in translation quality. It has sometimes been difficult for the expertise of native speakers and linguists to continue helping to improve models in this environment. However, the participation of speakers of languages, and of members of affected communities, is nonetheless still vital. In the very-low-resource domain, there are more errors in models and data – and consequently, more opportunities for native speakers to help improve the quality.

We stress that where possible, it is important to try to build relationships with native speakers and members of these communities, rather than simply interacting with them as crowd-workers at a distance. For this work, the authors reached out to members of as many communities as we could, having conversations with over 100 members of these communities, many of whom were active in this project (See Acknowledgements).

Here is an incomplete list of ways in which speakers of these languages helped us extend and improve machine translation to their languages:

- 1. **Understanding Data:** As in Kreutzer et al. (2022), we conducted an extensive review of the quality of our datasets (see Appendix Table 22). In addition to simply giving us an idea of which languages had higher or lower quality data, this also gave us valuable insights about other uses and aspects of the corpora that were useful beyond this project for instance, which corpora had more colloquial (or religious) text, and which dialects were mixed with other languages.
- 2. **Understanding errors in reference translations:** A variety of languages had extremely low automatic metrics (e.g. BLEU under 1.0), despite having large and clean corpora. For two such cases, native speakers helped us identify quality and fluency issues with our reference translations and that the model outputs often looked better than the references.
- 3. Specialized Filters: Our corpora for a few languages were polluted with related high-resource languages that had somehow passed all the previous rounds of filtering. For two cases, natives speakers helped design custom filters to remove the unwanted content, and for a third, they helped remove sensitive content.
- 4. **Transliteration and political sensitivity around script:** For one language, we were initially unaware that we were using the wrong script. We were using a script that was associated with colonial times, and had since been replaced in the entire region, and was a matter of political sensitivity. Native speakers both pointed out this issue and helped us transliterate the text to the appropriate script. (See Appendix Section C)
- 5. **Understanding crowd-worker annotations:** when we sent translations to crowd workers to rate their quality, several languages showed unusual rating patterns, or patterns that did not line up with our expectations. We were fortunate to have native speakers who helped us understand the ratings differentiate cases where raters were mis-calibrated against real quality issues. Freitag et al. (2021) explores some of these phenomena more.
- 6. Clarifying utility for Community: Even if one *can* build a translation model for a language, should one? For some groups, community desires may differ from what many in the machine translation community might expect (Long, 2007; Coffey, 2021; Hiraishi, 2021). And if the translation model is of imperfect quality, is that still helpful for the community or is it perhaps offensive? These are questions that can only be answered by members of the community. In our interviews, we generally found that native speakers of the languages we spoke to were very enthusiastic for even lower-quality translation offerings. This said, no one person can represent the entire community, and there is much to learn in how to handle situations where opinions and desires differ within a community.
- 7. **Commenting on Dialects:** Many "languages" have a wide variety of dialects, sometimes hardly mutually intelligible. Native speakers helped us understand when our models were producing a particular dialect, or mixing and matching them.
- 8. The correct name to use for a language: Whereas a language like French has a fairly unambiguous name, many languages have multiple names, some of which may be offensive or exclusive. Frequently there exists a colonial name (e.g. "Oriya" or "Lushai"), which may

be more widely known, but may also be disliked by the members of the community, as well as a native name (e.g. "Odia" and "Mizo") that is lesser known but preferred. Similarly, there may be names which may feel exclusive to some sub populations – for instance using the name "Manipuri" for the language of the Meitei ethnic group. Although the most common way to refer to the Meitei language is indeed "Manipuri", this is exclusive to the many other ethnic groups in the state of Manipur with their own languages.

7 CONCLUSIONS AND OPEN PROBLEMS

7.1 Main Findings

Starting with an initial seed dataset of monolingual sentences spanning over 1500 languages, we demonstrate that it is possible to build relatively clean web-mined monolingual text datasets for over 1000 languages. We highlight the importance of incorporating expressive semi-supervised LangID models, document-level consistency signals, and several word-based and custom filtering techniques to identify and filter web text in long-tail languages (Section 2.1). Using this approach we are able to build a multilingual unlabeled text dataset containing over 1 million sentences for more than 200 languages and over 100 thousand sentences in more than 400 languages (Section 2.2).

Training on this dataset and a parallel corpus spanning 112 languages, we build massively multilingual models capable of translating across 1000 languages (Section 3). We highlight the importance of model capacity when training highly multilingual translation models and the positive effect on zero-resource quality when increasing the number of languages in the model. We also describe the significant quality improvements achievable by incorporating large-scale back-translation and self-training, and share our findings towards developing practical, inference-friendly models for long-tail languages.

We evaluate our models on evaluation sets collected for 38 languages, and highlight the need for choosing the right automatic metric (CHRF) when evaluating long-tail languages (Section 4.2). Apart from automatic metrics on evaluation sets, we additionally release approximate reference-free quality scores of our 1000-language MT model to provide an indicator of web-trained multilingual model quality on hundreds of previously under-studied languages (Section 4.3). We perform human evaluations on a subset of the languages in distilled models, and highlight that it is possible to build high quality, practical MT models for long-tail languages utilizing the approach described in this work (Section 4.4).

Through qualitative and quantitative analysis of the model outputs, we reveal a few characteristic error modes of our models; including confusing distributionally similar and infrequent tokens, and also producing verbose and inaccurate translations for short or single word queries arising from the extreme data sparsity of the zero-resource setting (Sections 4.5 and 4.7). We furthermore highlight several other observations from our studies, including non-English-centric direct translation, zero-shot translation, the effect of terminal punctuation on translation quality, and the robustness of the model to the non-standard glyph usages that are common for many languages (Section 5).

Finally, we highlight several indispensable contributions of native speakers who helped us evaluate, understand, filter and improve our datasets and models; and helped us understand the overall context of how these models should fit in with their communities (Section 6).

7.2 RELATED WORK

There is a considerable wealth of literature on building highly multilingual text corpora, LangID models, and MT models. Our work differs largely in the scale, quality, and number of languages covered, together with the integration of many moving parts in the entire data-to-translation-model pipeline.

Access to multilingual datasets for NLP research has vastly improved over the past years. Since 2006, the *Web as Corpus* workshops have focused on the challenges around identifying relevant pages, extracting clean text, content de-duplication, and many other relevant topics (Barbaresi et al., 2020; Jakubíček et al., 2020). A variety of web-derived collections for hundreds of languages is available for anyone to download, such as the Corpora Collection at Leipzig University (Goldhahn et al., 2012), the Corpus of Global Language Use (Dunn, 2020), ParaCrawl (Esplà et al., 2019; Bañón et al., 2020), WikiMatrix (Schwenk et al., 2019), CCNET (Wenzek et al., 2020) and CCAligned (El-Kishky et al., 2020), OSCAR (Ortiz Suárez et al., 2019; Ortiz Suárez et al., 2020; Abadji et al., 2022), and several others; all of which have between 100 and 300 languages. The largest language coverage is probably An Crúbadán, which does not leverage LangID, and found (small amounts of) web data in about 2,000 languages (Scannell, 2007). These corpora have in turn enabled a variety of highly multilingual models, like mT5 (Xue et al., 2020), M2M-100 (Fan et al., 2020), and M4 (Arivazhagan et al., 2019; Siddhant et al., 2022).

Curating such datasets relies on the websites giving clues about the language of their contents (e.g. a language identifier in the URL) and on automatic language classification (LangID). It is commonly known that these automatically crawled and filtered datasets tend to have overall lower quality than hand-curated collections (Koehn et al., 2020), but their quality is rarely measured directly, and is rather judged through the improvements they bring to downstream applications (Schwenk et al., 2019). Therefore, many of these multilingual web corpora suffer from serious quality issues, especially for low-resource languages. A recent audit conducted by Kreutzer et al. (2022) on five public, multilingual datasets found pervasive issues. Many corpora claiming to be in one particular language in fact contained zero percent in-language content — and sometimes zero percent linguistic content entirely. Of the many issues contributing to this phenomenon, a fundamental one is the poor efficacy of LangID on low-resource languages.

Several works have investigated LangID at the level of multilinguality studied in this work. One relevant LangID implementation is Dunn (2020), achieving an F1 above 0.95 for 464 languages, and offering a thorough evaluation on different data sources and domains. The only LangID systems with higher coverage that we are aware of are those developed by Brown (2012; 2013; 2014), with the most recent version covering as many as 1,366 language varieties, with accuracy above 99%. Finally, Caswell et al. (2020) trains LangID models on 1,629 languages, and demonstrates that although they appear to have very high scores on held-out evaluation sets, in practice, when applied to web text, they produce datasets of almost unusable noisiness. Various error pathologies are detailed, and a few novel filtering techniques are proposed to counteract them, including TF-IIF filtering and semi supervised LangID (SSLID). The present work can be viewed as an extension of Caswell et al. (2020), and a fusion of it with translation technology.

Our MT modeling approach builds on several previous works on massively multilingual, zero-resource and self-supervised MT; differing primarily in terms of the scale of multilinguality, model capacity and the extreme data sparsity in our experimental setting. We call these approaches that combine different aspects of scale as M4: massively multilingual, massive machine translation⁵.

Multilingual Neural Machine Translation models were first introduced during the last decade (Firat et al., 2016a; Johnson et al., 2017), but the initial versions of these models were limited to a few languages (10–12). Over the last few years, there has been an explosion of work focusing on massively multilingual models that could translate between around 100 languages (Neubig & Hu, 2018; Aharoni et al., 2019b; Arivazhagan et al., 2019; Zhang et al., 2020; Tang et al., 2021; Fan et al., 2021). However, most work on massively multilingual MT has focused on the purely supervised setting. There are a few works that have ventured beyond the limitations of large-scale multilingual corpora, and trained MT models spanning over 1000 languages (Mueller et al., 2020), usually limited to narrow-domain (often religious) corpora.

Another stream of research on unsupervised MT developed modeling approaches to train MT models using monolingual datasets only (Lample et al., 2017; Artetxe et al., 2017; Song et al., 2019). With the advent of multilingual pre-training, with models like multilingual BERT (Devlin et al., 2019), XLM (Lample & Conneau, 2019), mBART (Liu et al., 2020) and others, the focus shifted towards fine-tuning pre-trained models with paired data in a sub-set of the pre-training languages to enable zero-resource translation in the remaining languages. These approaches are often complemented with large-scale back-translation (Sennrich et al., 2016; Edunov et al., 2018) to continue improving the model beyond its initial zero-shot performance.

Our work builds on Siddhant et al. (2020); Garcia et al. (2021b); Siddhant et al. (2022) that combines together multilingual supervised MT, zero-resource MT (Firat et al., 2016b) and self-supervised learning within a single model. We extend the work in Siddhant et al. (2022) by scaling to larger models, a more multilingual dataset, utilizing self-training and a novel filtering technique based on round-trip translation consistency and LangID predictions.

Apart from efforts focused on building highly multilingual web-mined corpora and MT models, another line of NLP research has focused on building datasets and NLP technologies for specific languages, not necessarily from web content. Many of these are grassroots, bottom-up efforts from the affected communities, organized through research collectives like Masakhane (\forall et al., 2020), Turkish Interlingua (Mirzakhalov et al., 2021a;b), and GhanaNLP (Azunre et al., 2021a); and conferences

 $^{^{5}}$ https://ai.googleblog.com/2019/10/exploring-massively-multilingual.html

and workshops like AfricaNLP⁶, AmericasNLP (Mager et al., 2021) and ArabNLP⁷. These efforts, in addition to providing datasets, frequently provide models and baselines, or even public interfaces, like the Khaya Translator Web App⁸ by GhanaNLP for West African languages, and the lesan.ai⁹ translation website for Ethiopian languages.

Participation is especially strong from the African continent, including corpora and models for pan East-African languages (Babirye et al., 2022), languages from the Horn of Africa (Hadgu et al., 2022), Ethiopian languages (Abate et al., 2018; Gezmu et al., 2021), Ugandan languages (Akera et al., 2022), Emakhuwa (Ali et al., 2021), South-African languages (Eiselen & Puttkammer, 2014), Setswana and Sepedi (Marivate et al., 2020), Yorùbá (Adelani et al., 2021b;a), Oshiwambo (Nekoto et al., 2022), Igbo (Ezeani et al., 2020), Zulu (Mabuya et al., 2021), Twi (Azunre et al., 2021b), Gbe (Hacheme, 2021), Bambara (Tapo et al., 2021), and Fon (Emezue & Dossou, 2020). Outside of Africa, corpora have been created for languages of the Americas, including for four indigenous languages of Peru in Bustamante et al. (2020), the numerous results on the largely South- and Central American languages from the first Americas NLP conference (Mager et al., 2021), and the Inuktitut language of Canada (Joanis et al., 2020). Datasets for lower-resourced languages of India have also sprung up, including the 13-language PMIndia (Haddow & Kirefu, 2020), and datasets focused on languages of the Northeast like Mizo (Thihlum et al., 2020), Khasi (Laskar et al., 2021) and Assamese (Laskar et al., 2020). Finally, a variety of such datasets and models are available for public use on HuggingFace¹⁰ or Zenodo¹¹. We believe language-specific efforts to be orthogonal and complementary to massively multilingual approaches for corpora building and modeling, as we elaborate further in Section 7.3.

7.3 FUTURE WORK

Barring a dramatic increase in the amount of web text available for long-tail languages, the types of errors produced by our zero-resource models (Section 4.5) are likely to persist. We highlight a few potential directions for future research that could help address the data sparsity that underlies the quality limitations of these models.

Utilizing dictionaries to ground distributionally similar words: One approach to address errors with distributionally similar words could involve helping ground the model's translations by utilizing bilingual dictionaries or similar resources. Dictionaries are relatively widely available and have already yielded promising results for individual language pairs (Xia et al., 2019; Duan et al., 2020; Karamanolakis et al., 2020; Reid et al., 2021). For languages where dictionaries do not exist or coverage is low, dictionaries are much cheaper to build as compared to a dataset of parallel sentences. Efforts to develop high-coverage dictionaries and modeling approaches to incorporate them in massively multilingual MT models could nicely complement a corpus of monolingual web text and massively multilingual MT.

Complementing massively multilingual modeling with language-specific efforts: The quality of web-mined datasets is unlikely to match that of language-specific, hand-curated datasets; and building hand-curated datasets might be the only way forward to build text datasets for languages with limited presence on the web. However, we believe the two approaches to be orthogonal and complementary. Leveraging highly multilingual web-mined datasets and models significantly reduces the amount of data and research efforts needed to build practical NLP technologies for these languages (Wang et al., 2020; Emezue & Dossou, 2021; Adelani et al., 2022; Alabi et al., 2022; Nekoto et al., 2022), and research efforts could be more efficient by building resources and modeling approaches that complement the weaknesses of web-based massively multilingual models. Furthermore, community-based contributions could yield other useful language-specific tools, like specialized data filters as in Section 4.8, tools to normalize orthography or script (like those described in Appendix C) or pre- and post-processors to correct certain mistakes, improve diacritization, etc.

⁶https://africanlp.masakhane.io/

http://www.arabic-nlp.net/

⁸https://ghananlp.org/project/translator-webapp/

⁹https://lesan.ai/translate

¹⁰https://huggingface.co/datasets?multilinguality=multilinguality:
translation&task_categories=task_categories:translation&sort=downloads

¹¹https://zenodo.org/communities/africanlp/

Leveraging multimodal datasets and models: A large proportion of the 7000+ languages spoken in the world have no written forms or standardized orthographic conventions. For a large majority there is limited amounts of text data available on the web. Being able to train models that can learn from and represent speech and text jointly (Zheng et al., 2021; Bapna et al., 2022; Chen et al., 2022; Bai et al., 2022; Tang et al., 2022) is essential to alleviate data sparsity and building more robust language technologies for such languages.

In future work we plan to investigate the above-mentioned and related threads of research, hopefully making progress towards building and supporting language and speech technologies for more languages.

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A COMPLETE HUMAN EVALUATION AND CHRF RESULTS FOR DISTILLED MODELS

Table 20 gives the performance of the distilled models, as measured both by humans on a seven point scale (nonsense to perfect), and in CHRF. Please keep in mind that human evaluation numbers are quite hard to compare across languages.

B COMPLETE AUDIT RESULTS

We rated samples of 100 sentences for 72 of the languages present in the dataset we crawled. The error metrics used are described in Table 21. The breakdown can be seen in Table 22.

