`MADLAD-400`: A Multilingual And Document-Level Large Audited Dataset

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Abstract

We introduce `MADLAD-400`, a manually audited, general domain 3T token monolingual dataset based on CommonCrawl, spanning 419 languages. We discuss the limitations revealed by self-auditing `MADLAD-400`, and the role data auditing had in the dataset creation process. We then train and release a 10.7B-parameter multilingual machine translation model on 250 billion tokens covering over 450 languages using publicly available data, and find that it is competitive with models that are significantly larger, and report the results on different domains. In addition, we train a 8B-parameter language model, and assess the results on few-shot translation. We make the baseline models [1] available to the research community.

1 Introduction

The availability of large multilingual corpora has accelerated the progress of multilingual natural language processing (NLP) models [69, 19, 47, 9, 51]. However, most publicly available general-domain multilingual corpora contain 100-200 languages [69, 51, 2], with some datasets containing more languages in specific domains such as religious content [4], children's books [45] or dialects [3].

A common approach to creating such datasets is to mine language specific data from general web crawls such as CommonCrawl [57, 43, 68] to create datasets. We simply take this approach and scale it. We train a document-level LangID model on 498 languages to obtain CommonCrawl annotations at a document level and obtain a 5-trillion token, document-level monolingual dataset.

However, such web-scale corpora are known to be noisy and contain undesirable content [53, 48, 21], with their multilingual partitions often having their own specific issues such as unusable text, misaligned and mislabeled/ambiguously labeled data [40]. To mitigate this, we manually audit our data. Based on our findings, we discard 79 of the languages from our preliminary dataset, rename or combine several languages and apply additional preprocessing steps. Finally, to validate the efficacy of our dataset, we train multilingual machine translation models of various sizes up to 10.7B parameters, as well as an 8B decoder-only model, and then evaluate these models on highly multilingual translation evaluation sets.

In Section 2, we describe the creation and composition of `MADLAD-400`, and discuss the results of the audit. Then, in Section 3, we describe the parallel data we collect using publicly available sources to train the multilingual machine translation models described in Section 4.1. In Section 4, we describe the training process of the multilingual machine translation models and 8B decoder-only model, and then evaluate these models on highly multilingual translation datasets. In Section 5 we describe our tests for memorization in the multilingual models that we release and discuss preliminary results. Finally, we discuss the limitations of this work and directions for future work.

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[1] https://github.com/google-research/google-research/tree/master/madlad_400
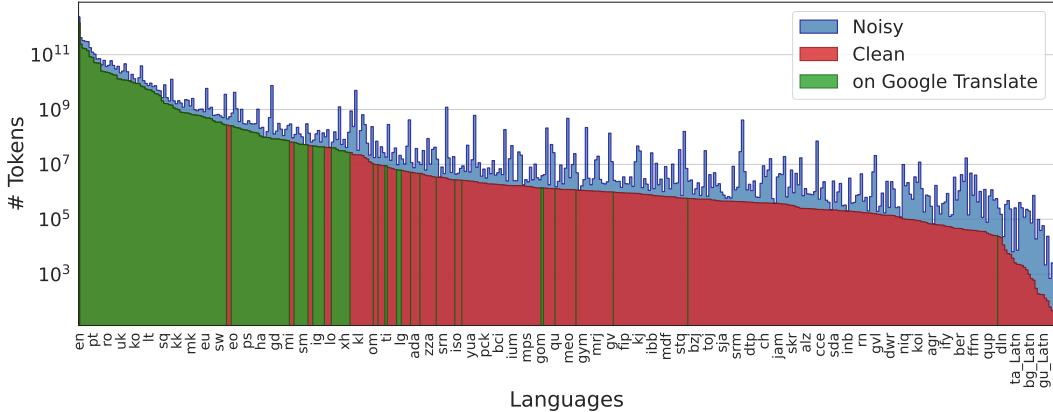
Figure 1: **Comparing the size of the noisy and clean monolingual datasets in `MADLAD-400`**. The difference is more noticeable on lower-resource languages, where noise effects are especially severe. For reference, languages supported by Google Translate are shaded in green. Note that, since this chart is in log scale, the difference in size is much greater than it may appear; for instance, for the lower-resource half of the dataset, the ratio is about 4× on median.

2 `MADLAD-400`

The process we follow to create `MADLAD-400` is similar to that of other large-scale web corpora [15, 68, 2, 51]. First, we collect as large a dataset of unlabeled web text as possible. More specifically, we use all available snapshots of CommonCrawl[2] as of August 20, 2022. After some preliminary data cleaning, we use a highly multilingual LangID model to provide document-level annotations (Section 2.2). Finally, we conduct a self-audit (Section 2.4), or quality review, of this preliminary dataset partitioned by language, and design filters to remove noisy content. When appropriate, we correct language names and remove languages from the preliminary dataset. We note that building `MADLAD-400` was an iterative process, and that while we describe one major quality review in depth, we conducted several stages of filtering. To reflect this, we describe the preprocessing steps and improvements made in chronological order.

We release two version of this dataset: a 5 trillion token `noisy` dataset, which is the dataset obtained before applying document-level LangID and the final filters, and a 3 trillion token `clean` dataset, which has a variety of filters applied based on our self-audit, though it naturally has a fair amount of noise itself. Each dataset is released in both a document-level form and a sentence-level form. Some overall statistics for these dataset versions are given in Table 2, with a graph visualizing the distribution of sizes (number of tokens) across languages in Figure 1. The final version of `MADLAD-400` has 419 languages, with a varied geographic distribution, as seen in Table 1.

Table 1: Geographic distribution of languages in `MADLAD-400`.

Continent	# Languages
Asia	149
Americas	66
Africa	87
Europe	89
Oceania	26
Constructed	2

Table 2: Overall statistics of both the `noisy` and `clean` partitions of `MADLAD-400`.

Dataset Version	# Documents		# Sentences		# Tokens	
	Total	Median	Total	Median	Total	Median
`MADLAD-400-noisy`	7.8B	27K	150B	240K	5.0T	7.1M
`MADLAD-400-clean`	4.0B	1.7K	100B	73K	2.8T	1.2M

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[2] https://commoncrawl.org/

2.1 Preliminary Filters

We carry out a few preliminary preprocessing steps on the web-crawled corpus: first, we deduplicate lines across documents [44]. Then, we filter out all pages that do not contain at least 3 lines of 200 or more characters (as done by Xue et al. [68]). We also use other commonly used filtering heuristics such as removing lines containing the word "Javascript" and removing pages that contain "lorem ipsum" and curly brackets "{" (as done by Raffel et al. [57]).

2.2 Language Identification (LangID)

We train a Semi-Supervised LangID model (SSLID) on 500 languages, following the recipe introduced by Caswell et al. [15]. We then filter the corpus on document-level LangID, which was taken to be the majority sentence-level LangID prediction. The resulting dataset is `MADLAD-400-noisy`. For the Additional details on these LangID models is in Appendix A.1.

2.3 Filtering Out Questionable Content

To assess the quality of this preliminary dataset, we inspected 20 sentences each from a subset of 30 languages in our dataset. Based on our observations, we introduced a score, `pct_questionable`. The `pct_questionable` score is simply the percentage of sentences in the input document that were "questionable". A sentence was considered questionable if any of the following were true:

1. **Document consistency:** Sentence-level LangID does not match the document-level LangID.
2. **List Case:** Over 50% percent of the tokens began in a capital letter (we apply this filter only if the sentence has at least 12 tokens.)
3. **Abnormal Lengths:** The sentence has under 20 characters or over 500 characters. We note that this is a bad heuristic for ideographic languages[3]).
4. **Technical Characters:** Over 20% of the characters in the sentence match [0-9{}+/()>].
5. **Cursed Regexes:** The sentence matched a "cursed regex". These are a heuristic set of substrings and regexes that we found accounted for a significant amount of questionable content in the data samples we observed. They are described in depth in Appendix A.2.

We removed all documents with a `percent_questionable` score greater than 20%. Furthermore, we removed any document with under 5 sentences.

2.4 Self-Audit (Quality Review)

After filtering out generally lower-quality content with the approach described above, we performed a self-audit of every corpus in this dataset, following Kreutzer et al. [40]. The aim of our self-audit was to correct any remaining systematic issues by either applying additional filters, renaming/merging language codes, or completely removing the language from the dataset. Although we do not speak most of the 498 languages, we were able to give high-level comments on the general quality. For each language, we inspected a sample of 20 documents. This task was evenly divided between the first two authors based in part on which scripts they could read. We used the following guidelines:

- If dataset is mostly plausibly in-language text, we can keep it. For unknown languages, search the web for a few sentences and look at the website and URL for language clues.
- If dataset is noisy but the noise looks filterable, leave a note of how to filter it.
- If the dataset is very noisy and does not look possible to filter, mark it for removal.
- Optionally put note that may be helpful for downstream users, e.g. if dataset is 100% Bible.

We made the decision to include languages that looked noisy, but omit any language that was majority noise, or only had 20 or fewer docs. While this is not a high quality bar, we hope it still has the potential to be useful to the research community, given that foundation models have demonstrated the potential to learn distributions for very few exammples [12]. The motivation for not releasing "nonsense" or tiny datasets is to avoid giving a false sense of how multilingual the dataset is ("Representation washing"), as recommended by **Quality at a Glance** [40].

Overall Results.   Of the 498 languages that we obtained LangID annotations for, we decided to omit 79 languages, bringing the final number of languages in `MADLAD-400` to 419. Based on

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[3]http://www.grcdi.nl/dqglossary/ideographic%20language.html

the self-audit, we also expanded the filters (particularly the cursed regexes), and made changes as described in Sections 2.5 and 2.6. We details stats for these languages in Appendix Section A.4.

For transparency, we provide full results of the self-audit in Appendix A.4. In Table 3, we provide an overview of the issues surfaced through this self-audit. We find that a significant fraction of languages contain mostly or entirely religious documents, while other issues include misrendered text, pornographic content, and boilerplate.

Table 3: Summary of results of the audit on the preliminary dataset comprising of 498 languages. Note that there may be multiple issues with data in one language.

# Languages...	
Audited	498
With significant amounts of Bible data	141
With significant amounts of JW data	37
With significant amounts of LDS data	2
With significant amounts of virama-based issues	8
With a significant number of short docs	42
With complaints about noise	28
With complaints about porn	10
With complaints about boilerplate	15
With a note to remove from the dataset	77

2.5 Additional Filters

Based on the results of the self-audit, we apply three additional filters.

Virama Filtering and Correction. Many languages using Brahmic Abugida (South and Southeast Asian scripts like Devanagari, Khmer, etc.) use some variant on the virama [4] character. We found that such languages in `MADLAD-400-noisy` had incorrectly encoded viramas: for example, तुम्हारे was rendered as तुम ़ हारे, where the middle character is a detached virama. Therefore, for the languages `bn, my, pa, gu, or, ta, te, kn, ml, si, th, tl, mn, lo, bo, km, hi, mr, ne, gom, as, jv, dv, bho, dz, hne, ks_Deva, mag, mni, shn, yue, zh, ja, kjg, mnw, ksw, rki, mtr, mwr` and `xnr`, we did a special filtering/correction step — we removed all extraneous spaces before virama characters. We provide the pseudocode and list of virama characters in Appendix A.2.

Zawgyi Encoded Data. We found that languages using Myanmar script like `my` and `mnw` appeared to have the same issues with virama characters that still remained after applying the virama correction. This was because a large fraction of Myanmar script data on the internet is Zawgyi encoded data, which appears to have the rendering issues described above if rendered in Unicode. Therefore, we used an open-source Zawgyi detector [5] to convert the encoding of documents with more than a 50% probability of being Zawgyi encoded into standard Unicode encoding.

Chinese-Specific Filters. The Mandarin (`zh`) data in CommonCrawl had a particular issue with pornographic content. We combed through the data and developed a list of strings likely to be present in pornographic content, and filtered out all documents containing the strings in the blocklist. This resulted in a 17% reduction in the number of documents and a 56% reduction in file size. We list these strings in Appendix A.2.

2.6 Correcting Other Systematic Issues.

Based on various specific notes from the self-audit, we made a variety of changes. Five datasets were found to be in the wrong language, and were renamed or merged into the correct dataset. Six

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[4] https://en.wikipedia.org/wiki/Virama
[5] https://github.com/google/myanmar-tools

languages that looked suspicious were run by native speakers of those or related languages, some of which were discarded, and some of which were merged into the correct dataset. Finally, we removed all languages with fewer than 20 documents. Details can be seen in Appendix A.3.

3 Parallel Data

To train the machine translation (MT) models described in Section 4.1, we also collect a dataset composed of publicly available datasets coming from various data sources. A full list of the data sources and associated language pairs are in Appendix A.5. The final dataset has 156 languages across 4.1B sentence pairs and 4124 language pairs total. In the rest of the paper, we refer to the input sentence to an MT model as the "source side" and the reference/output sentence as the "target side".

3.1 Filters

We describe the data preprocessing steps taken below. We find that a significant amount of data is filtered out, with the amount of data available 396 of 4.1k language pairs reducing by more than 40%.

Deduplication. We deduplicate sentence pairs that are an exact match on both the source and target.

Virama Filtering and Correction/Zawgyi Encoded Data. We observed the same issues described in Section 2.5, and used the same filters for sentence pairs where either the source language or target language belonged to the list of languages in Section 2.5.

Unmatched Toxicity Filters. We use the unmatched toxicity filters described by NLLBTeam et al. [51], but ultimately unusable for our purposes in most cases. For the languages ace, am, ar, az, bg, bm, bn, bs, cs, din, en, es, fa, fr, ga, gl, ha, hi, id, it, kk, ko, ml, ms, my, nl, no, nus, prs, ru, scn, sd, so, sv, tg, th, tt, ur, uz and zh, more than 3% of documents were marked as having unmatched toxicity. On closer inspection, we found that while zh and ko had a lot of pornographic content that was removed by the filtering process, most other languages removed sentences that had homonyms of non-toxic words. Similarly, languages like id, ur, tg, fa and no had data from Tanzil (Qur'an dataset), but the toxicity word lists contained words such as kafir, mercy and purity, that are not normally considered toxic content for our purpose of filtering the dataset using wordlists.

Source-Target Filters. We removed all sentences that have more than 75% overlap between the source and target side. To avoid filtering out valid entity translations, we only applied this filter on sentences longer than 5 tokens. In addition, we remove sentence pairs whose source length to target length ratio falls outside of $0.66 - 1.5$. We omitted this filter for the following, which are mainly non-whitespace languages: zh, ja, ko, km, my, lo, th, wuu, shn, zh_tw, zh_cn, iu, simple, dz, kr_Arab, din, nus and mi.

Script Filters. We removed all sentences that are less than 50% in-script for both the source and target language. For instance, if the sentence was supposed to be in kaa (Cyrillic script) but was 70% in the Latin script, we removed it.

3.2 Self-Audit (Quality Review)

Similar to the self-audit done for MADLAD-400, we conducted a review of the data sources that compose the parallel data we collected to verify the quality of this data. We collected 20 source-target pairs from each language, and assessed the data for the presence of offensive content, porn, and whether the data seemed to be of the correct language pair and whether the target sentence seemed to be a plausible translation. Since we did not have access to native speakers of all 157 languages, the latter was primarily based on guesses. In Appendix A.5 we provide full details of the instructions we provided to auditors, the results of the self-audit and any changes made the dataset.

3.3 A Note on Language Codes

As observed by Kreutzer et al. [40], the datasets used to create the parallel data (and `MADLAD-400`) use a variety of different language codes. We use the BCP-47 standard, which specifies the 2-letter ISO-693-1 code when applicable, and otherwise the ISO-693-3 code. Script tags and region tags are omitted when they are defined as the default value by CLDR [6], and otherwise included. For example, `ks` refers to Kashmiri in Nastaliq/Arabic script (CLDR default), whereas `ks_Deva` refers to Kashmiri in Devanagari. A detailed investigation of codes in `MADLAD-400` can be found in Appendix A.3.

3.4 Multiway Data

We create additional multiway data by applying the n-gram matching method ($n = 8$) from Freitag and Firat [25] to the processed dataset. Using this, and the publicly available data, we obtain 11.9B sentences across a total of 20742 language pairs. Full details may be found in Appendix A.7.

4 Experiments

We validate our data by training encoder-decoder machine translation models in Section 4.1 and decoder-only language models in Section 4.2, and test them on several translation benchmarks.

4.1 MT Models

We train models of various sizes: a 3B, 32-layer parameter model,[7] a 7.2B 48-layer parameter model and a 10.7B 32-layer parameter model. We share all parameters of the model across language pairs, and use a Sentence Piece Model [41] with 256k tokens shared on both the encoder and decoder side. Each input sentence has a `<2xx>` token prepended to the source sentence to indicate the target language [35].

We use both supervised parallel data with a machine translation objective and the monolingual `MADLAD-400` dataset with a MASS-style [62] objective to train this model. Each of these objectives is sampled with a 50% probability. Within each task, we use the recently introduced UniMax [18] sampling strategy to sample languages from our imbalanced dataset with a threshold of $N = 10$ epochs for any particular language. We also explored back-translation by randomly sampling 2M monolingual samples (or the total number of samples for that given language) for each language and translating them to/from English using the 3B model. Following Bapna et al. [9] (§3.5), we filter the back-translated data in a variety of ways. For a natural target and a back-translated source, we filter by round-trip ChrF to discourage hallucinations (threshold of 0.32), by ChrF between source and target to discourage copying (threshold of 0.30), by the length ratio of source to target (asymmetric bounds of (0.45, 1.6), and by LangID prediction of the source. We then finetune the 7.2B model for a $10,000$ steps by randomly mixing the original and the back-translated data with a combining ratio of 1:1. We list specific architecture and training details of these models in Appendix A.8.

4.2 Zero-shot Translation with Language Models

Given recent interest in the efficacy of unsupervised translation using large language models, we explore training language models solely on the monolingual data. We follow the same training schedule and model configurations from Garcia et al. [27]. In particular, we consider 8B decoder-only models, following the same model hyperparameters as previous work [17, 27]. We train these models using a variant of the UL2 objective [63] adapted for decoder-only models, and use the same configuration as previous work [27, 52]. We provide additional details in Appendix A.8.

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[6]https://cldr.unicode.org/
[7]Here and elsewhere, 'X-layer' means X encoder layers and also X decoder layers, for a total of 2X layers.

Table 4: Evaluation scores on WMT (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against NLLB-54B.

	NLLB	MT-3B	MT-7.2B	MT-10.7B	LM-8B			
					0-shot	1-shot	5-shot	10-shot
xx2en	34.2 / 60.4	33.4 / 60.0	34.9 / 60.6	**34.6 / 60.8**	2.3 / 17.3	25.1 / 51.4	26.2 / 52.9	26.2 / 53.4
en2xx	**31.1 / 58.0**	28.2 / 55.4	29.3 / 56.2	29.0 / 56.2	1.0 / 10.3	18.7 / 43.5	18.8 / 44.5	19.3 / 45.5
Average	**32.7 / 59.2**	30.8 / 57.7	32.1 / 58.4	31.8 / 58.5	1.6 / 13.8	21.9 / 47.4	22.5 / 48.7	22.8 / 49.4

4.3 Evaluation

We use the sacreBLEU [55] implementation of bleu[8] and chrf[9] as metrics. We evaluate our trained models on the following datasets:

WMT. We use the 15 WMT languages frequently used to evaluate multilingual machine translation models by Siddhant et al. [61], Kim et al. [38], Kudugunta et al. [42], NLLBTeam et al. [51]: `cs, de, es, fi, fr, gu, hi, kk, lv, lt, ro, rs, es, tr` and `zh`.

Flores-200. We evaluate on the languages in the Flores-200 dataset [51] that overlap with the languages available in either `MADLAD-400` or the parallel data described in Section 3. We list these languages in Appendix A.9. For non-English-centric pairs, we evaluate on a 272 language pair subset of the 40k language pairs possible due to computational constraints. We evaluate on all language pairs possible using the following languages as either source or target language: `en, fr, cs, zh, et, mr, eu, cy, so, ckb, or, yo, ny, ti, ln, fon` and `ss`. We obtained this set of languages by selecting every 10th language by number of tokens in MADLAD-400 (clean), starting with French (`fr`). Noticing that this had no Indian languages, we shifted `af` and `fo` (both close dialects of HRLS) down one index to `mr` and `or`, respectively. Finally, we noticed that this initial list had supervised and unsupervised languages, but didn't have a good representative of a "slightly supervised language", that is, one with a small but extant amount of parallel data. Therefore, we added `yo` to the list, which has the least parallel data of any supervised language. This resulting subset of languages also contains a nice variety of scripts: Latin, Chinese, Devanagari, Arabic, Odia, and Ethiopic scripts.

NTREX. We evaluate on the languages in the recently introduced NTREX dataset [23].

Gatones. Finally, we evaluate on the languages in GATONES, the in-house, 38-language eval set used in [9] and the GATITOS paper [36]. Again, we take the subset of languages overlapping with the languages available in either `MADLAD-400` or the parallel training data.

Table 5: Evaluation scores on Flores-200 (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against NLLB-54B. All metrics are computed with the sacrebleu reference implementation.

	NLLB	MT-3B	MT-7.2B	MT-10.7B	LM-8B			
					0-shot	1-shot	5-shot	10-shot
xx2en	**35.5 / 59.6**	29.7 / 54.4	30.9 / 55.4	31.9 / 56.4	2.0 / 13.3	20.5 / 44.1	22.3 / 46.9	22.4 / 47.6
en2xx	**20.7 / 50.**1	17.3 / 44.1	17.8 / 44.7	18.6 / 45.7	0.4 / 5.7	8.1 / 26.7	8.7 / 29.0	8.7 / 28.8
Mean	**28.2 / 54.9**	23.5 / 49.2	24.4 / 50.0	25.3 / 51.1	1.2 / 9.6	14.3 / 35.5	15.6 / 38.0	15.6 / 38.2
xx2yy	**13.7 / 40.5**	8.8 / 31.2	8.4 / 30.9	10.1 / 34.0	0.3 / 4.1	4.0 / 16.1	4.4 / 17.3	4.2 / 17.1

4.3.1 Few-shot evaluation for language modeling

We perform few-shot prompting to evaluate the language model with the following prompt:

`[sl]:`X_1`\n[tl]:`Y_1`\n\n[sl]:`X_2`\n[tl]:`Y_2`\n\n...[sl]:`X`\n[tl]:`

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[8] `BLEU+case.mixed+lang.<sl>-<tl>+ numrefs.1+smooth.exp+tok.<tok>+version.1.3.0,` tok=zh if tl=zh and 13a otherwise.

[9] `nrefs:1|case:mixed|eff:yes|nc:6|nw:0|space:no|version:2.3.1`

Table 6: Evaluation scores on the recently introduced NTREX test set (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against unsupervised baselines [10]. Note that LM-8B is evaluated on a 50% split of the NTREX data and is not comparable to the MT-model evaluations.

	Baziotis et al. [10]	MT-3B	MT-7.2B	MT-10.7B	LM-8B			
					0-shot	1-shot	5-shot	10-shot
Results on the subset of Baziotis et al. [10]								
xx2en	23.6 / 51.7	34.3 / 59.9	**36.1** / 61.0	35.9 / **61.1**	4.0 / 18.9	23.4 / 48.8	26.8 / 52.8	27.6 / 53.7
en2xx	15.9 / 44.8	22.3 / 50.2	**22.8** / 50.6	**22.8** / **51.0**	1.0 / 8.8	15.2 / 40.1	16.5 / 42.4	15.9 / 42.3
Average	19.8 / 51.7	28.3 / 55.1	**29.4** / 55.8	**29.4** / **56.1**	2.5 / 13.9	19.3 / 44.5	21.6 / 47.6	21.8 / 48.0
Results on full test sets								
xx2en	-	30.6 / 54.5	32.7 / 56.2	**33.6** / **57.6**	3.2 / 17.3	20.4 / 43.8	23.8 / 48.2	24.4 / 49.0
en2xx	-	16.5 / 39.6	17.6 / **41.9**	**17.9** / **41.9**	0.8 / 7.3	11.7 / 31.2	12.6 / 32.4	12.3 / 32.3
Average	-	23.5 / 47.0	25.1 / 49.0	**25.7** / **49.7**	2.0 / 12.3	16.0 / 37.4	18.1 / 40.2	18.3 / 40.6

where [sl] and [tl] denote the source and target language name (expressed in English. For example, when translating a sentence from en to te, we use [sl]=English and [tl]=Telugu), respectively. $X_\star$ and $Y_\star$ are demonstration examples used for prompting, and X is the test input.

For each test example, we randomly sample demonstration examples, which is simple yet performs competitively with more complicated strategies [66, 72]. In particular, we randomly select examples from the dev split of each dataset. Since NTREX does not have a dev split, we randomly sample 1000 examples as the dev set and use the rest for test evaluation.

4.4 Results

In Tables 4 and 6 we present evaluation scores on the WMT datasets and NTREX datasets, which are evaluation sets in the news domain. We find that both the 7.2B parameter model and the 10B parameter model is competitive with the significantly larger NLLB-54B model [51] on WMT. For the recent NTREX dataset, the only published results are small-scale results by Baziotis et al. [10].

In Table 5 we find that on Flores-200, our model is within 3.8 chrf of the 54B parameter NLLB model, while on **xxyy** pairs the 10.7B model is behind by 6.5 chrf. This is likely due to a combination of factors, including using a significantly smaller model (5x smaller), domain differences [10, 9], and back-translated data [60]. Similarly, in Table 7, we find that the 10.7B parameter model is within 5.7 chrf of the scores reported by Bapna et al. [9]. Again, it is very difficult to compare their results to ours; their two largest advantages are 1) iterative back-translation, and 2) access to a much larger in-house text data. In Table 8, we display the results for when we finetune the 7.2B parameter model on backtranslated data. While this setup is very likely sub-optimal, we see that back-translation greatly improves **en2xx** translation (by 3.0 chrf, in the case of Flores-200) in most cases. We note that the results we present are merely baselines to demonstrate the utility of MADLAD-400, and hope that future work builds upon these experiments by applying improved modeling techniques.

Finally, across all evaluation datasets, we find that while results on few-shot translation using the 8B language model increase with an increasing number of demonstrations, these results are still significantly weaker than the results of models trained on supervised data. We present per-language pair results on all datasets in Appendix A.10.

Table 7: Evaluation scores on the GATONES test set used by Bapna et al. [9] (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2.

	NTL (Bapna et al. [9])		MT-3B	MT-7.2B	MT-10.7B	LM-8B			
	1.6B	6.4B				0-shot	1-shot	5-shot	10-shot
xx2en	- / 37.2	- / **41.2**	13.3 / 34.6	14.8 / 36.0	**15.4** / 37.0	0.3 / 6.5	6.6 / 25.4	8.3 / 28.1	8.4 / 28.4
en2xx	- / 28.5	- / **33.1**	4.5 / 23.9	**5.4** / 26.2	**5.4** / 26.5	0.2 / 4.2	1.7 / 10.5	1.7 / 9.9	1.8 / 9.4
Average	- / 32.9	- / **37.2**	8.9 / 29.3	10.1 / 31.1	**10.4** / 31.8	0.3 / 5.4	4.2 / 18.0	5.0 / 19.0	5.1 / 18.9

Table 8: Evaluation scores on different test sets (depicted as `<bleu>` / `<chrf>`) for MT-7.2B trained with back-translated data (+BT).