Language Name (BCP-47)	score	сс	cb	ca	wl	nl	wd
Northeastern Dinka (dip)	100	100	0	0	0	0	0
Zarma (dje)	100	100	0	0	0	0	0
Dombe (dov)	100	100	0	0	0	0	0
Dyula (dyu)	100	100	0	0	0	0	0
Wayuu (guc)	100	100	0	0	0	0	0
Kalenjin (kln)	100	100	0	0	0	0	0
Wolaytta (wal)	100	100	0	0	0	0	0
Assyrian Neo-Aramaic (aii)	100	100	0	0	0	0	0
Igbo (ig)	99	98	2	0	0	0	0
Balinese (ban)	98	96	4	0	0	0	0
Latinized Hindi (hi-Latn)	98	98	0	0	2	0	0
Twi (ak)	97	94	6	0	0	0	0
Luyia (luy)	97	97	0	0	0	0	3
Ewe (ee)	96	91	9	0	0	0	0
Seselwa Creole French (crs)	94	92	4	1	3	0	0
Bhojpuri (bho)	94	94	0	0	6	0	0
Ilocano (ilo)	94	88	12	0	0	0	0
Caribbean Javanese (jvn)	94	87	13	0	0	0	0
Meiteilon (Manipuri) (mni)	93	87	12	0	0	1	0
Luba-Katanga (lu)	92	83	17	0	0	0	0
Krio (kri)	92	89	5	0	6	0	0
Latinized Tamil (ta-Latn)	91	81	19	0	0	0	0
Lingala (ln)	90	80	19	0	1	0	0
Maharasthra Konkani (knn)	89	85	8	1	6	0	0
Northern Sami (se)	89	86	5	0	9	0	0
Cherokee (chr)	88	78	20	0	1	1	0
Latinized Malayalam (ml-Latn)	87	76	21	1	2	0	0
Latinized Bengali (bn-Latn)	86	72	28	0	0	0	0
Maithili (mai)	86	83	5	1	11	0	0
Hiligaynon (hil)	84	80	8	0	9	3	0
Tok Pisin (tpi)	84	83	2	0	15	0	0
Latinized Chinese (zh-Latn)	84	80	7	0	13	0	0
Gulf Arabic (afb)	83	74	17	1	8	0	0
Minangkabau (min)	81	64	34	0	2	0	0
Chuvash (cv)	80	78	4	0	2	2	14
Tamazight (ber-Latn)	79	69	20	0	10	1	0
Latinized Telugu (te-Latn)	79	74	10	0	0	16	0
Libyan Arabic (ayl)	78	68	14	10	7	1	0
Newari (new)	78	76	3	0	21	0	0
Pangasinan (pag)	75	67	17	0	0	17	0
Waray (war)	75	67	17	0	17	0	0
Goan Konkani (gom)	73	67	5	13	13	2	0
Sanskrit (sa)	73	66	14	0	15	5	0
North Levantine Arabic (apc)	73	62	21	0	16	1	0
Sudanese Arabic (apd-SD)	72	60	4	34	2	0	0
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Ibibio (ibb)	72	63	17	0	20	0	0
Shona (sn)	72	43	57	0	0	0	0
Sena (seh)	71	71	0	0	29	0	0
Latinized Marathi (mr-Latn)	67	36	62	0	1	1	0
Ancient Greek (grc)	67	67	0	0	29	4	0
Makhuwa-Meetto (mgh)	67	67	0	0	33	0	0
Algerian Arabic (arq)	64	47	6	47	0	0	0
Latinized Goan Konkani (gom-Latn)	64	63	0	2	28	7	0
Ga (gaa)	58	58	0	0	0	0	41
Wolof (wo)	57	16	81	0	1	2	0
Nigerian Pidgin (pcm)	51	43	14	3	40	0	0
Saint Lucian Creole French (acf)	50	50	0	0	50	0	0
Kashmiri (ks-Deva)	48	47	1	2	17	33	0
Latinized Arabic (ar-Latn)	47	33	15	21	6	24	0
Kuanyama (kj)	43	43	0	0	57	0	0
Adangme (ada)	42	42	0	0	0	0	58
Anaang (anw)	36	26	19	0	54	1	0
Mesopotamian Arabic (acm)	34	6	0	93	1	0	0
North Ndebele (nd)	25	25	0	0	50	25	0
Moroccan Arabic (ar-MA)	16	1	24	9	59	7	0
Baluchi (bal)	10	10	0	0	90	0	0
Saidi Arabic (aec)	0	0	0	0	100	0	0
Eastern Baluchi (bgp)	0	0	0	0	100	0	0
Eastern Baluchi (bgp-Arab)	0	0	0	0	100	0	0
mean	74 -	68	10	-3	15	$\bar{2}$	$-\bar{2}$
median	80	74	5	0	3	0	0

Table 22: Results of an audit of the datasets we collected, conducted on sampled of 100 sentences each by a mix of native speakers and non-native speakers. The values are the percent of the audited sample that head each label. The "score" metric combines these numbers for an approximate notion of the percent of the data that is usable, and is described in Section 2.2.2.

B.1 STRICT RTT LANGID CHRF

In the main section of this paper (4.3), we reported the *loose* version of RTTLANGIDCHRF, which seems to correlate better with CHRF and data size. One issue with this score is that it doesn't penalize the model for producing content in the wrong language, whereas the *strict* version does.

Figure 3 shows strict RTTLANGIDCHRF as a function of log data size. Although the correlation is worse than with the loose version, there is a clear trend, and there appears to be some sort of upper bound in quality as a function of data size.

C TRANSLITERATION FOR MEITEILON

The large majority of the text we found online for Meiteilon (Manipuri) was in the Bengali script. Finding almost no Meiteilon in its native script, Meetei Mayek (mni-Mtei), we initially erroneously assumed that this script was archaic or only used in rare contexts. However, conversations with Meiteilon speakers quickly disillusioned us of this notion – not only is it used, but it is now on its way to being the primary script used in the state. Most likely, the reason our mni-Mtei corpus was so small was because the available text online was largely in non-Unicode fonts, and therefore inaccessible to our LangID model (which had not been trained to detect such non-Unicode data). Therefore, we needed to convert our Bengali-script corpus to Meetei Mayek. However, this is not a straightforward task for such a non-injective script as Bengali.

Meiteilon is a tonal Tibeto-Burman language that is one of the scheduled languages of India and a lingua franca of the Manipur state (Chelliah, 1997; Singh, 2011). The Meetei Mayek script is an indigenous script that was used to record Meiteilon until the 18th century when it was mostly superseded by the Bengali script. Despite recent Meetei Mayek gradual revitalization efforts by the Indian government, Meetei Mayek literacy is still quite low (Singh et al., 2007) and the available online



Figure 3: Plot of RTTLANGIDCHRF scores (strict) for languages as a function of log monolingual data size. This score has worse correlation with metrics like CHRF than the loose veriosn of RTTLANGIDCHRF, but shows an interesting trend when plotted versus data size like this. Compared to the loose version, languages much below the trend line on the right-hand side are often close to high-resource languages (E.g. Betawi/bew, Sabah Malay/msi, Godwari/gdx, Darija/ar-MA), indicating that their apparently large monolingual datasets are actually a result of over-triggering with a higher-resource language like Indonesian, and there are many wrong-language intermediate translations.

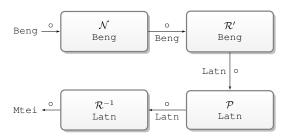


Figure 4: Bengali (Beng) to Meetei Mayek (Mtei) transliteration components. The script codes are denoted according to ISO 15924 (ISO, 2004).

Meiteilon data is mostly in Bengali script (Achom & Basu, 2015; Moirangthem & Nongmeikapam, 2021).

Meetei Mayek belongs to the Tibetan family of Brahmic scripts and is well suited for Meiteilon phonology representing a near bijective mapping between graphemes and phonemes of a language (Singh et al., 2007). Unlike the major Brahmic scripts, this script uses a special class of explicit silent final consonants (*lonsum iyek*) in closed syllable codas, but these consonants are represented as full letters rather than combining signs. In modern Meetei Mayek orthography, the falling tone is often unmarked or sometimes marked with full stop punctuation, whereas in the traditional literature a special *lum iyek* sign was used (Everson, 2007).

Unlike Meetei Mayek, the orthographic conventions for Meiteilon in Bengali script are ambiguous due to its larger letter inventory, where more than one Bengali letter or clusters of letters may map to a single Meiteilon sound (Singh et al., 2007; Khanganba & Jha, 2014). This implies that any Bengali to Meeitei Mayek transliteration mechanism needs to implement a many-to-one relation.

Our transliterator uses the open-source Nisaba library of finite-state script normalization and processing utilities (Johny et al., 2021). The script operations in Nisaba are efficiently and succinctly represented as weighted finite-state transducers (WFSTs) using Pynini finite-state grammars (Gorman, 2016; Gorman & Sproat, 2021). The main components of transliteration workflow are shown in Figure 4. The four component WFSTs are compiled into the final transliteration WFST $\mathcal{T} = \mathcal{N} \circ \mathcal{R}' \circ \mathcal{P} \circ \mathcal{R}^{-1}$, where "o" denotes FST composition operation (Mohri, 2009). The first component transducer \mathcal{N} implements visual normalization of the Bengali script input that consists of visually invariant normalization transformations including NFC (Johny et al., 2021). This is followed by the Meiteilon-specific Bengali to Latin script many-to-one mapping \mathcal{R}' that produces Latin script output in ISO 15919 format (ISO, 2001) augmented with some placeholder markers required for the next processing stage. ¹³

The third stage implements post-processing transformations \mathcal{P} that are required to resolve ambiguities represented by the placeholder markers (introduced by \mathcal{R}') based on the orthographic context. One example of such transformation is the resolution of the Bengali virama sign, whose original purpose in the Bengali script is to mark silent consonants pronounced without an inherent vowel in consonant clusters. Its Meetei Mayek counterpart, the apun iyek mark, functions differently — it only applies to a non-silent subset of consonants (i.e., all consonants excluding the set of lonsum iyek mentioned above). Hence, given the virama placeholder in the input, two finite-state context-dependent rewrites are required for the resolution: convert the preceding consonant to lonsum iyek representation and remove the placeholder if the preceding consonant sound is covered by the lonsum iyek set, otherwise simply convert the virama placeholder to apun iyek for all other cases.

The final transducer \mathcal{R}^{-1} implements reverse romanization transliterating unambiguous Latin script input in ISO 15919 format into corresponding representation in Meetei Mayek.

D TABLES OF NON-UNICODE FONTS

Table 23 shows the mappings of ASCII characters to Unicode points for a few fonts we ran into. We discovered these mappings by copy-pasting text from an environment where it rendered (e.g. a PDF) to one where the font wasn't installed (e.g. a text editor), and finding the Unicode character that looked like the way it rendered.

¹²https://github.com/google-research/nisaba

 $^{^{13}}$ This Nisaba operation is denoted \mathcal{R}' to distinguish it from the more general *reversible* romanization \mathcal{R} provided by Nisaba for Bengali and Assamese.

LP	avg	0	1	2	3	4	5	6	entropy	CHRF
en→ti	5.4	0	0	1	4	11	18		0.45	22.0
en→ay		0	0	2	5	17	36	40		33.3
en→bm	5.0	-	1	1	3	22	40	34		36.6
en→ts	4.9		0	2	6	24	32	37	0.57	46.5
en→lus	4.9	3	0	5	0	33	13	47	0.55	41.1
en→ilo	4.7	0	0	3	2	25	64	7	0.44	54.8
en→ff	4.6	1	1	4	7	24	45	18	0.61	37.2
en→ln	4.6	0	0	3	10	28	41	18	0.01	34.9
en→doi	4.5	0	0	2	3	38	50	6	0.49	40.9
en→kri	4.4	0	2	9	14	26	23	27	0.71	36.6
en→om	4.4	-	0	3	10	42	37	8	0.56	40.3
en→dv	1.1	2	2	8	12	33	29	14	0.71	45.6
en→sa	4.1	4	1	3	7	52	30	4	0.57	33.3
en→as	4.0	0	0	4	12	60	23	0	0.47	40.8
en→gom	4.0	4	1	14	11	38	12	21	0.71	41.5
en→lg	3.9		8	11	18	22	25	16	0.76	39.7
en→ak	3.8	0	0	19	0	69	0	12	0.39	34.6
en→ckb	3.6	1	2	14	32	30	13	9	0.70	44.3
en→nso	3.4	7	13	13	16	19	19	14	0.83	47.6
en→kl	3.2	13	3	19	13	29	10	13	0.79	40.7
en→mni-Mtei	3.2	0	0	24	32	43	1	0	0.51	47.7
en→gn	3.1	0	8	30	18	35	8	2	0.66	32.2
en→qu	2.1	4	4	20	30	36	6	0	0.65	37.2
en→ee	3.0	7	14	18	21	19	12	9	0.82	39.9
en→mai	3.0	8	1	30	20	30	8	4	0.71	40.2
en→pcm	2.7	20	9	22	4	27	10	9	0.78	57.5
en→bho	2.3	0	6	70	14	8	1	0	0.44	42.4
en→yua	2.1	0	30	42	17	8	2	1	0.59	32.8
- ti →en	1 4.U	-0	$-\bar{0}$	3-	- 9 -	31	⁻ 3 7 ⁻	21	0.62	-45.8
ay→en	10	2	1	5	6	12	48	27	0.61	38.8
ln→en	4.8	_	1	1	6	25	46	22	0.50	32.3
lg→en	5.6	0	1	2	3	4	8	82	0.34	41.1
mni-Mtei→en	3.5	0	1	20	14	65	1	0	0.44	62.9
bm→en	5.1	0	0	0	4	12	52	32	0.50	38.7
ts→en	4.0	1	1	8	14	27	33	17	0.00	47.5
lus→en	4.6	4	4	5	4	13	40	31	0.66	41.7
ilo→en	4.6	U	0	3	3	30	59	6	0.47	62.4
ff→en	4.6	7	1	10	4	13	11	54	0.63	45.8
doi→en	4.6	1	0	1	4	41	33	20	0.56	65.8
kri→en	5.0	0	1	6	8	13	18	53	0.59	64.8
om→en	4.6	0	0	1	7	37	50	7	0.50	41.9
dv→en	3.4	0	2	19	33	33	14	0	0.61	48.7
sa→en	4.4	^	1	1	4	55	33	6	0.48	48.9
as→en	5.2	0	2	8	2	10	15	64	0.51	60.4
gom→en	5.5		0	2	1	5	30	62	0.43	
ak→en	4.8	0	1	4	9	19	31	37	0.64	39.4
ckb→en	2.9		12	27	14	36	7	0	0.00	56.4
nso→en	3.4	2	12	14	18	34	9	12		
kl→en	4.6		3	11	5	25	9	46	0.65	39.6
gn→en	3.5	0	0	12	31	49	7	1	0.54	43.6
qu→en	2.9	0	4	28	47	18	5	0	0.57	
ee→en	4.5	_	3	8	12	13	22	39		
mai→en	3.2		2	38	15	25	19	0	0.62	
pcm→en	46	1	0	3	7	31	39	20	0.61	65.4
bho→en	2.4	0	0	15	44	31	10	0	0.56	
yua→en	3.4		1	20	36	29	13	2		

Table 20: Performance of the distilled student model in CHRF and human evaluation, on a scale from 0 (nonsense/wrong language) to 6 (perfect). The value in the "avg" column reports the weighted average score across all sentences. The value under each of the numbers from 0 to 6 is the percent of sentences that were given that rating. The entropy is included to flag suspicious rating patterns: a low entropy may mean that most raters are assigning the same score to all sentences.

Code	Weight	Description
CC	100	Natural in-language sentence. It's ok if it has a few small issues, like spelling
		errors or a few words from another language, or if it's a sentence fragment of
		reasonable length (about 5 words or more)
CB -	50	In-language, but low-quality. This could be ungrammatical text, boilerplate, or
		very short fragments.
CĀ	30	Correct but ambiguous whether it's in the correct language. This code is only
		applicable for dialects that are closely related to a major language. For instance,
		many short sentences in Gulf Arabic may also be valid in MSA, and many written
	l	Cantonese sentences might also be valid in Mandarin.
WD	20	8
		be in. This code is only applicable for dialects that are closely related to a similar
		dialect. For instance, it's supposed to be in Sa'idi Arabic but it's in Egyptian
		Arabic.
\overline{WL}	0	Wrong Language, but still linguistic content
NL -	0	Not a language – any sort of non-linguistic content. Proper nouns like "Ibuprofin",
	l	"Calvin Klein", or "Washington DC" also count as NL.

Table 21: Instructions descriptions of the error codes we used to rate samples of our datasets, along with the weight each one is given in the combined quality score.

Tamazight (ber-Latn)			Ewe (ee)	Mo	oré (mos)
ASCII	codepoint(s)	ASCII	codepoint(s)	ASCII	codepoint(s)
â	U+025B	0	U+025B U+0303	à	U+0269
ç	U+010D	1	U+025B	â	U+00E3
é	U+1E93	2	U+0256	è	U+025B
ê	U+1E25	3	U+028B	ê	U+1EBD
î	U+1E6D	4	U+0254	î	U+0129
O	U+01E7	5	U+0192	Î	U+0128
ô	U+1E5B	6	U+0263	ô	U+00F5
û	U+1E63	7	U+00E3	ù	U+028B
V	U+1E0D	8	U+1EBD	û	U+0169
Ä	U+0190	-	U+0254 U+0303	À	U+0196
Ç É	U+010C	[U+0169	Â	U+00C3
	U+1E92]	U+0292	È	U+0190
Ë	U+1E24	@	U+0189	Ê	U+1EBC
Ϊ	U+1E6C	&	U+00C3	Ô	U+00D5
O	U+01E6	%	U+0191	Ù	U+01B2
Ö	U+1E5A	•	U+014B	Û	U+0168
Ü	U+1E62	^	U+0194		
V	U+1E0C	=	U+0129		
\$	U+0263	~	U+014A		
£	U+0194	\$	U+0186		

Table 23: Three (possibly incomplete) fonts we reconstructed for three African languages that use an extended Latin character set. Table shows the mapping from the ASCII character to the "correct" Unicode codepoint.

E LIST OF LANGUAGES WITH REGIONS, APPROXIMATE SPEAKER COUNTS AND DATA SIZES

Information about the languages and datasets we found on the web, including the name, number of speakers, continent, script (writing system), cluster (see Section 2.1.3), langID F1 score for the SSLID model, and RTTLANGIDCHRF (loose) score. The RTTLANGIDCHRF score provides an approximate measure of quality of the model, but it should not be trusted as a reliable measure of translation quality (Section 4.3). Number of speakers refers to the estimated number of L1 speakers, following the estimates from van Esch et al. (2022).

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
en	7388M	English	550M	Europe	Latn	en	98.2	NA
es	1751M	Spanish	490M	Europe	Latn	es	98.8	77.8
de	1693M	German	83M	Europe	Latn	de	98.4	78.2
id	950M	Indonesian	200M	Asia	Latn	id	97.3	76.9
hu	724M	Hungarian	13M	Europe	Latn	hu	98.8	68.1
pl	687M	Polish	38M	Europe	Latn	pl	98.0	72.8
zh	676M	Chinese	1000M	Asia	Hans	zh	99.1	64.0
ko	672M	Korean	52M	Asia	Kore	ko	99.9	64.0
ja	652M	Japanese	130M	Asia	Jpan	ja	99.6	65.2
ru	570M	Russian	150M	Europe	Ćyrl	ru	97.3	74.0
tr	565M	Turkish	82M	Europe	Latn	tr	99.0	70.9
th	531M	Thai	20M	Asia	Thai	th	98.9	67.9
it	491M	Italian	61M	Europe	Latn	it	98.9	77.3
pt	485M	Portuguese	220M	Europe	Latn	pt	98.0	80.0
vi	477M	Vietnamese	96M	Asia	Latn	vi	99.7	73.8
fr	450M	French	75M	Europe	Latn	fr	97.6	77.7
ms	394M	Malay	80M	Asia	Latn	ms	92.3	77.5
nl	320M	Dutch	21M	Europe	Latn	nl	99.2	79.8
uk	320M	Ukrainian	32M	Europe	Cyrl	uk	99.2	72.1
SV	311M	Swedish	8M	Europe	Latn	SV	98.7	79.0
	301M	Romanian	19M	•	Latn		96.8	75.1
ro	300M	Czech	19M 10M	Europe		ro	98.9	73.1
CS £-				Europe	Latn	CS C-	95.9	70.3
fa	275M	Persian Standard Latvian	40M 2M	Asia	Arab	fa	93.0 98.5	70.5 75.5
lv	260M			Europe	Latn	lv		
ar	258M	Arabic	180M	Africa	Arab	ar	97.9	71.8
no	231M	Norwegian	5M	Europe	Latn	no	87.1	79.9
ta	220M	Tamil	76M	Asia	Taml	ta	100	67.9
el	173M	Modern Greek	13M	Europe	Grek	el	99.4	75.8
fi	171M	Finnish	5M	Europe	Latn	fi	97.0	72.3
hi	165M	Hindi	320M	Asia	Deva	hi	97.9	75.5
mr	156M	Marathi	83M	Asia	Deva	mr	99.5	69.8
sk	156M	Slovak	4M	Europe	Latn	sk	99.5	72.6
hy	154M	Eastern Armenian	6M	Europe	Armn	hy	100	70.5
kk	153M	Kazakh	11M	Europe	Cyrl	kk	99.6	60.6
da	152M	Danish	5M	Europe	Latn	da	97.0	79.3
mk	150M	Macedonian	1M	Europe	Cyrl	mk	98.8	77.6
bg	149M	Bulgarian	7M	Europe	Cyrl	bg	98.3	74.4
sr	141M	Serbian Standard	6M	Europe	Cyrl	sr	98.4	-
ml	139M	Malayalam	35M	Asia	Mlym	ml	100	62.5
az	135M	Azerbaijani	18M	Asia	Latn	az	98.3	70.9
is	134M	Icelandic	300K	Europe	Latn	is	97.5	78.6
te	127M	Telugu	82M	Asia	Telu	te	100	72.8
ne	116M	Nepali	16M	Asia	Deva	ne	99.3	65.6
et	112M	Estonian	1 M	Europe	Latn	et		73.5
he	108M	Modern Hebrew	4M	Europe	Hebr	he	100	-
mn	100M	Mongolian	5M	Asia	Cyrl	mn	97.3	61.5
ur	99M	Urdu	120M	Asia	Arab	ur	98.4	75.5
hr	97M	Croatian Standard	4M	Europe	Latn	hr	79.4	75.3
fil	95M	Filipino	22M	Asia	Latn	fil	97.3	80.6
lt	86M	Lithuanian	2M	Europe	Latn	lt	99.9	72.8
	84M	Brunei-Sabah	3M	Asia			99.9	69.6
msi	041/1	Malay	JIVI	Asia	Latn	ace-121	74.3	07.0
be	83M	Belarusian	3M	Europe	Cyrl	be	99.2	73.9

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
kn	80M	Kannada	43M	Asia	Knda	kn	100	71.5
my	78M	Burmese	33M	Asia	Mymr	my	99.7	53.3
bn	73M	Bengali	260M	Asia	Beng	bn	98.0	70.4
af	71M	Afrikaans	17M	Africa	Latn	af	97.7	82.1
eu	70M	Basque	500K	Europe	Latn	eu	99.9	72.9
gu	69M	Gujarati	56M	Asia	Gujr	gu	98.0	75.2
mi	67M	Maori	200K	Oceania	Latn	mi-4l	99.6	67.2
gdx	67M	Godwari	3M	Asia	Deva	bfz-151	70.5	74.2
gl	64M	Galician	2M	Europe	Latn	gl	94.2	76.9
sl	59M	Slovenian	2M	Europe	Latn	sl	97.9	72.7
lo	59M	Lao	20M	Asia	Laoo	kjg-21	100	72.0
gd	57M	Scottish Gaelic	50K	Europe	Latn	alq-41	99.4	74.5
so	56M	Somali	24M	Africa	Latn	aa-131	99.7	67.4
si	56M	Sinhala	16M	Asia	Sinh	si	100	61.3
uz	53M	Uzbek	57M	Europe	Latn	uz	99.8	62.2
sw	52M	Swahili	24M	Africa	Latn	SW	99.3	78.1
km	51M	Central Khmer	16M	Asia	Khmr	km	99.9	69.4
ha	51M	Hausa	70M	Africa	Latn	amo-71	99.4	70.5
wry	50M	Merwari	8M	Asia	Deva	bfz-151	68.2	-
ky	49M	Kirghiz	8M	Europe	Cyrl	ky	99.8	56.7
am	47M	Amharic	22M	Africa	Ethi	am	95.1	58.0
ca	44M	Catalan	4M	Europe	Latn	ca	99.5	75.0
ceb	44M	Cebuano	16M	Asia	Latn		99.1	73.9
		Yoruba			Latn	abx-111		73.7
yo	43M	TOTUDA	21M	Africa	Lam	bcq-Latn- 121	99.6	13.1
sd	42M	Sindhi	68M	Asia	Arab	bgq-Arab-4l	99.0	67.3
gju-Deva-	41M	Gujari	1M	Asia	Deva	bfz-151	68.6	-
IN	11171	Gujuri	11/1	risia	Deva	01Z-131	00.0	
co	41M	Corsican	50K	Europe	Latn	cjk-141	97.5	75.2
	40M	Malagasy	18M	Africa	Latn		99.9	65.4
mg	37M		28M	Anica	Guru	apy-71	99.9	71.9
pa ar-MA		Eastern Punjabi Arabic	180M	Africa	Arab	pa	46.1	69.0
_	36M 33M		5M	Anica		acm-91	93.8	67.2
bew		Betawi			Latn	abs-131		
ny	33M	Chichewa	12M	Africa	Latn	cjk-141	98.8	66.1
sq	32M	Albanian	5M	Europe	Latn	sq	99.3	79.0
ka	30M	Georgian	4M	Europe	Geor	ka	99.9	71.9
haw	30M	Hawaiian	50K	Americas	Latn	gah-111	99.7	58.3
hmn	28M	Hmong	3M	Europe	Latn	hmn-31	99.7	71.5
yi	28M	Yiddish	2M	Europe	Hebr	gv-31	100	84.8
ig	27M	Igbo	18M	Africa	Latn	dzg-51	99.0	68.6
ckb	25M	Central Kurdish	7M	Europe	Arab	ckb-21	99.3	60.0
tt	25M	Tatar	4M	Europe	Cyrl	tt	97.0	52.5
gsw	25M	Central Alemannic	5M	Europe	Latn	ang-71	93.2	73.3
arq	24M	Algerian Arabic	27M	Africa	Arab	acm-91	79.0	66.0
sm	24M	Samoan	500K	Oceania	Latn	mi-41	99.9	67.6
eo	24M	Esperanto	2M	Europe	Latn	eo	99.7	78.4
zu	23M	Zulu	11M	Africa	Latn	gup-81	96.3	71.3
st	23M	Southern Sotho	14M	Africa	Latn	cce-81	98.8	69.2
ru-Latn	23M	Russian	150M	Europe	Latn	bg-Latn-51	97.2	51.4
cy	22M	Welsh	700K	Europe	Latn	cy	99.7	79.4
la	22M	Latin	0K	Europe	Latn	la	93.2	67.9
or	21M	Odia	35M	Asia	Orya	or	100	63.2
mt	21M	Maltese	500K	Europe	Latn	mt	99.5	84.2
rkt	20M	Rangpuri	15M	Asia	Beng	bpy-71	98.8	59.2
ht	20M	Haitian	10M	Americas	Latn	ht	99.9	79.3
sn	18M	Shona	9M	Africa	Latn	cjk-141	99.6	68.6
bo	18M	Tibetan	1M	Asia	Tibt	bo-21	99.9	28.5
ps	18M	Nuclear Pashto	13M	Asia	Arab	ps	98.9	59.7
ga	17M	Irish	200K	Europe	Latn	ga	98.8	80.9
shu	16M	Chadian Arabic	1M	Africa	Arab	acm-91	89.5	-
xh	16M	Xhosa	19M	Africa	Latn	gup-81	97.8	69.0
lb	15M	Moselle Franco-	400K	Europe	Latn	lb	96.7	63.7
		nian		20.0pc			, 5.,	00.7
ku	15M	Kurdish	32M	Europe	Latn	ku	98.2	57.7
	1.0111		J =111	Lurope			70.2	27.7

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
tg	14M	Tajik	8M	Europe	Cyrl	tg	99.9	64.9
hi-Latn	14M	Hindi	320M	Asia	Latn	bgp-131	98.1	71.7
jv	13M	Javanese	85M	Asia	Latn	jv	99.4	77.0
apd-SD	13M	Sudanese Arabic	17M	Africa	Arab	acm-91	74.2	69.1
su	12M	Sundanese	39M	Asia	Latn	su	99.1	71.1
mzn	12M	Mazanderani	6M	Asia	Arab	apr-81	52.4	64.8
meo	11M	Kedah Malay	3M	Asia	Latn	ace-121	94.4	66.7
fy	11M	Western Frisian	800K	Europe	Latn	fy	99.7	71.7
mrw	10M	Maranao	800K	Asia	Latn	agn-14l	98.0	69.2
rw	10M	Kinyarwanda	11 M	Africa	Latn	rw	98.6	47.7
apc	10M	North Levantine Arabic	15M	Europe	Arab	abv-101	40.4	67.7
as	9M	Assamese	13M	Asia	Beng	as	99.7	63.7
aec	9M	Saidi Arabic	19M	Africa	Arab	abv-101	78.0	64.3
fo	9M	Faroese	50K	Europe	Latn	bn-Latn-61	98.0	71.6
pap	9M	Papiamento	600K	Americas	Latn	ach-101	94.8	61.4
sah	9M	Sakha	500K	Europe	Cyrl	az-RU-131	97.7	43.4
acm	9M	Gilit	26M	Europe	Arab	acm-91	35.2	64.2
uem	7111	Mesopotamian	20111	Europe	71140	uciii yi	33.2	01.2
1	01/1	Arabic	7001/	A -:-	T4		100	25.0
lus	8M	Mizo	700K	Asia	Latn	bgr-6l	100	35.9
grc	8M	Ancient Greek (to 1453)	0K	Europe	Grek	grc	99.9	-
dv	8M	Dhivehi	300K	Asia	Thaa	bpy-71	100	53.6
oc	7M	Occitan	500K	Europe	Latn	acf-101	96.7	73.4
luz	7M	Southern Luri	900K	Asia	Arab	fay-141	68.4	64.2
sa	6M	Sanskrit	100K	Asia	Deva	bho-131	97.8	57.6
bgp-Arab	6M	Eastern Balochi	2M	Asia	Arab	bal-131	55.1	-
ug	6M	Uyghur	10M	Asia	Arab	ckb-21	100	50.5
ba	6M	Bashkir	1M	Europe	Cyrl	az-RU-131	98.0	58.2
om	6M	Oromo	24M	Africa	Latn	amf-61	99.7	56.0
zza	5M	Zaza	2M	Europe	Latn	aeb-Latn- 111	71.7	-
zh-Latn	5M	Chinese	1000M	Asia	Latn	cqd-81	99.2	22.2
vas-Gujr	4M	Vasavi	1 M	Asia	Gujr	bhb-Gujr-31	78.7	68.5
vec	4M	Venetian	4M	Europe	Latn	bi-6l	94.5	73.5
tk	4M	Turkmen	8M	Europe	Latn	tk	99.9	57.5
hil	4M	Hiligaynon	6M	Asia	Latn	abx-111	99.3	70.8
ti	4M	Tigrinya	9M	Africa	Ethi	gez-81	99.9	57.0
syl	4M	Sylheti	23M	Asia	Beng	bpy-71	86.9	65.8
phr	4M	Pahari Potwari	2M	Asia	Arab	bal-131	54.5	73.6
ayl	4M	Libyan Arabic	5M	Africa	Arab	acm-91	86.3	65.0
el-Latn	3M	Modern Greek	13M	Europe	Latn	bg-Latn-51	98.9	26.0
kaa	3M	Kara-Kalpak	600K	Europe	Cyrl	az-RU-131	99.3	61.8
bs	3M	Bosnian Standard	9M	Europe	Cyrl	bs	70.8	74.1
bgp	3M	Eastern Balochi	2M	Asia	Latn	bgp-131	91.1	70.0
br	3M	Breton	200K	Europe	Latn	br-41	82.8	42.8
gdq	3M	Mehri	100K	Europe	Arab	acm-91	51.7	_
tet	3M	Tetum	500K	Asia	Latn	ceg-51	98.4	53.5
to	3M	Tonga (Tonga Islands)	200K	Oceania	Latn	mi-41	100	57.5
cv	3M	Chuvash	1M	Europe	Cyrl	az-RU-131	92.9	48.6
kfr	3M	Kachchi	900K	Asia	Gujr	bhb-Gujr-31	82.5	63.4
ilo	3M	Ilocano	9M	Asia	Latn	agn-14l	93.4	47.6
bg-Latn	3M	Bulgarian	7M	Europe	Latn	bg-Latn-51	97.2	65.0
bal	3M	Balochi	8M	Asia	Arab	bal-131	23.0	61.8
hif	2M	Fiji Hindi	500K	Oceania	Latn	bgp-131	99.6	69.4
mey	2M	Hassaniyya	3M	Africa	Arab	acm-91	69.5	-
dz	2M	Dzongkha	200K	Asia	Tibt	bo-21	98.2	39.5
tn	2M	Tswana	8M	Africa	Latn	cce-81	90.5	66.5
bn-Latn	2M	Bengali	260M	Asia	Latn	bn-Latn-61	98.5	57.5
lg	2M	Ganda	4M	Africa	Latn	cgg-151	98.7	58.2
te-Latn	2M	Telugu	82M	Asia	Latn	bgp-131	98.6	59.3
mde	2M	Maba (Chad)	300K	Africa	Arab	acm-91	48.5	-
	•							