	WMT		Flores-200		NTREX		GATONES	
	MT-7.2B	+BT	MT-7.2B	+BT	MT-7.2B	+BT	MT-7.2B	+BT
xx2en	**34.9 / 60.6**	33.8 / 60.4	**30.9 / 55.4**	27.2 / 53.9	**32.7** / 56.2	31.0 / **56.5**	**14.8 / 36.0**	10.2 / 34.5
en2xx	29.3 / 56.2	**29.8 / 56.9**	17.8 / 44.7	**18.5 / 47.7**	17.6 / 41.9	**18.4 / 44.4**	**5.4 / 26.2**	3.5 / 26.1
average	**32.1** / 58.4	31.8 / **58.6**	**24.4** / 50.0	22.8 / **50.8**	**25.1** / 49.0	24.7 / **50.4**	**10.1 / 31.1**	6.9 / 30.3
xx2yy	-	-	8.4 / 30.9	8.4 / **31.9**	-	-	-	-

5 Training Data Extraction and Memorization

Generative models have been shown to regurgitate training data [13] that may plagiarize, violate copyright assumptions, or infringe privacy. It can be difficult to assess and prevent these cases because such information may be paraphrased in ways that are difficult for automated systems to detect [32]. Instead, existing literature measures memorization in generative models to estimate the propensity for disallowed outputs. Typically, this means prompting a language model with some prefix of length P and comparing generated outputs of length S with the training data to see if they are 'novel' or if the generation is simply a regurgitation of its training data [13, 6, 32, 33, 14]. In the multilingual setting this may present new risks because tail languages may be more vulnerable to memorization [6].

The Difficulty of Assessing Memorization in Translation Settings. While memorization has been well-studied for language models, assessing the extent of memorization is difficult within translation settings. This is primarily because translation has a significantly smaller space of valid outputs, as opposed to many possible continuations for language modeling. This presents some difficulty in extending common memorization tests for language generation to translation. As an illustrative example, consider the case of translating to the same target language as the source (`"translate_copy"`). Performing a standard training data extraction attack would test if the generation matches the continuation. However, success would not indicate training data extraction as the adversary would have already had access to it.[10] Thus, we modify the standard framework for testing memorization to better identify *additional* leaked data.

Memorization in Translation Settings We define memorization in `translate_copy` to be when the model outputs any generation with length $S > P$ that matches the continuation; then, $S - P$ captures the additional bits. In cases where the source and target language are different (`"translate_diff"`), performing a similar test would require knowledge of which part of the continuation exactly corresponded to the prompt. Given that such an alignment is not easily obtained, we instead use the relative token lengths between the continuation and the prompt to choose an appropriate size of S. For example, if at training time the continuation for the target language was $1.5\times$ larger, we set $S = P \cdot 1.5 + \delta$ where δ captures the additional bits. For each of `translate_copy` and `translate_diff`, we sample $2,000$ sequences for each language and choose $P = 50$. We then perform both a verbatim match of the generation with the continuation and an approximate match requiring 90% Levenshtein similarity similar to [32].

Results. We show the per-language and average training data extraction rates, for both the `translate_copy` and `translate_diff` settings in Figure 2, with S set to test for 50 tokens of additional information leakage. We find that translate models can memorize and regurgitate their training data, even beyond what is contained in the prompt. We also observe that some lower resource languages may exhibit higher memorization rates, however we observe no strong correlation between the resource level and the level of memorization. In the `translate_diff` tests, we observe much lower memorization - we hypothesize this may be due to the higher difficulty of the task. Even though many languages have nontrivial memorization, we found that many languages exhibited no memorization across the samples tested (257/370 for `translate_copy` and 130/146 for `translate_diff`). We also present results for approximate memorization in Appendix A.12, which show that translate models may also paraphrase memorizations leading to even higher memorization rates.

Discussion Our preliminary experiments show that memorization can exist in the translation setting. However, capturing when memorization is intended or beneficial versus undesired is still an open

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[10]Though membership inference may be possible.
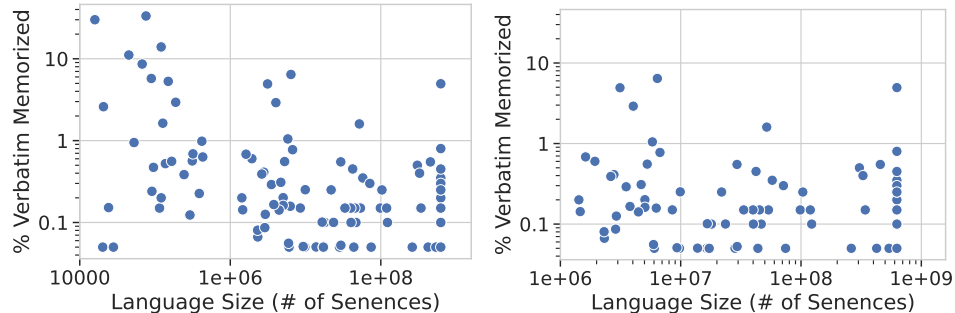
Figure 2: **Monolingual (translate_copy) data used in translation is more likely to be memorized.** Verbatim training data extraction rates for both `translate_copy` (**left**) and `translate_diff` (**right**) data. Extraction performed on the 3B parameter model using a $S = P + 50$. In monoway, 257/370 languages exhibited no memorization in testing and 130/146 for multiway.

question. To aid future research in this direction, we design and include "canaries"—carefully crafted data designed to be outliers to the natural training distribution that can be used to analyze memorization. Canaries enable studying memorization in the multilingual and machine translation settings by measuring the capability to extract canaries added to the training set [6, 33]. As with Anil et al. [6], our canaries are designed to share characteristics with the natural training data so as to better ground memorization evaluation in practical risks. The canaries are also designed tosl be outliers to assess varying degrees of risk. To ensure similarity with natural data, canaries are generated by sampling and then randomly modifying real data in a manner similar to [6], where each source of randomness defines the canary type. In total, we generate $1,945,631$ canaries across both the monolingual `MADLAD-400` dataset and the parallel data ($\approx 0.0026\%$ of the training data). The methodology for each canary type and the exact distribution of canaries are detailed in Appendix A.11.

6 Related Work

Extensive work has been done to mine general purpose datasets for multilingual machine translation and language modeling. Xue et al. [68] introduce mC4, a general web domain corpus on 101 languages to train mT5, a pretrained language model for downstream NLP tasks. Similarly, Conneau et al. [19] introduce CC-100, later extended to CC100-XL by Lin et al. [47]. The OSCAR corpus [2] is also a mined dataset that supports 166 languages and the ROOTS corpus is a compiled dataset that contains 46 natural languages. Glot500-C [31] covers 511 languages: however, it is not clear how many of these languages comprise solely of religious texts. Bapna et al. [9] create an internal dataset on 1500+ languages, while NLLBTeam et al. [51] mine a dataset from CommonCrawl and ParaCrawl [22]. Recently, Leong et al. [45] created a 350+ language dataset from children's books.

In addition, there have been efforts to get better represented corpora and models for languages often underrepresented in general multilingual corpora: Serengeti [3] introduces a dataset and associated model trained on 517 African languages and language varieties, while IndicTrans2 [26] introduces a machine translated model for the 22 scheduled languages in India.

7 Limitations

While we used thorough self-audits to guide the creation of `MADLAD-400`, we note that most audits were conducted by non-speakers of the languages in `MADLAD-400`; as a result, many types of noise, like machine-generated or disfluent content, could not be detected. Moreover, toxicity detectors, classifiers and filters that work reliably for all the 419 languages in `MADLAD-400` do not exist, limiting the extent to which we can clean and document [21, 8] the dataset. It is possible that issues still remain, so we encourage users to report issues that will be listed on the project Github page[11]. This paucity extends to the availability of multilingual evaluation sets for these languages - we could only evaluate our models on 204 of the languages in `MADLAD-400`. Additionally, even

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[11]https://github.com/google-research/google-research/tree/master/madlad_400

though decoder-only models are often evaluated on NLP tasks that are not necessarily machine translation [30, 7, 5], we did not conduct such evaluations - most available benchmarks cover only 30-50 languages of which most are not tail languages (which forms the focus of `MADLAD-400`). We instead leave this to future work. Finally, during our self-audit we noted the skew of data on the long tail towards specific domains such as religious texts. We hope that these limitations motivate the creation of more language-specific corpora not captured by web crawls, and the development of language-specific data cleaning tools and practices.

8 Conclusion

Through `MADLAD-400`, we introduce a highly multilingual, general web-domain, document-level text dataset. We perform a self-audit of this dataset for quality on samples of all 498 languages, develop filters, and remove spurious datasets, for a total of 419 languages in the release. We carefully describe the dataset creation process, laying out the iterations of audits and improvements upon the preliminary dataset along with observations that guided our decisions. We hope that this encourages creators of large-scale pretraining datasets both to put in their due diligence for manually inspecting and dealing with data, and also to describe and publicize the process in a level of detail that is reproducible and insightful for downstream users. This increased visibility into the dataset creation cycle can in turn improve model development and enable responsible data use [58]. Using `MADLAD-400`, we train and release large machine translation and general NLP models and evaluate them thoroughly. We hope that this further motivates work towards language technologies that are more inclusive of the rich language diversity housed by humanity.

9 Ethics Statement

Innovation in NLP technologies in English has been accelerated by training large scale deep learning models [20, 12] on massive web corpora [16, 73, 57]. However, on the long tail of written languages in the world there is a lack of high quality general data sources [37] that impede the progress of NLP tools for other languages. We hope that making an audited and cleaned corpus such as `MADLAD-400` available mitigates this issue. While we extensively cleaned `MADLAD-400`, the extent to which we can preprocess this data is limited by how not all languages have available tools for removing problematic content such as porn, toxic content, PII, copyrighted content or noise. We urge practitioners to carefully consider their target usecase before using `MADLAD-400`.

Acknowledgements

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A Appendix

A.1 LangID Details

Following *Language Id In the Wild* [15], we trained a Transformer-Base [65] Semi-Supervised LangId model (SSLID) on 498 languages. The training data is as described in *Language ID in the Wild*, with the differences that 1) training data is sampled to a temperature of T=3 to reduce over-triggering on low-resource languages; and 2) the data is supplemented with web-crawled data from the same paper (that has already been through the various filters described therein). The purpose of adding this data is to increase robustness to web-domain text, and possibly distill some of the filters used to create the web-crawl. The languages chosen for this model were roughly the top 498 by number of sentences in the dataset reported by *Language ID in the Wild*. The complete list may be seen in Table 9.

Table 9: BCP-47 codes, name, script and amount of data associated with all languages in MADLAD-400. The last 79 languages, with entries of "-", were languages that the LangID model was trained to detect, but was omitted after the self-audit.

BCP-47	Name	Script	docs (noisy)	docs (clean)	sents (noisy)	sents (clean)	chars (noisy)	chars (clean)
total	-	-	7.8B	4B	148.4B	105.5B	33.3T	18.3T
median	-	-	21.6K	1.5K	202.3K	61.8K	63.6M	8.5M
en	English	Latn	3.6B	1.8B	87.9B	53.4B	15T	9T
ru	Russian	Cyrl	823M	402.5M	823M	12.4B	3.1T	1.8T
es	Spanish	Latn	476.4M	250.9M	8.3B	4.5B	2.1T	1.1T
fr	French	Latn	384.2M	218.9M	7.9B	5B	2T	1T
de	German	Latn	478.6M	225.1M	11.5B	6B	2.2T	1T
it	Italian	Latn	238.9M	126.4M	4.5B	2.5B	1.2T	553.1B
pt	Portuguese	Latn	209.2M	124.2M	4B	2.4B	791.5B	499.8B
pl	Polish	Latn	145.1M	90.9M	3.3B	2.4B	505B	356.4B
nl	Dutch	Latn	134.5M	86.6M	134.5M	2.3B	698.5B	334.5B
vi	Vietnamese	Latn	92.8M	55M	1.6B	1B	342B	228.8B
tr	Turkish	Latn	107M	56.4M	107M	1.2B	328.8B	198.9B
sv	Swedish	Latn	65.2M	35.2M	65.2M	1B	422.6B	153.7B
id	Indonesian	Latn	120.9M	38M	2.2B	747.5M	443B	148.3B
ro	Romanian	Latn	60.8M	35.4M	60.8M	746.4M	244.1B	148.2B
cs	Czech	Latn	72.1M	38.3M	1.7B	1B	272.2B	147.9B
zh	Mandarin Chinese	Hans	29.3M	19.9M	492.3M	298.8M	333B	142.3B
hu	Hungarian	Latn	47.6M	29.7M	1.3B	806.3M	223.6B	134.9B
ja	Japanese	Jpan	23.3M	21.8M	326M	321.6M	133.3B	132.2B
th	Thai	Thai	19M	17.4M	19M	385.8M	118.6B	117.6B
fi	Finnish	Latn	35.8M	20.4M	1B	650.3M	202.2B	101.1B
fa	Persian	Arab	58.1M	23.1M	920.6M	493.5M	220.4B	96.7B
uk	Ukrainian	Cyrl	46.6M	25M	1B	599.9M	164.2B	95.2B
da	Danish	Latn	38.5M	17.9M	1.1B	508M	252B	83.1B
el	Greek	Grek	52.4M	20.9M	808M	445.4M	173.2B	80.9B
no	Norwegian	Latn	34.7M	14.9M	34.7M	498.7M	305.6B	74.8B
bg	Bulgarian	Cyrl	27.2M	12.8M	599.4M	360.3M	95.6B	57.8B
sk	Slovak	Latn	23.2M	11.9M	487.9M	300.6M	77.8B	45.7B
ko	Korean	Kore	19.7M	12.7M	628.6M	471.8M	65.9B	43.8B
ar	Arabic	Arab	67.6M	12.4M	876.6M	182.6M	243B	43.2B
lt	Lithuanian	Latn	15.3M	8.7M	374M	256.9M	58.6B	41.3B
ca	Catalan	Latn	17.9M	9.5M	258.6M	153M	56.5B	34.6B
sl	Slovenian	Latn	12M	6.3M	316M	180M	47.8B	30.5B
he	Hebrew	Hebr	14.1M	7.2M	302.2M	196.8M	54.9B	30.5B
et	Estonian	Latn	8.8M	5.5M	223.8M	176.3M	40.1B	28.7B
lv	Latvian	Latn	8.4M	5M	186.1M	138.5M	36.7B	23.9B
hi	Hindi	Deva	9.9M	4.5M	254.4M	152M	39.9B	20.1B
sq	Albanian	Latn	5.5M	3.6M	5.5M	56.1M	17B	12.7B
ms	Malay	Latn	14.1M	2.3M	14.1M	55.2M	58.8B	12.5B
az	Azerbaijani	Latn	5.2M	3.3M	90.3M	70.9M	16.3B	11.9B
sr	Serbian	Cyrl	4.7M	2M	4.7M	64M	18.6B	11B
ta	Tamil	Taml	5.6M	2.6M	122.5M	81.9M	19.2B	10.6B
hr	Croatian	Latn	23M	2.8M	476.6M	53M	85.1B	9.6B
kk	Kazakh	Cyrl	3.1M	1.8M	87.4M	59.1M	13.4B	8.6B
is	Icelandic	Latn	2.9M	1.6M	73.7M	39.3M	14.9B	6.4B
ml	Malayalam	Mlym	3.7M	2.1M	75M	52M	10.5B	6.3B
mr	Marathi	Deva	2.9M	1.7M	2.9M	50M	8.7B	5.5B
te	Telugu	Telu	2.5M	1.7M	59M	46.4M	7.4B	5.1B
af	Afrikaans	Latn	2.9M	868.7K	51.9M	30M	11.8B	4.8B
gl	Galician	Latn	4.2M	1.3M	45.3M	18.8M	15.6B	4.8B
fil	Filipino	Latn	4.2M	901.5K	67.4M	19.2M	14.6B	4.7B
be	Belarusian	Cyrl	2M	1.1M	48.8M	31.3M	7.2B	4.6B

16

mk	Macedonian	Cyrl	2.9M	1.4M	41.3M	22.6M	9.1B	4.5B
eu	Basque	Latn	2.1M	1.2M	41.7M	24.8M	6.9B	4.3B
bn	Bengali	Beng	4.3M	1.1M	151.2M	38.6M	16.8B	4.3B
ka	Georgian	Geor	3.1M	936.5K	53.7M	26.6M	10.3B	3.8B
mn	Mongolian	Cyrl	2.2M	879.9K	43.3M	24M	7.9B	3.5B
bs	Bosnian	Cyrl	12.9M	1.4M	163.6M	9M	39.5B	3.3B
uz	Uzbek	Latn	1.4M	669.9K	25.7M	17.5M	5.2B	3.3B
ur	Urdu	Arab	967.2K	467.2K	29M	18.4M	5.2B	2.7B
sw	Swahili	Latn	1.3M	537.8K	1.3M	9.5M	4.6B	2.4B
yue	Cantonese	Hant	465.9K	309.3K	2.8M	2.4M	2.4B	2.3B
ne	Nepali	Deva	876.4K	453.5K	876.4K	20.4M	3.9B	2.2B
kn	Kannada	Knda	1.6M	657.8K	32.9M	19.2M	4.6B	2.2B
kaa	Kara-Kalpak	Cyrl	1.1M	586.4K	19.8M	13.3M	3.8B	2.2B
gu	Gujarati	Gujr	1.3M	659.7K	28.9M	18.1M	3.9B	2.1B
si	Sinhala	Sinh	788K	349.2K	22.1M	16M	3.4B	1.9B
cy	Welsh	Latn	4.9M	430.7K	68.3M	7.4M	26.4B	1.7B
eo	Esperanto	Latn	1.4M	260K	33.9M	9.3M	5.5B	1.7B
la	Latin	Latn	2.9M	319.2K	85.7M	13.8M	8.2B	1.5B
hy	Armenian	Armn	2M	397.5K	31.1M	9.9M	8.1B	1.5B
ky	Kyrghyz	Cyrl	751.1K	367.6K	14.3M	9.6M	2.5B	1.4B
tg	Tajik	Cyrl	789.2K	328.2K	789.2K	7.4M	2.6B	1.4B
ga	Irish	Latn	5.3M	286K	31.7M	6.9M	30.6B	1.4B
mt	Maltese	Latn	1.2M	265.1K	1.2M	5.6M	3.2B	1.3B
my	Myanmar (Burmese)	Mymr	176.5K	172.4K	176.5K	10.1M	1.3B	1.3B
km	Khmer	Khmr	297.8K	285.7K	5M	5M	1.1B	1.1B
tt	Tatar	Cyrl	2.1M	346.9K	60.2M	8.6M	12.1B	1B
so	Somali	Latn	729.2K	293.2K	729.2K	3.1M	2.1B	992.4M
ku	Kurdish (Kurmanji)	Latn	671.9K	218.9K	10.7M	4.9M	2.1B	849.9M
ps	Pashto	Arab	429.9K	252.9K	5.1M	3.6M	1.4B	848.9M
pa	Punjabi	Guru	368.2K	150.6K	368.2K	6M	1.6B	797.1M
rw	Kinyarwanda	Latn	681.8K	226.5K	681.8K	1.9M	1.7B	749.1M
lo	Lao	Laoo	229.1K	216K	2.9M	2.8M	706.9M	697.6M
ha	Hausa	Latn	443.9K	173.5K	4.5M	2.4M	1.3B	630.2M
dv	Dhivehi	Thaa	264.4K	167.2K	4.3M	3.5M	877.3M	603.1M
fy	W. Frisian	Latn	1.7M	210K	12.1M	3.7M	3.7B	592.3M
lb	Luxembourgish	Latn	7.6M	146K	47.1M	3.4M	58.4B	575.5M
ckb	Kurdish (Sorani)	Arab	622.7K	148.9K	5.6M	2.5M	2.2B	572.7M
mg	Malagasy	Latn	295.2K	115.4K	4.5M	2.6M	1.3B	548.5M
gd	Scottish Gaelic	Latn	206K	94.3K	3.7M	2.4M	812M	526M
am	Amharic	Ethi	245.2K	106.3K	7.1M	5.3M	869.9M	509M
ug	Uyghur	Arab	227.1K	106.5K	4.5M	3.1M	998.5M	504.6M
ht	Haitian Creole	Latn	425.6K	110.4K	6.7M	2.6M	994.5M	461.5M
grc	Ancient Greek	Grek	364.8K	70.7K	13.7M	2.8M	2B	417.8M
hmn	Hmong	Latn	241.3K	75.2K	3.5M	1.9M	1.2B	408.8M
sd	Sindhi	Arab	115.6K	65.9K	115.6K	2.4M	561M	380.4M
jv	Javanese	Latn	999.5K	69.5K	13M	2M	2.3B	376.1M
mi	Maori	Latn	711.9K	79.5K	5.9M	1.9M	1.6B	371.9M
tk	Turkmen	Latn	180.2K	82.5K	180.2K	1.8M	575.2M	369M
ceb	Cebuano	Latn	617.5K	66.2K	6.7M	1.6M	1.5B	357.7M
yi	Yiddish	Hebr	160.6K	64.9K	3.3M	1.9M	838.4M	352.6M
ba	Bashkir	Cyrl	372.4K	90.3K	9.3M	2.6M	766.5M	320.7M
fo	Faroese	Latn	382.9K	97.8K	3.9M	1.8M	923.3M	314.9M
or	Odia (Oriya)	Orya	139.6K	100.5K	139.6K	3.1M	437.2M	309.5M
xh	Xhosa	Latn	310.9K	53.7K	2.9M	1.4M	749.5M	287.3M
su	Sundanese	Latn	336.6K	55K	336.6K	1.6M	967.2M	286.7M
kl	Kalaallisut	Latn	85.9K	46K	2.1M	1.5M	403.9M	279.1M
ny	Chichewa	Latn	181.6K	52.2K	181.6K	1.5M	611.2M	277.5M
sm	Samoan	Latn	137.8K	52.6K	1.9M	1.3M	607.9M	276.3M
sn	Shona	Latn	3.1M	60.2K	3.1M	1.2M	10.6B	266M
co	Corsican	Latn	546.7K	55.4K	6.1M	1.3M	1.1B	265.5M
zu	Zulu	Latn	372.3K	53.8K	3.8M	1.2M	1.2B	257.4M
ig	Igbo	Latn	130.4K	54.4K	2.1M	1.4M	846.1M	251.4M
yo	Yoruba	Latn	115K	52.1K	2M	1.2M	415.6M	239M
pap	Papiamento	Latn	259.1K	54.5K	259.1K	1.4M	1.4B	229.9M
st	Sesotho	Latn	96.8K	40.4K	96.8K	1.1M	381.5M	226.9M
haw	Hawaiian	Latn	310.4K	45.7K	7.1M	1M	892M	214.2M
as	Assamese	Beng	53.9K	33.8K	2.4M	1.7M	275.8M	182.1M
oc	Occitan	Latn	2.4M	36.4K	2.4M	1.6M	6.7B	177.6M
cv	Chuvash	Cyrl	599.4K	47.3K	12M	1.6M	1B	168.9M
lus	Mizo	Latn	91.5K	36.4K	1.4M	863.5K	298.3M	167.3M
tet	Tetum	Latn	291K	40.4K	1.9M	475.7K	1.6B	152.3M
gsw	Swiss German	Latn	7.6M	42.7K	64.5M	1M	42.3B	149.2M
sah	Yakut	Cyrl	1.3M	29.2K	1.3M	1.2M	2.2B	148.2M
br	Breton	Latn	705.4K	33.2K	7.8M	731.7K	3.7B	125.4M
rm	Romansh	Latn	238.1K	33.8K	238.1K	603.4K	391M	100.2M
sa	Sanskrit	Deva	154.3K	7.1K	154.3K	1.1M	512.5M	88.8M
bo	Tibetan	Tibt	6.2K	6.2K	1.1M	1.1M	88.7M	88.7M
om	Oromo	Latn	846.1K	18.9K	846.1K	469.8K	1.9B	88.5M
se	N. Sami	Latn	54.3K	23.9K	879.5K	493.3K	148.4M	84.6M
ce	Chechen	Cyrl	59.3K	15K	991.1K	460.1K	130.6M	67.8M
cnh	Hakha Chin	Latn	44.4K	21.6K	688.6K	406.9K	110.8M	63M