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
nso	2M	Pedi	14M	Africa	Latn	cce-81	98.6	68.0
rm	2M	Romansh	50K	Europe	Latn	rm	99.9	61.7
za	2M	Northern Daic	15M	Asia	Latn	cqd-81	98.7	27.3
tpi	2M	Tok Pisin	4M	Oceania	Latn	bi-6l	99.3	61.3
pcm	2M	Nigerian Pidgin	30M	Africa	Latn	pcm	97.9	71.1
mtq	2M	Muong	1M	Asia	Latn	blt-Latn-41	96.3	-
cnh	2M	Haka Chin	100K	Asia	Latn	bgr-6l	99.9	37.2
iba	2M	Iban	2M	Asia	Latn	amo-71	99.8	54.8
ja-Latn	2M	Japanese	130M	Asia	Latn	dgz-51	98.6	20.9
ium	2M	Iu Mien	800K	Asia	Latn	cqd-81	98.9	18.9
crs	2M	Seselwa Creole	50K	Africa	Latn	acf-101	99.8	72.9
		French						
se	1.5M	North Saami	50K	Europe	Latn	bn-Latn-61	90.2	-
kha	1.4M	Khasi	800K	Asia	Latn	ace-121	99.9	38.3
ln	1.4M	Kinshasa Lingala	15M	Africa	Latn	jbu-81	96.4	56.1
tyv	1.4M	Tuvinian	300K	Europe	Cyrl	sty-21	99.4	47.4
ce	1.4M	Chechen	1M	Europe	Cyrl	ce-31	99.9	41.6
mai	1.3M	Maithili	17M	Asia	Deva	awa-141	98.6	60.8
nr	1.3M	South Transvaal	1M	Africa	Latn	gup-81	86.3	_
		Ndebele				8-1		
dty	1.3M	Dotyali	800K	Asia	Deva	bho-131	77.6	57.8
ts	1.3M	Tsonga	13M	Africa	Latn	cjk-14l	72.9	55.0
fj	1.3M	Fijian	300K	Oceania	Latn	fj-41	98.8	37.5
ak	1.3M	Akan	13M	Africa	Latn	abr-51	93.8	49.5
kaa-Latn	1.3M	Kara-Kalpak	600K	Europe	Latn	bcq-Latn-	86.7	55.9
nuu Zuu	1.01.1	Time Timpun	00011	Zurope	Zau	121	0017	00.5
os	1.3M	Iron Ossetian	600K	Europe	Cyrl	gaw-81	93.5	55.2
bik	1.2M	Bikol	2M	Asia	Latn	abx-111	94.4	68.7
ber-Latn	1.2M	Berber	2M	Africa	Latn	alq-41	99.7	32.9
ctd-Latn	1.2M	Tedim Chin	300K	Asia	Latn	bgs-91	99.5	23.5
tly-IR	1.2M	North-Central	900K	Europe	Arab	fay-141	88.7	63.1
-		Talysh		•		-		
plk	1.1M	Kohistani Shina	200K	Asia	Arab	bal-131	65.1	-
tks	1.1M	Takestani	200K	Asia	Arab	fay-141	88.9	-
kmz	1.1M	Khorasan Turkic	400K	Asia	Arab	fay-141	60.7	64.4
mnw	1.1M	Mon	900K	Asia	Mymr	ksw-31	99.9	24.4
scl	1M	Shina	400K	Asia	Arab	bal-131	30.1	-
ml-Latn	1M	Malayalam	35M	Asia	Latn	bgp-131	98.7	58.2
el-CY	1M	Modern Greek	13M	Europe	Grek	el-CY	99.6	71.0
skr	1M	Saraiki	26M	Asia	Arab	doi-Arab-51	99.8	65.1
udm	1M	Udmurt	300K	Europe	Cyrl	ady-91	98.1	45.6
bbc	900K	Batak Toba	2M	Asia	Latn	ace-121	98.3	47.9
war	900K	Waray (Philip-	3M	Asia	Latn	bgs-91	98.3	70.8
		pines)				_		
mki	900K	Dhatki	200K	Asia	Arab	bal-131	26.8	-
srn	900K	Sranan Tongo	100K	Americas	Latn	djk-31	98.4	56.9
pck	900K	Paite Chin	50K	Asia	Latn	bgs-91	99.5	32.3
gn	900K	Guarani	5M	Americas	Latn	gn-61	98.8	50.3
qu	800K	Quechua	9M	Americas	Latn	ae-Latn-101	98.3	48.8
kj	800K	Kuanyama	600K	Africa	Latn	kj-51	98.5	39.9
bug	800K	Buginese	5M	Asia	Latn	amo-71	83.5	-
ee	800K	Ewe	4M	Africa	Latn	avn-31	99.5	49.6
ltg	800K	East Latvian	200K	Europe	Latn	gaw-81	94.9	63.7
hsb	800K	Upper Sorbian	5K	Europe	Latn	ach-101	59.6	-
kl	700K	Kalaallisut	50K	Americas	Latn	bi-6l	87.7	34.1
bho	700K	Bhojpuri	51M	Asia	Deva	bho-131	96.6	56.2
ta-Latn	700K	Tamil	76M	Asia	Latn	bgp-131	99.1	53.8
ve	700K	Venda	2M	Africa	Latn	cce-81	99.9	52.9
bi	700K	Bislama	200K	Oceania	Latn	bi-6l	99.1	-
az-RU	700K	Azerbaijani	18M	Europe	Cyrl	az-RU-131	99.7	58.1
kbd	700K	Kabardian	2M	Europe	Cyrl	ady-91	87.7	46.1
nut	600K	Nung (Viet Nam)	1M	Asia	Latn	blt-Latn-41	97.9	-
hif-Deva	600K	Fiji Hindi	500K	Oceania	Deva	awa-141	89.5	69.9

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
ar-Latn	600K	Arabic	180M	Europe	Latn	aeb-Latn- 111	95.2	29.5
krc	600K	Karachay-Balkar	300K	Europe	Cyrl	az-RU-131	98.5	52.7
chm	600K	Mari	500K	Europe	Cyrl	az-RU-131	99.5	44.5
pag	600K	Pangasinan	1M	Asia	Latn	agn-141	92.0	48.9
mui	600K	Musi	3M	Asia	Latn	abs-131	90.4	62.5
shn	600K	Shan	3M	Asia	Mymr	ksw-31	100	40.3
gom-Latn	500K	Goan Konkani	2M	Asia	Latn	bgp-131	99.0	56.0
noe	500K	Nimadi	2M	Asia	Deva	ahr-131	99.2	62.8
mh	500K	Marshallese	50K	Oceania	Latn	kpj-51	100	31.4
min	500K	Minangkabau	6M	Asia	Latn	ace-121	100	59.1
yue	500K	Yue Chinese	84M	Asia	Hant	yue	99.1	55.4
new	500K	Kathmandu Valley Newari	900K	Asia	Deva	ahr-131	98.3	51.4
cjk	500K	Chokwe	1M	Africa	Latn	cjk-141	98.7	43.7
jax	500K	Jambi Malay	1M	Asia	Latn	abs-131	85.8	69.1
bft	500K	Balti	300K	Asia	Arab	bal-131	13.7	-
dov	500K	Dombe	2M	Africa	Latn	dov-91	100	44.8
kv	500K	Komi	200K	Europe	Cyrl	ady-91	95.2	44.0
cfm	500K	Falam Chin	100K	Asia	Latn	bgr-6l	99.9	36.7
fay	500K	Fars Dialects	50K	Asia	Arab	fay-141	60.9	62.3
mr-Latn	500K	Marathi	83M	Asia	Latn	bgp-131	98.0	64.5
lu	400K	Luba-Katanga	2M	Africa	Latn	jbu-81	98.3	39.1
wa	400K	Walloon	600K	Europe	Latn	acf-101	91.2	54.1
yua	400K	Yucatec Maya	800K	Americas	Latn	chd-61	99.3	57.9
abv	400K	Baharna Arabic	300K	Europe	Arab	abv-101	8.1	-
sg	400K	Sango	2M	Africa	Latn	enx-41	99.7	31.0
iso	400K	Isoko	400K	Africa	Latn	ajg-81	99.9	35.1
kac	400K	Southern Jinghpaw	900K	Asia	Latn	ace-121	100	38.4
syr	400K	Syriac	1M	Europe	Syrc	ach-101	99.9	40.4
pam	400K	Pampanga	2M	Asia	Latn	agn-141	99.5	52.5
afb	400K	Gulf Arabic	5M	Europe	Arab	abv-101	4.1	-
qxq	400K	Qashqa'i	2M	Asia	Arab	fay-141	61.8	61.0
ada	400K	Adangme	800K	Africa	Latn	ada-131	99.7	44.1
ctg	400K	Chittagonian	15M	Asia	Beng	bpy-71	90.9	65.2
kg	400K	Kongo	6M	Africa	Latn	jbu-81	93.8	-
mtr	400K	Mewari	5M	Asia	Deva	bfz-151	89.2	44.8
io	400K	Ido	5K	Europe	Latn	acf-101	84.6	-
pmy	400K	Papuan Malay	500K	Asia	Latn	abs-131	88.3	68.3
ss-SZ	400K	Swati	3M	Africa	Latn	gup-81	87.3	64.7
mwr	400K	Marwari	8M	Asia	Deva	bfz-151	97.3	- 43.6
ktu nd	400K	Kituba (DRC)	5M 2M	Africa	Latn	jbu-81	99.8	43.0 69.1
	300K	Zimbabwean Nde- bele		Africa	Latn	gup-81	98.6	
kek	300K	Kekchí	800K	Americas	Latn	kek-21	100	35.1
mfe	300K	Morisyen	1M	Africa	Latn	acf-101	100	66.0
bua	300K	Buriat	400K	Europe	Cyrl	bua-21	96.9	44.5
tvl	300K	Tuvalu	50K	Oceania	Latn	mi-41	99.6	-
chk	300K	Chuukese	50K	Oceania	Latn	chk-2l	100	34.4
dcc	300K	Deccan	13M	Asia	Arab	bal-131	89.2	61.2
gom	300K	Goan Konkani	2M	Asia	Deva	awa-141	85.6	59.2
pon	300K 300K	Pohnpeian Avar	50K 800K	Oceania	Latn	bgs-91	99.7 99.1	39.9 45.8
av mfb	300K			Europe Asia	Cyrl	ady-91	99.1	
sjp	300K	Bangka Surjapuri	300K 1M	Asia	Latn Deva	abs-131 bho-131	96.3	66.6 55.4
sjp tiv	300K	Tiv	2M	Africa	Latn	bim-31	100	27.7
ady	300K	Adyghe	600K	Europe	Cyrl	ady-91	89.2	43.2
btx	300K	Batak Karo	600K	Asia	Latn	ban-31	100	39.1
WO	300K	Wolof	4M	Africa	Latin	aeb-Latn-	99.3	50.1
						111		
tsc bne	300K	Tswa Chhattisgarhi	1M 18M	Africa Asia	Latn Deva	cce-81	98.6 os o	66.9 56.9
hne	300K 300K	Central-Southern	18M 3M			bho-131	98.9 99.6	56.9 31.0
ay	300 K	Aymara	JIVI	Americas	Latn	auc-6l	99.0	31.0

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
pa-Arab	300K	Eastern Punjabi	28M	Asia	Arab	doi-Arab-51	96.4	64.3
gag	300K	Gagauz	600K	Europe	Latn	aeb-Latn- 111	99.0	61.9
raj	300K	Rajasthani	18M	Asia	Deva	bfz-151	88.0	47.9
que	200K	K'iche'	2M	Americas	Latn	acr-41	99.9	38.8
zyj	200K	Youjiang Zhuang	900K	Asia	Latn	cqd-81	99.1	26.4
bhb-Gujr	200K	Bhili	3M	Asia	Gujr	bhb-Gujr-31	98.2	-
ho	200K	Hiri Motu	100K	Oceania	Latn	gah-111	99.4	32.6
	200K 200K	Zapotec	400K	Americas	Latn	=	100	32.0
zap crh	200K 200K	Crimean Tatar	500K			zaa-51 az-RU-131	99.7	53.1
				Europe	Cyrl			
mam	200K	Mam	500K	Americas	Latn	chd-6l	99.8	28.3
rhg-Latn	200K	Rohingya	2M	Asia	Latn	bn-Latn-6l	98.7	50.0
rom	200K	Romani	4M	Europe	Latn	rmc-31	99.1	44.0
mgh	200K	Makhuwa-Meetto	7M	Africa	Latn	apu-131	99.6	30.0
lrc	200K	Northern Luri	2M	Asia	Arab	apr-81	67.2	-
kmz-Latn	200K	Khorasan Turkic	400K	Asia	Latn	aeb-Latn- 111	93.0	54.9
myv	200K	Erzya	400K	Europe	Cyrl	ady-91	98.0	36.3
ace	200K	Acehnese	4M	Asia	Latn	ace-121	99.7	50.1
bns	200K	Bundeli	3M	Asia	Deva	awa-141	87.8	-
acw	200K	Hijazi Arabic	14M	Europe	Arab	abv-101	6.4	-
nan-Latn-	200K	Min Nan Chinese	59M	Asia	Latn	cdo-51	100	27.1
TW quh	200K	South Bolivian Ouechua	3M	Americas	Latn	ae-Latn-10l	99.9	39.2
gbm	200K	Garhwali	3M	Asia	Deva	bfz-151	95.1	53.9
ctu	200K	Chol	200K	Americas	Latn	chz-131	100	29.8
acq	200K	Ta'izzi-Adeni Ara-	7M	Europe	Arab	abv-10l	12.3	-
•		bic		•		a0v-101		
bfy	200K	Bagheli	8M	Asia	Deva	awa-141	91.5	62.0
gv	200K	Manx	5K	Europe	Latn	gv-31	98.3	36.6
xmm	200K	Manado Malay	800K	Asia	Latn	abs-131	94.5	59.7
mel	200K	Central Melanau	100K	Asia	Latn	abx-111	89.7	74.2
ksw	200K	S'gaw Karen	1M	Asia	Mymr	ksw-31	100	38.0
seh	200K	Sena	2M	Africa	Latn	cjk-141	99.5	52.5
msb	200K	Masbatenyo	400K	Asia	Latn	abx-111	99.4	57.3
tsg	200K	Tausug	1M	Asia	Latn	abx-111	98.4	54.0
dtp	200K	Central Dusun	100K	Asia	Latn	dtb-41	100	23.9
yap	200K	Yapese	5K	Oceania	Latn	bru-61	99.3	-
kum	200K	Kumyk	400K	Europe	Cyrl	az-RU-131	99.9	47.9
fon	200K	Fon	1M	Africa	Latn	ada-131	99.9	40.9
alt	200K	Southern Altai	50K	Europe	Cyrl	alt	100	43.4
wal	200K	Wolaytta	2M	Africa	Latn	drs-Latn-81	99.7	29.6
en-Arab	200K	English	550M	Europe	Arab	abv-101	97.4	56.5
nzi	200K	Nzima	300K	Africa	Latn	bov-41	100	40.6
cak	200K	Kaqchikel	400K	Americas	Latn	acr-41	100	24.1
ban	200K	Balinese	3M	Asia	Latn	ban-31	100	51.7
zne	200K	Zande	1M	Africa	Latn	agt-6l	99.5	16.9
bm	200K 200K	Bambara	14M	Africa	Latn	ada-131	99.1	42.1
mdh	200K	Maguindanao	1M	Asia	Latn	agn-14l	96.4	43.7
xal	200K 200K	Oirad-Kalmyk-	400K	Europe	Cyrl	-	91.5	42.8
xai	200K	Darkhat	400K	Europe	Cyll	az-RU-131	71.3	42.6
abs	200K	Ambonese Malay	2M	Asia	Latn	abs-131	88.8	63.7
tzo	200K	Tzotzil	200K	Americas	Latn	aeb-Latn- 111	99.9	29.5
bgc	200K	Haryanvi	13M	Asia	Deva	ahr-131	91.7	56.9
vkt	200K	Tenggarong Kutai	200K	Asia	Latn	abs-131	93.6	64.8
doi	200K	Malay Kangri-Dogri	2M	Asia	Deva	bfz-151	93.5	_
gez	200K	Geez	0K	Africa	Ethi	gez-81	87.6	_
rwr	200K	Marwari (India)	8M	Asia	Deva	bfz-151	84.9	
tum	200K	Tumbuka	2M	Africa	Latn	cjk-14l	47.9	-
ang	200K	Old English (ca.	0K	Europe	Latn	ang-71	97.6	_
ang	2001	450-1100)	OIX	Lutope	Latti	ang-/1	71.0	-

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
nia	200K	Nias	800K	Asia	Latn	ceg-51	100	23.1
bts	200K	Batak Simalungun	1 M	Asia	Latn	agn-141	100	34.1
ng	200K	Ndonga	800K	Africa	Latn	kj-51	95.0	35.0
ach	200K	Acoli	1M	Africa	Latn	ach-101	99.6	21.0
rcf	200K	Réunion Creole	600K	Africa	Latn	acf-101	99.3	66.9
		French						
kos	200K	Kosraean	5K	Oceania	Latn	ceg-51	98.8	_
skg	200K	West Malagasy	1M	Africa	Latn	apy-71	93.4	57.6
		Sakalava						
mrj	200K	Western Mari	5K	Europe	Cyrl	az-RU-131	94.3	45.8
bci	200K	Baoulé	2M	Africa	Latn	ada-131	98.9	32.1
ch	200K	Chamorro	50K	Oceania	Latn	ayo-41	98.9	31.9
qvi	200K	Imbabura High-	300K	Americas	Latn	guw-51	100	38.7
4,1	20011	land Quichua	20011	rimericas	Datii	quw 51	100	50.7
gym	200K	Ngäbere	200K	Americas	Latn	gym	100	19.5
cyo	150K	Cuyonon	100K	Asia	Latn	agn-14l	85.0	69.1
-	150K	Ems-Weser Frisian	5K	Europe	Latn	apr-81	89.6	-
stq	150K	Tulu	2M	Asia	Knda	lmn-Knda-	100	49.4
tcy	130K	Tulu	21 VI	Asia	Kiida	21	100	47.4
meu	150K	Motu	50K	Oceania	Latn	gah-111	99.1	27.4
pau	150K	Palauan	50K	Oceania	Latn	pau	100	_
bas	150K	Basa (Cameroon)	300K	Africa	Latn	bas-111	99.4	21.0
guc	140K	Wayuu	300K	Americas	Latn	guc	100	18.5
quy	140K	Ayacucho	900K	Americas	Latn	ae-Latn-10l	99.7	29.8
quy	1401	Quechua	700IX	Timericas	Latii	ac-Latti-101	JJ.1	27.0
gu-Latn	140K	Gujarati	56M	Asia	Latn	bgp-131	98.1	60.9
mad	140K	Madurese	7M	Asia	Latn	ade-41	99.8	44.7
cbk	140K	Chavacano	700K	Asia	Latn	cbk	100	-
awa	140K	Awadhi	4M	Asia	Deva	awa-141	98.1	61.4
brx	130K	Bodo-Mech	1M	Asia	Deva	ahr-131	100	32.8
koi	130K	Komi-Permyak	50K	Europe	Cyrl		93.7	40.6
	130K	Mapudungun	300K	Americas	Latn	ady-91	99.6	33.6
arn		1 0				arn-61		
nv	130K	Navajo Eastern Huasteca	200K	Americas	Latn	nv-21	99.2 99.7	24.6 29.4
nhe	130K	Nahuatl	400K	Americas	Latn	azz-71	99.1	29. 4
fip	130K	Fipa	200K	Africa	Latn	dov-91	100	32.0
dyu	130K	Dyula	16M	Africa	Latn	ada-131	99.8	27.8
xnr	130K	Kangri	2M	Asia	Deva	bfz-151	96.2	57.7
kbp	130K	Kaligii Kabiyé	1M	Africa			100	32.1
		-			Latn	kbp-2l		
kw	130K	Cornish	5K	Europe	Latn	br-41	92.6	-
kri 	130K	Krio	4M	Africa	Latn	cjk-141	99.6 97.5	61.0
rn	130K	Rundi	9M	Africa	Latn	cgg-151		-
mdf	120K	Moksha	5K	Europe	Cyrl	ady-91	84.8	-
tzh	120K	Tzeltal	400K	Americas	Latn	arn-61	99.4	30.9
cab	120K	Garifuna	200K	Americas	Latn	bch-10l	100	18.8
trp	120K	Kok Borok	800K	Asia	Latn	ace-121	99.8	38.3
mkn	120K	Kupang Malay	200K	Asia	Latn	abs-131	98.6	53.7
rki	120K	Rakhine	2M	Asia	Mymr	rki	99.9	49.2
gyn	120K	Guyanese Creole	600K	Americas	Latn	bzj-9l	99.4	71.8
		English						
syl-Latn	120K	Sylheti	23M	Asia	Latn	bn-Latn-61	99.1	-
max	120K	North Moluccan	700K	Asia	Latn	abs-131	91.3	-
	10077	Malay	50017	A.C.:	Ŧ .		00 =	25.5
izz	120K	Izi	500K	Africa	Latn	anw-81	99.7	26.6
dje	110K	Zarma-Kaado	2M	Africa	Latn	ang-71	99.6	22.2
smt	110K	Simte	50K	Asia	Latn	bgs-91	99.9	-
iu	110K	Inuktitut	50K	Americas	Cans	crm-31	99.8	26.9
bmm	110K	Northern Betsimis-	1 M	Africa	Latn	apy-71	91.8	-
	1107-	araka Malagasy	E007-				60 -	20.5
lhu	110K	Lahu	500K	Asia	Latn	hni-81	99.9	29.3
djk	110K	Aukan	50K	Americas	Latn	djk-31	100	35.3
cuk	110K	San Blas Kuna	50K	Americas	Latn	bnj-61	100	12.3
mni	110K	Manipuri	2M	Asia	Beng	mni	99.9	37.9
mak	100K	Makasar	5M	Asia	Latn	mak	100	19.2

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
bto	100K	Iriga Bicolano	200K	Asia	Latn	agn-141	95.2	64.6
tab	100K	Tabasaran	100K	Europe	Cyrl	ce-31	100	33.4
mps	100K	Dadibi	50K	Oceania	Latn	mps-31	99.8	-
mbt	100K	Matigsalug	50K	Asia	Latn	mbt	100	21.5
		Manobo						
gui	100K	Eastern Bolivian Guaraní	50K	Americas	Latn	gui	100	20.6
fan	100K	Fang (Equatorial Guinea)	1M	Africa	Latn	bas-111	99.1	31.0
ngu	100K	Central Guerrero Nahuatl	200K	Americas	Latn	azz-71	99.7	28.3
srm	100K	Saramaccan	50K	Americas	Latn	djk-31	100	-
ms-Arab- BN	100K	Malay	80M	Asia	Arab	mfa-31	92.7	53.9
ndc-ZW	100K	Ndau	2M	Africa	Latn	cjk-141	99.0	60.5
nnb	100K	Nande	900K	Africa	Latn	cgg-151	99.7	35.7
ber	100K	Berber	2M	Africa	Tfng	ber	100	26.5
ibb	100K	Ibibio	2M	Africa	Latn	anw-81	98.6	48.3
nyu	90K	Nyungwe	400K	Africa	Latn	cjk-14l	98.0	_
gub	90K	Guajajára	50K	Americas	Latn	abr-51	100	_
kmb	90K	Kimbundu	4M	Africa	Latn	dov-91	100	25.0
trw	90K	Torwali	50K	Asia	Arab	bal-131	88.4	43.8
nij	90K	Ngaju	900K	Asia	Latn	kje-6l	100	38.9
cgg	90K	Chiga	2M	Africa	Latn	cgg-151	99.3	50.5
twu	90K	Termanu	50K	Asia	Latn	bhw-91	100	19.9
kn-Latn	90K	Kannada	43M	Asia	Latn	bgp-131	98.6	46.0
ms-Arab	90K	Malay	80M	Asia	Arab	mfa-31	88.9	55.7
	90K	Ojibwe	50K	Americas	Latn		99.9	33.1
oj acf	90K	Saint Lucian Cre-	200K	Americas		agr-31	100	48.9
acı	90K	ole French	200K	Americas	Latn	acf-101	100	40.9
cac	90K	Chuj	50K	Americas	Latn	cac	100	13.8
jiv	90K	Shuar	50K	Americas	Latn	bn-Latn-61	100	12.0
alz	90K	Alur	2M	Africa	Latn	adh-51	99.6	21.3
akb	90K	Batak Angkola	800K	Asia	Latn	akb-4l	100	15.4
ff	90K	Fula	12M	Africa	Latn	aa-131	90.6	40.6
aa	80K	Afar	2M	Africa	Latn	aa-131	99.7	19.8
miq	80K	Mískito	200K	Americas	Latn	miq-21	100	19.1
bgz	80K	Banggai	100K	Asia	Latn	amo-71	92.7	56.2
nyn	80K	Nyankole	2M	Africa	Latn	cgg-151	99.7	37.7
adh	80K	Adhola	400K	Africa	Latn	adh-51	100	18.5
bzj	80K	Belize Kriol En-	200K	Americas	Latn	bzj-9l	100	57.9
J		glish				-		
nyo	80K	Nyoro	700K	Africa	Latn	cgg-151	99.3	46.7
kfy	80K	Kumaoni	2M	Asia	Deva	bfz-151	93.8	
kjb	80K	Q'anjob'al	50K	Americas	Latn	cbr-6l	96.7	14.3
frp	80K	Arpitan	100K	Europe	Latn	acf-101	90.4	26.0
jvn	80K	Caribbean Javanese	50K	Americas	Latn	jvn	100	26.9
mdy	80K	Male (Ethiopia)	100K	Africa	Ethi	mdy	100	22.7
hae	80K	Eastern Oromo	4M	Africa	Latn	amf-61	99.5	48.6
qxr	80K	Cañar Highland Quichua	200K	Americas	Latn	quw-51	99.7	37.7
noa	80K	Woun Meu	50K	Americas	Latn	cbv-61	99.9	-
krj	70K	Kinaray-a	400K	Asia	Latn	abx-111	99.5	58.9
hui	70K	Huli	200K	Oceania	Latn	hui-31	99.9	12.0
enq	70K	Enga	200K	Oceania	Latn	avt-121	99.5	12.1
sgj	70K	Surgujia	1M	Asia	Deva	bho-131	97.5	56.8
lrl	70K	Larestani	200K	Asia	Arab	fay-141	56.8	-
gof	70K	Gofa	400K	Africa	Ethi	drs-Latn-81	99.6	24.1
sxn	70K	Sangir	200K	Asia	Latn	sxn	100	31.9
hus	70K	Huastec	100K	Americas	Latn	chd-6l	100	19.6
tuc	70K	Mutu	5K	Oceania	Latn	bmu-61	100	-
maz	70K	Central Mazahua	50K	Americas	Latn	jic-31	100	15.7
hix	70K	Hixkaryána	5K	Americas	Latn	hix	99.6	-
	•	-						

		Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
ks	70K	Kashmiri	6M	Asia	Arab	doi-Arab-51	96.5	47.0
clu	70K	Caluyanun	50K	Asia	Latn	abx-111	98.9	-
acx	70K	Omani Arabic	1M	Europe	Arab	abv-101	4.9	-
prk	70K	South Wa	800K	Asia	Latn	ace-121	100	26.3
mas	70K	Masai	1M	Africa	Latn	big-51	99.8	16.2
pis	70K	Pijin	400K	Oceania	Latn	bi-6l	100	21.3
amu	70K	Guerrero Amuzgo	50K	Americas	Latn	amu	100	12.0
myu	70K	Mundurukú	5K	Americas	Latn	bch-101	99.9	-
kjg	70K	Khmu	700K	Asia	Laoo	kjg-21	100	37.1
sda	70K	Toraja-Sa'dan	800K	Asia	Latn	kje-61	98.4	20.1
kpg	70K	Kapingamarangi	5K	Oceania	Latn	kpg	100	-
bus	70K	Bokobaru	50K	Africa	Latn	akp-41	99.5	16.5
mag	70K	Magahi	28M	Asia	Deva	bho-131	99.6	57.7
dwr	70K	Dawro	500K	Africa	Latn	drs-Latn-81	100	19.8
sja	70K	Epena	5K	Americas	Latn	mpm-41	99.1	-
ahk	60K	Akha	600K	Asia	Latn	ahk	100	26.2
ffm	60K	Maasina Fulfulde	1M	Africa	Latn	aa-131	98.6	29.0
xav	60K	Xavánte	5K	Americas	Latn	xav	87.5	-
chr	60K	Cherokee	50K	Americas	Cher	chr	100	19.7
kyz	60K	Kayabí	5K	Americas	Latn	avt-121	71.1	-
tll	60K	Tetela	800K	Africa	Latn	kj-51	99.9	24.8
tee	60K	Huehuetla Tepe- hua	5K	Americas	Latn	tee-21	99.9	-
niq	60K	Nandi	1M	Africa	Latn	awk-41	98.8	20.0
din	60K	Dinka	1M	Africa	Latn	din-31	99.7	27.6
nog	60K	Nogai	50K	Europe	Cyrl	bcq-Latn-	100	51.6
		_		•	-	121		
tca	60K	Ticuna	50K	Americas	Latn	tca	100	8.6
abt	60K	Ambulas	50K	Oceania	Latn	abt-31	99.8	10.3
bhw	60K	Biak	50K	Asia	Latn	bhw-91	100	20.5
dln	60K	Darlong	5K	Asia	Latn	bla-71	99.9	-
xog	60K	Soga	3M	Africa	Latn	cgg-151	99.4	56.6
cbt	60K	Shawi	5K	Americas	Latn	cbt-21	100	-
vep	60K	Veps	5K	Europe	Latn	gaw-81	90.9	142
gil	60K	Gilbertese	100K	Oceania	Latn	aaz-6l	100	14.3
tyz	60K	Tày Balsa (Banin)	3M	Asia	Latn	blt-Latn-41	99.5	22.8
bqc ksd	60K 60K	Boko (Benin) Kuanua	200K 50K	Africa Oceania	Latn Latn	akp-41 apb-131	99.8 99.2	19.0 15.4
tob	60K	Toba	50K	Americas	Latn	apo-131 hni-81	100	13.4
bru	60K	Eastern Bru	50K	Asia	Latn	bru-61	100	21.4
sat-Latn	60K	Santali	6M	Asia	Latn	aaz-61	98.9	40.0
msy	60K	Aruamu	5K	Oceania	Latn	msy-21	99.6	-
cbu	60K	Candoshi-Shapra	5K	Americas	Latn	apu-131	99.1	_
shp	60K	Shipibo-Conibo	50K	Americas	Latn	apu-131	100	_
qub	60K	Huallaga Huánuco	50K	Americas	Latn	qub-71	99.5	26.0
quo	0011	Quechua	5011	Timericus	Latin	quo /1	,,,,	20.0
agr	60K	Aguaruna	50K	Americas	Latn	agr-31	100	14.6
emp	60K	Northern Emberá	50K	Americas	Latn	cbv-61	99.6	12.3
suz	60K	Sunwar	50K	Asia	Deva	suz	100	17.2
maa	60K	San Jerónimo Tecóatl Mazatec	50K	Americas	Latn	kcg-91	100	-
ifk	60K	Tuwali Ifugao	50K	Asia	Latn	bnc-81	100	19.9
arc	50K	Official Aramaic (700-300 BCE)	0K	Europe	Syrc	ach-101	80.0	-
bim	50K	Bimoba	400K	Africa	Latn	bim-31	100	15.6
otq	50K	Querétaro Otomi	50K	Americas	Latn	ann-31	99.9	47.0
tdx	50K	Tandroy Malagasy	1M	Africa	Latn	apy-71	99.6	48.2
tav	50K	Tatuyo	5K	Americas	Latn	des-41	100	-
pir	50K	Wa'ikhana	5K	Americas	Latn	des-41	99.6	-
ded	50K	Dedua	5K	Oceania	Latn	bru-61	99.7	-
txu	50K	Kayapó	5K	Americas	Latn	apn-31	99.2	-
qvh	50K	Huamalíes-Dos de	50K	Americas	Latn	qub-71	100	19.7
		Mayo Huánuco Quechua						

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
mav	50K	Sateré-Mawé	5K	Americas	Latn	bwu-41	100	-
ubu	50K	Umbu-Ungu	50K	Oceania	Latn	gbi-81	99.9	11.8
toj	50K	Tojolabal	50K	Americas	Latn	toj-41	100	27.2
inb	50K	Inga	50K	Americas	Latn	inb	100	-
aoj	50K	Mufian	50K	Oceania	Latn	aoj	99.6	-
mbb	50K	Western Bukidnon	50K	Asia	Latn	mbb-31	85.9	-
		Manobo						
acr	50K	Achi	50K	Americas	Latn	acr-41	99.9	21.1
xtd	50K	Diuxi-Tilantongo	5K	Americas	Latn	mpm-41	99.9	_
		Mixtec						
kjh	50K	Khakas	50K	Europe	Cyrl	kjh	100	37.9
dyi	50K	Djimini Senoufo	50K	Africa	Latn	dyi	100	18.5
mpm	50K	Yosondúa Mixtec	50K	Americas	Latn	mpm-41	99.7	-
kwi	50K	Awa-Cuaiquer	50K	Americas	Latn	bla-71	100	_
bjj	50K	Kanauji	10M	Asia	Deva	awa-141	97.8	55.4
amn	50K	Amanab	5K	Oceania	Latn	amn-21	99.9	- -
	50K	Palikúr	5K	Americas			98.7	-
plu	50K	Tohono O'odham	50K	Americas	Latn Latn	plu	100	
ood						alq-41		-
czt	50K	Zotung Chin	50K	Asia	Latn	czt	100	19.9
tbg	50K	North Tairora	50K	Oceania	Latn	amp-121	100	- 50.6
gjk	50K	Kachi Koli	600K	Asia	Arab	bal-131	77.3	59.6
crn	50K	El Nayar Cora	50K	Americas	Latn	cok-21	99.7	-
cni	50K	Asháninka	50K	Americas	Latn	apu-131	100	13.0
qup	50K	Southern Pastaza	1M	Americas	Latn	qup-21	99.7	-
		Quechua						
ify	50K	Keley-i Kallahan	50K	Asia	Latn	ify	99.9	-
srq	50K	Sirionó	5K	Americas	Latn	srq-31	98.9	-
tbz	50K	Ditammari	200K	Africa	Latn	gej-41	100	16.1
aeb	50K	Tunisian Arabic	11M	Africa	Arab	abv-101	13.1	-
sus	50K	Susu	1M	Africa	Latn	bas-111	100	20.5
itv	50K	Itawit	100K	Asia	Latn	bnj-61	99.9	28.9
cce	50K	Chopi	800K	Africa	Latn	cce-81	99.4	33.3
qwh	50K	Huaylas Ancash Quechua	300K	Americas	Latn	nhg-31	100	25.4
taa	50V	•	2M	A fried	Lote	11 71	100	144
teo	50K	Teso		Africa	Latn	bla-7l	100	14.4
lon	50K	Malawi Lomwe	2M	Africa	Latn	cjk-14l	99.5	-
gun	50K	Mbyá Guaraní	50K	Americas	Latn	gn-6l	99.4	-
ppk	50K	Uma	50K	Asia	Latn	pmf-21	100	-
ann	50K	Obolo	200K	Africa	Latn	ann-31	100	26.3
laj	50K	Lango (Uganda)	2M	Africa	Latn	adh-51	99.7	25.7
eza	50K	Ezaa	600K	Africa	Latn	anw-81	99.7	29.2
caf	50K	Southern Carrier	5K	Americas	Latn	bpr-71	99.9	-
lex	50K	Luang	50K	Asia	Latn	kje-61	100	-
msm	50K	Agusan Manobo	50K	Asia	Latn	atd-41	100	24.6
tuf	50K	Central Tunebo	5K	Americas	Latn	tuf	100	-
quf	50K	Lambayeque	50K	Americas	Latn	ae-Latn-101	99.5	-
		Quechua						
bzc	50K	Southern Betsimis-	2M	Africa	Latn	apy-71	96.4	61.4
		araka Malagasy						
jbo	50K	Lojban	0K	Europe	Latn	bi-6l	98.0	-
yss	50K	Yessan-Mayo	5K	Oceania	Latn	bom-51	99.9	_
tzj	50K	Tz'utujil	50K	Americas	Latn	tzj	100	13.4
qvc	40K	Cajamarca	50K	Americas	Latn	qvc	100	16.4
1		Quechua				1		
stp	40K	Southeastern Tepe-	50K	Americas	Latn	cbr-6l	100	-
-		huan						
wsk	40K	Waskia	50K	Oceania	Latn	aom-101	97.7	_
knj	40K	Akateko	50K	Americas	Latn	knj-81	99.3	15.8
qvz	40K	Northern Pastaza	50K	Americas	Latn	quw-51	100	-
7.~	.011	Quichua				q 51	100	
pad	40K	Paumari	5K	Americas	Latn	anw-81	100	_
cbi	40K 40K	Cha'palaa	5K	Americas	Latn	cbi	100	-
							99.9	
tac	40K	Lowland Tarahu-	50K	Americas	Latn	alp-21	77.7	-
	I	mara						