ilo	Ilocano	Latn	69.8K	11.8K	889.2K	365.1K	187.9M	59.4M
hil	Hiligaynon	Latn	126.8K	10.6K	1.1M	379.7K	293.5M	57.2M
udm	Udmurt	Cyrl	67.1K	13.4K	942.7K	510.3K	106M	55.5M
os	Ossetian	Cyrl	172.1K	12.6K	172.1K	359.3K	233.5M	50.1M
lg	Luganda	Latn	61.1K	13K	510.9K	166.1K	160.7M	48M
ti	Tigrinya	Ethi	20.8K	7.3K	20.8K	481.3K	95.4M	44.6M
vec	Venetian	Latn	1.1M	11.1K	10M	209.7K	1.8B	43.8M
ts	Tsonga	Latn	34.7K	5.2K	34.7K	248.6K	377.2M	38.8M
tyv	Tuvinian	Cyrl	61.6K	9.1K	596.6K	268.3K	80.2M	38.5M
kbd	Kabardian	Cyrl	154.7K	7.5K	1.4M	257.2K	321.4M	36.8M
ee	Ewe	Latn	14.1K	4.5K	353.6K	246.7K	67.9M	32.8M
iba	Iban	Latn	34K	7.6K	326.9K	126.1K	251.4M	30.5M
av	Avar	Cyrl	107.6K	6.3K	806.1K	190.1K	129M	30.2M
kha	Khasi	Latn	37.8K	12.1K	235.5K	75.2K	88.6M	30.2M
to	Tonga (Tonga Islands)	Latn	14.3K	4.6K	14.3K	149K	58.2M	29.9M
tn	Tswana	Latn	138.2K	4.8K	138.2K	174.4K	302.3M	29.2M
nso	Sepedi	Latn	376.2K	4.4K	376.2K	188.4K	2B	28.2M
fj	Fijian	Latn	17K	4K	410K	164.1K	67.7M	28M
zza	Zaza	Latn	370.1K	6K	3.3M	229.2K	617.3M	26.3M
ak	Twi	Latn	19.5K	4.8K	341.7K	210.2K	74.5M	24.8M
ada	Adangme	Latn	6.5K	3.1K	291.5K	199.2K	38.9M	24.2M
otq	Querétaro Otomi	Latn	17.6K	5.6K	17.6K	114.8K	65M	23.4M
dz	Dzongkha	Tibt	1.9K	1.9K	191.7K	191.7K	22.7M	22.7M
bua	Buryat	Cyrl	9.8K	5.3K	252K	144.6K	38M	21.7M
cfm	Falam Chin	Latn	9.1K	4.9K	199.6K	128.6K	32.9M	21.5M
ln	Lingala	Latn	94.7K	3.3K	718.7K	139K	291.8M	21.5M
chm	Meadow Mari	Cyrl	81.5K	4.7K	929.1K	179.7K	132.2M	21.3M
gn	Guarani	Latn	87.1K	3.9K	770.9K	162.6K	140.7M	20.8M
krc	Karachay-Balkar	Cyrl	359.5K	4.8K	2.3M	153.9K	369.5M	20.7M
wa	Walloon	Latn	70.6K	2.8K	1.5M	127.2K	198.8M	20.4M
hif	Fiji Hindi	Latn	702K	2.4K	7.9M	124.7K	9.1B	19.1M
yua	Yucateco	Latn	10.4K	4K	141.6K	77.6K	36.8M	17.2M
srn	Sranan Tongo	Latn	16.7K	2.3K	16.7K	139.5K	49.1M	17M
war	Waray (Philippines)	Latn	1M	2.9K	114M	96.2K	3.5B	16.1M
rom	Romani	Latn	22.9K	4.2K	22.9K	76.1K	59M	15.9M
bik	Central Bikol	Latn	44.8K	3.1K	376.7K	77K	102.3M	15.7M
pam	Pampanga	Latn	174.2K	2.8K	174.2K	23.3K	324M	15.5M
sg	Sango	Latn	4.2K	2.1K	154K	117.9K	22.6M	15.5M
lu	Luba-Katanga	Latn	10.6K	1.4K	316K	112.1K	54.2M	15.4M
ady	Adyghe	Cyrl	74.9K	4.2K	446.8K	96.9K	67.9M	14.8M
kbp	Kabiyè	Latn	5.9K	3K	247.9K	128.3K	30.8M	14.6M
syr	Syriac	Syrc	3.5K	716	326.4K	197.1K	31.5M	14M
ltg	Latgalian	Latn	13.1K	4.1K	213.7K	87.3K	29.2M	13.9M
myv	Erzya	Cyrl	164.8K	3.1K	164.8K	130K	120.3M	13.8M
iso	Isoko	Latn	3.7K	1.7K	155.8K	111.5K	23M	13.7M
kac	Kachin	Latn	5.9K	2.6K	109.2K	77.4K	26.6M	13.6M
bho	Bhojpuri	Deva	13.6K	4.1K	306.2K	118.5K	37.6M	13.4M
ay	Aymara	Latn	8.1K	2.5K	196.7K	83.8K	34.5M	13.1M
kum	Kumyk	Cyrl	4.2K	2.5K	132.2K	89.7K	18.2M	12.4M
qu	Quechua	Latn	149.7K	2.4K	1M	87K	200.6M	12.2M
za	Zhuang	Latn	824.7K	1.7K	19.2M	53.9K	3B	12.1M
pag	Pangasinan	Latn	49.6K	1.6K	49.6K	88.8K	92.9M	12M
ngu	Guerrero Nahuatl	Latn	3.8K	1.5K	3.8K	87.1K	21.4M	11.8M
ve	Venda	Latn	3.8K	1.9K	97.8K	79.4K	19M	11.7M
pck	Paite Chin	Latn	8.9K	1.3K	8.9K	69.7K	39.8M	11.5M
zap	Zapotec	Latn	5.5K	1.8K	202.3K	93.5K	26.4M	11.4M
tyz	Tày	Latn	8K	1.7K	454.8K	104.6K	46.3M	11.3M
hui	Huli	Latn	2K	1.7K	80.1K	74.7K	11.8M	10.9M
bbc	Batak Toba	Latn	72.3K	1.3K	718.3K	73.2K	151.3M	10.6M
tzo	Tzotzil	Latn	2.8K	1.4K	100.4K	75.7K	15.9M	10.6M
tiv	Tiv	Latn	3.8K	1.1K	3.8K	80.7K	20.4M	10.2M
ksd	Kuanua	Latn	14.9K	2K	533K	78.6K	62.4M	10M
gom	Goan Konkani	Deva	4.6K	2.1K	178.3K	108K	19.8M	10M
min	Minangkabau	Latn	28.2K	1.5K	500.9K	75.6K	70.5M	9.9M
ang	Old English	Latn	66.5K	803	1.8M	86.7K	193M	9.8M
nhe	E. Huasteca Nahuatl	Latn	3K	1.7K	3K	57.7K	15.6M	9.8M
bgp	E. Baluchi	Latn	355.7K	2.4K	5.6M	43.3K	1.1B	9.8M
nzi	Nzima	Latn	2.5K	1.4K	2.5K	71.8K	14.4M	9.4M
nnb	Nande	Latn	4.9K	1.1K	4.9K	70.2K	27.7M	9.1M
nv	Navajo	Latn	17.1K	12.6K	17.1K	86.5K	24.8M	9.1M
zxx	Noise	-	118.8K	1.8K	3.8M	49.3K	501K	6.6K
bci	Baoulé	Latn	7.4K	1.3K	124.8K	87.1K	32.8M	9M
kv	Komi	Cyrl	59.1K	1.9K	584.3K	88.8K	91.4M	9M
new	Newari	Deva	6.6K	1.6K	6.6K	85K	21.2M	8.8M
mps	Dadibi	Latn	2.7K	1.2K	132.8K	71.9K	16M	8.7M
alt	S. Altai	Cyrl	2.6K	1.4K	110.1K	65.9K	14.3M	8.7M
meu	Motu	Latn	5.9K	1.7K	232.1K	72.6K	27.2M	8.6M
bew	Betawi	Latn	311.1K	2.7K	10.4M	58.4K	1.4B	8.5M
fon	Fon	Latn	5.3K	1.1K	222.9K	67.3K	34M	8.3M
iu	Inuktitut	Cans	5.4K	2.5K	92.6K	53.1K	17.5M	8.3M
abt	Ambulas	Latn	1.6K	1.3K	122.7K	110.3K	9.6M	8.2M

mgh	Makhuwa-Meetto	Latn	5.5K	1.2K	151.8K	61.2K	24.1M	8.2M
mnw	Mon	Mymr	1.1K	1.1K	144.8K	144.7K	8.1M	8.1M
tvl	Tuvalu	Latn	2.3K	933	72.9K	53.6K	12.6M	8.1M
dov	Dombe	Latn	3.5K	923	129.8K	56.7K	20.7M	8M
tlh	Klingon	Latn	516.9K	3.1K	516.9K	46.9K	1.4B	7.8M
ho	Hiri Motu	Latn	2K	1.5K	57K	47.8K	12.3M	7.8M
kw	Cornish	Latn	176.9K	2.3K	1M	51.6K	327.8M	7.7M
mrj	Hill Mari	Cyrl	97.1K	1.4K	97.1K	60.3K	100.6M	7.6M
meo	Kedah Malay	Latn	790.7K	4.7K	16.5M	39K	3B	7.5M
crh	Crimean Tatar	Cyrl	5.1K	1.2K	170.9K	61.8K	18.8M	7.5M
mbt	Matigsalug Manobo	Latn	1.6K	969	86K	45.4K	14.6M	7.5M
emp	N. Emberá	Latn	3.6K	1.2K	106.4K	75.4K	14.5M	7.4M
ace	Achinese	Latn	65.5K	966	632.5K	32.5K	146.1M	7.4M
ium	Iu Mien	Latn	100.3K	1.7K	6.2M	54.9K	314M	7.4M
mam	Mam	Latn	23K	1.5K	446.3K	52.9K	70.4M	7.2M
gym	Ngäbere	Latn	1.5K	820	73.7K	49.6K	10.3M	6.9M
mai	Maithili	Deva	54.3K	1.2K	1M	60.2K	156M	6.8M
crs	Seselwa Creole French	Latn	7.6K	873	282.4K	40.1K	40.1M	6.8M
pon	Pohnpeian	Latn	5.7K	1.5K	167.8K	48.7K	18.3M	6.7M
ubu	Umbu-Ungu	Latn	2.2K	846	113.5K	47.5K	15.9M	6.7M
fip	Fipa	Latn	3.7K	729	165.6K	49K	25.7M	6.6M
quc	K'iche'	Latn	4.4K	1.5K	89.2K	41.2K	16.6M	6.4M
gv	Manx	Latn	501.9K	1.6K	18.8M	26.9K	933.1M	6.2M
kj	Kuanyama	Latn	112.2K	2.1K	881.8K	22.6K	339.6M	6M
btx	Batak Karo	Latn	3.1K	1K	81.7K	43.9K	13.1M	5.9M
ape	Bukiyip	Latn	7K	814	147K	56.1K	71M	5.8M
chk	Chuukese	Latn	2.8K	1.1K	98.8K	44K	12M	5.8M
rcf	Réunion Creole French	Latn	21.6K	2.6K	21.6K	50.5K	30.2M	5.7M
shn	Shan	Mymr	889	788	46.4K	46.2K	5.7M	5.7M
tzh	Tzeltal	Latn	1.7K	702	41.7K	33.9K	9.3M	5.6M
mdf	Moksha	Cyrl	71K	1.6K	394.7K	45.1K	65.8M	5.5M
ppk	Uma	Latn	2.6K	1.1K	85.8K	34.9K	13.2M	5.5M
ss	Swati	Latn	8.1K	1.1K	8.1K	30.4K	23.7M	5.5M
gag	Gagauz	Latn	33.9K	1.6K	491K	37K	84.9M	5.2M
cab	Garifuna	Latn	1.2K	629	50.4K	37.5K	7.5M	5.1M
kri	Krio	Latn	39.1K	786	271.2K	38.8K	86.4M	5M
seh	Sena	Latn	5.6K	545	68.8K	37.2K	14.9M	4.9M
ibb	Ibibio	Latn	74.1K	818	516.5K	36.3K	190.9M	4.9M
tbz	Ditammari	Latn	5.1K	1.1K	128.7K	37.5K	22M	4.8M
bru	E. Bru	Latn	3K	1.1K	89.7K	48.2K	12.9M	4.8M
enq	Enga	Latn	7.1K	793	241.9K	39.1K	68.5M	4.8M
ach	Acoli	Latn	2K	915	63K	40.1K	9M	4.7M
cuk	San Blas Kuna	Latn	4.1K	899	76.5K	34.3K	24.7M	4.6M
kmb	Kimbundu	Latn	1.3K	538	60.4K	36.9K	8.4M	4.6M
wo	Wolof	Latn	36.4K	871	303.4K	25.4K	213.4M	4.5M
kek	Kekchí	Latn	3.2K	782	70.4K	38.4K	13.6M	4.4M
qub	Huallaga Huánuco Quechua	Latn	972	705	61K	51.1K	5.9M	4.4M
tab	Tabassaran	Cyrl	7.8K	1.2K	226.4K	26.8K	33.7M	4.4M
bts	Batak Simalungun	Latn	3.2K	869	109.1K	29.1K	20.8M	4.2M
kos	Kosraean	Latn	2.2K	881	44.6K	27.8K	6.5M	4.2M
rwo	Rawa	Latn	938	572	938	45.5K	5.1M	4.2M
cak	Kaqchikel	Latn	1.2K	617	70.4K	32.6K	7.6M	4.2M
tuc	Mutu	Latn	3.5K	635	193.2K	50.3K	17.2M	4.1M
bum	Bulu	Latn	4.7K	559	103.8K	36.5K	18.8M	4M
cjk	Chokwe	Latn	3.6K	586	144.1K	24.1K	22.5M	3.9M
gil	Gilbertese	Latn	3.9K	586	151.5K	24.1K	24.1M	3.9M
stq	Saterfriesisch	Latn	111.9K	809	111.9K	27.7K	243.1M	3.8M
tsg	Tausug	Latn	353.8K	789	353.8K	17.9K	1.1B	3.8M
quh	S. Bolivian Quechua	Latn	1K	501	42K	29.9K	5.8M	3.7M
mak	Makasar	Latn	1K	555	32.5K	20.4K	6.1M	3.7M
arn	Mapudungun	Latn	2.4K	593	64.5K	26.2K	10.2M	3.7M
ban	Balinese	Latn	8K	637	150.9K	16.3K	35.4M	3.6M
jiv	Shuar	Latn	1.7K	696	80.9K	32K	9.6M	3.5M
sja	Epena	Latn	1.3K	527	67.7K	24.9K	7.7M	3.4M
yap	Yapese	Latn	1.9K	638	37.6K	19.5K	6.9M	3.3M
tcy	Tulu	Knda	10.7K	632	338.7K	37.1K	41.6M	3.3M
toj	Tojolabal	Latn	736	452	736	26.1K	4.3M	3.3M
twu	Termanu	Latn	2.5K	539	109.9K	24.4K	14.2M	3.2M
xal	Kalmyk	Cyrl	71.8K	913	498.5K	30.8K	64.7M	3.2M
amu	Guerrero Amuzgo	Latn	1.8K	511	72K	25.2K	9.6M	3.2M
rmc	Carpathian Romani	Latn	2.4K	738	2.4K	25.8K	7.9M	3.2M
hus	Huastec	Latn	825	569	26.5K	23.7K	4.4M	3.1M
nia	Nias	Latn	2K	408	2K	25K	11.3M	3.1M
kjh	Khakas	Cyrl	1.5K	672	42.8K	28.7K	4.5M	3.1M
bm	Bambara	Latn	21.9K	702	172.3K	24.5K	48.4M	3M
guh	Guahibo	Latn	1.9K	331	104.9K	28.4K	11.2M	3M
mas	Masai	Latn	15.2K	405	216.8K	17.6K	42.1M	3M
acf	St Lucian Creole French	Latn	4.9K	730	81.9K	24.6K	11.6M	3M
dtp	Kadazan Dusun	Latn	4.6K	1.3K	51.2K	7.9K	12.7M	3M
ksw	S'gaw Karen	Mymr	560	536	16.1K	16K	2.9M	2.9M
bzj	Belize Kriol English	Latn	983	404	33.6K	26.4K	4.5M	2.9M

din	Dinka	Latn	128.4K	611	885.8K	23.6K	210M	2.9M
zne	Zande	Latn	1.3K	239	61.9K	21.3K	8.2M	2.8M
mad	Madurese	Latn	103.8K	509	500.6K	18.5K	111.8M	2.8M
msi	Sabah Malay	Latn	686.7K	1.9K	686.7K	22.6K	2.6B	2.7M
mag	Magahi	Deva	631	138	62.6K	22.1K	10.7M	2.6M
mkn	Kupang Malay	Latn	956	402	33.1K	25.4K	3.4M	2.6M
kg	Kongo	Latn	4.7K	365	85.5K	21.7K	16.6M	2.6M
lhu	Lahu	Latn	46K	377	975K	15.7K	208.6M	2.5M
ch	Chamorro	Latn	12.9K	449	147.5K	16K	63.5M	2.5M
qvi	Imbabura H. Quichua	Latn	1.2K	266	48.4K	19.3K	6.5M	2.3M
mh	Marshallese	Latn	4.6K	296	235.1K	13K	24.9M	2.2M
djk	E. Maroon Creole	Latn	560	246	30.9K	24.4K	3.7M	2.2M
sus	Susu	Latn	664	437	664	15.2K	3.7M	2.1M
mfe	Morisien	Latn	7.5K	320	198.8K	18.2K	26.9M	2.1M
srm	Saramaccan	Latn	847	227	847	17.3K	6.3M	2M
dyu	Dyula	Latn	1.2K	483	55.8K	19.7K	5.7M	2M
ctu	Chol	Latn	690	366	35.5K	20.6K	3.6M	2M
gui	E. Bolivian Guaraní	Latn	1.1K	409	62.7K	24.8K	6.5M	2M
pau	Palauan	Latn	1.7K	185	1.7K	13.1K	12.4M	2M
inb	Inga	Latn	387	343	17.3K	17K	2M	1.9M
bi	Bislama	Latn	71.9K	311	308.5K	13.6K	132.4M	1.9M
mni	Meiteilon (Manipuri)	Beng	1.2K	290	38.1K	13.2K	6.4M	1.8M
guc	Wayuu	Latn	537	214	22.9K	12.5K	3.4M	1.8M
jam	Jamaican Creole English	Latn	12.7K	416	68.5K	15.8K	25.8M	1.7M
wal	Wolaytta	Latn	2.6K	286	128K	14K	17M	1.7M
jac	Popti'	Latn	8.2K	303	61.6K	11.9K	15.7M	1.7M
bas	Basa (Cameroon)	Latn	4.2K	216	105.2K	14.9K	25.7M	1.7M
gor	Gorontalo	Latn	1.7K	303	53.3K	6.5K	9.4M	1.7M
skr	Saraiki	Arab	3.8K	107	279.3K	17.1K	32.2M	1.7M
nyu	Nyungwe	Latn	1.2K	195	1.2K	11K	7.7M	1.6M
noa	Woun Meu	Latn	902	234	902	11.5K	5.2M	1.6M
sda	Toraja-Sa'dan	Latn	1.6K	317	43.2K	6.2K	15.8M	1.6M
gub	Guajajára	Latn	31.7K	271	160.4K	25K	44.7M	1.6M
nog	Nogai	Cyrl	970	419	970	11K	2.6M	1.6M
cni	Asháninka	Latn	1K	261	46K	14K	5.9M	1.6M
teo	Teso	Latn	2.8K	274	131.5K	13.7K	15.3M	1.6M
tdx	Tandroy-Mahafaly Malagasy	Latn	1.7K	262	26.3K	13.2K	7M	1.6M
sxn	Sangir	Latn	587	197	587	9.9K	3.4M	1.5M
rki	Rakhine	Mymr	331	251	331	7.8K	1.6M	1.5M
nr	South Ndebele	Latn	10.7K	246	10.7K	11.3K	49M	1.5M
frp	Arpitan	Latn	148K	550	3.5M	8.2K	535.4M	1.4M
alz	Alur	Latn	2.2K	195	59.3K	12.2K	7.9M	1.4M
taj	E. Tamang	Deva	146	65	21.6K	14.3K	2.3M	1.4M
lrc	N. Luri	Arab	42.4K	587	351.9K	9K	85.3M	1.4M
cce	Chopi	Latn	847	116	23.2K	11K	3.3M	1.3M
rn	Rundi	Latn	8.2K	323	8.2K	11.1K	33.2M	1.3M
jvn	Caribbean Javanese	Latn	1K	213	36.2K	7.8K	5.3M	1.2M
hvn	Sabu	Latn	737	200	33.9K	7K	4.3M	1.2M
nij	Ngaju	Latn	1K	183	1K	9.2K	4.7M	1.2M
dwr	Dawro	Latn	452	215	22.1K	11.1K	2.2M	1.2M
izz	Izii	Latn	423	237	21.7K	14.5K	2.1M	1.1M
msm	Agusan Manobo	Latn	520	177	520	8.6K	2.5M	1.1M
bus	Bokobaru	Latn	467	322	21.4K	12.1K	2.1M	1.1M
ktu	Kituba (DRC)	Latn	3.3K	144	115.5K	7.8K	18.5M	1.1M
chr	Cherokee	Cher	964	301	33.8K	7.5K	4.7M	1M
maz	Central Mazahua	Latn	585	170	21.3K	8.2K	2.9M	951.7K
tzj	Tz'utujil	Latn	471	136	11.1K	7.3K	1.9M	884.2K
suz	Sunwar	Deva	226	186	226	11.3K	1M	855.2K
knj	W. Kanjobal	Latn	229	126	10.1K	9.2K	1.1M	855K
bim	Bimoba	Latn	410	40	31.1K	6.3K	3.2M	793.4K
gvl	Gulay	Latn	37.9K	126	213K	6.9K	141M	789.2K
bqc	Boko (Benin)	Latn	275	228	9.8K	8.2K	997K	788.4K
tca	Ticuna	Latn	410	117	20K	7.3K	2.3M	786K
pis	Pijin	Latn	1.1K	139	62K	7.2K	7.7M	764K
prk	Parauk	Latn	1.1K	18	12.3K	4.3K	3.1M	734.8K
laj	Lango (Uganda)	Latn	6.5K	144	61K	6.4K	15.8M	730.5K
mel	Central Melanau	Latn	119.3K	103	878.4K	3.7K	315.2M	729.6K
qxr	Cañar H. Quichua	Latn	2.6K	153	40.8K	6.4K	6.6M	724K
niq	Nandi	Latn	26.7K	226	26.7K	4.2K	72.1M	716.2K
ahk	Akha	Latn	244	77	6.2K	4.1K	1.3M	715.5K
shp	Shipibo-Conibo	Latn	874	150	22.4K	3.7K	3.8M	710.4K
hne	Chhattisgarhi	Deva	3K	146	118.4K	4.3K	12M	697K
spp	Supyire Senoufo	Latn	733	123	733	5.8K	4.4M	682.5K
koi	Komi-Permyak	Cyrl	20.7K	196	153.9K	5K	17.1M	664.5K
krj	Kinaray-A	Latn	1.5K	96	54.6K	3.8K	7.6M	616.5K
quf	Lambayeque Quechua	Latn	522	86	8.4K	5.2K	1.5M	609K
luz	S. Luri	Arab	90.5K	354	1.2M	6.7K	329.4M	590.7K
agr	Aguaruna	Latn	465	93	16.1K	3.6K	2.3M	554.5K
tsc	Tswa	Latn	12.6K	82	12.6K	4K	23.4M	521.3K
mqy	Manggarai	Latn	69.3K	119	309K	2.5K	78.9M	506.5K
gof	Gofa	Ethi	2.8K	97	33.8K	5.5K	5.5M	506K

gbm	Garhwali	Deva	2.5K	137	50.8K	3.8K	9.1M	499.6K
miq	Mískito	Latn	236	45	6.4K	3.5K	1.2M	485.6K
dje	Zarma	Latn	913	100	40.2K	3.7K	4.7M	480.7K
awa	Awadhi	Deva	5.8K	126	100.1K	8.4K	11.1M	475K
bjj	Kanauji	Deva	830	107	39.6K	8K	3.1M	439.7K
qvz	N. Pastaza Quichua	Latn	534	88	6.8K	3.5K	1.2M	438.3K
sjp	Surjapuri	Deva	19K	31	498.2K	2.9K	94.3M	430K
tll	Tetela	Latn	200	37	200	2.7K	2.2M	409.8K
raj	Rajasthani	Deva	1.8K	40	1.8K	5.7K	7.1M	405K
kjg	Khmu	Laoo	113	84	3K	2.9K	408.5K	399K
bgz	Banggai	Latn	32K	7	864.1K	17K	79.3M	391.1K
quy	Ayacucho Quechua	Latn	588	78	28.1K	2.7K	4.5M	368.2K
cbk	Chavacano	Latn	10.1K	78	43.8K	2K	10.3M	339.3K
akb	Batak Angkola	Latn	1K	71	21.3K	408	5.2M	337.8K
oj	Ojibwa	Cans	2.5K	135	2.5K	1.6K	9.6M	337.1K
ify	Keley-I Kallahan	Latn	611	79	19.8K	2.8K	2.6M	334K
mey	Hassaniyya	Arab	14.8K	127	109.9K	3K	36.2M	323.5K
ks	Kashmiri	Arab	5.6K	51	53.9K	3.3K	9.4M	320.9K
cac	Chuj	Latn	212	77	3.4K	1.8K	978.7K	319.8K
brx	Bodo (India)	Deva	322	62	5.3K	2.4K	1.1M	304.4K
qup	S. Pastaza Quechua	Latn	169	53	4.3K	2.5K	763.8K	297.8K
syl	Sylheti	Beng	5.9K	61	5.9K	4.3K	21.5M	293.1K
jax	Jambi Malay	Latn	1.5M	58	30M	2.3K	6.8B	290.2K
ff	Fulfulde	Latn	13.6K	26	150K	5K	22.8M	277.6K
ber	Tamazight (Tfng)	Tfng	2.7K	79	12.6K	1.2K	6.4M	265.9K
tks	Takestani	Arab	63.7K	127	63.7K	6.8K	88.9M	260.8K
trp	Kok Borok	Latn	12.8K	36	12.8K	1.7K	29.9M	257.3K
mrw	Maranao	Latn	11.3K	29	11.3K	1K	27.8M	257.2K
adh	Adhola	Latn	2.6K	87	107.2K	1K	14.5M	254.9K
smt	Simte	Latn	1.4K	34	1.4K	703	6.8M	245.4K
srr	Serer	Latn	41.1K	91	41.1K	2.3K	63.6M	240.6K
ffm	Maasina Fulfulde	Latn	1.8K	65	30.1K	2K	4.6M	236.1K
qvc	Cajamarca Quechua	Latn	3.4K	27	14.6K	2.2K	5M	233.7K
mtr	Mewari	Deva	1.8K	11	1.8K	2.2K	7.6M	231.1K
ann	Obolo	Latn	464	56	5K	1.6K	760.9K	215.1K
kaa-Latn	Kara-Kalpak (Latn)	Latn	375.2K	61.2K	3.6M	1.3M	1.5M	209.5K
aa	Afar	Latn	39.5K	32	176.1K	1.3K	63.3M	200K
noe	Nimadi	Deva	2K	22	2K	2.2K	13.8M	195.3K
nut	Nung (Viet Nam)	Latn	29K	67	29K	1.5K	23.5M	184.1K
gyn	Guyanese Creole English	Latn	32.6K	45	211.7K	2.1K	34.5M	177.7K
kwi	Awa-Cuaiquer	Latn	382	37	16.9K	2.2K	1.8M	172.8K
xmm	Manado Malay	Latn	24.5K	58	218.8K	1.2K	48.7M	171.3K
msb	Masbatenyo	Latn	811	41	811	1K	4.4M	167.5K
el-Latn	Greek (Latn)	Latn	-	-	-	-	-	-
doi	Dogri	Deva	-	-	-	-	-	-
mtq	Muong	Latn	-	-	-	-	-	-
dln	Darlong	Latn	-	-	-	-	-	-
cyo	Cuyonon	Latn	-	-	-	-	-	-
abs	Ambonese Malay	Latn	-	-	-	-	-	-
hi-Latn	Hindi (Latn)	Latn	-	-	-	-	-	-
shu	Chadian Arabic	Arab	-	-	-	-	-	-
yaq	Yaqui	Latn	-	-	-	-	-	-
nyo	Nyoro	Latn	-	-	-	-	-	-
cgg	Chiga	Latn	-	-	-	-	-	-
sxu	Upper Saxon	Latn	-	-	-	-	-	-
mdh	Maguindanaon	Latn	-	-	-	-	-	-
rwr	Marwari (India)	Deva	-	-	-	-	-	-
xnr	Kangri	Deva	-	-	-	-	-	-
mui	Musi	Latn	-	-	-	-	-	-
skg	Sakalava Malagasy	Latn	-	-	-	-	-	-
ymm	Maay	Latn	-	-	-	-	-	-
ctd-Latn	Tedim Chin (Latn)	Latn	-	-	-	-	-	-
ayl	Libyan Arabic	Arab	-	-	-	-	-	-
kjb	Q'anjob'al	Latn	-	-	-	-	-	-
rhg-Latn	Rohingya (Latn)	Latn	-	-	-	-	-	-
bmm	N. Betsimisaraka Malagasy	Latn	-	-	-	-	-	-
azg	San Pedro Amuzgos Amuzgo	Latn	-	-	-	-	-	-
kfy	Kumaoni	Deva	-	-	-	-	-	-
bto	Rinconada Bikol	Latn	-	-	-	-	-	-
ja-Latn	Japanese (Latn)	Latn	-	-	-	-	-	-
mfb	Bangka	Latn	-	-	-	-	-	-
ru-Latn	Russian (Latn)	Latn	-	-	-	-	-	-
tuf	Central Tunebo	Latn	-	-	-	-	-	-
ctg	Chittagonian	Beng	-	-	-	-	-	-
pmy	Papuan Malay	Latn	-	-	-	-	-	-
xog	Soga	Latn	-	-	-	-	-	-
te-Latn	Telugu (Latn)	Latn	-	-	-	-	-	-
ber-Latn	Tamazight (Latn)	Latn	-	-	-	-	-	-
mdy	Male (Ethiopia)	Ethi	-	-	-	-	-	-
az-RU	Azerbaijani (Russia)	Cyrl	-	-	-	-	-	-
ta-Latn	Tamil (Latn)	Latn	-	-	-	-	-	-

BCP-47	Name	Script	docs (noisy)	docs (clean)	sents (noisy)	sents (clean)	chars (noisy)	chars (clean)
clu	Caluyanun	Latn	-	-	-	-	-	-
tly-IR	Talysh (Iran)	Arab	-	-	-	-	-	-
ng	Ndonga	Latn	-	-	-	-	-	-
bzc	S. Betsimisaraka Malagasy	Latn	-	-	-	-	-	-
nan-Latn-TW	Min Nan Chinese (Latn)	Latn	-	-	-	-	-	-
ml-Latn	Malayalam (Latn)	Latn	-	-	-	-	-	-
max	North Moluccan Malay	Latn	-	-	-	-	-	-
ar-Latn	Arabic (Latn)	Latn	-	-	-	-	-	-
gom-Latn	Goan Konkani (Latn)	Latn	-	-	-	-	-	-
bg-Latn	Bulgarian (Latn)	Latn	-	-	-	-	-	-
nd	North Ndebele	Latn	-	-	-	-	-	-
zyj	Youjiang Zhuang	Latn	-	-	-	-	-	-
rkt	Rangpuri	Beng	-	-	-	-	-	-
kn-Latn	Kannada (Latn)	Latn	-	-	-	-	-	-
zh-Latn	Chinese (Latn)	Latn	-	-	-	-	-	-
el-CY	Greek (Cypress)	Grek	-	-	-	-	-	-
dcc	Deccan	Arab	-	-	-	-	-	-
bgc	Haryanvi	Deva	-	-	-	-	-	-
mwr	Marwari	Deva	-	-	-	-	-	-
vkt	Tenggarong Kutai Malay	Latn	-	-	-	-	-	-
cr-Latn	Cree (Latn)	Latn	-	-	-	-	-	-
apd-SD	Sudanese Arabic	Arab	-	-	-	-	-	-
trw	Torwali	Arab	-	-	-	-	-	-
bn-Latn	Bengali (Latn)	Latn	-	-	-	-	-	-
gu-Latn	Gujarati (Latn)	Latn	-	-	-	-	-	-
gju	Gujari	Arab	-	-	-	-	-	-
sat-Latn	Santali (Latn)	Latn	-	-	-	-	-	-
ndc-ZW	Ndau	Latn	-	-	-	-	-	-
kmz-Latn	Khorasani Turkish (Latn)	Latn	-	-	-	-	-	-
mr-Latn	Marathi (Latn)	Latn	-	-	-	-	-	-
en-Cyrl	English (Cyrl)	Cyrl	-	-	-	-	-	-
en-Arab	English (Arab)	Arab	-	-	-	-	-	-
ms-Arab	Malay (Jawi)	Arab	-	-	-	-	-	-
ms-Arab-BN	Malay (Jawi, Brunei)	Arab	-	-	-	-	-	-
bhb-Gujr	Bhili	Gujr	-	-	-	-	-	-
pa-Arab	Lahnda Punjabi (PK)	Arab	-	-	-	-	-	-
syl-Latn	Sylheti (Latn)	Latn	-	-	-	-	-	-
ff-Adlm	Fulah	Latn	-	-	-	-	-	-
pcm	Nigerian Pidgin	Latn	-	-	-	-	-	-
tpi	Tok Pisin	Latn	-	-	-	-	-	-
gjk	Kachi Koli	Arab	-	-	-	-	-	-
bfy	Bagheli	Deva	-	-	-	-	-	-
sgj	Surgujia	Deva	-	-	-	-	-	-
nyn	Nyankole	Latn	-	-	-	-	-	-
BCP-47	Name	Script	docs (noisy)	docs (clean)	sents (noisy)	sents (clean)	chars (noisy)	chars (clean)

A.2   Filtering Details

Cursed Substrings   Following is the list of cursed substrings that we used to filter the monolingual data. Here are a few general notes about these strings:

1. low quality sentences ending in the pipe character were very common. (Note: this was not Devanagari-script text using a Danda.)
2. The last few regexes are meant to match A N T S P E A K, *List Case*, and weirdly regular text (for instance, lists of shipping labels or country codes)

Here is the complete list of cursed substrings and cursed regexes, along with the function used for filtering:

```
# this implementation is for demonstration and not very efficient;
# to speed it up, use string inclusion (`in`) instead of regex for
# all but the last four, and for those use a compiled regex.
def is_cursed(s):
  return any(re.findall(curse, s) in s for curse in CURSED_SUBSTRINGS)


CURSED_SUBSTRINGS = [' \u2116', '\ufffd\ufffd\ufffd', '\\|\\s*$', ' nr\\.$',
'aute irure dolor ', ' sunt in culpa qui ', 'orem ipsum ', ' quis nostrud ',
' adipisicing ', ' dolore eu ', ' cupidatat ', 'autem vel eum', 'wisi enim ad',
```

```
' sex ', ' porn ', '\u9ec4\u8272\u7535\u5f71', 'mp3', 'ownload',
'Vol\\.', ' Ep\\.', 'Episode', ' \u0433\\.\\s*$', ' \u043a\u0433\\.\\s*$',
' \u0448\u0442\\.', 'Develop', 'Facebook', ' crusher ', ' xxx ',
' ... ... ... ... ... ... ... ... ...',
' .... .... .... .... .... .... .... .... ....',
' [^ ] [^ ] [^ ] [^ ] [^ ] [^ ] [^ ] [^ ] [^ ]',
', ..,,? ..,,? ..,,? ..,,?',
]
```

Virama Correction   Below is the virama substitution code:

```
_VIRAMA_CHARS = (
'\u094d\u09cd\u0a4d\u0acd\u0b4d\u0bcd\u0c4d\u0ccd\u0d3b'
'\u0d3c\u0d4d\u0dca\u0e3a\u0eba\u0f84\u1039\u103a\u1714'
'\u1734\u17d2\u1a60\u1b44\u1baa\u1bab\u1bf2\u1bf3\u2d7f'
'\ua806\ua82c\ua8c4\ua953\ua9c0\uaaf6\uabed\u10a3f\u11046'
'\u1107f\u110b9\u11133\u11134\u111c0\u11235\u112ea\u1134d'
'\u11442\u114c2\u115bf\u1163f\u116b6\u1172b\u11839\u1193d'
'\u1193e\u119e0\u11a34\u11a47\u11a99\u11c3f\u11d44\u11d45'
'\u11d97\u1031\u1057\u1058\u1059\u1056\u1060\u1062\u1068'
'\u1063\u1067\u1068\u1069\u105e\u105f\u1036\u103d\u102d'
'\u102f\u102e\u102d\u1030\u1033\u1034\u1035\u102f\u1032'
'\u102c\u103c\u103d\u103e\u102b\u1037\u1038\u25cc\u25cc'
'\u000a\u1071\u1072\u1073\u1074\u1082\u1083\u1084\u1085'
'\u1086\u1087\u1088\u1089\u108a\u108b\u108c\u108d\u108f'
'\u109a\u109b\u109c\u109d\ua9e5\uaa7b\uaa7c\uaa7d'
)


def remove_viramas(x: str) -> str:
  return '%s' % regex.sub(r' ([%s]) ' % _VIRAMA_CHARS, '\\1', x)
```

Chinese Porn Filter   Below is the Chinese porn filter list:

```
zh_pornsignals = [
'caoporn', 'caoprom', 'caopron', 'caoporen', 'caoponrn', 'caoponav', 'caopom',
'caoorn', '99re', 'dy888', 'caopro', 'hezyo', 're99', '4438x', 'zooskool',
'xfplay', '7tav', 'xxoo', 'xoxo', '52av', 'freexx', '91chinese', 'anquye',
'cao97', '538porm', '87fuli', '91pron', '91porn', '26uuu', '4438x', '182tv',
'kk4444', '777me', 'ae86', '91av', '720lu', 'yy6080', '6080yy', 'qqchub',
'paa97', 'aiai777', 'yy4480', 'videossexo', '91free',
'\u4e00\u7ea7\u7279\u9ec4\u5927\u7247',
'\u5077\u62cd\u4e45\u4e45\u56fd\u4ea7\u89c6\u9891',
'\u65e5\u672c\u6bdb\u7247\u514d\u8d39\u89c6\u9891\u89c2\u770b',
'\u4e45\u4e45\u514d\u8d39\u70ed\u5728\u7ebf\u7cbe\u54c1',
'\u9ad8\u6e05\u6bdb\u7247\u5728\u7ebf\u770b',
'\u65e5\u672c\u6bdb\u7247\u9ad8\u6e05\u514d\u8d39\u89c6\u9891',
'\u4e00\u7ea7\u9ec4\u8272\u5f55\u50cf\u5f71\u7247',
'\u4e9a\u6d32\u7537\u4eba\u5929\u5802',
'\u4e45\u4e45\u7cbe\u54c1\u89c6\u9891\u5728\u7ebf\u770b',
'\u81ea\u62cd\u533a\u5077\u62cd\u4e9a\u6d32\u89c6\u9891',
'\u4e9a\u6d32\u4eba\u6210\u89c6\u9891\u5728\u7ebf\u64ad\u653e',
'\u8272\u59d1\u5a18\u7efc\u5408\u7ad9',
'\u4e01\u9999\u4e94\u6708\u556a\u556a',
'\u5728\u7ebf\u89c6\u9891\u6210\u4eba\u793e\u533a',
'\u4e9a\u6d32\u4eba\u6210\u89c6\u9891\u5728\u7ebf\u64ad\u653e',
'\u4e45\u4e45\u56fd\u4ea7\u81ea\u5077\u62cd',
```

```
'\u4e00\u672c\u9053',
'\u5927\u9999\u8549\u65e0\u7801',
'\u9999\u6e2f\u7ecf\u5178\u4e09\u7ea7',
'\u4e9a\u6d32\u6210\u5728\u4eba\u7ebf\u514d\u8d39\u89c6\u9891',
'\u5929\u5929\u8272\u7efc\u5408\u7f51',
'\u5927\u9999\u8549\u4f0a\u4eba\u4e45\u8349',
'\u6b27\u7f8e\u4e00\u7ea7\u9ad8\u6e05\u7247',
'\u5929\u5929\u9c81\u591c\u591c\u556a\u89c6\u9891\u5728\u7ebf',
'\u514d\u8d39\u9ec4\u7247\u89c6\u9891\u5728\u7ebf\u89c2\u770b',
'\u52a0\u6bd4\u52d2\u4e45\u4e45\u7efc\u5408',
'\u4e45\u8349\u70ed\u4e45\u8349\u5728\u7ebf\u89c6\u9891',
'\u97e9\u56fd\u4e09\u7ea7\u7247\u5927\u5168\u5728\u7ebf\u89c2\u770b',
'\u9752\u9752\u8349\u5728\u7ebf\u89c6\u9891',
'\u7f8e\u56fd\u4e00\u7ea7\u6bdb\u7247',
'\u4e45\u8349\u5728\u7ebf\u798f\u5229\u8d44\u6e90',
'\u556a\u556a\u556a\u89c6\u9891\u5728\u7ebf\u89c2\u770b\u514d\u8d39',
'\u6210\u4eba\u798f\u5229\u89c6\u9891\u5728\u7ebf\u89c2\u770b',
'\u5a77\u5a77\u6211\u53bb\u4e5f',
'\u8001\u53f8\u673a\u5728\u7ebf\u56fd\u4ea7',
'\u4e45\u4e45\u6210\u4eba\u89c6\u9891',
'\u624b\u673a\u770b\u7247\u798f\u5229\u6c38\u4e45\u56fd\u4ea7',
'\u9ad8\u6e05\u56fd\u4ea7\u5077\u62cd\u5728\u7ebf',
'\u5927\u9999\u8549\u5728\u7ebf\u5f71\u9662',
'\u65e5\u672c\u9ad8\u6e05\u514d\u8d39\u4e00\u672c\u89c6\u9891',
'\u7537\u4eba\u7684\u5929\u5802\u4e1c\u4eac\u70ed',
'\u5f71\u97f3\u5148\u950b\u7537\u4eba\u8d44\u6e90',
'\u4e94\u6708\u5a77\u5a77\u5f00\u5fc3\u4e2d\u6587\u5b57\u5e55',
'\u4e9a\u6d32\u9999\u8549\u89c6\u9891\u5728\u7ebf\u64ad\u653e',
'\u5929\u5929\u556a\u4e45\u4e45\u7231\u89c6\u9891\u7cbe\u54c1',
'\u8d85\u78b0\u4e45\u4e45\u4eba\u4eba\u6478\u4eba\u4eba\u641e',
]
```

A.3 Other issues fixed after the self-audit

Consulting Language Speakers   For a few languages, we had strong suspicions that the text was noisy or spurious, but were unable to acertain the quality of the data. In these cases we asked a native speaker to audit the data. Based on their recommendations, we did the following:

1. `zh`, `zh_Latn`: This resulted in the special filters described below.
2. `en_Arab`, `tly_IR`: This data was found to boilerplate, so we removed this data.
3. `fa`, `bho`: No changes were made.

Language Renames and Merges   For several languages, we found that (mostly by checking URLs) the corpora were in languages different from the LangID predictions. This led to the following changes:

1. `dty` renamed to `zxx-xx-dtynoise`, aka a "language" of noise. This is mainly mis-rendered PDFs and may have practical applications for denoising, or for decoding such garbled PDFs.
2. `fan` renamed to `bum`
3. `cjk` merged into the `gil` dataset
4. `bjj` merged into the `awa` dataset
5. `ss-SZ` renamed to `ss` – this was a result of inconsistent data labels.

A.4 Monolingual Data Details

Notes from rounds 2 and 3 of the self-audit can be seen in Table 10. Some of these notes may refer to previous, less filtered versions of the data, especially those with a "r1" (meaning "round 1"). Some of them however do have some useful information about quirks of problems with the current dataset. The overall statistics of `MADLAD-400` are in Table 9.

Table 10: Notes that we made about individual samples while auditing them. Some languages have notes from the earlier round of auditing in parentheses, e.g. '(r1: get this checked by Hindi speaker)'. Notes from Round 0, which were used to find cursed substrings, were not kept.

BCP-47	notes
aa	some pretty bad data but also some good data. filter on "Woo" (case sensitive) (r1: ok)
abs	all short nonsense remove (r1: ok)
abt	fine; bible (r1: ok)
ace	good; bible (r1: ok)
acf	good; bible (r1: ok)
ach	good; bible (r1: ok)
ada	good; bible; likely mixed with gaa (r1: ok but odd character usage LATIN CAPITAL LETTER OPEN O when it should be lower case in the middle of words)
adh	good; bible (r1: ok, lots bible)
ady	good (r1: ok but weird boilerplate)
af	good (r1: ok)
agr	good; bible (r1: ok; some AL in Arabic script)
ahk	good; bible; crazy diacritics (r1: ok but weird: lots of u748 MODIFIER LETTER VOICING)
ak	good; much but not all bible (r1: ok)
akb	good; bible (r1: empty)
alt	WAIT THIS IS AMAZING IT IS ACTUALLY ALTAI! e.g. from urls like https://altaicholmon.ru/2020/02/28/jarashty-la-jajaltany-jarkyndu-lekeri/ (r1: ok but there are just lots of numbers...not very clean)
alz	good; bible (r1: ok; bible)
am	good (r1: ok)
amu	good; bible; crazy diacritics (r1: empty)
ang	much noise but some good Old English in there! (r1: ok; wikipedia; one document that is just "lastfootwear.com" 1M times)
ann	good; all from wikimedia incubator (r1: ok)
apd-SD	terribly questionable; probably remove (r1: maybe ok, but looks like lots of template....maybe remove)
ape	good; bible (r1: remove)
ar	good (r1: ok)
ar-Latn	terrible, 0pct correct, remove (r1: remove)
arn	good; bible (r1: ok)
as	good (r1: ok)
av	good (r1: ok)
awa	OK; should be used with caution and suspicion (r1: remove)
awa	all bible in awadhi (awa). Renamed from bjj (r1: remove)
ay	good; mix of bible and other news sources (r1: ok but very noisy)
ayl	remove. not ayl. (r1: uh this is all Arabic with "homo" in English...remove?)
az	good (r1: ok)
az-RU	good; a lot of JW (r1: ok)
azg	70pct short noise; 30pct good bible (r1: empty)
ba	ok (r1: ok)
ban	ok bible (r1: ok)
bas	ok; has some fun blog stuff! (r1: empty)
bbc	ok (r1: ok)
bci	ok bible (r1: ok; bible)
be	ok (r1: ok)
ber	ok great! (r1: ok; Mixed in French)
ber-Latn	ok (r1: ok)
bew	mostly blogs. i have no way of knowing if this is standard indonesian or not (r1: ok; noisy)
bfy	very bad. remove unless it looks better after filtering short docs; remove (r1: remove)
bg	ok (r1: ok)
bg-Latn	ok (r1: ok but questionable...Slavic speaker review needed)
bgc	super sketch. Remove unless short doc filter leaves some. remove (r1: very questionable....Hindi speaker review)
bgp	almost all ur-Latn. consider removing or renaming (r1: very questionable. Remove? mainly ur-Latn)
bgz	idk maybe ok but probably bad (r1: remove. Wow, this is amazing. It is in all sorts of languages – the only thing they share is that they each have like 500 question marks)
bhb-Gujr	bad. remove. all junk gu. (r1: remove; great noise?)
bho	mostly from anjoria.com. Ankur reviews and says that it looks like valid Bhojpuri for the most part (r1: questionable but ok?)
bi	good! fun! (r1: ok)
bik	ok. keep in mind the bik vs bcl issue. (r1: ok)
bim	good; bible (r1: empty)
bm	good (r1: ok but these headers are LONG)
bmm	terrible. filter on short and reevaluate (r1: remove)
bn	ok (r1: ok)
bn-Latn	ok (r1: ok)
bo	needs some serious script filtering. but there is some ok data in there. (r1: ok)
bqc	ok; bible (r1: ok but too short?)
br	ok after shortfilter (r1: ok)
bru	ok; bible (r1: ok)
brx	quite good! (r1: ok but questionable...Hindi speaker review?)
bs	good (r1: ok)
bto	bad; remove unless short filter keeps enough (r1: empty)
bts	ok; mostly bible (r1: ok)
btx	ok probably (r1: ok)
bua	ok (r1: ok)
bum	ok bible; but technically wrong language. Data is in Bulu, not Fang, though they are closely related, so ranamed from "fan"

bus	ok; bible; about 50bzc (r1: ok bible)
bzj	ok bible (r1: ok)
ca	ok (r1: ok i guess....but is it actually italian?)
cab	ok jw (r1: ok)
cac	ok bible (r1: ok bible)
cak	ok bible (r1: ok bible)
cbk	ok bible; not Spanish (r1: remove; all Spanish)
cce	ok jw (r1: empty)
ce	ok (r1: ok)
ceb	ok (r1: ok)
cfm	ok mostly from chinland.co (r1: ok)
cgg	rather noisy but potentialy ok. not sure if WL or not (r1: ok)
ch	ok; not sure about WL (r1: ok)
chk	ok bible (r1: ok bible)
chm	ok; fyi watch out for yandex translationese (r1: ok)
chr	ok bible (r1: ok bible)
ckb	ok (r1: ok)
clu	ok bible (r1: ok)
cnh	good, some local news! not sure if WL (r1: ok)
cni	ok; bible; lots of mixed in content in not,cob,cpc,arl (r1: ok)
co	ok;l i suspect lots of MT (r1: ok i guess?)
cr-Latn	noise and lorem ipsom. But some ok Cree text. (r1: mostly Lorem Ipsom. remove? Or release with note? there is some plausible stuff here too.)
crh	ok (r1: ok but review with russian speaker as it could be russian....)
crs	ok (r1: ok)
cs	ok (r1: ok)
ctd-Latn	ok; from some local news? (r1: ok)
ctg	probably terrible probably remove (r1: very questionable....remove?)
ctu	ok bible (r1: ok bible)
cuk	ok bible (r1: ok bible)
cv	good (r1: ok)
cy	ok after shortfilter; OK (r1: ok)
cyo	terrifying noise; remove (r1: empty)
da	ok (r1: ok)
dcc	remove (r1: empty)
de	ok (r1: ok)
din	ok after short doc filter (r1: ok but LONG headers uh oh)
dje	ok; mostly but not all bible (r1: ok bible)
djk	ok; bible+jw (r1: empty)
dln	ok bible (r1: empty)
doi	ok actually nice! (r1: sus; review by hindi speaker)
dov	ok bible + jw (r1: ok)
dtp	ok; mostly from www.newsabahtimes.com.my (r1: ok)
dv	good (r1: ok)
dwr	ok; bible; mixed script (r1: empty)
dyu	ok bible (r1: empty)
dz	ok; hidden parallel text; maybe actually bo; mainly buddhist (r1: ok; mixed dz-Latn)
ee	good; mostly religious (r1: ok bible)
el	ok (r1: ok)
el-CY	bad (r1: v suspicious; mainly comma lists or boilerplate; remove)
el-Latn	good; a lot of old content! (r1: ok)
emp	ok bible (r1: ok)
en	ok (r1: ok)
en-Arab	Ali reviewed; this is not good data. remove. (r1: idk review w/Arabic reader)
en-Cyrl	ok ... some fr-Cyrl too and maybe others (r1: OMG LOL yes ok)
enq	ok bible (r1: ok bible)
eo	ok; likely a lot of MT (r1: ok)
es	good (r1: ok)
et	ok (r1: ok)
eu	ok (r1: ok; lots of poetry?)
fa	consulted Ali; he says it's ok (r1: ok)
ff	ok after shortfilter (r1: some noise but some nice stuff! ok!)
ff-Adlm	good (r1: ok sweet)
ffm	ok bible; mixed fulfulde dialects; consider mergind with ff (r1: ok but idk the dialect)
fi	ok (r1: ok but lotsa headers)
fil	ok more bible than expected for such a major language (r1: ok pls note in release that this is the same as tl)
fip	ok jw ; but wrong language. mostly Mambwe-Lungu and Bemba, not Fipu (mgr+bem vs fip) (r1: ok bible)
fj	ok (r1: ok bible lotsa noise)
fo	good (r1: ok TODO check that this is not icelandic review)
fon	ok mostly jw but not all (r1: ok bible)
fr	ok (r1: ok)
frp	fair amount from wikipedia. (r1: remove; all noise + hashtags)
fy	ok plausible but i bet there is a lot of Dutch in there (r1: ok)
ga	ok some en noise (r1: ok)
gag	has 1-2 cyrillic examples with small amts of arabic script noise (r1: ok)
gbm	ok (r1: ok)
gd	ok (r1: ok; but barely)
gil	empty; but merged in data in "cjk" (r1: empty)
gil	this is all in gil (Kiribati). merged into "gil" (r1: empty)
gjk	empty remove (r1: empty)
gju	remove short boilerplate (r1: empty)

gl	ok (r1: ok)
gn	ok some broken characters some bible (r1: ok)
gof	ok some bible (r1: empty)
gom	ok (r1: ok)
gom-Latn	filter on really short boilerplate in en; some porn; after: ok very noisy ; some ok stuff ; release with disclaimer (r1: ok)
gor	ok bible (r1: ok)
grc	warning: this is likely polyphonic greek, not ancient greek (r1: ok but idk diff between ancient and modern greek)
gsw	wtf is happening here; keep with disclaimer; STILL BOILERPLATE (r1: ok but idk diff between gsw and de)
gu	ok (r1: ok some en boilerplate)
gu-Latn	filter short en boillerplate and repetitive sentences (r1: lots of social media pages and some porn)
gub	ok bible (r1: empty)
guc	ok bible (r1: ok)
guh	ok bible (r1: ok)
gui	ok bible (r1: ok)
gv	filter short repetitive sentenecs; still same but keep (r1: ok)
gvl	filter short boilerplate mostly bible (r1: ok)
gym	ok biblle (r1: ok)
gyn	remove boilerplate and porn (r1: remove)
ha	ok (r1: ok)
haw	ok scam tv products (r1: ok but filter u65533 REPLACEMENT CHARACTER)
hi	ok some porn (r1: ok but some en boilerplate)
hi-Latn	filter porn this is half porn (r1: ok but some hi and en)
hif	ok some en noise and religious (r1: ok it is in Latin)
hil	ok some en boilerplate (r1: ok)
hmn	ok (r1: ok)
hne	ok (r1: ok)
ho	ok (r1: ok but but split between wiki boilerplate and actual content)
hr	ok (r1: ok)
ht	ok (r1: ok)
hu	ok (r1: ok)
hui	ok some bible (r1: ok bible)
hus	ok bible (r1: some wiki boilerplate)
hvn	ok religiooous text (r1: ok bible)
hy	ok (r1: ok)
iba	ok jw data (r1: ok)
ibb	ok bible and repeated @ (r1: ok but bible and some repeated lines)
id	ok (r1: ok)
ify	ok bible (r1: empty)
ig	ok (r1: ok)
ilo	ok some bible (r1: some repetitive content)
inb	ok bible (r1: remove; it's a single bible doc lol)
is	ok (r1: ok)
iso	ok jw (r1: ok)
it	ok (r1: ok)
iu	filter script some is en rest is iu script (r1: ok filter latin script)
ium	filter out zh (r1: remove mostly en)
iw	ok (r1: ok has some codemixing because of boilerplate)
izz	ok bible (r1: empty)
ja	ok a little en mixed in (r1: ok but some porn)
ja-Latn	remove maybe low quality short and repeated (r1: ok some noise that is manga pages in english)
jac	ok bible (r1: remove 'home loan' repeated over and over)
jam	ok bible (r1: ok)
jax	filter mostly text.medjugorje.ws boilerplate (r1: remove)
jiv	ok bible
jv	ok (r1: ok)
jvn	ok bible (r1: ok)
ka	ok (r1: ok)
kaa	ok (FYI cyrllic) (r1: ok)
kaa-Latn	ok urls are .ru or .kz (r1: ok)
kac	ok (r1: ok)
kbd	ok many .ru (r1: ok some repetitive text and en noise)
kbp	not sure if right script wiki says latin (r1: ok)
kek	ok jw bible (r1: ok bible)
kfy	filter virama issue (r1: ok)
kg	ok bible jw (r1: ok)
kha	ok (r1: ok some repetitive boilerplate)
kj	ok (r1: filter english out)
kjb	ok bible (r1: empty)
kjg	ok bible (r1: empty)
kjh	ok .ru domain (r1: ok)
kk	ok (r1: ok)
kl	ok (r1: ok)
km	ook (r1: ok)
kmb	ok bible jw (r1: ok)
kmz-Latn	ok soome ar script noise (r1: ok)
kn	ok (r1: ok)
kn-Latn	filter en noise of karnataka govt websites (r1: filter porn there is too much porn and repetitive content)
knj	ok bible (r1: empty)
ko	ok (r1: ok)
koi	ok (r1: ok)
kos	ok lds bible (r1: ok bible)