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
ngl	40K	Mozambique Lomwe	2M	Africa	Latn	cjk-141	96.2	-
kaq	40K	Capanahua	50K	Americas	Latn	bgs-91	100	_
jam	40K	Jamaican Creole	3M	Americas	Latn	bzj-9l	99.9	57.9
Janaa		English				, /-		
сру	40K	South Ucayali Ashéninka	5K	Americas	Latn	apu-131	99.2	15.0
en-Cyrl	40K	English	550M	Europe	Cyrl	az-RU-131	98.0	87.3
car	40K	Galibi Carib	5K	Americas	Latn	car	100	-
gju	40K	Gujari	1M	Asia	Arab	doi-Arab-51	98.9	51.3
pab	40K	Parecís	5K	Americas	Latn	pab-21	99.9	-
yuj	40K	Karkar-Yuri	5K	Oceania	Latn	amp-121	98.0	-
jac	40K	Popti'	5K	Americas	Latn	ayo-41	98.1	-
mjc	40K	San Juan Colorado Mixtec	50K	Americas	Latn	cta-41	99.6	-
med	40K	Melpa	100K	Oceania	Latn	cwt-41	100	13.6
qvs	40K	San Martín Quechua	50K	Americas	Latn	qup-21	99.7	-
urb	40K	Urubú-Kaapor	5K	Americas	Latn	bhw-91	99.7	-
bnp	40K	Bola	50K	Oceania	Latn	bch-10l	99.0	-
yle	40K	Yele	5K	Oceania	Latn	bib-21	100	-
acu	40K	Achuar-Shiwiar	5K	Americas	Latn	acu-81	99.1	-
cof	40K	Tsafiki	5K	Americas	Latn	bmr-31	100	-
poh	40K	Poqomchi'	50K	Americas	Latn	hni-81	100	12.6
gbi	40K	Galela	50K	Asia	Latn	gbi-81	100	13.6
kto	40K	Kuot	5K	Oceania	Latn	bkv-4l	99.9	-
bfz	40K	Mahasu Pahari	1M	Asia	Deva	bfz-151	94.4	-
cao	40K 40K	Chácobo	5K 5K	Americas Americas	Latn	auc-61	99.7 100	-
myy aaz	40K	Macuna Amarasi	50K	Aniericas	Latn Latn	cub-2l	100	15.3
nch	40K	Central Huasteca	200K	Asia	Latn	aaz-61 azz-71	95.7	19.2
		Nahuatl						
ixl	40K	Ixil	100K	Americas	Latn	ctp-41	100	15.1
rwo	40K	Rawa	50K	Oceania	Latn	gbi-81	99.9	-
azg	40K	San Pedro Amuz- gos Amuzgo	50K	Americas	Latn	azg-41	100	-
yaq	40K	Yaqui	50K	Americas	Latn	yaq	99.6	-
iou	40K	Tuma-Irumu	5K	Oceania	Latn	awx-21	97.0	-
qvw	40K	Huaylla Wanca Quechua	300K	Americas	Latn	qub-71	100	16.7
snn	40K	Siona-Tetete	5K	Americas	Latn	azg-41	100	-
sxu	40K	Central East Mid- dle German	2M	Europe	Latn	ang-71	99.9	64.3
bch	40K	Bariai	5K	Oceania	Latn	bch-101	98.8	
bud	40K	Ntcham	300K	Africa	Latn	amf-61	100	17.2
tih	40K	Timugon Murut	5K	Asia	Latn	tih-21	99.8	-
mcd	40K	Sharanahua	5K	Americas	Latn	cbt-21	100	-
apn	40K	Apinayé	5K	Americas	Latn	apn-31	91.4	-
yaa	40K	Yaminahua	5K 900K	Americas	Latn	yaa	100	- 19 O
mqy	40K 40K	Manggarai Yakan	900K 100K	Asia Asia	Latn	abs-131	97.8 99.8	48.9 23.6
yka rmc	40K 40K	Central Romani	100K 100K	Europe	Latn Latn	bpr-71 rmc-31	100	25.7
tfr	40K	Teribe	5K	Americas	Latn	pxm-21	100	-
tna	40K	Tacana	5K	Americas	Latn	nhg-31	100	_
nhy	40K	Northern Oaxaca	50K	Americas	Latn	nhy-31	99.7	
nfa	40K	Nahuatl Dhao	5K	Asia		•	99.1	
	40K 40K	Francisco León	50K	Asia Americas	Latn Latn	bhw-91	99.1 98.4	-
zos		Zoque				ayo-41		-
zpz	40K	Texmelucan Zapotec	5K	Americas	Latn	srq-31	100	-
mqj	40K	Mamasa	50K	Asia	Latn	kje-61	97.9	14.5
xsi	40K	Sio	5K	Oceania	Latn	kij-21	99.9	-
srr	40K	Sereer	1 M	Africa	Latn	aa-131	81.6	21.4

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
hac	40K	Gurani	400K	Asia	Arab	fay-14l	68.6	52.1
yal	40K	Yalunka	100K	Africa	Latn	bas-111	100	16.4
aey	40K	Amele	5K	Oceania	Latn	aey-61	97.3	-
lep-Tibt	40K	Lepcha	50K	Asia	Tibt	lep-Tibt	100	9.9
kia	40K	Kim	50K	Africa	Latn	cut-51	99.9	_
sef	40K	Cebaara Senoufo	3M	Africa	Latn	ada-131	98.7	41.1
lac	40K	Lacandon	5K	Americas	Latn	lac	99.8	_
rro	40K	Waima	50K	Oceania	Latn	apb-131	97.7	_
cav	40K	Cavineña	5K	Americas	Latn	aak-31	99.9	_
bvz	40K	Bauzi	5K	Asia	Latn	adz-31	100	_
	40K	Panao Huánuco	50K	Americas	Latn		99.5	17.3
qxh	40K		JUK	Americas	Laui	qub-71	99.3	17.3
m of	40V	Quechua Matsés	5K	A	Lote	21	100	
mcf	40K			Americas	Latn	con-31	100	-
gvl	40K	Gulay	200K	Africa	Latn	dzg-51	92.6	-
alq	40K	Algonquin	5K	Americas	Latn	alq-41	99.9	-
gum	40K	Guambiano	50K	Americas	Latn	cjp-41	100	-
cr-Latn	40K	Cree	200K	Americas	Latn	ach-101	24.2	-
guh	40K	Guahibo	50K	Americas	Latn	acu-81	100	10.8
sri	40K	Siriano	5K	Americas	Latn	cbv-61	99.2	-
kvn	40K	Border Kuna	50K	Americas	Latn	guo-21	100	-
acn	40K	Longchuan	50K	Asia	Latn	acn-111	100	14.4
		Achang						
mxb	40K	Tezoatlán Mixtec	50K	Americas	Latn	kcg-91	98.9	-
ppo	40K	Folopa	5K	Oceania	Latn	pab-21	98.2	-
atd	40K	Ata Manobo	50K	Asia	Latn	atd-41	70.9	-
zam	40K	Cuixtla-Xitla Za-	5K	Americas	Latn	srq-31	100	_
		potec				•		
mti	40K	Maiwa (Papua	5K	Oceania	Latn	dgz-51	99.8	_
		New Guinea)						
jic	40K	Tol	5K	Americas	Latn	jic-31	100	_
cui	40K	Cuiba	5K	Americas	Latn	acu-81	100	_
ata	40K	Pele-Ata	5K	Oceania	Latn	ata-51	98.8	_
cnk	40K	Khumi Chin	50K	Asia	Latn	cdo-51	100	16.9
bnc	40K	Bontok	50K	Asia	Latn	bnc-81	99.6	15.5
con	40K	Cofán	5K	Americas	Latn	con-31	100	-
	40K	Guayabero	5K	Americas	Latn		100	_
guo	40K	Chortí	50K	Americas	Latn	guo-21	100	12.5
caa	30K	Gitonga		Africa		caa	99.9	
toh		Konkomba	400K		Latn Latn	cce-81		29.9 17.3
xon	30K		900K	Africa		daa-31	98.6	
rug	30K	Roviana	5K	Oceania	Latn	akb-4l	99.9	-
bbb	30K	Barai	5K	Oceania	Latn	asg-101	99.6	-
chf	30K	Tabasco Chontal	50K	Americas	Latn	chd-61	100	20.3
cub	30K	Cubeo	5K	Americas	Latn	cub-21	100	-
tke	30K	Takwane	2M	Africa	Latn	tke	97.3	
ape	30K	Bukiyip	50K	Oceania	Latn	aon-131	69.9	
tuo	30K	Tucano	5K	Americas	Latn	meh-31	99.3	
npl	30K	Nahuatl, South-	300K	Americas	Latn	nhy-31	94.5	-
		eastern Puebla						
mmx	30K	Madak	5K	Oceania	Latn	avt-121	98.4	
ifa	30K	Amganad Ifugao	50K	Asia	Latn	bnc-81	99.7	-
boj	30K	Anjam	5K	Oceania	Latn	boj-41	100	-
ter	30K	Terena-Kinikinao-	50K	Americas	Latn	enx-41	100	-
		Chane						
mpx	30K	Misima-Paneati	50K	Oceania	Latn	aui-141	97.5	-
msk	30K	Mansaka	50K	Asia	Latn	agn-141	100	34.2
sdh	30K	Southern Kurdish	3M	Asia	Arab	fay-141	70.2	-
ber-Arab	30K	Berber	2M	Africa	Arab	abv-101	99.5	21.1
zia	30K	Zia	5K	Oceania	Latn	avt-121	96.2	-
mna	30K	Mbula	5K	Oceania	Latn	bmu-61	99.0	
apy	30K	Apalaí	5K	Americas	Latn	apy-71	99.2	_
kdi	30K	Kumam	200K	Africa	Latn	adh-51	99.9	15.8
aon	30K	Bumbita Arapesh	5K	Oceania	Latn	aon-131	76.9	-
mpg	30K	Marba	200K	Africa	Latn	agt-6l	100	13.1
mlp	30K	Bargam	5K	Oceania	Latn	hni-81	98.4	-
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BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
kyc	30K	Kyaka	50K	Oceania	Latn	avt-121	99.2	-
huu	30K	Murui Huitoto	5K	Americas	Latn	aak-31	100	-
sll	30K	Salt-Yui	5K	Oceania	Latn	aon-131	97.6	-
quw	30K	Tena Lowland	1M	Americas	Latn	quw-51	99.9	-
•		Ouichua				-		
bkq	30K	Bakairí	5K	Americas	Latn	abr-51	99.2	-
yaf	30K	Yaka-Pelende-	900K	Africa	Latn	jbu-81	99.6	27.3
<i>y</i>		Lonzo				3 · · · ·		
ncl	30K	Michoacán Nahu-	5K	Americas	Latn	azz-71	98.8	-
		atl						
sgb	30K	Mag-Anchi Ayta	5K	Asia	Latn	kqp-41	100	-
rop	30K	Kriol	5K	Oceania	Latn	bg-Latn-51	99.7	-
rkb	30K	Rikbaktsa	5K	Americas	Latn	apy-71	99.2	-
kqc	30K	Doromu-Koki	5K	Oceania	Latn	adz-31	99.5	_
kew	30K	West Kewa	50K	Oceania	Latn	aau-141	95.4	11.5
snp	30K	Siane	50K	Oceania	Latn	knj-81	100	_
cjp	30K	Cabécar	5K	Americas	Latn	cip-41	100	_
viv	30K	Iduna	5K	Oceania	Latn	aui-141	99.5	_
sim	30K	Mende (Papua	5K	Oceania	Latn	apb-131	98.2	_
51111	3011	New Guinea)	311	Occama	Latin	аро-131	70.2	
xsm	30K	Kasem	200K	Africa	Latn	lia-31	100	12.2
iws	30K	Sepik Iwam	5K	Oceania	Latn	avt-121	98.8	-
amm	30K	Ama (Papua New	5K	Oceania	Latn	amm	99.4	_
anni	JOK	Guinea)	JK	Occama	Latii	aiiiii)). T	_
onm	30K	Oksapmin	5K	Oceania	Latn	51	98.8	_
opm	30K	Kaiwá	50K	Americas	Latn	agg-51	98.8	-
kgk						gn-6l		
mta	30K	Cotabato Manobo	50K	Asia	Latn	mta	100	17.0
bef	30K	Benabena	50K	Oceania	Latn	avt-121	99.7	12.2
ura	30K	Urarina	5K	Americas	Latn	bmr-31	100	-
tim	30K	Timbe	50K	Oceania	Latn	bom-51	99.9	-
ife	30K	Ifè	100K	Africa	Latn	ife	99.9	18.7
gqr	30K	Gor	50K	Africa	Latn	dzg-51	93.0	-
haz	30K	Hazaragi	2M	Asia	Arab	fay-141	13.9	57.8
row	30K	Dela-Oenale	5K	Asia	Latn	bhw-91	98.6	-
lcm	30K	Tungag	50K	Oceania	Latn	apb-131	97.0	-
wos	30K	Hanga Hundi	5K	Oceania	Latn	aau-141	99.5	-
agn	30K	Agutaynen	50K	Asia	Latn	agn-141	99.9	-
lew	30K	Ledo Kaili	400K	Asia	Latn	kzf-31	100	18.0
mbc	30K	Macushi	50K	Americas	Latn	mbc	100	-
byx	30K	Qaqet	5K	Oceania	Latn	acn-111	97.7	-
apz	30K	Safeyoka	5K	Oceania	Latn	amp-121	99.2	-
qxn	30K	Northern Conchu-	200K	Americas	Latn	qub-71	99.1	18.2
		cos Ancash						
		Quechua			_			
rgu	30K	Ringgou	50K	Asia	Latn	bhw-91	98.0	-
for	30K	Fore	50K	Oceania	Latn	awb-41	99.7	-
sny	30K	Saniyo-Hiyewe	5K	Oceania	Latn	amp-121	97.1	-
mop	30K	Mopán Maya	5K	Americas	Latn	chd-61	100	-
men	30K	Mende (Sierra	3M	Africa	Latn	men	100	20.8
		Leone)						
arl	30K	Arabela	5K	Americas	Latn	arl	100	-
hvn	30K	Hawu	100K	Asia	Latn	aom-101	100	15.8
bba	30K	Baatonum	600K	Africa	Latn	bas-111	100	17.0
des	30K	Desano	5K	Americas	Latn	des-41	99.9	-
tue	30K	Tuyuca	5K	Americas	Latn	cbc-21	100	-
ino	30K	Inoke-Yate	50K	Oceania	Latn	ata-51	100	-
tod	30K	Toma	200K	Africa	Latn	moa-21	100	16.9
ots	30K	Estado de México	50K	Americas	Latn	kcg-91	99.9	-
		Otomi				J		
bpr	30K	Koronadal Blaan	200K	Asia	Latn	bpr-71	97.3	13.6
aau	30K	Abau	5K	Oceania	Latn	aau-141	98.2	-
khz	30K	Keapara	50K	Oceania	Latn	gah-111	97.6	-
bum	30K	Bulu (Cameroon)	900K	Africa	Latn	bas-111	98.6	29.9
aer	30K	Eastern Arrernte	5K	Oceania	Latn	aer	100	-
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BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
azz	30K	Highland Puebla Nahuatl	200K	Americas	Latn	azz-71	99.7	13.5
dah	30K	Gwahatike	5K	Oceania	Latn	aon-131	97.2	_
yml	30K	Iamalele	5K	Oceania	Latn	fj-41	99.7	-
bzh	30K	Mapos Buang	50K	Oceania	Latn	apb-131	97.5	-
kgp	30K	Kaingang	50K	Americas	Latn	bzj-9l	100	-
tpz	30K	Tinputz	5K	Oceania	Latn	ach-101	99.3	-
bex	30K	Jur Modo	50K	Africa	Latn	bbo-31	100	11.0
mek	30K	Mekeo	50K	Oceania	Latn	fj-41	99.1	-
sbl	30K	Botolan Sambal	50K	Asia	Latn	kqp-41	100	23.0
uvl	30K	Lote	5K	Oceania	Latn	ata-51	98.4	-
abx	30K	Inabaknon	50K	Asia	Latn	abx-111	96.4	-
ese	30K	Ese Ejja	5K	Americas	Latn	ese-21	100	-
mcb	30K	Machiguenga	5K	Americas	Latn	apu-131	100	-
pma	30K	Paama	5K	Oceania	Latn	ktm-41	99.4	15.6
qvm	30K	M-Y-L Quechua	50K	Americas	Latn	qub-71	99.6	15.6
mbj	30K 30K	Nadëb	5K 200K	Americas Africa	Latn Latn	bgp-131	99.2 100	- 16.8
gso chd	30K	Southwest Gbaya Highland Oaxaca	200K 5K	Americas	Latn	bas-111 chd-61	99.6	10.6
Cita	30K	Chontal	JK	Americas	Latti	Clid-61	99.0	-
SSX	30K	Samberigi	5K	Oceania	Latn	aui-141	99.9	-
zaa	30K	Sierra de Juárez Zapotec	5K	Americas	Latn	zaa-51	100	-
bqp	30K	Busa	50K	Africa	Latn	akp-41	99.7	_
kgf	30K	Kulungtfu-	5K	Oceania	Latn	kgf-41	99.6	_
C		Yuanggeng-Tobo						
tvk	30K	Southeast Am-	5K	Oceania	Latn	gaw-81	99.1	-
pah	30K	brym Tenharim-	5K	Americas	Latn	gn-6l	99.7	-
		Parintintin-Diahoi						
mog	30K	Mongondow	200K	Asia	Latn	awb-41	100	18.6
zas	30K	Santo Domingo Al-	5K	Americas	Latn	jic-31	100	-
zpl	30K	barradas Zapotec Lachixío Zapotec	5K	Americas	Latn	cbr-6l	99.4	_
pib	30K	Yine Zapotec	5K	Americas	Latn	pib	71.2	_
omw	30K	South Tairora	50K	Oceania	Latn	amp-121	99.9	_
faa	30K	Fasu	5K	Oceania	Latn	apr-81	99.6	_
dob	30K	Dobu	100K	Oceania	Latn	aui-14l	99.1	13.2
dnw	30K	Western Dani	200K	Asia	Latn	bmu-6l	100	13.5
gor	30K	Gorontalo	1M	Asia	Latn	bco-81	100	18.4
hak	30K	Hakka Chinese	30M	Asia	Latn	cdo-51	91.6	28.0
poe	30K	San Juan Atzingo	5K	Americas	Latn	mix-41	99.5	-
	30K	Popoloca Gwich'in	5K	A	T 4	21	00.0	
gwi	30K	Napu	5K	Americas Asia	Latn Latn	agr-31	99.9 100	-
npy kpr	30K	Korafe-Yegha	5K	Oceania	Latn	gah-111 aom-101	97.6	-
vid	30K	Vidunda	50K	Africa	Latn	cwe-101	100	17.1
yva	30K	Yawa	50K	Asia	Latn	wnc-31	100	-
llg	30K	Lole	50K	Asia	Latn	bhw-91	94.6	_
sps	30K	Saposa	5K	Oceania	Latn	apb-131	97.3	_
wmw	30K	Mwani	100K	Africa	Latn	bep-41	99.5	19.9
mif	30K	Mofu-Gudur	50K	Africa	Latn	meq-31	100	16.1
fuf	30K	Pular	3M	Africa	Latn	aa-131	99.9	20.9
kbq	30K	Kamano	50K	Oceania	Latn	aau-141	98.8	11.8
fuv	30K	Nigerian Fulfulde	12M	Africa	Latn	aa-131	98.1	-
ptu	30K	Bambam	50K	Asia	Latn	atq-21	99.7	-
pri	30K	Paicî	5K	Oceania	Latn	ae-Latn-101	97.2	-
en-Deva	30K	English	550M	Europe	Deva	awa-141	97.1	75.9
ymm	30K	Maay	3M	Africa	Latn	aa-131	99.8	-
bmh	30K	Kein	5K	Oceania	Latn	acn-111	98.1	-
zpo	30K	Amatlán Zapotec	50K	Americas	Latn	zaa-51	88.4	- 20 6
smk	30K	Bolinao	50K	Asia	Latn	br-41	99.0	28.6
amp mic	30K 30K	Alamblak Mi'kmaq	5K 5K	Oceania Americas	Latn Latn	amp-121 hni-81	97.6 100	-
	1	1					0	