krc	ok (r1: ok some repetitive content)
kri	ok boilerplate noise bible jw (r1: remove repetitive)
ks	ok shorter docs (r1: ok)
ksd	ok bible (r1: ok bible)
ksw	ok bible (r1: ok)
ktu	ok bible jw (r1: ok)
ku	ok (r1: ok)
kum	ok (r1: ok)
kv	ok a lil boilerplate vibes (r1: ok)
kw	ok short boilerplate bible wiki; ok some porn (r1: ok filter english)
kwi	ok bible (r1: ok)
ky	ok (r1: ok)
la	ok some broken chars
laj	ok bible
lb	ok shorter text; ok AFTER
lg	ok lot of www.bukedde.co.ug in this
lhu	ok bible
ln	ok bible jw
lo	ok many entities in latin script
lrc	ok
lt	ok
ltg	ok mostly www.lakuga.lv
lu	ok jw
lus	ok
luz	terrible; remove
lv	ok
mad	remove mostly short text
mag	ok fix virama issue
mai	ok mild amounts of en noise
mak	ok bible
mam	ok bible jw
mas	ok some amount of bible
max	remove short some ru
maz	ok bible jw
mbt	ok bible
mdf	ok some short docs
mdh	filter porn short text and repetitive boilerplate
mdy	ok bible
mel	remove noisy en
meo	ok mostly blogs
meu	ok bible
mey	mostly short and noisy borderline
mfb	remove short boilerplate
mfe	ok mostly bible maybe some french creole short doc noise
mg	ok some bible jw
mgh	ok bible jw
mh	ok jw lds
mi	ok
min	ok mostly wiki and bible
miq	ok
mk	ok
mkn	ok bible
ml	ok
ml-Latn	ok some short docs
mn	ok
mni	ok
mnw	remove en noise and boilerplate
mps	ok bible
mqy	bible remove short docs
mr	ok fix virama
mr-Latn	remove mostly porn and short docs
mrj	remove short docs; ok
mrw	ok remove short docs
ms	ok
ms-Arab	ok mostly utusanmelayu website
ms-Arab-BN	ok not sure if same as ms-Arab
msb	ok bible
msi	ok filter short docs
msm	ok bible
mt	ok
mtq	remove short doc repetitive
mtr	ok fix virama remove en noise
mui	remove short docs
mwr	filter short docs fix virama
my	filter noise and en fix virama
myv	maybe has .ru urls
nan-Latn-TW	ok
nd	ok
ndc-ZW	ok
ne	ok
new	ok

ng	ok
ngu	ok
nhe	ok
nia	ok
nij	ok
niq	ok
nl	ok
nnb	ok
no	ok
noa	ok
noe	ok
nog	ok
nr	ok
nso	ok
nut	ok
nv	ok
ny	ok
nyn	ok
nyo	ok
nyu	ok
nzi	ok
oc	ok
oj	ok
om	ok
or	ok
os	ok
otq	ok
pa	ok
pa-Arab	ok
pag	bible
pam	remove
pap	ok
pau	ok
pck	ok
pcm	ok
pis	bible
pl	ok
pmy	remove
pon	bible
ppk	bible
prk	ok
ps	ok
pt	ok
qu	ok
qub	bible
quc	bible
quf	bible
quh	bible
qup	bible
quy	bible
qvc	bible
qvi	bible
qvz	bible
qxr	bible
raj	ok
rcf	ok
rhg-Latn	remove
rki	ok
rkt	ok
rm	ok
rmc	ok
rn	bible
ro	ok
rom	bible
ru	ok
ru-Latn	ok
rw	ok
rwo	bible
rwr	remove
sa	ok
sah	ok
sat-Latn	good! all from local news sources
sd	good
sda	ok bible
se	good
seh	ok jw
sg	ok jw
sgj	remove
shn	mostly English boilerplate. filter by latin text before releasing
shp	ok bible
shu	quite questionable. prob remove

si	good
sja	ok bibe
sjp	terible; probably remove; check again after short filter
sk	ok
skg	terrible; remove
skr	ok; some pnb mixed in
sl	ok
sm	ok
smt	ok bible but lots of different bibles!
sn	ok
so	good
spp	ok bible
sq	good
sr	ok
srm	ok; bible + jw
srn	ok bible + jw
srr	remove; englishboilerplate
ss	good mix of data ; renamed from "ss"
st	ok
stq	ok i think ?
su	good
sus	hella sus jk ok bible
suz	ok bible
sv	ok
sw	ok
sxn	ok bible ; also wild diacritics
sxu	rvisit after shortfilter
syl	idk maybe ok ?
syl-Latn	revist or remove after shortfilter
syr	good; practictitioners should keep dialect in mind.
ta	ok
ta-Latn	good text .... but pornographic, like all Indic-Latn datasets
tab	idk plausibly ok
taj	ok bible
tbz	good mostly bible but not all
tca	ok bible + jw
tcy	good; mostly wikipedia; likely some konkani mixed in
tdx	ok jw
te	ok a lot of weirdly low quality looking content like commerce
te-Latn	great good text....but all pornographic stories + blogs, like all Indic-Latn text
teo	ok bible
tet	good ; actually a lot of fun data!
tg	good
th	ok
ti	ok; poor tigray
tiv	ok jw
tk	ok; a few weird docs
tks	ok bible but again i think some mixed dialects
tlh	ok, but why tf are there websites in klingon? all MT ?
tll	ok jw
tly-IR	deeply sus; remove after shortfilter
tn	good
to	good ; news bible government
toj	ok jw
tpi	empy
tr	ok
trp	good ; lots of random stuff
trw	sus; remove
ts	good
tsc	ok
tsg	much noise but some good data too!
tt	good plus some nonunicode misrendered PDF
tuc	ok bible
tuf	ok bible
tvl	ok jw
twu	ok bible, but also i think it's lots of mixed similar dialects
tyv	ok fun stuff plus some russian noise i think
tyz	ok bible bu again i think some mixed dialects
tzh	ok jw
tzj	ok bible
tzo	ok bible + jw
ubu	ok bible
udm	ok
ug	ok
uk	ok
ur	ok
uz	ok some cyrllic noise
ve	ok mostly bible jw
vec	very noisy has wiki from other langs and .it websites so not sure if vec
vi	ok
vkt	1 doc remove

wa	ok lots of wiki stuff
wal	ok bible + jw
war	ok but v sus. Pls filter out wikipedia
wo	ok; mostly bible. PS i have found that Wolof web-crawled data is often bad, so pls give an extra look if you want
xal	ok has .ru sites though
xh	ok
xmm	very noisy lots of dj tiktok and peppa pig repeated
xnr	ok maybe fix virama though it seems fine
xog	ok bible and stories
yap	ok
yaq	remove
yi	ok
ymm	remove
yo	ok
yua	ok
yue	pretty low quality; mostly not Canto
za	revisit after shortfilter
zap	ok JW. PS pls note that at least some Zapotec speakers view it as one language, not as a million dialects like ISO does
zh	mixed simplified and trad; also much porn
zh-Latn	revisit after shortfilter
zne	ok jw
zu	good
zxx-xx-dtynoise	BEAUTIFUL NOISE rename but keep as beautiful xample. (was called "dty")
zyj	deeply bad data .. revisit after shortfilter
zza	good ; also pls note that the Zazaki community is often super into NLP for Zazaki

A.5 Parallel Data Details

To create the dataset described in Section 3, we use the data sources described in Table 11. After preprocessing, we obtain a dataset with a total of 157 different languages and 4.1B sentence pairs that vary from `en-es` with 280.3M sentence pairs to `zu-en` with 7959 sentence pairs. The list of language pairs along with the associated data count is available along with the model checkpoints.

Table 11: The various data sources used to create the parallel data used to train our MT models with the number of available languages and language pairs. (*for NewsCommentary v14 we only use Kazakh (`kk`) data)

Dataset	Version	# Language Pairs	# Languages
Europarl [39]	v7	40	21
	v9	12	8
Paracrawl [22]	-	64	41
TED57 [70]	-	114	58
Tanzil [64]	-	1560	40
NewsCommentary [1]	v10	6	3
	v14*	2	1
	v16	200	15
Wikimatrix [59]	-	1620	85
Wikititles [1]	v2	12	14
OPUS100 [71]	-	198	100
SETimes [64]	-	90	10
UNv1.0 [74]	-	20	5
Autshumato [28]	-	10	5
PMIndia [29]	v1	13	13
CVIT [54]	MKB (v0), PIB (v1.3)	110	11
Inuktitut [34]	-	2	1
NLPC [24]	-	2	1
JESC [56]	-	2	1
KFTT [50]	v1.0	2	1
ASPEC [49]	-	2	1

A.6 Language Codes

The specifics of the language code changes described in Section 4.1 that we made are as follows:

Table 12: Preprocessed multiway data divided by target language in decreasing order of number of # Sentence Pairs.

Language (Code)	# Sentence Pairs	Language (Code)	# Sentence Pairs
English (en)	6825073150	Malagasy (mg)	1190715
Spanish (es)	630962081	Punjabi (pa)	1122414
German (de)	542301841	Hausa (ha)	952163
French (fr)	540506439	Latin (la)	882038
Portuguese (pt)	355008897	Inuktitut (iu)	841459
Italian (it)	283297447	Myanmar (Burmese) (my)	759196
Dutch (nl)	272264696	Walloon (wa)	706400
Swedish (sv)	183450145	Uzbek (uz)	695915
Czech (cs)	166419080	Luxembourgish (lb)	645610
Polish (pl)	154989834	Assamese (as)	623321
Mandarin Chinese (zh)	147268699	Pashto (ps)	606852
Danish (da)	145764833	Armenian (hy)	603397
Hungarian (hu)	136980377	Sindhi (sd)	597211
Russian (ru)	134568973	Northern Sami (se)	585304
Romanian (ro)	117227121	Bashkir (ba)	551617
Slovak (sk)	102889505	Amharic (am)	548828
Finnish (fi)	100468712	Somali (so)	543643
Greek (el)	97855862	Dhivehi (dv)	543145
Arabic (ar)	83364997	Kurdish (Kurmanji) (ku)	483477
Bulgarian (bg)	68424658	French (Canada) (fr_CA)	472160
Lithuanian (lt)	66562681	Odia (Oriya) (or)	465494
Slovenian (sl)	65876962	Faroese (fo)	434288
Latvian (lv)	59061871	Kannada (kn)	417255
Norwegian (no)	57783339	Kinyarwanda (rw)	386133
Estonian (et)	47403866	Wu Chinese (wuu)	369891
Japanese (ja)	42480849	Lombard (lmo)	366147
Korean (ko)	33987656	Egyptian Arabic (arz)	353218
Catalan (ca)	28627098	Uyghur (ug)	337582
Croatian (hr)	28475191	Limburgan (li)	304279
Turkish (tr)	26508188	Aragonese (an)	251004
Ukrainian (uk)	26258530	Sicilian (scn)	249682
Icelandic (is)	24073502	Dzongkha (dz)	248172
Persian (fa)	23237370	Meiteilon (Manipuri) (mni)	242426
Indonesian (id)	19860783	Maori (mi)	234833
Vietnamese (vi)	18803243	Nuer (nus)	231194
Hebrew (he)	17171755	Magahi (mag)	230839
Macedonian (mk)	15900226	Bhojpuri (bho)	230378
Irish (ga)	14939080	Shan (shn)	229967
Galician (gl)	14305858	Friulian (fur)	228928
Serbian (sr)	13989182	Kashmiri (ks)	228580
Albanian (sq)	13904626	Sardinian (sc)	227585
Basque (eu)	13755514	Kanuri (kr_Arab)	227549
Maltese (mt)	12583626	Dinka (din)	227233
Esperanto (eo)	11431440	Venetian (vec)	225065
Hindi (hi)	11044239	Chhattisgarhi (hne)	224085
Bosnian (bs)	10906114	Ligurian (lij)	222513
Serbo-Croatian (sh)	10592606	Central Atlas Tamazight (tzm)	222365
Bengali (bn)	8394639	Tamasheq (taq_Tfng)	220907
Sinhala (si)	7363378	Dari (prs)	220899
Thai (th)	6623168	Banjar (bjn)	220753
Malayalam (ml)	5995504	Achinese (ace_Arab)	220651
Tamil (ta)	5552495	Tamasheq (taq)	219708
Marathi (mr)	5517596	Banjar (bjn_Arab)	219020
Telugu (te)	5379834	Achinese (ace)	217062
Malay (ms)	5241831	Bambara (bm)	216698
Filipino (fil)	4532364	Balinese (ban)	215965
Urdu (ur)	4526509	Moroccan Arabic (ary)	214226
Taiwanese Mandarin (zh_Hant)	3782804	Nigerian Fulfulde (fuv)	209659
Swahili (sw)	3220515	Silesian (szl)	209224
Nepali (ne)	2833740	Kashmiri (ks_Deva)	208575
Norwegian Nynorsk (nn)	2726466	Buginese (bug)	207209
Azerbaijani (az)	2353731	Guarani (gn)	201241
Kazakh (kk)	2153356	Latgalian (ltg)	200302
Tajik (tg)	2005810	Crimean Tatar (crh_Latn)	192342
Low German (nds)	1942746	Kanuri (kr)	191037
Occitan (oc)	1934958	Scottish Gaelic (gd)	162882
Georgian (ka)	1882623	Bavarian (bar)	159419
Belarusian (be)	1808663	Javanese (jv)	144974
Tatar (tt)	1763087	Mongolian (mn)	132599
Western Frisian (fy)	1500410	Zulu (zu)	130485
Afrikaans (af)	1459139	Kyrghyz (ky)	128832
Breton (br)	1431191	Low German (Netherlands) (ndsNL)	113101
English (simple) (en_xx_simple)	1413074	Mirandese (mwl)	96829
Khmer (km)	1330590	Ido (io)	72811
Gujarati (gu)	1309569	Igbo (ig)	41296
Cebuano (ceb)	1255728	Turkmen (tk)	40650
Welsh (cy)	1229401	Yiddish (yi)	37128
Xhosa (xh)	1219701	Yoruba (yo)	26589
		Total # Sentence Pairs	11944961985

1. We use `fil` for Filipino/Tagalog, not `tl`

2. We use `ak` for Twi/Akan, rather than `tw`. This includes Fante.

3. Unfortunately, we use the macro code `chm` for Meadow Mari (instead of the correct `mhr`), and `mrj` for Hill Mari

4. By convention, we use `no` for Norwegian Bokmål, whereas some resources use `nb`

5. By convention we use `ps` for Pashto instead of `pbt` (Southern Pashto)

6. By convention, we use `ms` for Standard Malay, not `zlm`

7. By convention, we use `sq` for Albanian, and don't distinguish dialects like Gheg (`aln`) and Tosk (`als`)

8. We use `ber` as the code for Tamazight, after consultation with Tamazight speakers opining that the dialect distinctions are not significant. Other resources use the individual codes like `tzm` and `kab`.

9. We use the macrocode `qu` for Quechua. In practice, this seems usually to be a mix of the Ayacucho and Cusco dialects. Other resources, like NLLB, may use the dialect code, e.g. `quy` for Ayacucho Chanka. The same is true for a few other macro codes, like `ff` (Macro code for Fulfulde, whereas other sources may use e.g. `fuv`.)

10. Really, there are notes that can be made about almost any code, from the well-accepted conventions like `zh` for Mandarin, to many dialectical notes, like which variant of Hmong really is the `hmn` data? But The above ones are made specifically for ones where we are aware of other datasources floating out there that use different conventions.

A.7 Multiway Data Details

On creating the multiway data described in Section 3.4, we obtain a dataset with 11.9B sentence pairs across 19.7k language pairs. In Table 12, we list the combined number of sentence pairs for each target language.

A.8 Model Training Details

MT Model Training   We train models of various sizes: a 3B, 32-layer parameter model,[12] a 7.2B 48-layer parameter model and a 10.7B 32-layer parameter model. We describe the specifics of the model architecture in Table 13.

We share all parameters of the model across language pairs, and use a Sentence Piece Model (SPM) [41] with 256k tokens shared on both the encoder and decoder side. We train the SPM model on upto 1M sentence samples of the sentences in the sentence-level version of `MADLAD-400`, supplemented by data from the languages in the parallel data used to train MT models when not available in `MADLAD-400` with a temperature of $T = 100$ and a character coverage of 99.9995%.

Each input sentence has a `<2xx>` token prepended to the source sentence to indicate the target language [35]. We use both supervised parallel data with a machine translation objective and the monolingual `MADLAD-400` dataset with a MASS-style [62] objective to train this model. Each of these objectives is sampled with a 50% probability. Within each task, we use the recently introduced UniMax [18] sampling strategy to sample languages from our imbalanced dataset with a threshold of $N = 10$ epochs for any particular language.

We used a square root learning rate decay schedule over the total number of training steps, starting at 0.01 and ending at X, as well as the AdaFactor optimizer with `factorized=False` and 10k warmup steps. We note that for the 10.7B model we use a dropout probability of $p = 0.2$ instead of $p = 0.1$ in order to mitigate overfitting to low-resource languages.

Language Model Training   We follow the same training schedule and model configurations from Garcia et al. [27]. In particular, we consider 8B decoder-only models, following the same model hyperparameters as previous work [17, 27]. We train these models using a variant of the UL2 objective [63] adapted for decoder-only models, and use the same configuration as previous work [27, 52]. We point the reader to these papers for a detailed overview of the training process, and include basic architectural details in Table 13. We use the same SPM trained for the MT models.

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[12]Here and elsewhere, 'X-layer' means X encoder layers and also X decoder layers, for a total of 2X layers.

Table 13: Architecture and training details for the various models we train in this work using `MADLAD-400`.

Model	SPM Size	Training Objective	# Attn Heads	# Enc. Layers	# Dec. Layers	Model Dim	Hidden Dim	Batch Size	Max. Seq. Length	Training Steps
3B MT Model		MT+MASS	16	32	32	1024	8192	4096	256	1M
7.2B MT Model	256k	MT+MASS	16	32	32	2048	8192	4096	256	500k
10.7B MT Model		MT+MASS	32	48	48	2048	16384	4096	256	250k
8B LM		UL2	16	N/A	32	4096	16384	1024	1024	500k

Table 14: Languages on which we evaluate the trained models for each multilingual evaluation set.

Datasets	Languages Evaluated
WMT	cs, de, es, fi, fr, gu, hi, kk, lv, lt, ro, rs, es, tr, zh
Flores-200	ac_Arab, ace, af, am, ar, arz, as, awa, ay, az, ba, ban, be, ber, bg, bho, bjn_Arab, bjn, bm, bn, bo, bs, bug, ca, ceb, ckb, crh_Latn, cs, cy, da, de, din, dyu, dz, ee, el, eo, es, et, eu, fa, ff, fi, fil, fj, fo, fon, fr, fur, ga, gd, gl, gn, gu, ha, hi, hne, hr, ht, hu, hy, id, ig, ilo, is, it, he, ja, jv, ka, kac, kbp, kg, kk, km, kmb, kn, ko, kr_Arab, kr, ks_Deva, ks, ky, lb, lg, li, lij, lmo, ln, lo, lt, ltg, lus, lv, mag, mai, mg, mi, min, mk, ml, mn, mni, mr, ms, mt, my, ne, nl, nn, no, nso, nus, ny, oc, om, or, pa, pag, pap, pl, ps, pt, quy, rn, ro, ru, rw, sa, sc, scn, sd, sg, shn, si, sk, sl, sm, sn, so, sq, sr, ss, st, su, sv, sw, szl, ta, taq_Tfng, taq, te, tg, th, ti, tk, tn, tr, ts, tt, ug, uk, ur, vec, vi, war, wo, xh, yi, yo, zh_Hant, zh, zu
NTREX	af, am, ar, az, ba, be, bem, bg, bn, bo, bs, ca, ckb, cs, cy, da, de, dv, dz, ee, el, en_GB, en_IN, es, es_MX, et, eu, fa, fa_AF, ff, fi, fil, fj, fo, fr, fr_CA, ga, gl, gu, ha, hi, hmn, hr, hu, hy, id, ig, is, it, iw, ja, ka, kk, km, kn, ko, ku, ky, lb, lo, lt, lv, mey, mg, mi, mk, ml, mn, mr, ms, mt, my, nd, ne, nl, nn, no, nso, ny, om, pa, pl, ps, pt, pt_PT, ro, ru, rw, sd, shi, si, sk, sl, sm, sn, so, sq, sr, sr_Latn, ss, sv, sw, ta, te, tg, th, ti, tk, tn, to, tr, tt, ty, ug, uk, ur, uz, ve, vi, wo, xh, yo, yue, zh, zh_Hant, zu
Gatones	ady, ak, as, av, ay, ba, ban, bbc, bci, ber_Latn, bew, bho, bm, bo, ce, chr, ckb, cv, doi, dv, dyu, dz, ee, ff, gn, gom, ilo, iso, kl, kri, lg, ln, lus, mad, mai, meo, min, mni, nso, om, or, qu, quc, rw, sa, sg, skr, ti, tiv, tk, ts, tt, ug, wo, yua, zza

We use a square root learning rate decay schedule over 500k steps, starting at 0.01 and ending at 0.001, as well as the AdaFactor optimizer with `factorized=False` with 10k warmup steps. We describe the evaluation setup in Section 4.3.1.

A.9 Languages Evaluated

In Table 14, we list the languages for which we evaluate the models trained as described in Sections 4.1 and 4.2.

A.10 Results Details

In Tables 15, 19, 16, 17 and 18 we list the WMT, NTREX, Gatones, Flores-200 and Flores-200 (direct pairs) chrf and SacreBLEU scores respectively by language pair along with the model checkpoints.

Table 15: Evaluation scores on WMT (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against NLLB-54B.

| | NLLB | MT-3B | MT-7.2B | MT-10.7B | LM-8B | | | |
					0-shot	1-shot	5-shot	10-shot
csen	33.6 / 58.8	34.8 / 59.9	35.7 / 60.5	35.3 / 60.4	3 / 22.2	27.6 / 53.7	26.7 / 51.8	28.2 / 54
deen	37.7 / 62.4	37.3 / 62.5	38.1 / 63	38 / 63	3.3 / 23.6	26 / 51.9	29.7 / 55.2	30.1 / 55.5
esen	37.6 / 61.7	38.1 / 62.4	38.5 / 62.6	38.5 / 62.7	2.2 / 19	30 / 55.2	31.5 / 57.4	32.3 / 58.4
eten	34.7 / 61.1	36.2 / 61.9	37.4 / 62.8	37.4 / 62.9	4.7 / 24.7	26.4 / 52.8	27.9 / 55	27.7 / 54.5
fien	28.8 / 55.7	32.8 / 59.1	33.5 / 59.4	33.3 / 59.6	1.6 / 16.8	27.1 / 53.5	26.2 / 52	26.3 / 52.6
fren	41.9 / 65.7	42.2 / 65.6	42.7 / 65.9	42.4 / 65.8	2 / 18.6	28.9 / 54.8	35.1 / 60.7	35.6 / 61.1
guen	31.2 / 58.9	30.4 / 58.2	29.9 / 58	29.9 / 57.9	1 / 13	22.2 / 50.7	21.9 / 51.2	24.1 / 53.2
hien	37.4 / 64.2	33.5 / 61.3	36.1 / 62.7	35.5 / 62.4	1.2 / 10.2	23.4 / 52.3	23.4 / 54.5	24.4 / 54.5
kken	30.2 / 58.4	12.3 / 48.1	22.9 / 49.8	19.9 / 52.1	2.4 / 14.2	15.3 / 41.2	11.5 / 40.9	11.9 / 41.6
lten	29.7 / 58.8	34.5 / 60.9	35.3 / 61.4	35.1 / 61.5	3 / 21.4	24.1 / 51.1	26.1 / 52.8	28.1 / 54.9
lven	24.8 / 53.1	27.7 / 55.6	28.1 / 56	28.3 / 56.1	1.3 / 15.7	21.4 / 49.3	21.4 / 49.2	22 / 50.1
roen	43.4 / 66.4	43.6 / 66.6	44.4 / 67	44.4 / 67.1	4.1 / 24.8	34.9 / 58.9	36.1 / 59.9	36.2 / 60.5
ruen	39.9 / 63.8	39.9 / 64.4	40.7 / 64.9	40.5 / 64.9	2.1 / 16.4	32.7 / 56.9	34.1 / 58.5	27.4 / 53.7
tren	34.3 / 60.5	33.2 / 58.9	34.3 / 59.7	34.1 / 59.8	1.6 / 16.8	21.7 / 48.1	21.7 / 47.7	22.1 / 48.7
zhen	28.5 / 56.4	24.9 / 55.6	26.2 / 56	25.7 / 56.2	0.4 / 1.6	15.3 / 40	19.3 / 46.2	16.9 / 47
encs	25.2 / 53.2	26.2 / 53.8	27 / 54.2	26.8 / 54.2	0.7 / 10.3	18.5 / 45.2	19.3 / 48	19.6 / 47.9
ende	33 / 62	33.7 / 62.5	35 / 63.2	35 / 63.2	1.6 / 16.2	19.7 / 48.1	21.9 / 53	21.9 / 54.3
enes	37.2 / 61.1	37.3 / 61.1	37.7 / 61.3	37.4 / 61.3	0.9 / 13.9	28.4 / 53.7	30.2 / 55.6	30.9 / 56.3
enet	27 / 59.3	27.6 / 60.4	28.3 / 61	28.4 / 61.1	0.5 / 10.7	20.1 / 52.5	19.9 / 51.2	20.8 / 53.4
enfi	27.7 / 61.7	28.3 / 60	29 / 60.4	27.8 / 60.6	0.5 / 10.5	18.1 / 49	19.8 / 51.6	20.2 / 51.9
enfr	44.2 / 67.7	44.8 / 67.2	45.3 / 67.6	45.6 / 67.7	1 / 13.7	32.8 / 58.6	32.1 / 57.6	32.7 / 59.5
engu	17.6 / 50	18.6 / 51.3	19.2 / 52.1	18.8 / 52	0.1 / 0.3	0.2 / 1.2	0.1 / 1.4	0.1 / 1.6
enhi	26 / 53.5	23.4 / 50.1	24.2 / 50.8	24.5 / 51.1	1.5 / 10.6	16.9 / 42.6	15.7 / 40.5	16.7 / 42.7
enkk	34.8 / 65.2	7.6 / 44.2	12.9 / 47	10.7 / 47.1	0.2 / 5.2	6.1 / 37.6	6.2 / 37.7	5.7 / 38.9
enlt	37 / 66.9	26.5 / 59	27.2 / 59.5	27 / 59.6	1.1 / 14.2	20.6 / 53.3	20.9 / 53.6	20.1 / 53.1
enlv	21.3 / 53.6	23.9 / 55.8	25.2 / 56.6	24.8 / 56.4	1 / 12.4	18.3 / 48.5	19.7 / 52	19.8 / 51.6
enro	33.4 / 60.4	35.5 / 61.4	35.5 / 61.5	35.6 / 61.7	3.7 / 21	29.6 / 56.5	25.3 / 54	29.5 / 56.4
enru	44.8 / 67.4	32.9 / 57.8	33.6 / 58.4	33.6 / 58.3	0.6 / 2.5	20.4 / 44	22.3 / 47	23.8 / 49.4
entr	23.3 / 58.3	24.2 / 57.2	26.1 / 58.3	25.9 / 58.1	0.5 / 10.9	11.1 / 42.2	11 / 46.4	8.6 / 46.1
enzh	33.9 / 30.1	32.6 / 29.8	33.3 / 30.9	33.6 / 31.1	0.9 / 2.7	20.2 / 18.9	16.9 / 18.1	19 / 19
xx2en	34.2 / 60.4	33.4 / 60.0	34.9 / 60.6	**34.6 / 60.8**	2.3 / 17.3	25.1 / 51.4	26.2 / 52.9	26.2 / 53.4
en2xx	**31.1 / 58.0**	28.2 / 55.4	29.3 / 56.2	29.0 / 56.2	1.0 / 10.3	18.7 / 43.5	18.8 / 44.5	19.3 / 45.5
Average	**32.7 / 59.2**	30.8 / 57.7	32.1 / 58.4	31.8 / 58.5	1.6 / 13.8	21.9 / 47.4	22.5 / 48.7	22.8 / 49.4

Table 16: Evaluation scores on the GATONES test set used by Bapna et al. [9] (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2.

| | NTL (Bapna et al. [9]) | | MT-3B | MT-7.2B | MT-10.7B | LM-8B | | | |
	1.6B	6.4B				0-shot	1-shot	5-shot	10-shot
ady_en	- / 53.7	- / 54.8	32.7 / 58.8	34.2 / 59.8	33.9 / 60.1	1.5 / 12.4	18.9 / 50.2	25 / 54.2	21.1 / 52.1
ak_en	- / 31.7	- / 36.3	6.9 / 27	10.4 / 29.9	9.3 / 29	0.1 / 5.5	3.6 / 15.5	1.8 / 18.6	1.9 / 16.6
as_en	- / 52.9	- / 58.6	30.6 / 55.6	32.1 / 56.8	33.8 / 58	1 / 9.7	17.4 / 44.5	19.4 / 47.4	21.1 / 48.6
av_en	- / 48.1	- / 48.1	19.7 / 47.8	21.3 / 50.6	21.5 / 50.9	0.3 / 6.1	11.6 / 32.5	10.3 / 40.2	11.1 / 40.6
ay_en	- / 32.3	- / 30.8	9.1 / 28.7	11.3 / 29	11.3 / 30.1	0.2 / 5.6	1.4 / 13.7	5.9 / 23.1	5.5 / 22.6
ba_en	- / 42.3	- / 45.8	4.5 / 23.3	5.4 / 24	6.9 / 27.2	0.2 / 2.9	8.7 / 30.3	7.6 / 35	7.7 / 34.6
ban_en	- / 32.2	- / 35.4	10.1 / 30.9	10.3 / 31.2	10.9 / 32.4	0.2 / 6.6	2.2 / 21.2	4.7 / 24.6	4.7 / 22.7
bbc_en	- / 40.9	- / 44	12.4 / 36.6	12.1 / 36.7	13.3 / 38	0.2 / 6.6	5.6 / 27.5	7.7 / 29.4	7.9 / 28.4
bci_en	- / 11.6	- / 10.8	2.7 / 19.7	3.6 / 20.4	3.9 / 21.4	0 / 4	0.6 / 9.5	1.9 / 15.3	
bew_en	- / 49.8	- / 51.8	25.3 / 50.1	26.6 / 51.4	26.7 / 51.7	0.7 / 10.8	20.3 / 44.8	23.8 / 49.2	21.3 / 48.3
bho_en	- / -10000	- / -10000	28.6 / 55.8	25.6 / 52.9	29.3 / 56.3	0.6 / 7.4	17.7 / 45.6	20 / 49.1	21.6 / 49.7
bm_en	- / 27.6	- / 36.3	11.9 / 32.8	10.6 / 31.7	12.6 / 33.9	0.1 / 4.2	0.1 / 11.5	1.2 / 11	1.2 / 14.4
ce_en	- / 44.6	- / 44.9	11.4 / 36	12.5 / 37	13.5 / 37.3	0.6 / 7.5	11.4 / 36.4	9.4 / 33.2	15.1 / 41.3
chr_en	- / 16.3	- / 15.6	1.1 / 5.9	0.6 / 8	0.9 / 7.2	0 / 0.6	0.2 / 12.8	0.3 / 12.6	0.1 / 10
cv_en	- / 39.9	- / 46.3	19 / 42.8	21.2 / 44.9	22.9 / 46.6	0.3 / 5.7	7.5 / 24.6	13 / 38	12.2 / 36.3
doi_en	- / 57.4	- / 63.1	15.3 / 43.1	16 / 42.9	18 / 45	0.2 / 4.7	6.9 / 31.9	8.8 / 35.2	6.1 / 36.4
dv_en	- / 37	- / 45.2	20.1 / 45.3	21.4 / 47.1	22.5 / 47.7	0.8 / 8.9	11.4 / 35.5	13.2 / 38.1	14.6 / 41.5
dyu_en	- / 23.9	- / 23.5	7.6 / 28	6.7 / 27.7	8.6 / 30	0 / 4.6	2 / 14.1	2.3 / 16.2	1.3 / 15.1
ee_en	- / 29.1	- / 33.5	8.6 / 25.8	11.1 / 28.9	10.4 / 28.3	0.1 / 6	2 / 17.6	2.1 / 18.9	3.1 / 16.4
en_ady	- / 21.8	- / 28.2	0.6 / 8.8	2 / 14.2	1.4 / 11.6	0.1 / 0.6	2.1 / 18.9	0.4 / 11.2	1.7 / 28.6
en_ak	- / 32.1	- / 34.3	2.2 / 17.9	4.1 / 21.9	3.9 / 21.2	0.3 / 5.9	0.1 / 3.5	0.1 / 4.5	0 / 3.1
en_as	- / 36.3	- / 36.7	8.4 / 36.7	8.4 / 36.9	8.7 / 38	0.1 / 1.8	0.7 / 17.6	0.7 / 18.4	0.9 / 19.1
en_av	- / 26.1	- / 28.1	1.7 / 17.5	1.8 / 21.5	1.9 / 20.4	0.1 / 0.5	0.1 / 4.5	0.5 / 15.8	0.1 / 5.9
en_ay	- / 30	- / 30.5	1.4 / 17	2.4 / 21.7	2.1 / 21.6	0.2 / 6.2	0.5 / 9.3	0.2 / 4.7	0 / 3.4
en_ba	- / 37.6	- / 38.4	2.3 / 22.1	3.6 / 25.3	4 / 26.8	0.1 / 0.9	0.2 / 8.8	0.2 / 9.3	0.1 / 5.7

en_ban	- / 31.8	- / 33.1	3.9 / 30.8	3.7 / 30.9	4 / 31.5	0.2 / 8.5	0.7 / 14.1	0.1 / 4.4	0.1 / 8.5
en_bbc	- / 34.9	- / 35.4	1.9 / 26.8	2.6 / 28.8	3.1 / 29.5	0.1 / 4.4	0.4 / 12.5	0.1 / 8.1	0.1 / 7.1
en_bci	- / 14.1	- / 14.7	1.5 / 12.7	2 / 13.8	2.4 / 14.9	0.1 / 4.8	0 / 2.2	1.1 / 8.8	0 / 1.7
en_bew	- / 45.7	- / 46	7.9 / 35.6	12.6 / 44.9	12.7 / 45.5	0.1 / 6.2	7.5 / 35.2	10.4 / 41.9	11.7 / 43.9
en_bho	- / 0	- / 40.6	12.8 / 39.5	12 / 38.4	12.7 / 40.1	0.2 / 3.8	2.9 / 24.6	4.1 / 28.8	5.8 / 30.5
en_bm	- / 28.7	- / 34.3	6.5 / 28.5	6.1 / 27.2	7.1 / 30.5	0.2 / 5.5	0.1 / 4.8	0 / 2.6	0 / 2.1
en_ce	- / 23.5	- / 23.7	3.4 / 9	7.5 / 22.9	1.9 / 15.2	0.2 / 1.3	0.8 / 8.7	0 / 1.2	0.1 / 3.5
en_ckb	- / 0	- / 41.6	7.5 / 38.7	7.9 / 38.4	6.7 / 35.4	0.1 / 0.6	0.2 / 8.2	0.2 / 9	0.2 / 11.1
en_cv	- / 28.1	- / 32.1	3.1 / 25.6	3.1 / 25.6	3.1 / 25.8	0.1 / 0.9	0.1 / 5	0.1 / 5.5	0 / 4.5
en_doi	- / 29.9	- / 25.5	0.7 / 0.8	0.7 / 0.8	0.7 / 0.8	0.1 / 0.2	0.3 / 10.1	0.3 / 11	0.1 / 5.9
en_dv	- / 43.2	- / 43.7	2.9 / 38	3.5 / 40.2	3.8 / 40.8	0.1 / 0.2	0.6 / 0.4	0.6 / 0.5	0.5 / 0.4
en_dyu	- / 12.7	- / 20.4	1.9 / 19.4	2.3 / 19.6	2.2 / 20.1	0.1 / 4	0.4 / 11.2	0 / 4.6	0 / 1.5
en_ee	- / 35.9	- / 39.2	4.1 / 23.7	6.1 / 27.1	6 / 26.6	0 / 4.7	0.1 / 4.2	0 / 2.9	0 / 2.1
en_ff	- / 31.1	- / 32.3	3 / 21.4	3.3 / 21.3	3.7 / 22.9	0.1 / 5.5	0 / 12	0 / 1.8	0 / 3.3
en_gn	- / 24.3	- / 32.2	6.3 / 30.8	6.4 / 30.3	6.4 / 31.4	0.2 / 6.7	0.2 / 14.6	0.1 / 4.4	0 / 2.5
en_gom	- / 1.1	- / 39.1	1.2 / 20.1	2.1 / 23.5	4.3 / 28.2	0.1 / 0.7	0.6 / 15.3	0.5 / 16.8	1.2 / 20
en_ilo	- / 49.7	- / 52.4	13.9 / 37.8	16.2 / 41.3	16.9 / 42.8	0.3 / 7.1	2.5 / 23.6	3.4 / 25.7	2.1 / 24.8
en_iso	- / 16.5	- / 30.5	2.1 / 16.3	2.4 / 18.2	3.1 / 17.4	0.2 / 4.3	0 / 3.2	0.1 / 7.2	0 / 4.2
en_kl	- / 0	- / 23.1	2.6 / 29.5	3.6 / 33	3.4 / 33.6	0.2 / 4.6	0.4 / 9	0.1 / 4.7	0 / 4.8
en_kri	- / 32.7	- / 34.9	2.6 / 22.2	2.3 / 18.2	3.4 / 22.7	0.3 / 5.9	0.7 / 11.3	0.2 / 8.7	0.7 / 16.4
en_lg	- / 35.9	- / 38	1.7 / 23.6	1.6 / 25.8	2 / 27.4	0.1 / 5.3	0 / 3.6	0 / 3.6	0 / 2.6
en_ln	- / 12.7	- / 33.9	0.3 / 11.7	0.4 / 13.6	0.6 / 15.2	0 / 5.8	0 / 2.7	0 / 2.9	0 / 1.7
en_lus	- / 16.9	- / 39.3	7.7 / 31.1	10.6 / 35.6	10.2 / 34.7	0.2 / 5.6	0.1 / 4.8	0.1 / 4.7	0.1 / 4.2
en_mad	- / 29.8	- / 30.2	2.1 / 23.8	3.3 / 25.9	4 / 25.5	0.1 / 6.8	0.1 / 4.6	0.1 / 6.4	0.1 / 3.2
en_mai	- / 34.1	- / 37.6	12.7 / 42.4	13.2 / 41.2	14 / 43.2	0.1 / 0.8	1.6 / 18.2	3.4 / 28.9	3.4 / 29.5
en_meo	- / 50.9	- / 50.7	39.3 / 63	46.3 / 68.9	44.1 / 67.6	2.2 / 13.2	47.4 / 70.4	46.5 / 70.3	48.3 / 70.8
en_min	- / 51.8	- / 56.1	10.7 / 44.7	12.9 / 47.2	10 / 45	0.1 / 7.3	5.7 / 35.9	4.7 / 34.7	6.3 / 39.9
en_mni	- / 35.7	- / 38.2	7.1 / 38.9	7.9 / 39.4	7.9 / 40.6	0.1 / 0.3	0.1 / 1.7	0 / 1.7	0 / 0.6
en_nso	- / 45	- / 41.6	11.1 / 34.4	14.4 / 38.2	13.4 / 37.3	0.2 / 4.5	0.1 / 5.9	0.1 / 5.6	0.1 / 5
en_om	- / 36	- / 39.1	1 / 20	1.7 / 26.9	1.9 / 26.4	0.1 / 5.8	0 / 4.4	0 / 2.6	0 / 2.4
en_qu	- / 29.8	- / 33.1	1.5 / 19.5	2.3 / 21.1	1 / 22.4	0 / 6	0.1 / 6.7	0 / 2.2	0 / 1.1
en_quc	- / 22.8	- / 22.9	0.5 / 10.1	1 / 12.7	1.4 / 14.2	0.2 / 5.9	0 / 5.7	0 / 3.2	0 / 4.5
en_sa	- / 26.9	- / 28.4	1.3 / 24	1.5 / 26.9	1.8 / 27.8	0 / 1.2	0 / 5.3	0 / 5.7	0 / 6.2
en_sg	- / 12.7	- / 20.7	0.4 / 18.5	0.5 / 18.2	0.5 / 18.5	0 / 4.7	0 / 1.3	0.1 / 22.2	0 / 1.3
en_skr	- / 32.8	- / 31.3	1.3 / 21.9	1.5 / 24.9	1.9 / 25	0 / 0.1	0.1 / 7.9	0 / 6	0 / 4.8
en_ti	- / 19.9	- / 21.1	1.3 / 12.8	1.5 / 15.6	1.7 / 15.8	0.1 / 0.3	0 / 0.6	0 / 0.6	0 / 0.4
en_tiv	- / 13.7	- / 23	1 / 16.2	1.3 / 18.5	1 / 17.9	0.2 / 4.7	0.4 / 9.3	0 / 2.3	0 / 3.7
en_ts	- / 17.4	- / 45.5	6.4 / 33.6	8.9 / 37.4	7.4 / 35.7	0.1 / 5.2	0.1 / 4.1	0.1 / 5.8	0.1 / 5
en_yua	- / 30.6	- / 31.6	3.5 / 19	1.4 / 17.2	3 / 19.5	0.2 / 6.2	0.6 / 9.9	0.1 / 4	0.1 / 7
en_zza	- / 22.1	- / 22.6	1.7 / 19.8	1.1 / 18	1.3 / 17.6	0 / 3.6	0 / 8.9	0 / 2.6	0 / 1.6
ff_en	- / 33.7	- / 41.2	7.8 / 26.8	8.3 / 26.5	9.4 / 29.2	0.1 / 4.4	0.4 / 12.5	1.1 / 15.4	1.3 / 13.6
gn_en	- / 26.7	- / 38.9	12.9 / 35.5	12.7 / 35.2	13.7 / 37	0.2 / 6	1.5 / 16.7	3.9 / 22.2	2.6 / 19.8
gom_en	- / 50.7	- / 55.5	20.5 / 45.7	20.4 / 45	21 / 45.7	0.1 / 1.2	10.5 / 33.2	16.6 / 42.1	15.7 / 41
ilo_en	- / 50.8	- / 43.4	17.3 / 44.2	28.6 / 52.7	29.6 / 52.8	0.2 / 5.7	13.7 / 38.9	20.1 / 42.7	18 / 42.1
iso_en	- / 17.9	- / 29.4	5.8 / 24.3	7.7 / 25.3	8.2 / 26.1	0.1 / 4.5	1.1 / 16	1.6 / 14.4	2.3 / 17.2
kri_en	- / 48.7	- / 56.5	13.2 / 37	15.6 / 39.5	17.3 / 41.5	0.1 / 6	10.5 / 31.3	7.5 / 31.1	10.5 / 33.2
lg_en	- / 32.6	- / 37.9	6.3 / 24.1	8.9 / 26.7	8.2 / 27.1	0 / 3.9	1.9 / 18.9	2.5 / 18.3	3.3 / 17.3
ln_en	- / 28.2	- / 30.4	0.8 / 13.1	0.9 / 14.2	0.8 / 14.8	0.1 / 5.1	0.3 / 15.2	1 / 15	0.9 / 12.7
lus_en	- / 22.6	- / 34.5	13 / 35.7	18.4 / 40.9	17.9 / 41.2	0.6 / 12	7.5 / 31	12.1 / 33.6	10.8 / 33.4
mad_en	- / 44.9	- / 50.5	8.5 / 34	10.4 / 34.3	11.9 / 36.7	0.1 / 5.9	3.8 / 22.5	3.9 / 24.9	5 / 26.8
mai_en	- / 57.8	- / 61.6	30.9 / 57	29.2 / 55.7	33.3 / 58.8	0.9 / 9.3	15.3 / 45.1	20.5 / 50.1	20.3 / 49.2
meo_en	- / 66.1	- / 67.9	44.4 / 66.4	46.2 / 67.8	45.5 / 67.5	0.9 / 9.4	38.7 / 61.5	39.6 / 63.3	41.1 / 63.7
min_en	- / 58.8	- / 62.4	26.2 / 52.4	25.3 / 50.8	29 / 55.1	0.4 / 7.7	16.7 / 39.3	20.9 / 49.1	21.7 / 49.5
mni_en	- / 54.8	- / 56.4	32.2 / 55.9	31 / 54.9	33.4 / 57	0 / 1.9	1.2 / 17.5	2.6 / 20.4	2.7 / 20.5
nso_en	- / 45.8	- / 51.3	17.6 / 40.2	21.1 / 43.2	21.1 / 43.4	0.2 / 6.1	5.7 / 23.9	7.6 / 28.7	6.1 / 27.3
om_en	- / 32.1	- / 38.1	5.7 / 25.8	9.4 / 30.6	9.4 / 31.3	0.2 / 6.2	0.8 / 18.9	2.8 / 19	2.3 / 20.2
qu_en	- / 29.9	- / 32.5	6.7 / 27.2	7.3 / 27.6	7.5 / 28.2	0.1 / 6.1	2.5 / 18.1	1.8 / 13.7	2.3 / 18.8
quc_en	- / 24.4	- / 26.7	1.9 / 17.6	2 / 15.9	2.8 / 19.3	0.1 / 7.1	1.3 / 11.4	1.6 / 13.9	0.9 / 12.3
sa_en	- / 43.5	- / 46.3	15.1 / 39	17.3 / 40.4	14.5 / 37.9	2.6 / 18.1	7 / 35.8	7.4 / 34.8	9.8 / 37.3
sg_en	- / 13.4	- / 13.8	0.5 / 12.5	0.6 / 13.5	0.7 / 14.1	0 / 3.2	0 / 17	0.2 / 9.1	0.2 / 12.1
skr_en	- / 44.4	- / 48.4	9 / 35.5	12.5 / 38.8	12.5 / 39.1	0.3 / 8.5	6.5 / 28.5	9 / 33.2	8.5 / 34.3
ti_en	- / 37.9	- / 44.2	11.7 / 34	15.2 / 38.2	15.2 / 38.2	0.3 / 7.1	5.3 / 22.3	7.1 / 27.4	7 / 26.3
tiv_en	- / 14.1	- / 15	2.7 / 14	2.9 / 14.8	3 / 15.4	0.1 / 3.8	0.9 / 12.3	1.1 / 11.8	0.9 / 12.2
ts_en	- / 25.5	- / 43	14.3 / 35.7	18.5 / 40.5	17.8 / 40	0.3 / 7.5	1 / 16.3	7.6 / 25.9	8.7 / 27.8
yua_en	- / 34.6	- / 40.7	6 / 27	7.1 / 28.3	9.7 / 30.9	0.2 / 6.9	0.8 / 11.3	3.3 / 20.2	4.4 / 19.2
zza_en	- / 23.4	- / 23.2	4.6 / 22.4	5.1 / 22.8	5.2 / 24.2	0.2 / 10.6	1.9 / 18.9	3.3 / 21.3	2.3 / 20.6
xx2en	- / 37.2	- / **41.2**	13.3 / 34.6	**15.5** / 36.5	14.8 / 36.0	0.3 / 6.5	6.6 / 25.4	8.3 / 28.1	8.4 / 28.4
en2xx	- / 28.5	- / **33.1**	4.5 / 23.9	**5.5** / 26.4	5.4 / 26.2	0.2 / 4.2	1.7 / 10.5	1.7 / 9.9	1.8 / 9.4
Average	- / 32.9	- / **37.2**	8.9 / 29.3	**10.5** / 31.5	10.1 / 31.1	0.3 / 5.4	4.2 / 18.0	5.0 / 19.0	5.1 / 18.9

Table 17: Evaluation scores on en-centric Flores-200 pairs (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against NLLB-54B. All metrics are computed with the sacrebleu reference implementation.