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
gkn	30K	Gokana	50K	Africa	Latn	bcq-Latn- 121	100	22.4
cbs	30K	Cashinahua	5K	Americas	Latn	cbs	100	-
gvc	30K	Kotiria	5K	Americas	Latn	des-41	100	-
xla	30K	Kamula	5K	Oceania	Latn	ktm-41	99.6	-
sab	30K	Buglere	50K	Americas	Latn	sab	100	-
spp	30K	Supyire Senoufo	500K	Africa	Latn	spp	100	12.0
gvn	30K	Kuku-Yalanji	5K	Oceania	Latn	gvn-61	99.6	-
trc	30K	Copala Triqui	50K	Americas	Latn	cut-51	88.0	-
thk	30K	Tharaka	200K	Africa	Latn	thk	100	20.9
poy	30K	Pogolo	200K	Africa	Latn	dov-91	100	15.7
gej	30K	Gen	300K	Africa	Latn	gej-41	100	24.1
aak	30K	Ankave	5K	Oceania	Latn	aak-31	100	-
rnl	30K	Halam	5K	Asia	Latn	akb-41	100	-
kpf	30K	Komba	50K	Oceania	Latn	avt-121	98.6	-
ghs ·	30K	Guhu-Samane	50K	Oceania	Latn	agg-51	99.2	-
ajg	30K	Aja (Benin)	600K	Africa	Latn	ajg-81	99.8	29.7
bmu	30K 30K	Burum-Mindik	5K	Oceania Africa	Latn	bmu-6l	97.4	16.3
fuq	30K	Central-Eastern Niger Fulfulde	500K	Апса	Latn	aa-131	100	10.3
gvf	30K	Golin	50K	Oceania	Latn	aon-131	98.2	12.6
cbv	30K	Kakua	5K	Americas	Latn	cbv-61	100	-
ake	30K	Akawaio	50K	Americas	Latn	ake	100	-
usp	30K	Uspanteco	5K	Americas	Latn	acr-41	100	-
kpj	30K	Karajá	5K	Americas	Latn	kpj-51	98.6	-
mtp	30K	Wichí Lhamtés Nocten	5K	Americas	Latn	kqp-41	100	-
tku	30K	Upper Necaxa To- tonac	5K	Americas	Latn	tku-21	99.6	-
wnc	30K	Wantoat	5K	Oceania	Latn	wnc-31	99.8	-
sgw	30K	Sebat Bet Gurage	1M	Africa	Ethi	gez-81	99.2	35.6
pwg	20K	Gapapaiwa	5K	Oceania	Latn	asg-101	97.7	-
huv	20K	San Mateo del Mar Huave	50K	Americas	Latn	huv	100	-
tly-Cyrl- RU	20K	North-Central Talysh	900K	Europe	Cyrl	az-RU-131	99.8	28.7
kmu	20K	Kanite	5K	Oceania	Latn	gah-111	99.9	_
bhb	20K	Bhili	3M	Asia	Deva	awa-14l	100	44.2
ljp	20K	Lampung Api	800K	Asia	Latn	hui-31	100	25.3
wrs	20K	Waris	5K	Oceania	Latn	acn-111	98.7	-
ttc	20K	Tektiteko	5K	Americas	Latn	azz-71	100	_
myb	20K	Mbay	50K	Africa	Latn	kpj-51	99.1	14.2
mhx	20K	Maru	50K	Asia	Latn	lsi-21	100	15.9
knv	20K	Tabo	5K	Oceania	Latn	bco-81	99.9	_
mbl	20K	Maxakalí	5K	Americas	Latn	arn-61	99.3	_
nhi	20K	Zacatlán-	50K	Americas	Latn	bjr-4l	98.7	
		Ahuacatlán- Tepetzintla Nahu-						
41	2017	atl	5017		т.		100	
tby	20K	Tabaru	50K	Asia	Latn	gbi-81	100	-
soq	20K	Kanasi	5K	Oceania	Latn	acn-111	98.8	-
agg	20K	Angor	5K	Oceania	Latn	agg-51	99.0	-
kwd	20K	Kwaio	50K	Oceania	Latn	knj-81	99.9	
ssg	20K	Seimat	5K	Oceania	Latn	gaw-81	96.3	
zaj abr	20K 20K	Zaramo Ahirani	5K 2M	Africa Asia	Latn	cwe-101	99.2 99.1	- 32 3
ahr pmf	20K 20K	Anirani Pamona	2M 100K	Asia Asia	Deva Latn	ahr-131	100	32.3 14.2
pmf	20K 20K	Coatlán Mixe	50K	Asia Americas	Latn Latn	pmf-21	100	
mco tva	20K 20K	Tii	50K 50K	Americas Asia	Lain Latn	dyo-31 bhw-91	94.5	-
txq lif	20K 20K	Limbu	800K	Asia Asia		lif	94.3	-
	20K 20K	Yucuna	800K 5K	Asia Americas	Deva Latn	111 acu-81	100	-
yen kln	20K 20K	Kalenjin	9M	Africa	Latn	cro-31	99.9	12.5
XSU	20K 20K	Sanumá	5K	Americas	Latn	XSU	100	12.3
nus	20K 20K	Nuer	900K	Africa	Latn	din-31	100	22.8
iius	201	11001	JOOK	minea	Latti	um-31	100	22.0

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
nak	20K	Nakanai	50K	Oceania	Latn	bch-101	98.9	-
lid	20K	Nyindrou	5K	Oceania	Latn	gaw-81	99.2	-
spl	20K	Selepet	5K	Oceania	Latn	gah-111	99.5	-
aom	20K	Ömie	5K	Oceania	Latn	aom-101	99.9	-
nhg	20K	Tetelcingo Nahuatl	5K	Americas	Latn	nhg-31	100	-
cpu	20K	Pichis Ashéninka	50K	Americas	Latn	apu-131	96.9	13.3
muh	20K	Mündü	50K	Africa	Latn	muh	100	-
nmz	20K	Nawdm	200K	Africa	Latn	amf-61	99.9	14.7
taj	20K	Eastern Tamang	300K	Asia	Deva	taj-21	100	18.3
nca	20K	Iyo	5K	Oceania	Latn	kgf-41	99.3	-
ik	20K	Alaskan Inupiaq	5K	Americas	Latn	bla-71	99.6	_
gam	20K	Kandawo	5K	Oceania	Latn	gam-31	99.1	_
kue	20K	Kuman	100K	Oceania	Latn	agt-61	99.1	13.1
bbr	20K	Girawa	5K	Oceania	Latn	acn-111	96.0	-
roo	20K	Rotokas	5K	Oceania	Latn	amp-121	91.7	_
big	20K	Biangai	50K	Oceania	Latn	big-51	100	_
dip	20K	Northeastern	5M	Africa	Latn	din-31	100	14.9
r		Dinka						,
aeb-Latn	20K	Tunisian Arabic	11M	Africa	Latn	aeb-Latn- 111	76.9	15.4
lee	20K	Lyélé	100K	Africa	Latn	lee	99.6	12.4
bgs	20K	Tagabawa	50K	Asia	Latn	bgs-91	92.3	-
apb	20K	Sa'a	50K	Oceania	Latn	apb-131	99.5	-
kmh	20K	Kalam	50K	Oceania	Latn	dtb-41	99.5	_
soy	20K	Miyobe	50K	Africa	Latn	soy	100	-
gfk	20K	Patpatar	5K	Oceania	Latn	acn-111	98.4	_
nvm	20K	Namiae	5K	Oceania	Latn	dgz-51	99.1	-
bgr	20K	Bawm Chin	50K	Asia	Latn	bgr-6l	100	-
gnn	20K	Gumatj	5K	Oceania	Latn	bch-10l	100	_
qxo	20K	Southern Conchu-	900K	Americas	Latn	qub-71	98.9	17.1
q.r.o	2011	cos Ancash Quechua	,,,,,,,,	1111011045	2	quo /1	,,,,	1,,12
cbr	20K	Cashibo- Cacataibo	5K	Americas	Latn	cbr-6l	100	-
bhl	20K	Bimin	5K	Oceania	Latn	aey-61	99.6	-
amr	20K	Amarakaeri	5K	Americas	Latn	amr	100	-
kde	20K	Makonde	1M	Africa	Latn	cwe-101	98.3	24.4
zad	20K	Cajonos Zapotec	5K	Americas	Latn	ctp-41	100	-
bps	20K	Sarangani Blaan	200K	Asia	Latn	bpr-71	97.4	15.3
mks	20K	Silacayoapan Mix- tec	50K	Americas	Latn	mks	99.6	-
muy	20K	Muyang	50K	Africa	Latn	dgc-61	100	12.8
ncu	20K	Chumburung	50K	Africa	Latn	ncu	100	15.0
stn	20K	Owa	5K	Oceania	Latn	apr-81	100	-
sd-Deva	20K	Sindhi	68M	Asia	Deva	bfz-151	98.3	34.4
hub	20K	Huambisa	5K	Americas	Latn	acu-81	98.8	-
cpb	20K	Ucayali-Yurúa Ashéninka	5K	Americas	Latn	apu-131	97.0	14.2
mio	20K	Pinotepa Nacional Mixtec	50K	Americas	Latn	cta-41	100	-
chz	20K	Ozumacín Chinan- tec	5K	Americas	Latn	chz-9l	100	-
aia	20K	Arosi	5K	Oceania	Latn	aia	100	-
ian	20K	Iatmul	5K	Oceania	Latn	agg-51	99.9	-
way	20K	Wayana	5K	Americas	Latn	way	100	-
ndz	20K	Ndogo	50K	Africa	Latn	bcq-Latn- 121	100	-
agd	20K	Agarabi	50K	Oceania	Latn	acn-111	98.5	-
mcp	20K	Makaa	50K	Africa	Latn	mcp	100	15.0
wbp	20K	Warlpiri	5K	Oceania	Latn	gvn-6l	99.9	-
mox	20K	Molima	5K	Oceania	Latn	aui-141	96.2	-
tbc	20K	Takia	50K	Oceania	Latn	aau-141	97.7	12.4
sxb	20K	Suba	100K	Africa	Latn	cgg-151	99.9	25.0
kbm	20K	Iwal	5K	Oceania	Latn	gam-31	99.8	-

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
bon	20K	Bine	5K	Oceania	Latn	bon	99.7	-
pls	20K	San Marcos Tlal- coyalco Popoloca	50K	Americas	Latn	knj-81	100	-
vmy	20K	Ayautla Mazatec	5K	Americas	Latn	nhr-21	98.6	-
nop	20K	Numanggang	5K	Oceania	Latn	aau-141	98.7	_
qvn	20K	North Junín Quechua	50K	Americas	Latn	qvn	100	17.1
cgc	20K	Kagayanen	50K	Asia	Latn	cgc-21	100	22.4
kwj	20K	Kwanga	50K	Oceania	Latn	avt-121	97.3	-
kcg	20K	Tyap	100K	Africa	Latn	kcg-91	100	13.9
enx	20K	Southern Lengua	5K	Americas	Latn	enx-41	99.0	-
mfy	20K	Mayo	50K	Americas	Latn	ese-21	99.9	_
aby	20K	Aneme Wake	5K	Oceania	Latn	aby-41	100	_
cco	20K	Comaltepec Chinantec	50K	Americas	Latn	cco	100	-
boa	20K	Bora	5K	Americas	Latn	boa	100	-
ikw	20K	Ikwere	200K	Africa	Latn	anw-81	99.9	20.1
lmn-	20K	Lambadi	6M	Asia	Knda	lmn-Knda-	100	33.3
Knda						21		
rai	20K	Ramoaaina	50K	Oceania	Latn	apb-131	95.9	-
leu	20K	Kara (Papua New Guinea)	5K	Oceania	Latn	apb-131	99.1	-
sue	20K	Suena	5K	Oceania	Latn	avt-121	99.6	-
auc	20K	Waorani	5K	Americas	Latn	auc-61	100	-
kdc	20K	Kutu	50K	Africa	Latn	cwe-101	97.7	19.1
awb	20K	Awa (Papua New	5K	Oceania	Latn	awb-41	99.9	-
		Guinea)						
kpw	20K	Kobon	50K	Oceania	Latn	aon-131	99.6	-
mux	20K	Bo-Ung	50K	Oceania	Latn	gbi-81	99.5	11.2
mqb	20K	Mbuko	50K	Africa	Latn	blw-21	100	-
kne	20K	Kankanaey	200K	Asia	Latn	bnc-81	100	25.7
blz	20K	Balantak	50K	Asia	Latn	bjp-4l	100	14.2
vmw	20K	Makhuwa	3M	Africa	Latn	apu-131	99.9	16.2
tcs	20K	Torres Strait Cre- ole	5K	Oceania	Latn	bg-Latn-51	99.4	-
mie	20K	Ocotepec Mixtec	50K	Americas	Latn	mie	99.9	-
mhy	20K	Ma'anyan	200K	Asia	Latn	amo-71	99.5	34.7
btd	20K	Batak Dairi	1M	Asia	Latn	aom-101	100	21.5
lem	20K	Nomaande	5K	Africa	Latn	box-31	100	-
hop	20K	Hopi	5K	Americas	Latn	hop	99.9	-
ken	20K	Kenyang	50K	Africa	Latn	ken-31	97.3	-
ssd	20K	Siroi	5K	Oceania	Latn	bch-101	99.1	-
kms	20K	Kamasau	5K	Oceania	Latn	cwt-41	97.4	-
yuw	20K	Yau (Morobe Province)	5K	Oceania	Latn	amp-121	97.6	-
agt	20K	Central Cagayan Agta	5K	Asia	Latn	agt-61	97.6	-
maj	20K	Jalapa De Díaz Mazatec	50K	Americas	Latn	kcg-91	100	-
tpm	20K	Tampulma	50K	Africa	Latn	sil-31	100	-
khs	20K	Kasua	5K	Oceania	Latn	aui-141	99.9	-
kzf	20K	Da'a Kaili	400K	Asia	Latn	kzf-31	100	16.6
ign	20K	Ignaciano	50K	Americas	Latn	acu-81	100	11.3
mwv	20K	Mentawai	50K	Asia	Latn	bjp-4l	100	14.7
cul	20K	Culina	5K	Americas	Latn	cul	100	-
apu	20K	Apurinã	5K	Americas	Latn	apu-131	99.9	-
nej	20K	Northern Puebla Nahuatl	50K	Americas	Latn	bjr-41	100	18.6
xnn	20K	Northern Kankanay	50K	Asia	Latn	bnc-81	99.2	24.4
bvd	20K	Baeggu	5K	Oceania	Latn	bvc-41	99.1	-
nko	20K	Nkonya	50K	Africa	Latn	ktj-61	100	-
cwe	20K	Kwere	50K	Africa	Latn	cwe-101	97.6	21.7
tap	20K	Taabwa	300K	Africa	Latn	tap	100	23.5