	NLLB	MT-3B	MT-7.2B	MT-10.7B	LM-8B			
					0-shot	1-shot	5-shot	10-shot
en_ace_Arab	0.4 / 21.1	1.4 / 26.6	1.4 / 25.3	1.3 / 26.9	0 / 0.1	0 / 0.5	0 / 2.9	0 / 2.2
en_ace	9.3 / 41.4	8.3 / 39.6	6.5 / 36.6	7.6 / 39.1	0.1 / 3.7	0.9 / 15.3	0.8 / 21.1	0.7 / 22.4
en_acm	10.3 / 35.4	0.6 / 0.8	0.4 / 0.8	0.6 / 0.8	0 / 0.4	4.8 / 34.6	8.3 / 43.3	6.1 / 41.1
en_acq	13.6 / 46.8	0.6 / 0.8	0.4 / 0.7	0.6 / 0.8	0.1 / 1.2	5.9 / 36.1	10.1 / 43.5	9.7 / 44
en_aeb	12 / 42.1	0.6 / 0.8	0.6 / 0.8	0.6 / 0.8	0.1 / 1.2	1.4 / 20.3	4.1 / 35.4	4.9 / 37.2
en_af	38.4 / 66.6	38.8 / 66.1	40.9 / 67.6	40.4 / 67.3	0.7 / 10.5	31.2 / 62.2	36.9 / 64.1	38.6 / 64.3
en_ajp	20.5 / 56	0.7 / 1.3	0.6 / 1.3	0.7 / 1.3	0 / 1	9.5 / 41.9	9.3 / 43.1	9.7 / 44.5
en_am	15 / 42.2	8.5 / 31.2	8.8 / 32.2	9.1 / 32.5	0 / 0.2	0.1 / 0.6	0.2 / 0.7	0.2 / 0.7
en_apc	20.4 / 54.9	0.8 / 1.2	0.6 / 1.2	0.7 / 1.1	0 / 1	6 / 37.7	5.5 / 39	4.4 / 40
#N/A en_ar_MA	11.7 / 43.5	0.4 / 0.9	0.3 / 0.8	0.3 / 0.8	0 / 1.1	0.2 / 5.5	1 / 24.7	0.2 / 15.3
en_ar	29.7 / 60.6	27.3 / 57.9	28.2 / 58.4	27.7 / 58.2	0.1 / 1.2	12.6 / 44	17.5 / 50.2	18 / 50.6
en_ars	23.2 / 54.2	0.4 / 0.6	0.3 / 0.6	0.4 / 0.6	0.1 / 1.1	11.6 / 42.3	15.1 / 48.3	16.2 / 49.4
en_arz	16.7 / 50.9	16.6 / 48.7	15.1 / 47	16.4 / 48.9	0.1 / 1.2	2.6 / 27	3.4 / 34.8	6 / 38.6
en_as	7.9 / 40.3	7.3 / 37.3	8.1 / 38.9	8 / 39.2	0 / 0.9	0.2 / 12.9	0.7 / 21.8	0.6 / 21.3
en_ast	29.8 / 59.6	1.1 / 2.1	2 / 13.6	1.1 / 2	0.2 / 7.8	6.4 / 38.4	9.7 / 44.6	11.2 / 45.9
en_awa	18.5 / 50.7	10.3 / 43.8	9.5 / 42.3	10.2 / 44.4	0 / 0.3	0.8 / 16.5	7.2 / 38	5 / 38.6
en_ay	4 / 34.5	0.8 / 16.7	1.1 / 19.5	1.4 / 20.9	0 / 2.6	0 / 2	0 / 7	0 / 4.1
en_az	14.1 / 47.1	12.5 / 44.2	13.5 / 45.3	13.9 / 46.4	0.1 / 5.4	8.4 / 38.8	9.7 / 42.8	10.6 / 43.7
en_azb	1.3 / 27.8	0.2 / 0.6	0.2 / 0.6	0.2 / 0.6	0 / 0.1	0 / 0.8	0 / 6.9	0 / 5.6
en_ba	18.7 / 51	5.9 / 28.7	7.8 / 31.7	10.4 / 36.8	0 / 0.3	0.3 / 10.8	0.3 / 19.8	0.2 / 16.4
en_ban	15.3 / 48.4	13.1 / 45.5	11.1 / 42.4	13.4 / 45.9	0.1 / 5.5	0.4 / 10.3	0.7 / 21.7	1.7 / 30.4
en_be	14.4 / 45.7	12.3 / 40.5	13.5 / 42.1	13.6 / 42.8	0.1 / 2.6	11.5 / 40.9	11.5 / 41.5	11.1 / 41.6
en_bem	10.5 / 42.3	1.6 / 2.4	2.7 / 17.7	1.6 / 2.7	0.2 / 4.4	0 / 4.9	0.1 / 10.1	0.1 / 7.9
en_ber	8.1 / 34.3	6.6 / 31	6.2 / 30.6	7.5 / 33.4	0 / 0.2	0 / 0.5	0 / 2	0 / 1
en_bg	41.6 / 67.1	43.5 / 68.9	43.9 / 69.2	44.1 / 69.3	0.7 / 5.7	32.2 / 60.2	33 / 61.4	33.4 / 62.2
en_bho	17.3 / 45.2	13.4 / 41	11.7 / 38.8	13.8 / 42.1	0.1 / 2.1	1.4 / 19.5	4.6 / 31.7	4 / 31.2
en_bjn_Arab	1.1 / 20.3	3.3 / 30.5	2.9 / 28.6	3.6 / 31	0 / 0	0 / 1.1	0 / 4.4	0 / 1.5
en_bjn	19.2 / 51.8	15.8 / 49.6	13.3 / 45.6	15.8 / 49.8	0 / 2.4	1 / 17.2	4.9 / 36.3	3 / 34.9
en_bm	6.8 / 32.9	4.9 / 27.8	4.3 / 26.8	5.7 / 30.1	0 / 3.1	0 / 6.3	0 / 11.2	0.1 / 7.8
en_bn	19.4 / 54.2	14 / 47.2	14.8 / 48.2	14.8 / 48.3	0.1 / 3.7	4.5 / 35	8.2 / 44.4	7.1 / 44.3
en_bo	0.8 / 38.6	13.8 / 26.4	15.9 / 29.4	15.9 / 30.2	0 / 0.1	0 / 0	0 / 1.4	0 / 1
en_bs	33.2 / 61.4	33.4 / 61.9	34 / 62.3	34.6 / 62.9	0.3 / 5.9	24 / 53.6	27.6 / 56.9	26.9 / 57.5
en_bug	6.5 / 38.3	5.8 / 36.6	5.3 / 34.7	5.8 / 37.2	0.1 / 4.3	0 / 2.2	0 / 6.7	0.1 / 8.4
en_ca	43.9 / 66.8	45.8 / 67.5	46.4 / 68	46.7 / 68.4	0.9 / 11.3	35.9 / 60.7	36.3 / 61.8	37.1 / 61.9
en_ceb	30.3 / 59.6	7.4 / 26.5	8.3 / 27.6	9.4 / 29.4	0.2 / 3.3	9.1 / 39.8	9.3 / 39.4	10.3 / 40.7
en_cjk	2.7 / 28.3	1.3 / 2.4	1.2 / 16.6	1.4 / 3.8	0 / 3.3	0 / 1.3	0.1 / 6.2	0 / 6.2
en_ckb	13.2 / 52.5	9.2 / 44.9	9.8 / 45	9.4 / 44.4	0 / 0.1	0.1 / 5.6	0.2 / 14	0.1 / 13.5
en_crh_Latn	16.8 / 51	13.2 / 47.3	10.9 / 44.1	13.8 / 48.4	0.1 / 3.6	0.4 / 15.2	1.1 / 27.5	1.3 / 28.2
en_cs	33.6 / 59.8	34.8 / 61.3	34.7 / 61.1	35.6 / 61.5	0.2 / 5.6	22.5 / 52.1	26.2 / 54.5	25.9 / 54.6
en_cy	51.6 / 72.5	41.7 / 62.4	45.7 / 66.4	44.7 / 65.6	0.1 / 5.1	1.5 / 15.2	8.8 / 38.4	4.9 / 35.6
en_da	44.5 / 68.4	48 / 71.1	47.9 / 71.1	48.3 / 71.3	0.6 / 8.5	40.3 / 65.3	41 / 65.4	42.1 / 66.8
en_de	39.6 / 65.2	41.5 / 67.1	42 / 67.5	42.2 / 67.4	0.5 / 10.1	27.6 / 56.3	28.4 / 57.4	29.1 / 58
en_din	3.8 / 26.8	3.4 / 25.1	3.2 / 24.7	3.3 / 25.9	0.1 / 3.4	0 / 2.9	0 / 10.6	0 / 0.9
en_dyu	1.7 / 19.8	2 / 21	2.3 / 21.1	2.1 / 22.1	0 / 2.7	0 / 2.7	0 / 7.4	0 / 5.8
en_dz	0.6 / 45.4	34.2 / 42.5	32.3 / 41	37 / 45.1	0 / 0	0 / 1	0 / 3.4	0 / 2.4
en_ee	13.2 / 41.9	5.2 / 26.9	6.8 / 29.2	5.9 / 28.4	0 / 3.2	0.1 / 3.4	0.1 / 7.5	0.1 / 5.9
en_el	28 / 54.2	29.2 / 55.9	29 / 55.8	29.5 / 56.3	0.3 / 2.4	19 / 46.5	21.5 / 48.8	20.9 / 48.9
en_eo	35.3 / 63.9	33.6 / 62.6	34.1 / 63	34.3 / 63.7	0.2 / 5.4	5.1 / 32.4	12.6 / 47.2	9.4 / 44.8
en_es	28.1 / 56	28 / 56.4	28.4 / 56.6	28.5 / 56.7	0.3 / 8.9	22.6 / 50.6	23.6 / 52.1	23.7 / 52.2
en_et	27.1 / 59.9	29 / 61.3	28.5 / 61.2	29.8 / 61.8	0.2 / 6	20.4 / 54.1	22.7 / 55.5	23.1 / 55.5
en_eu	17.2 / 54.9	18.3 / 55.5	18.6 / 55.7	19.3 / 57.2	0 / 5.5	8.3 / 45.5	12.5 / 51.1	12.5 / 51.3
en_fa_AF	27.8 / 55.4	0.5 / 1	0.4 / 0.9	0.5 / 0.9	0 / 0.1	14.7 / 44.4	21.6 / 48.4	19.4 / 48.4
en_fa	24.9 / 53.5	24.8 / 51.2	25.3 / 51.4	25.1 / 51.7	0.1 / 0.8	15.3 / 44.7	20.7 / 49.5	20.1 / 49.2
en_ff	3.9 / 0	2.2 / 23.4	2.5 / 24	2.5 / 25.1	0 / 3.6	0 / 20	0 / 3.8	0 / 7.8
en_fi	26.2 / 59.4	26.9 / 61.7	27.3 / 62	27.7 / 62.6	0.1 / 7.2	19.1 / 52.5	20 / 53.9	19.9 / 54.2
en_fil	36.5 / 62.3	28.6 / 56.5	28.8 / 56.3	28.2 / 56.5	0.3 / 6.4	29 / 55.6	31.1 / 58.3	31.1 / 57.9
en_fj	20.1 / 48.8	9 / 32.5	11.1 / 35.6	10.4 / 34	0.1 / 4	0.1 / 13.9	0.1 / 9.4	0.1 / 8.3
en_fo	26.3 / 51.8	16.9 / 40	18.5 / 41.5	17.7 / 41.2	0.1 / 7.3	5.6 / 29.4	6.1 / 31.1	7.7 / 33.2
en_fon	3.1 / 23.5	1.6 / 15.6	1.9 / 16	1.6 / 15.9	0 / 0.3	0 / 1	0 / 1.9	0 / 1.6
en_fr	51.4 / 71.4	52.5 / 72.1	53.4 / 72.5	53.2 / 72.5	0.4 / 9.2	36.1 / 61.4	39.1 / 63.5	38.8 / 63.2
en_fur	34 / 58.7	28.8 / 55.8	24.7 / 51.4	28.8 / 56.1	0.1 / 5.6	0.7 / 18.1	3.1 / 28.8	3 / 30.5
en_ga	34.4 / 60.4	32.8 / 59.7	33.2 / 60	33.4 / 60.2	0.1 / 6.7	0.6 / 9.2	1.7 / 21.4	2 / 22.9
en_gd	21.6 / 53.6	19.7 / 48	23.2 / 51.8	21.3 / 50.2	0.1 / 2.3	0.2 / 6	0.3 / 14.9	0.2 / 12.8
en_gl	36 / 61.9	37.1 / 63.1	37.1 / 63	37.4 / 63.5	0.2 / 8	29.8 / 57.4	31.5 / 58.8	31.5 / 58.9
en_gn	9.8 / 40.4	11.6 / 40.9	10.9 / 38.9	12.5 / 41.8	0.1 / 3.9	0.1 / 5.6	0.3 / 15.2	0.1 / 9
en_gu	25 / 56.6	18.7 / 50.3	20.1 / 51.4	20.4 / 52.1	0 / 0.2	0.2 / 0.8	0.1 / 2	0 / 1.4
en_ha	28.8 / 56	16.9 / 44.4	18.9 / 45.3	18.7 / 47.1	0.1 / 2.6	0.2 / 6.2	0.2 / 12	0.3 / 13.9
en_hi	34.6 / 59.3	30.4 / 54.1	31 / 54.6	32.2 / 55.8	0.2 / 4.1	17.9 / 46.5	24.7 / 49.7	22.9 / 49.7
en_hne	27.1 / 57.5	19.9 / 51.2	17.8 / 49	20.4 / 52.1	0 / 0.2	1.7 / 23.8	2.4 / 31.2	2.9 / 33.2
en_hr	31.9 / 60.1	32.3 / 61.5	32.1 / 61	32.8 / 61.6	0.9 / 12.5	24.7 / 54.4	25.2 / 55.9	25.9 / 56.8
en_ht	25.1 / 53.9	18.8 / 47.7	23.5 / 52.1	22.5 / 51.3	0.1 / 4.7	0.9 / 15.9	4.1 / 30.2	3.3 / 28.8
en_hu	27.6 / 58.7	29.1 / 60	28.9 / 59.9	29.4 / 60.4	0.2 / 6.3	19 / 49.8	18.8 / 50.9	20.2 / 52.1

37

en_hy	21.4 / 57.8	15.9 / 47.2	19.5 / 53.7	20.1 / 53.9	0 / 0.2	0.5 / 0.9	0.5 / 0.7	0.5 / 0.7
en_id	46.6 / 70.6	43.5 / 68.5	44.5 / 69	44.7 / 69.5	0.1 / 5.8	34.1 / 62.4	38.6 / 65.5	39 / 65.4
en_ig	16.9 / 43.6	13.1 / 34.6	16.1 / 38.7	16.2 / 38.5	0.1 / 3.4	0.2 / 8.6	0.2 / 8.7	0.1 / 6.5
en_ilo	25.6 / 55.8	15.6 / 42.4	17.7 / 45.7	17.9 / 45.8	0.1 / 4.5	3.7 / 29.6	3.5 / 29.6	1.9 / 28.3
en_is	25.3 / 52.8	25.9 / 53.5	27.5 / 54.2	27.3 / 54.5	0.8 / 11.7	24.1 / 51	24.3 / 51.7	24 / 51.6
en_it	31.8 / 59.9	32.4 / 60.3	32.2 / 60.3	32.7 / 60.5	0.4 / 10.8	24.5 / 54.2	24.8 / 53.7	25.1 / 54.6
en_he	34.7 / 62.6	30.5 / 59.3	32.5 / 61.1	31.4 / 60.6	0.1 / 0.9	15.7 / 46.7	19.9 / 50.6	19.7 / 50.9
en_ja	0 / 35	8.8 / 34.3	9.3 / 35.5	9.4 / 35.9	0 / 1.6	0.2 / 29.3	0 / 30.5	0 / 30.7
en_jv	28.6 / 57.2	12.1 / 37.9	14.5 / 42.2	16.4 / 44.4	0.1 / 5.1	2.7 / 25.4	8.1 / 39.1	9.3 / 40
en_ka	15 / 52.6	2.8 / 17.4	2.2 / 14.8	2.3 / 15.8	0.2 / 5.7	10.9 / 46.4	10.7 / 48.7	10 / 48.6
en_kab	10 / 37.9	0.7 / 1.4	0.9 / 12.4	0.7 / 1.9	0 / 3.4	0.1 / 9.6	0 / 9.6	0 / 5.9
en_kac	12 / 39.1	2.9 / 22.8	3.6 / 23.9	4 / 25.3	0.1 / 3.6	0.3 / 16.1	0.1 / 8.8	0 / 7.6
en_kam	4.3 / 28.8	1.2 / 2.3	2 / 17.7	1.4 / 3.6	0.1 / 4.5	0.7 / 10.3	0 / 4.9	0.1 / 5.7
en_kbp	6.9 / 30.4	1.4 / 14.7	2.3 / 16.4	2.1 / 16.9	0.1 / 2.3	0.1 / 5	0.1 / 5.5	0 / 3.3
en_kea	18.2 / 44.9	1.5 / 3.1	1.8 / 10	1.5 / 3.1	0.5 / 8.7	1.1 / 23.8	0.5 / 19	2.1 / 28.6
en_kg	16.6 / 48.2	0.8 / 14.7	1 / 16.3	1.4 / 19	0.3 / 7.8	0.1 / 7.9	0.1 / 6.9	0 / 6.3
en_ki	11.6 / 40.1	1.2 / 2.2	2.5 / 15.5	1.2 / 1.8	0.4 / 7.3	0.3 / 8.3	0.1 / 6.5	0.1 / 6
en_kk	22.2 / 56	17.1 / 50.2	18.7 / 52.2	18.8 / 53.1	0.5 / 7.7	13.4 / 48.7	12.6 / 50	10.4 / 49.7
en_km	3.7 / 45	5.3 / 40.6	5.2 / 40.7	5.4 / 41.4	0.1 / 0.7	0.9 / 29.2	0.2 / 28.5	0.1 / 24.7
en_kmb	2.9 / 28.3	1.7 / 19.8	1.8 / 19.1	1.4 / 19.4	0.2 / 6	0.2 / 8	0 / 8.4	0 / 4.9
en_kn	21.3 / 58.2	11.9 / 49.2	13.8 / 50.9	13.3 / 51.3	0.1 / 0.4	0.1 / 1.6	0 / 0.8	0 / 0.4
en_ko	14.3 / 38	14.7 / 36.2	14.9 / 36.7	15.1 / 37.1	0.3 / 3.2	5.5 / 24.3	4.9 / 25.5	4 / 25.6
en_kr_Arab	0.3 / 12.7	0.5 / 20.8	0.5 / 20.5	0.5 / 22.2	0.1 / 0.5	0 / 4	0 / 4.1	0 / 2.1
en_kr	3.9 / 31.5	3.8 / 28.4	3.3 / 27.2	4 / 29.9	0.3 / 6.3	0 / 11.4	0.1 / 13.3	0 / 4.4
en_ks_Deva	1.8 / 20.4	1.9 / 21.2	1.6 / 19.8	1.9 / 21.6	0.2 / 1.2	0.2 / 8.3	0 / 4.3	0 / 3.9
en_ks	6.7 / 38.9	6.6 / 35.6	5.8 / 32.9	7.2 / 36.5	0 / 0.3	0.1 / 4.7	0 / 3.6	0 / 2.9
en_ku	12.2 / 42.3	0.3 / 0.5	0.3 / 0.7	0.5 / 0.8	0.2 / 6.4	0.5 / 14	0.4 / 15.4	0.4 / 15.8
en_ky	13.7 / 49.1	10.9 / 44.7	13.4 / 48.1	12.3 / 46.9	0.2 / 1.7	1.5 / 25.9	1 / 27.8	0.6 / 26
en_lb	27.8 / 59.1	14.7 / 38	16 / 38.2	16.9 / 41.3	0.4 / 10.6	3.3 / 34.1	3.5 / 34.9	4 / 35.7
en_lg	9.9 / 44.7	3.5 / 27	4 / 30.3	3.7 / 29.6	0.3 / 7.4	0.4 / 13.9	0.2 / 11.5	0.1 / 10.9
en_li	19 / 51.6	18.4 / 51.1	15.6 / 47.1	18.4 / 51.5	0.8 / 12.5	2.9 / 30.5	5.9 / 38.9	6.5 / 39.8
en_lij	28.7 / 56.1	29.5 / 55.2	24.9 / 50.3	29.5 / 55.4	0.5 / 10.6	1.9 / 25.6	3.5 / 32.1	2.4 / 32
en_lmo	8 / 38.7	6.7 / 32.2	5 / 27.9	6.7 / 32.9	0.4 / 9.1	1.2 / 19.6	1 / 21.8	2.3 / 26.9
en_ln	19.1 / 50.8	2.1 / 18.1	2.3 / 18.8	2.7 / 20.8	0.4 / 9.4	0.7 / 11.4	0.1 / 9.3	0.2 / 10.6
en_lo	6.8 / 53.4	9.9 / 47.1	9.8 / 46.8	9.7 / 50.5	0.2 / 1	1.9 / 35.2	1.4 / 38	1.3 / 39.5
en_lt	27.3 / 58.1	29 / 60.1	29.1 / 60.5	30.1 / 61.1	1.5 / 13.8	22 / 54.3	21.9 / 54.2	22.5 / 54.4
en_ltg	26 / 56.8	25.3 / 57.4	21.5 / 53.3	26.3 / 58.9	0.3 / 8.7	3.2 / 29.9	2.5 / 29.5	3.5 / 31.2
en_lua	6.4 / 39.4	1.4 / 2.2	2.1 / 12	1.5 / 2.6	0.3 / 5.7	0.3 / 12.6	0.3 / 11.6	0.1 / 8.1
en_luo	11.7 / 41.7	1.1 / 2.7	2.4 / 18.3	1.1 / 2.7	0.2 / 2.9	0.1 / 20.8	0.1 / 11.6	0 / 5.4
en_lus	11.3 / 40.9	9.5 / 33.7	11.7 / 37.4	11.3 / 36.7	0.4 / 7.4	0.1 / 11.5	0.2 / 11	0.1 / 7.4
en_lv	28.6 / 57.9	32.8 / 61.8	32.7 / 61.9	32.9 / 62	1.4 / 11.8	25.2 / 54.9	26.1 / 56.1	26.2 / 56.4
en_mag	32.2 / 61.2	26.2 / 55.3	22.5 / 51.6	26.8 / 56.3	0 / 0.3	11.6 / 41.4	6.7 / 41	6 / 40
en_mai	16.6 / 50.7	8.3 / 42.5	12.2 / 45.3	10.3 / 44.3	0.1 / 0.9	4.8 / 35.9	3.3 / 34.7	3.4 / 35.6
en_mg	17.7 / 54.2	17 / 50.8	18.5 / 53.1	18 / 52.8	0.3 / 7.1	1.7 / 20.1	0.5 / 17	0.2 / 13.5
en_mi	18.9 / 45.9	18.6 / 44.1	16.8 / 42	19.1 / 45.2	0.4 / 7.9	0.5 / 11.5	0.4 / 12.1	0.3 / 10.8
#N/A en_min	23.4 / 55.6	12.4 / 44.9	14.1 / 45.6	10 / 43.2	0.2 / 6.5	7.6 / 38.5	8 / 39.2	5.6 / 37.7
en_mk	35.6 / 63.2	36.6 / 64.8	37.7 / 65.2	37.4 / 65	1 / 3.4	30.8 / 59.6	30.5 / 59.8	31.2 / 60.3
en_ml	17.1 / 57.3	9.2 / 47.1	9.4 / 47	9.1 / 49.2	0.5 / 8.6	5.8 / 42.8	6.4 / 46.1	5.6 / 47.7
en_mn	14.8 / 47.7	12.2 / 44.4	14.8 / 47.8	14.7 / 47.7	0.1 / 0.7	0.6 / 0.8	0.6 / 6	0.3 / 2.4
en_mni	7.8 / 44.3	6.6 / 38	7 / 39.2	7.4 / 40.4	0.1 / 0.2	0 / 4.3	0 / 4.8	0 / 3
en_mos	4.5 / 26.4	0.9 / 2.3	1.2 / 16.6	0.8 / 2.2	0.2 / 6.1	0.3 / 14.2	0 / 6.5	0 / 3.5
en_mr	17.6 / 52.1	10 / 39.1	9.9 / 37.7	11.8 / 42	0.1 / 0.9	10.7 / 42.8	8.6 / 43.1	8.6 / 44
en_ms	42.2 / 68.5	37.3 / 64.8	39.3 / 66.2	38.1 / 65.7	1.3 / 13.9	35.8 / 65	37.2 / 65.6	36.2 / 65.4
en_mt	35.6 / 70.8	51.7 / 71.7	52.7 / 72.2	52.5 / 72.2	0.4 / 8.9	5.2 / 34.3	5.4 / 38.5	2.9 / 36.7
en_my	2.9 / 40.1	3.3 / 40.5	3.1 / 39.1	3.5 / 38.3	0 / 0.2	0.1 / 5.7	0 / 9.9	0.1 / 12.9
en_ne	16.7 / 49.7	10.3 / 41.8	10.4 / 42.1	11.7 / 45.2	0.4 / 0.7	3.3 / 34.8	2.6 / 34.4	2.1 / 34.9
en_nl	27.5 / 57.8	28.6 / 59.3	28.7 / 59.4	28.8 / 59.4	1.6 / 15.9	22.5 / 53.7	22.4 / 54.3	23.2 / 54.6
en_nn	28.1 / 56.1	33.6 / 61.3	34.6 / 61.6	34.3 / 61.8	3 / 15.2	27.6 / 56.1	29.2 / 57.2	29.8 / 57.6
en_no	32.9 / 61.2	34.7 / 62.8	34.4 / 62.4	34.5 / 62.8	2.5 / 15.8	29.1 / 57.5	30.8 / 59.3	31.1 / 59.8
en_nso	23.7 / 53.3	12.8 / 37.7	15.7 / 41.1	14.5 / 40.5	0.3 / 4.5	0.6 / 11.8	0.2 / 10	0.2 / 9.1
en_nus	6.5 / 31.5	4.8 / 29.3	3.9 / 27.7	5 / 30.2	0.2 / 4.3	0 / 2.7	0 / 2.1	0 / 0.7
en_ny	13.6 / 48.7	8.1 / 38.6	11.5 / 44.9	10.6 / 43.5	0.4 / 8.1	0.7 / 16.4	0.4 / 15.7	0.4 / 17.2
en_oc	34 / 61.1	38.1 / 63	39.6 / 64.3	39.7 / 64.7	0.4 / 10.5	6.9 / 38.6	7.8 / 40.1	8.6 / 41.1
en_om	5.4 / 43.3	1.1 / 22.8	1.7 / 29.3	1.8 / 29.1	0.1 / 7.4	0.1 / 10.6	0 / 7.9	0 / 6.3
en_or	15.1 / 50.4	12.4 / 46.7	13.3 / 47.5	13.1 / 47.8	0.1 / 0.2	0.4 / 0.9	0.3 / 0.8	0.3 / 0.8
en_pa	24.5 / 51	20.7 / 45.7	21.4 / 46.5	21.1 / 46.5	0.1 / 0.3	0.9 / 6	0.3 / 1.7	0.2 / 1.8
en_pag	17.3 / 49.6	7.1 / 35.4	10.2 / 38.4	11.1 / 39.2	0.6 / 7.4	0.7 / 20.9	4.3 / 30.7	4.9 / 32.2
en_pap	37.8 / 61.5	15.5 / 46.5	20 / 49.4	16 / 47	0.6 / 11.4	2.7 / 28.5	5.7 / 34.6	6.7 / 36.6
en_pl	22.2 / 52.1	23.3 / 53.7	23.6 / 53.8	23.7 / 53.9	1 / 11.6	16.7 / 46.7	16.2 / 47.9	17.5 / 48.3
en_ps	15.5 / 40.8	15.1 / 38.7	15.3 / 38.8	15.4 / 39.1	0.1 / 0.9	0.4 / 12.1	0.2 / 10	0.1 / 8.9
en_pt	47.9 / 69.6	49.9 / 71.5	51 / 72	51.4 / 72.3	3 / 17.8	38.8 / 63.5	41 / 65.1	40.7 / 65.4
en_quy	3.6 / 31.2	1.5 / 22.8	2 / 18.6	1.3 / 25.5	0.2 / 8.7	0.3 / 14.5	0.1 / 8.8	0 / 6.7
en_rn	12.9 / 47.3	5 / 31.8	5.9 / 32.6	5.5 / 30.7	0.3 / 5.5	0.5 / 13.9	0.5 / 15.5	0.2 / 12.9
en_ro	38.4 / 63.6	42 / 66.2	42.3 / 66.2	42.4 / 66.5	4.4 / 20	32.6 / 58.1	34.8 / 60.5	35.4 / 60.9
en_ru	32.3 / 59	32.2 / 59.6	33 / 60.1	32.5 / 59.8	1.1 / 4.4	22.5 / 49.4	23.9 / 52.4	25.4 / 53.2
en_rw	21.1 / 53.8	1.8 / 14.6	0.3 / 9.6	0.9 / 11.9	0.5 / 6.9	0.8 / 15.7	0.5 / 15.5	0.5 / 17
en_sa	1.7 / 31.6	1.6 / 27	1.8 / 30.5	2 / 31.7	0.1 / 0.9	0.1 / 11.6	0.1 / 13.5	0.1 / 14.7
#N/A en_sc	30 / 58.1	24.2 / 52.8	19.3 / 47.4	24.5 / 53.3	0.5 / 10.3	2.7 / 27	0.8 / 21.4	1.1 / 23.8
en_scn	17.7 / 50.5	15.3 / 48.5	13.8 / 45.3	15.6 / 49.1	0.5 / 9.3	1.3 / 22.6	1.5 / 26.3	1.8 / 28
en_sd	23 / 50.1	19.8 / 43.7	17.5 / 42	18.4 / 42.5	0.1 / 0.5	0.8 / 6	0.7 / 13.7	0.4 / 10
en_sg	9 / 38	6 / 30.1	5.8 / 29.2	6.4 / 30.7	0.2 / 8.3	0.2 / 10.1	0.2 / 10.6	0.1 / 5.3