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
wrk	20K	Garrwa	5K	Oceania	Latn	wrk	100	-
gah	20K	Alekano	50K	Oceania	Latn	gah-111	97.6	-
yam	20K	Yamba	50K	Africa	Latn	pny-21	100	7.0
geb	20K	Kire	5K	Oceania	Latn	bmu-6l	100	-
ctp	20K	Western Highland Chatino	50K	Americas	Latn	ctp-41	83.9	-
mbs	20K	Sarangani Manobo	50K	Asia	Latn	mbb-31	99.6	16.0
nlg	20K	Gela	50K	Oceania	Latn	bgt-41	99.0	-
nsn	20K	Nehan	5K	Oceania	Latn	bgt-41	99.4	-
bao	20K	Waimaha	5K	Americas	Latn	bao	99.7	-
cle	20K	Lealao Chinantec	5K	Americas	Latn	chz-91	100	-
mvn	20K	Minaveha	5K	Oceania	Latn	gah-111	98.2	-
tpt	20K	Tlachichilco Tepe- hua	5K	Americas	Latn	gam-31	100	-
zyp	20K	Zyphe	50K	Asia	Latn	arn-61	99.9	-
pio	20K	Piapoco	5K	Americas	Latn	pio	100	-
bgx-Latn	20K	Rumelian Turkish	300K	Europe	Latn	aeb-Latn- 111	95.6	59.5
myx	20K	Masaaba	3M	Africa	Latn	cgg-151	99.8	25.0
tsz	20K	Purepecha	50K	Americas	Latn	apu-131	100	15.2
dww	20K	Dawawa	5K	Oceania	Latn	abt-31	98.3	-
gnw	20K	Western Bolivian Guaraní	5K	Americas	Latn	gnw	100	-
ksr	20K	Borong	5K	Oceania	Latn	kpj-51	98.5	-
otn	20K	Tenango Otomi	50K	Americas	Latn	kcg-91	100	15.1
gdn	20K	Umanakaina	5K	Oceania	Latn	asg-101	99.5	-
kmo	20K	Kwoma	5K	Oceania	Latn	abt-31	100	_
nii	20K	Nii	50K	Oceania	Latn	nii	100	_
tsw	20K	Salka-Tsishingini	200K	Africa	Latn	asg-101	98.1	15.9
not	20K	Nomatsiguenga	5K	Americas	Latn	cot-21	100	-
ury	20K	Orya	5K	Asia	Latn	bzj-91	100	_
anv	20K	Denya	50K	Africa	Latn	anv	100	_
pbc	20K	Patamona	50K	Americas	Latn	pbc	100	_
blt-Latn	20K	Tai Dam	800K	Asia	Latn	blt-Latn-41	99.7	24.4
aii	20K	Assyrian Neo- Aramaic	800K	Europe	Syrc	ach-101	100	35.7
mhl	20K	Mauwake	5K	Oceania	Latn	aon-131	65.5	_
myk	20K	Mamara Senoufo	700K	Africa	Latn	myk	100	13.2
mee	20K	Mengen	5K	Oceania	Latn	ata-51	99.8	-
kpx	20K	Mountain Koiali	5K	Oceania	Latn	apr-81	99.1	_
udu	20K	Uduk	50K	Africa	Latn	knj-81	100	_
mnp	20K	Min Bei Chinese	10M	Asia	Latn	cdo-51	99.8	16.2
alp	20K	Alune	50K	Asia	Latn	alp-21	100	_
wiu	20K	Wiru	50K	Oceania	Latn	gbi-81	99.0	_
gyr	20K	Guarayu	5K	Americas	Latn	gn-6l	100	-
meq	20K	Merey	50K	Africa	Latn	meq-31	100	-
kjs	20K	East Kewa	50K	Oceania	Latn	aau-141	95.3	11.4
mcq	20K	Ese	50K	Oceania	Latn	acn-111	96.7	-
ong	20K	Olo	50K	Oceania	Latn	kpz-21	99.9	-
tnn	20K	North Tanna	5K	Oceania	Latn	nwi-51	99.9	
coe	20K	Koreguaje	5K	Americas	Latn	coe	99.9	
hrx	20K	Hunsrik	3M	Americas	Latn	hrx-21	99.6	
tte	20K	Bwanabwana	5K	Oceania	Latn	aui-141	98.3	-
yut	20K	Yopno	5K	Oceania	Latn	dtb-41	99.2	_
sgz	20K	Sursurunga	5K	Oceania	Latn	apb-131	97.7	
ceg	20K	Chamacoco	5K	Americas	Latn	ceg-51	100	_
qul	20K	North Bolivian Quechua	100K	Americas	Latn	ae-Latn-101	99.6	20.9
mvp	20K	Duri	100K	Asia	Latn	kje-61	99.7	14.4
xed	20K	Hdi	50K	Africa	Latn	cko-51	100	-
bqj	20K	Bandial	50K	Africa	Latn	bkv-41	99.6	
duo	20K	Dupaninan Agta	5K	Asia	Latn	dgc-61	99.5	
mza	20K	Santa María Za-	5K	Americas	Latn	mpm-41	99.6	
		catepec Mixtec			-			

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
mva	20K	Manam	5K	Oceania	Latn	gah-111	97.7	-
akh	20K	Angal Heneng	50K	Oceania	Latn	aau-141	97.8	12.0
blw	20K	Balangao	50K	Asia	Latn	blw-21	92.5	-
luy	20K	Luhya	1M	Africa	Latn	cgg-151	99.7	20.6
mnb	20K	Muna	300K	Asia	Latn	ata-51	100	13.5
nou	20K	Ewage-Notu	50K	Oceania	Latn	aom-101	99.9	-
ebk	20K	Eastern Bontok	50K	Asia	Latn	bnc-81	97.7	-
tpp	20K	Pisaflores Tepehua	5K	Americas	Latn	tee-21	100	-
wim	20K	Wik-Mungkan	5K	Oceania	Latn	beu-21	99.9	-
avt	20K	Au	5K	Oceania	Latn	avt-121	98.3	_
blh	20K	Kuwaa	50K	Africa	Latn	bcq-Latn- 121	100	-
mfi	20K	Wandala	50K	Africa	Latn	acu-81	100	13.5
eri	20K	Ogea	5K	Oceania	Latn	agt-61	98.3	-
mpt	20K	Mian	5K	Oceania	Latn	amp-121	98.1	_
swp	20K	Suau	5K	Oceania	Latn	apb-131	99.4	_
nho	20K	Takuu	5K	Oceania	Latn	bgt-41	96.0	_
aso	20K	Dano	50K	Oceania	Latn	aso	100	11.6
wnu	20K	Usan	5K	Oceania	Latn	amp-121	96.7	-
zav	20K	Yatzachi Zapotec	5K	Americas	Latn	cut-51	100	_
bcw	20K	Bana	50K	Africa	Latn	bcw-31	100	_
dgz	20K	Daga	5K	Oceania	Latn	dgz-51	99.8	_
ipi	20K	Ipili	50K	Oceania	Latn	gbi-81	99.5	_
nsu	20K	Sierra Negra Nahu-	50K	Americas	Latn	nhy-31	99.5	_
nsu	2010	atl	3010	Timericas	Latii	IIIIy-31	77.5	_
urt	20K	Urat	5K	Oceania	Latn	aey-61	99.1	-
obo	20K	Obo Manobo	50K	Asia	Latn	atd-41	100	16.1
zpi	20K	Santa María	5K	Americas	Latn	zaa-51	100	_
1		Quiegolani Za- potec						
sat-Deva	20K	Santali	6M	Asia	Deva	bho-131	98.1	_
cjv	20K	Chuave	50K	Oceania	Latn	bom-51	97.5	_
ifu	20K	Mayoyao Ifugao	50K	Asia	Latn	bnc-81	100	_
atg	20K	Ivbie North-	50K	Africa	Latn	ajg-81	100	_
atg	2011	Okpela-Arhe	3011	Milica	Latii	ajg-oi	100	
icr	20K	San Andres Creole	50K	Americas	Latn	bzj-91	100	-
neb	20K	English Toura (Côte	50K	Africa	Latn	avn-31	100	8.9
		d'Ivoire)						
apr	20K	Arop-Lokep	5K	Oceania	Latn	apr-81	99.2	-
aoz	20K	Uab Meto	800K	Asia	Latn	aaz-61	100	15.5
mca	20K	Maca	5K	Americas	Latn	hrx-21	100	-
tiy	20K	Tiruray	50K	Asia	Latn	cjp-4l	100	13.2
gdr	20K	Wipi	5K	Oceania	Latn	aon-131	98.4	-
kqw	20K	Kandas	5K	Oceania	Latn	apb-131	93.8	-
zaw	20K	Mitla Zapotec	50K	Americas	Latn	toj-41	100	-
atq	20K	Aralle-Tabulahan	50K	Asia	Latn	atq-21	99.9	-
ruf	20K	Luguru	700K	Africa	Latn	cwe-101	100	17.3
kje	20K	Kisar	50K	Asia	Latn	kje-6l	100	-
fai	20K	Faiwol	5K	Oceania	Latn	bnj-61	99.8	-
zpq	20K	Zoogocho Zapotec	5K	Americas	Latn	cut-51	100	-
men	20K	Masana	200K	Africa	Latn	dzg-51	50.7	47.6
nlc	20K	Nalca	50K	Asia	Latn	mps-31	100	-
yby	20K	Yaweyuha	5K	Oceania	Latn	aau-141	97.6	-
pao	20K	Northern Paiute	5K	Americas	Latn	chq-31	99.9	
mcu	20K	Donga Mambila	50K	Africa	Latn	mcu-21	100	7.6
kbc	20K	Kadiwéu	5K	Americas	Latn	etr-21	100	-
djr	20K	Djambarrpuyngu	5K	Oceania	Latn	bch-101	100	-
zae	20K	Yareni Zapotec	5K	Americas	Latn	rmc-31	100	-
wer	20K	Weri	50K	Oceania	Latn	acn-111	99.2	-
maw	20K	Mampruli	200K	Africa	Latn	cko-51	100	14.1
kud	20K	Auhelawa	5K	Oceania	Latn	aui-141	98.0	-
dad	20K	Marik	5K	Oceania	Latn	amp-121	94.4	-

Ignaciano Chiquitano	100 98.6 97.2 100 100 97.6 100 100	31.9 15.4 16.5 - 10.9 12.3
tano 20K Ono 50K Oceania Latn kgf-4l wuv 20K Wuvulu-Aua 5K Oceania Latn aom-10l gay 20K Gayo 300K Asia Latn abs-13l gng 20K Ngangam 50K Africa Latn ada-13l nim 20K Nilamba 700K Africa Latn ess-4l snc 20K Sinaugoro 50K Oceania Latn gah-11l	98.6 97.2 100 100 97.6 100 100	31.9 15.4 16.5 -
ons 20K Ono 50K Oceania Latn kgf-4l wuv 20K Wuvulu-Aua 5K Oceania Latn aom-10l gay gay 20K Gayo 300K Asia Latn abs-13l gng 20K Ngangam 50K Africa Latn ada-13l nim 20K Nilamba 700K Africa Latn ess-4l snc 20K Sinaugoro 50K Oceania Latn gah-11l	98.6 97.2 100 100 97.6 100 100	31.9 15.4 16.5 -
wuv 20K Wuvulu-Aua 5K Oceania Latn aom-10l gay 20K Gayo 300K Asia Latn abs-13l gng 20K Ngangam 50K Africa Latn ada-13l nim 20K Nilamba 700K Africa Latn ess-4l snc 20K Sinaugoro 50K Oceania Latn gah-11l	98.6 97.2 100 100 97.6 100 100	31.9 15.4 16.5 -
gay 20K Gayo 300K Asia Latn abs-131 9 gng 20K Ngangam 50K Africa Latn ada-131 nim 20K Nilamba 700K Africa Latn ess-41 snc 20K Sinaugoro 50K Oceania Latn gah-111	97.2 100 100 97.6 100 100	31.9 15.4 16.5 - 10.9
gng 20K Ngangam 50K Africa Latn ada-131 nim 20K Nilamba 700K Africa Latn ess-41 snc 20K Sinaugoro 50K Oceania Latn gah-111	100 100 97.6 100 100	15.4 16.5 - 10.9
nim 20K Nilamba 700K Africa Latn ess-4l snc 20K Sinaugoro 50K Oceania Latn gah-111	100 97.6 100 100	16.5 - 10.9
snc 20K Sinaugoro 50K Oceania Latn gah-111	97.6 100 100	- 10.9
	100 100	10.9
nhu 20K Noone 50K Africa Latn cme-51		122
	100	12.5
		-
61	99.7	-
	99.4	-
	100	13.5
	98.3	-
	100	10.3
121	99.8	-
T I I I I I I I I I I I I I I I I I I I	99.5	-
· ·	99.5	-
	99.9	13.5
	100	- 17.3
2017	100 99.3	17.3
	99.3 98.7	-
	100	_
,	100	12.6
	99.5	-
<u>-</u>	100	_
1	100	_
	99.9	-
due 15K Umiray Dumaget 5K Asia Latn dgc-61	100	-
Agta		
	98.4	24.8
	100	-
	100	-
	100	21.8
	100	-
zab 14K San Juan Guelavía 50K Americas Latn toj-4l Zapotec	99.7	-
mig 14K San Miguel El 50K Americas Latn mig	60.8	-
Grande Mixtec		
	97.6	
	99.1	-
Nagtipunan		
iry 14K Iraya 50K Asia Latn agn-14l	96.8	_
	90.8 99.9	15.9
	93.1	-
	100	_
	100	_
	100	13.4
30	100	-
nwi 14K Southwest Tanna 5K Oceania Latn nwi-51	100	-
1	98.1	-
ztq 14K Quioquitani- 5K Americas Latn gv-31 Quieri Zapotec	99.7	-
	93.9	_
	100	_
Mixtec		
	100	12.8
cnt 14K Tepetotutla Chi- 5K Americas Latn chz-91	100	-
nantec		

BCP-47	Mono	Language Name	Speak.	Cont.	Script	Clust.	F1	RTT
bdd	14K	Bunama	5K	Oceania	Latn	aui-141	97.3	-
bm-Nkoo	14K	Bambara	14M	Africa	Nkoo	bm-Nkoo-21	78.3	12.1
myw	14K	Muyuw	5K	Oceania	Latn	aon-131	97.9	-
box	14K	Buamu	200K	Africa	Latn	box-31	100	13.1
prf	13K	Paranan	50K	Asia	Latn	dgc-61	99.6	-
ziw	13K	Zigula-	400K	Africa	Latn	cwe-101	98.3	17.6
		Mushungulu						
maq	13K	Chiquihuitlán	5K	Americas	Latn	chz-91	99.9	-
		Mazatec						
yrb	13K	Yareba	5K	Oceania	Latn	aby-41	100	-
lwo	13K	Luwo	50K	Africa	Latn	chq-31	100	13.2
ozm	13K	Koonzime	50K	Africa	Latn	mcu-21	100	9.5
csk	13K	Jola-Esulalu	50K	Africa	Latn	csk-31	100	13.0
kdl	13K	Tsikimba	50K	Africa	Latn	asg-101	99.0	16.3
hno	13K	Northern Hindko	4M	Asia	Arab	bal-131	40.5	32.3
waj	13K	Waffa	5K	Oceania	Latn	waj	99.8	-
kkc	12K	Odoodee	5K	Oceania	Latn	adh-51	99.8	-
mil	12K	Peñoles Mixtec	50K	Americas	Latn	mib-21	100	-
ndj	12K	Ndamba	50K	Africa	Latn	dov-91	100	15.9
ngp	12K	Ngulu	100K	Africa	Latn	cwe-101	98.3	16.3
okv	11K	Orokaiva	50K	Oceania	Latn	aom-101	99.1	14.6
nnq	11K	Ngindo	200K	Africa	Latn	nnq-41	99.9	13.9
grt	11K	Garo	1M	Asia	Beng	bpy-71	100	-
psh	11K	Southwest Pashayi	50K	Asia	Arab	fay-141	15.5	38.0
hnd	11K	Southern Hindko	600K	Asia	Arab	bal-131	17.3	-
tgp	11K	Movono	5K	Oceania	Latn	akb-41	100	-
tbo	10K	Tawala	50K	Oceania	Latn	aui-141	98.5	-
bxh	9K	Buhutu	5K	Oceania	Latn	aui-141	93.2	-
mfa	7K	Kelantan-Pattani	1M	Asia	Arab	mfa-31	95.9	23.2
		Malay						