en_shn	5.5 / 42	5.4 / 37.5	5 / 37.3	5.6 / 39.6	0.2 / 1.2	0.1 / 3.1	0 / 2.6	0 / 3.6
en_si	14.7 / 48	13.5 / 46	13.4 / 45.2	14.2 / 47.6	0 / 0.4	0.5 / 1	0 / 0.7	0.1 / 0.8
en_sk	35.2 / 61.6	35.7 / 62.5	36.3 / 62.9	36.8 / 63.1	1.5 / 13.9	27.7 / 55.4	28.6 / 56	26.5 / 55.8
en_sl	31.7 / 58.7	32.3 / 59.9	32.9 / 60.2	33.3 / 60.6	0.8 / 12.7	23.7 / 52.4	25.1 / 54.1	24.8 / 53.3
en_sm	26.8 / 50.9	17.9 / 43.6	20.8 / 46.5	20.5 / 46.8	0.5 / 7.4	0.6 / 14	0.3 / 11.4	0.2 / 8.9
en_sn	12.6 / 48.8	7 / 38.2	9.3 / 42.3	8.8 / 41.8	0.5 / 7	0.8 / 16.6	0.4 / 17	0.3 / 16
en_so	12.6 / 47.3	9.4 / 41.8	10.3 / 43.4	10.2 / 43	0.2 / 6.8	0.7 / 15.3	0.2 / 12.9	0.2 / 13.2
en_sq	33.2 / 60.6	29.8 / 58.6	30.9 / 59.5	30.4 / 59.3	1.2 / 11.7	28.5 / 56.8	28.7 / 56.6	29 / 57.7
en_sr	35.9 / 62.1	34.9 / 61.6	35.8 / 62.4	36.2 / 62.7	0.5 / 2	29.2 / 57.4	29.9 / 58.4	30.4 / 58.1
en_ss	10.7 / 49.2	4.1 / 33.4	5.1 / 34.7	5.3 / 36	0.5 / 7.2	0.5 / 14.9	0.1 / 11.5	0.1 / 9.5
en_st	18.9 / 49.2	9.6 / 34.7	15.4 / 43.1	14.1 / 41.6	0.6 / 8.7	1 / 15.3	0.5 / 13.3	0.3 / 11.9
en_su	15.9 / 48.3	14.4 / 45.5	18.7 / 50.6	18.5 / 50.4	0.5 / 9	5.8 / 35.5	7 / 37.9	7.8 / 38.3
en_sv	44.2 / 68.1	47 / 70.8	47.2 / 70.8	47 / 70.8	2.5 / 15.8	37.7 / 64.2	39.4 / 65	39.1 / 65.3
en_sw	32.6 / 61.2	29.3 / 57.6	30.4 / 58.1	30.4 / 58.5	0.3 / 9	1.5 / 21.1	1.4 / 22.8	1.3 / 25.7
en_szl	27 / 56.7	24.9 / 56.1	21.6 / 51.8	26.2 / 56.7	0.5 / 9.3	6.9 / 36.7	4.9 / 35.1	4.3 / 35.8
en_ta	19.8 / 59.4	12.4 / 51.4	13 / 52.6	13.9 / 54.1	0.4 / 10.7	8.6 / 47.8	7.8 / 49.2	8.1 / 49.5
en_taq_Tfng	0.7 / 19.3	0.6 / 21.2	0.5 / 20.4	0.7 / 21.7	0.1 / 0.4	0 / 7.8	0 / 2	0 / 1.4
en_taq	4.2 / 25.9	3 / 24.6	3.3 / 24.7	3.6 / 25.7	0.2 / 8	0.1 / 4.7	0 / 2.8	0 / 4.7
en_te	24.8 / 60.1	16.7 / 51.4	17.6 / 52.1	17.5 / 52.7	0.7 / 9	10.9 / 45.9	8.3 / 47.5	10.5 / 49.6
en_tg	24 / 54	6.1 / 26.6	9.2 / 31.3	10.2 / 32.6	0.1 / 0.6	1.4 / 21	0.8 / 22.6	0.9 / 24.4
en_th	6 / 51.4	8 / 44.1	7.6 / 43.1	8 / 44.3	0.1 / 10	7.1 / 48.5	7.5 / 48.7	4 / 49.2
en_ti	6 / 27.9	1.8 / 15.7	2.5 / 18.6	2.5 / 18.9	0.1 / 0.3	0 / 1	0 / 0.8	0 / 0.6
en_tk	13.7 / 46.2	13.9 / 44.5	17.5 / 50.7	17.3 / 49.9	0.2 / 6.9	0.8 / 19.9	0.9 / 22.9	0.7 / 22.6
en_tn	23 / 51	10.6 / 34.8	14 / 38.6	12.2 / 37.7	0.5 / 8.2	0.6 / 14.5	0.3 / 11.5	0.2 / 10
en_tpi	18.3 / 42.8	1.1 / 2.7	3.4 / 22.2	1 / 2.3	0.6 / 5.4	0.7 / 16.7	1.4 / 22.8	0.3 / 11.3
en_tr	30.1 / 61.8	29.9 / 60.5	31 / 61.2	30.5 / 61.4	1.2 / 14.4	16.9 / 51	15 / 51.6	15.7 / 52.1
en_ts	23.3 / 53.2	9.1 / 34.7	12 / 38.1	10.3 / 37	0.5 / 7.8	0.3 / 6.9	0.2 / 10.5	0.2 / 10.3
en_tt	18.4 / 50.6	7 / 31.5	10.2 / 36.5	13.1 / 42.4	0.1 / 1	1.8 / 25.1	0.5 / 21.7	0.5 / 23.4
en_tum	10.5 / 38.5	1.4 / 2.2	2.2 / 15.3	1.5 / 2.5	0.4 / 7.4	0.2 / 14.8	0.4 / 13.8	0.1 / 10
en_ug	13.8 / 50.6	5.9 / 33.4	6.9 / 34.2	8.8 / 39.8	0 / 0.3	0.2 / 1.9	0.1 / 1.2	0.1 / 1.6
en_uk	31.5 / 59.1	30.6 / 58.9	30.9 / 59.4	31.1 / 59.4	1.6 / 7.8	23.3 / 52.3	24.4 / 53.5	23.5 / 53.4
en_umb	2.8 / 31.2	1.6 / 2.9	1.4 / 10.5	1.4 / 2.5	0.2 / 6.1	0.1 / 11.5	0 / 5.6	0 / 4.6
en_ur	23.7 / 51.1	18.8 / 44	20.1 / 44.8	20.3 / 45.4	0.1 / 0.8	7.7 / 33.4	6.1 / 34.5	2.9 / 30.3
en_uz	17.6 / 55.7	0.6 / 1.3	0.5 / 1.1	0.6 / 1.1	0.1 / 6.8	2.5 / 30.3	3.5 / 38.5	4.6 / 43.9
en_vec	22.8 / 54.8	25.1 / 56.4	22 / 52.2	25.2 / 56.7	0.4 / 12.8	3.5 / 29.6	5.6 / 37.7	7.6 / 41.2
en_vi	42.3 / 59.6	39.1 / 57.2	40.5 / 58.2	40.5 / 58.6	2.2 / 10.3	35.2 / 54	35.7 / 54.7	34 / 54.4
en_war	31.7 / 59.3	9.8 / 31.1	18.5 / 44.9	13.7 / 44	0.7 / 7.5	5.9 / 33.5	8.7 / 38.8	10.4 / 40.3
en_wo	6.8 / 31.8	1.2 / 13.2	1 / 12.6	1.4 / 15.4	0.3 / 7.7	0.1 / 5.5	0.1 / 7	0 / 3.5
en_xh	15.2 / 54.7	11.3 / 47.4	12.5 / 50.1	12.5 / 49.2	0.2 / 7.7	0.4 / 15.4	0.3 / 16.1	0.2 / 16.2
en_yi	11.9 / 41.8	8.7 / 34.8	6.6 / 36.3	7.9 / 32.5	0.2 / 0.7	0.8 / 13.6	0.9 / 17.6	0.5 / 16.3
en_yo	6 / 27.4	2.6 / 19.7	2.7 / 20.3	2.9 / 20.7	0.3 / 6.3	0.1 / 10.6	0.1 / 5.2	0 / 3.2
en_yue	2 / 20.8	0.3 / 2.2	0.2 / 2	0.3 / 2	0.1 / 2.5	0.1 / 24.7	1.2 / 25.5	0.8 / 25.3
en_zh_Hant	15.4 / 17.6	5.5 / 30.4	6.3 / 31.8	36.5 / 32.1	0.1 / 3	1.2 / 21.4	3.6 / 22.3	1.3 / 21.9
en_zh	31.2 / 29.3	5.8 / 35.7	6.1 / 36.6	41.3 / 36.5	2.9 / 3.3	29.2 / 26.2	30.1 / 26.7	29.8 / 26
en_zu	19.7 / 58.8	11.2 / 44.7	13.8 / 48.6	13.4 / 47.6	0.3 / 7.1	0.4 / 13.9	0.3 / 17	0.2 / 17
ace_Arab_en	13.6 / 37.9	17.1 / 43.5	16.6 / 42.7	19.1 / 45.8	0 / 0.7	0.8 / 13.6	1.5 / 16.5	1.6 / 18.5
ace_en	31.3 / 53.9	23.6 / 49	21.1 / 46.9	25 / 50.8	0 / 3	3.3 / 22.9	8.5 / 32.8	6.8 / 33.7
acm_en	40.1 / 65	34.2 / 60.8	35.8 / 61.7	35.2 / 61.6	0.1 / 1.6	25.9 / 52.3	28.4 / 55.3	28 / 55.1
acq_en	42.4 / 66.7	36.5 / 62.5	37.3 / 62.9	37.4 / 63.3	0.1 / 2	23.5 / 51.4	30.1 / 57.1	29.5 / 57.1
aeb_en	36 / 61.4	28.5 / 55.5	30.4 / 57.1	30.1 / 56.9	0.1 / 2.4	19 / 44.5	22.4 / 49	24.3 / 51.3
af_en	59.2 / 77.1	58.7 / 76.8	60.1 / 77.9	60 / 77.7	2.4 / 18	51.7 / 71.5	54.3 / 74	54.9 / 74
ajp_en	46.6 / 68.9	38.1 / 62.8	37.7 / 62.4	39.6 / 64	0.1 / 1.5	32.7 / 58.3	32.7 / 58	31.2 / 58.7
am_en	36.5 / 61.8	32.6 / 57.9	36.9 / 61.1	35.9 / 60.6	0.2 / 4.8	20.3 / 47.1	22.7 / 49.6	22.9 / 50
apc_en	42.5 / 66.7	34.1 / 60.6	34.7 / 60.7	36.2 / 62.1	0.1 / 2	26.2 / 52.1	28.7 / 55	29.9 / 56.3
ar_MA_en	32.2 / 0	23 / 50.3	24.5 / 51.2	25.1 / 51.7	0 / 1.4	15.3 / 43.4	19.3 / 45.5	18.1 / 46.8
ar_en	45.3 / 68.6	41.7 / 66.4	44.4 / 68.1	43.1 / 67.5	0.3 / 4.9	32.9 / 58.1	34.9 / 60.7	35.5 / 60.6
ars_en	43.8 / 67.8	40.3 / 65.4	42.7 / 66.7	41.7 / 66.5	0.1 / 2	28.3 / 52.4	34.7 / 59.9	34.5 / 60
arz_en	37.2 / 62.7	30.2 / 57.5	29.1 / 56.5	31.7 / 58.9	0.1 / 1.5	24.7 / 51.1	25 / 52.9	25.3 / 53.4
as_en	33.9 / 59.8	29.5 / 55.7	31.8 / 57.4	31.2 / 57.3	0.1 / 1.6	14.7 / 43.3	19.4 / 47.4	19.4 / 47.9
ast_en	43 / 66.4	37.3 / 62.5	39.7 / 64.2	39.8 / 64.5	1.2 / 13.3	26.2 / 56.1	29.2 / 57	31.6 / 58.3
awa_en	42.8 / 67.4	34.6 / 61.6	33.5 / 60.2	36.6 / 62.9	0.1 / 2.5	19.8 / 47.2	23.9 / 53.4	23.8 / 53.8
ay_en	12.1 / 33.7	6.1 / 27.4	7.9 / 28.4	8.3 / 29.6	0 / 2.3	0.5 / 16.4	3 / 18.8	2.8 / 19.1
az_en	27.2 / 56.5	19.7 / 47.7	20.7 / 47.2	25.1 / 52.7	1.3 / 15.7	18.8 / 47.5	20.2 / 49.5	20 / 48.7
azb_en	20.8 / 47.7	4.8 / 30.2	6.7 / 31.7	6.3 / 32	0.1 / 3.4	2.1 / 23.3	4.2 / 31.2	5.4 / 30.1
ba_en	33.6 / 60.1	6.7 / 25.7	8.2 / 26.8	10 / 29.2	0.1 / 2.9	13.1 / 36.1	19.7 / 46.7	19.3 / 46.8
ban_en	38.2 / 62.3	29 / 55.6	25.5 / 52.4	30.3 / 57	0.2 / 5.4	8.8 / 34.8	15.9 / 43.9	16.7 / 43.9
be_en	23.7 / 55.4	17.9 / 49.3	17.6 / 49.4	21.6 / 52.9	0.8 / 11.5	18.4 / 48.3	19.6 / 50.9	19.6 / 51.5
bem_en	29.6 / 52.4	7.4 / 30.4	8.6 / 31.5	10 / 33.2	0 / 2.5	1.2 / 14.7	5.4 / 22.2	4 / 21.9
ber_en	19.7 / 0	16.6 / 41.6	14.6 / 39.9	17.6 / 43.1	0.1 / 1.7	0.1 / 14.8	0.5 / 13.7	0.2 / 11.9
bg_en	43.1 / 68.3	42.2 / 67.8	43.6 / 68.9	43.2 / 68.5	1.8 / 15.5	34.1 / 62.7	36.8 / 64.1	37.8 / 64.5
bho_en	34.6 / 60.7	28.5 / 56	25.5 / 53.5	28.9 / 56.8	0.1 / 2.4	16.5 / 43.8	19.6 / 48.5	17 / 48
bjn_Arab_en	19.2 / 43.3	21.7 / 47.2	20.3 / 46.1	23.8 / 49.8	0 / 0.9	0.5 / 15.3	1.7 / 18.1	1.8 / 18.1
bjn_en	40.1 / 63.3	30.2 / 55.9	26.1 / 52.3	32 / 57.5	0.1 / 3.5	10.9 / 40.4	17.6 / 44.4	20.3 / 45.5
bm_en	19.6 / 42.2	14.1 / 37.1	12.9 / 36.3	15.5 / 39.4	0 / 2	1.7 / 12.8	1.9 / 17.8	2.3 / 18.8
bn_en	38.7 / 64.2	34.9 / 60.6	37 / 62.5	36.2 / 61.8	0.2 / 2.7	21.8 / 50.7	25.2 / 53.9	26.3 / 54.8
bo_en	15.6 / 40.9	12.6 / 38.1	12.6 / 38.2	14.6 / 41.1	0 / 1	1.9 / 20.5	5.9 / 29.6	5.6 / 29
bs_en	45.2 / 68.8	44.1 / 68.4	45 / 69.1	44.9 / 69.2	1.5 / 13.7	36.2 / 62.3	38.5 / 64.5	39 / 65
bug_en	23.1 / 48.4	17.7 / 43.6	15.7 / 42	18.9 / 45.3	0.1 / 3.3	1.8 / 18.7	5.6 / 28	5.9 / 27.6
ca_en	49 / 71.1	48.5 / 71	50.3 / 72.2	50 / 72	2.2 / 16.1	41.8 / 66.6	42.5 / 67.1	43 / 67.2
ceb_en	45.6 / 66.8	34.8 / 60.2	34.1 / 59.4	36.6 / 61.2	0.3 / 5.7	31.9 / 56.4	32.2 / 57.2	33.6 / 58.5
cjk_en	11.3 / 32.7	4.8 / 23.8	5 / 24.7	5.6 / 26.5	0 / 2.3	1.2 / 16.2	2 / 17.7	2.3 / 18.8

39

ckb_en	37.5 / 61.6	28.3 / 53.1	34.4 / 59	34.2 / 59	0.2 / 4.4	18 / 42.1	22.5 / 48.6	22.8 / 49.5
crh_Latn_en	35.9 / 61.8	29.2 / 56.8	25 / 53.1	29.1 / 57	0.1 / 4.8	16.1 / 40.3	18.8 / 45.2	17.8 / 46.6
cs_en	41.2 / 66.4	41.3 / 66.6	42.3 / 67.3	42.3 / 67.3	2.1 / 18.1	34.7 / 61.4	35.8 / 62.5	36.1 / 62.9
cy_en	60 / 77.1	57.5 / 75.6	60.6 / 77.7	60.8 / 77.7	1.2 / 12.5	43.9 / 65.5	48.5 / 69.2	47.5 / 68.6
da_en	49.5 / 71.2	50.1 / 72.3	51.8 / 73.3	50.8 / 72.8	1.6 / 15.1	44.5 / 68.2	44.1 / 68.9	44.7 / 68.9
de_en	45.8 / 69.2	45.5 / 69.5	46.4 / 70.1	46.5 / 70	1.6 / 15.9	37.8 / 63.3	39.5 / 64.9	38 / 64.6
din_en	12.7 / 32.9	10.3 / 31.1	9.5 / 31.1	11 / 32.8	0 / 2.2	1.2 / 18.8	1.6 / 16.3	2.4 / 19.3
dyu_en	8.5 / 30	7.9 / 31.5	7.9 / 31.3	8.9 / 33.5	0 / 2.3	1.1 / 15.3	1.9 / 17.4	2.3 / 18.2
dz_en	17 / 44	12.9 / 40.4	12 / 39.2	13.7 / 41.6	0 / 0.8	0.7 / 16.4	2 / 22.4	1.9 / 22.7
ee_en	17.8 / 42	10.3 / 33.3	14.3 / 37.4	13.3 / 36.6	0.1 / 4.7	2.5 / 17.5	5 / 23.2	4.4 / 24.3
el_en	40 / 64.9	37.8 / 63.3	38.9 / 64.2	38.8 / 64	1.3 / 12.8	32.3 / 58.4	32.9 / 59.7	33.1 / 60
eo_en	47.8 / 70.1	45.8 / 68.5	47.2 / 69.4	47.1 / 69.5	9.8 / 31	38.3 / 63.3	40.4 / 64.7	40.9 / 65.3
es_en	33.8 / 61.4	31.5 / 61	32.2 / 61.3	32.5 / 61.4	4.5 / 23.9	26.4 / 56	27.6 / 57.8	27.7 / 57.9
et_en	38.8 / 64.6	39.4 / 64.9	40.3 / 65.6	39.6 / 65.5	7.9 / 28	31.8 / 59.2	32.5 / 59.8	32.6 / 59.8
eu_en	34.4 / 61.2	32.6 / 58.6	34.3 / 60	34.4 / 60.4	4.4 / 23	25.5 / 53.8	24.7 / 52.9	26.2 / 54.5
fa_AF_en	41.3 / 0	37.9 / 63	38.7 / 63.2	39.4 / 64.1	2.2 / 11.6	28.7 / 53.7	31.1 / 56.4	32.4 / 57.8
fa_en	40.9 / 65.6	37.7 / 62.9	40.3 / 64.8	39.4 / 64.3	3.9 / 16.4	31.1 / 57.6	30.8 / 57.2	32.3 / 58.7
ff_en	13.5 / 0	10.5 / 33.2	10.1 / 33.1	12.4 / 35.8	0.2 / 10.5	2.6 / 15.7	2.5 / 16.9	2.4 / 18.2
fi_en	36.9 / 63	36.1 / 62.6	36.7 / 63	37.1 / 63.3	3.8 / 22.9	27.9 / 55.8	29.8 / 57.4	30.5 / 58.3
fil_en	51.5 / 71.3	47.1 / 68.2	49.5 / 70	49.6 / 70.1	2.5 / 17.9	40.4 / 63.9	40.7 / 64.4	39.7 / 64.6
fj_en	21.6 / 45.4	12.2 / 36	14.6 / 39.2	14.5 / 38.8	0.3 / 10.8	5.1 / 24.8	5.2 / 24.1	4.3 / 26.2
fo_en	37.1 / 59.5	27.5 / 52.8	31 / 56.1	36.7 / 59.9	6.1 / 26	30.1 / 54.4	32.7 / 56.5	33.9 / 57.4
fon_en	12.9 / 35.4	3.9 / 25.1	5.6 / 26.3	6.4 / 27.8	0.1 / 7.9	0.8 / 12.6	1.5 / 17.9	1.8 / 18.3
fr_en	47.9 / 70.1	46.1 / 69.5	47.2 / 70.3	47.1 / 70.1	2.8 / 21.5	39.1 / 64.5	39.9 / 64.9	40 / 65.1
fur_en	45.3 / 68.6	36.9 / 63	30.8 / 58	37.4 / 63.4	3.6 / 23.8	24.2 / 50.3	24.2 / 53.4	23 / 54.7
ga_en	45.9 / 68.1	43.4 / 67	45.8 / 69	45.9 / 68.8	3.3 / 21.1	29.4 / 53.8	31.9 / 57.4	34.2 / 59.4
gd_en	36.8 / 60.9	33.4 / 58.9	37.3 / 61.9	37.5 / 61.6	2.1 / 18.1	21.7 / 46.8	22.8 / 49.1	22.1 / 49.6
gl_en	45.6 / 68.9	44.1 / 68.5	46 / 69.7	45.8 / 69.6	5.3 / 19.6	35.9 / 62.7	36.6 / 63.8	36.9 / 64.4
gn_en	27.7 / 52	19.5 / 45	18.2 / 44	20.8 / 46.9	0.6 / 11.9	5 / 26.3	8 / 30.8	8.1 / 29.9
gu_en	44.6 / 68.4	39.7 / 64.9	41.9 / 66.1	41.2 / 65.5	2.1 / 13.4	25.4 / 54.1	28 / 56.7	28.7 / 57.2
ha_en	36.4 / 58.7	31.8 / 54.5	35.9 / 57.9	35.4 / 57.6	0.8 / 15	17.2 / 40.1	21.6 / 44.8	21.1 / 45.7
hi_en	44.4 / 68.3	40.4 / 65.1	42.9 / 66.6	41.7 / 65.9	2.9 / 12.9	26.1 / 53.9	30.9 / 58.8	32.8 / 60.1
hne_en	52.2 / 73.8	40.1 / 65.5	35.1 / 61.7	41.9 / 66.9	0.5 / 4.9	22.4 / 52.1	21.5 / 53.8	23.2 / 54.5
hr_en	38.7 / 64.4	39 / 64.8	39.9 / 65.4	39.6 / 65.3	6.4 / 25.6	33.8 / 60.3	34.9 / 61	35.8 / 62
ht_en	39.9 / 64	39.3 / 63.5	40.5 / 64.3	40.9 / 65.1	0.9 / 10.9	26.9 / 52.6	29.4 / 55	29.4 / 56.5
hu_en	37.3 / 63.7	37.5 / 63.9	38.2 / 64.4	38.1 / 64.5	3.6 / 22.9	29.1 / 57.1	29.6 / 58	29.7 / 58
hy_en	42.3 / 67	33.5 / 59.4	40.7 / 65.2	40.1 / 64.8	2.5 / 13.6	27 / 54	31.1 / 58.5	31.6 / 59.7
id_en	46.5 / 69	42.6 / 66.6	45.3 / 68.4	44.1 / 67.7	2.4 / 16.1	38.4 / 63.4	38.8 / 63.6	37.7 / 63.1
ig_en	33.2 / 55.9	25 / 48.5	29.7 / 52.8	29.2 / 52.7	0.5 / 11.9	10.8 / 31.5	11.3 / 32.3	9.6 / 36.1
ilo_en	41 / 63.6	24.2 / 50.6	33.3 / 57.3	32.5 / 57	0.6 / 12.6	19.8 / 44.5	19.8 / 44	20.6 / 47.2
is_en	34.9 / 59.3	36.9 / 61	38 / 62.3	37.7 / 62	7.2 / 28.5	31.8 / 57.2	33 / 58.7	32 / 57.8
it_en	36.6 / 63.3	34.7 / 63	35.4 / 63.6	35.6 / 63.6	4.7 / 24	29.9 / 57.9	29.4 / 59.5	29.8 / 59.7
he_en	46.5 / 69	43.3 / 65.9	46.4 / 68.4	45.5 / 68.1	4.1 / 13.9	38.3 / 63	39.7 / 64	38.9 / 63.9
ja_en	30.3 / 58.2	27.6 / 55.7	28.8 / 55.9	28.9 / 56.9	0.1 / 0.6	19.3 / 49.8	19.6 / 48.8	20.3 / 49.2
jv_en	43.6 / 65.2	25.9 / 51.9	29.9 / 55.4	29.7 / 54.8	1.7 / 14.5	27.4 / 52.3	28.3 / 52.8	29.2 / 53.6
ka_en	31.4 / 59.5	21.5 / 48.9	21.3 / 48.8	28.7 / 55.6	1.9 / 9.9	22.4 / 50.9	24.4 / 53.6	25.2 / 54.7
kab_en	27.5 / 50.2	6.6 / 28.2	8.2 / 30.6	8.3 / 31.1	0.3 / 10.4	1.8 / 16.8	3.9 / 19.3	2.9 / 19.5
kac_en	18.6 / 43.7	6.3 / 30.1	9.2 / 32.4	10.1 / 34.1	0.2 / 8.2	1.4 / 13	3.2 / 20	2.9 / 20.2
kam_en	13.7 / 35.7	6.6 / 26.8	7.4 / 27.5	8.8 / 29.6	0.2 / 8	2.3 / 18.1	2.9 / 20.5	3.4 / 20.5
kbp_en	13.1 / 35.7	7.9 / 30.8	9.5 / 32.6	9.7 / 32.8	0.2 / 8.6	1 / 9.9	2.3 / 20.6	2.3 / 21.3
kea_en	48.1 / 70.1	34.5 / 60.5	33.6 / 59.1	36 / 61.7	0.6 / 10	16.8 / 41.2	23.3 / 49	23.6 / 50.5
kg_en	21.1 / 44.6	6.9 / 30.6	8.7 / 32.3	9.3 / 33.3	0.1 / 5.2	2 / 18.1	3.4 / 20.1	2.8 / 21.5
ki_en	25.6 / 49.5	7.6 / 30.6	8.7 / 30.6	9.5 / 32.5	0.1 / 8	2.5 / 18.4	3.3 / 19.3	2.6 / 20.7
kk_en	36 / 61.9	32.2 / 58.7	33.8 / 59.4	33.6 / 59.6	3.6 / 14.3	24.8 / 52.2	26.9 / 54.4	26.3 / 54.1
km_en	35.6 / 60.6	33.7 / 59.6	36.5 / 61.3	35.6 / 60.9	1.5 / 13.1	24.5 / 52.4	25.4 / 53.3	26.8 / 54.5
kmb_en	13.7 / 35.7	5.7 / 27	6.5 / 27.6	7.9 / 29.3	0.1 / 8.9	2.2 / 15.3	2.9 / 18.5	2 / 18.3
kn_en	36.9 / 63.1	31 / 58.3	32.8 / 59	32.6 / 59.4	0.7 / 6.8	17.6 / 45.5	20.9 / 50.6	22.9 / 52.3
ko_en	31.2 / 59	30.8 / 58.6	33.1 / 60.2	32.5 / 59.9	0.7 / 2.9	20.6 / 49	23.4 / 52	22 / 52.3
kr_Arab_en	3.2 / 21.2	5.4 / 24.1	5.2 / 24.1	6.9 / 26.2	0.1 / 5.5	0.6 / 12.1	1.2 / 16	0.8 / 14.5
kr_en	16.1 / 38.7	13.1 / 36.9	12.3 / 36.5	14.4 / 39	0.2 / 11.6	1.6 / 17.4	3.5 / 18.9	2.9 / 19.5
ks_Deva_en	27 / 52.7	21.5 / 48.2	19.8 / 46.5	23.5 / 50.4	0.3 / 5.3	4.2 / 27	3.5 / 26.3	4.7 / 27.7
ks_en	36.7 / 62.2	26.4 / 54	25.8 / 53.4	29.8 / 56.6	0.4 / 6.6	5.4 / 28.9	7.3 / 30.4	4.2 / 28.9
ku_en	29.8 / 54.6	29.1 / 54.2	30.8 / 55.5	32.2 / 56.8	1.8 / 16	16.7 / 40.9	21.6 / 47.4	21.6 / 49.1
ky_en	24.1 / 52.5	20.2 / 47.4	26.6 / 54.4	24.8 / 52.4	1.7 / 12.8	14.2 / 41.2	17.6 / 46.1	16.6 / 45.4
lb_en	49 / 71.2	19.1 / 47.2	21.3 / 49	23.1 / 50.8	3.5 / 20.6	35.3 / 60.6	38.2 / 63	36.8 / 63.2
lg_en	25.3 / 48.2	13.2 / 34.9	16.5 / 38.7	15.8 / 38.4	0.3 / 10.9	5.7 / 23.2	5.4 / 25.5	6.1 / 27.2
li_en	44.6 / 67.1	35.4 / 60.6	29.5 / 55.9	35.8 / 61.3	4.9 / 27.4	25.9 / 51.4	27.5 / 52.9	28.5 / 53.3
lij_en	49.2 / 70.8	40.6 / 65.5	33.6 / 60.2	40.3 / 65.3	4 / 24.5	26 / 53.5	26.2 / 54.7	24.4 / 55.2
lmo_en	42.9 / 66.3	34.8 / 60.3	30.2 / 56.8	35.7 / 61.3	2.3 / 20.6	20.6 / 47.6	22.2 / 50.2	23 / 50.9
ln_en	28.9 / 52.1	5.7 / 27.4	5.8 / 27.2	6.8 / 29.5	0.3 / 11.3	6.6 / 27.3	6.6 / 25.5	6.8 / 29.9
lo_en	39.5 / 63.4	35.1 / 60.1	37.7 / 61.9	38.4 / 63.2	1.1 / 10.2	26.1 / 52.8	28.2 / 55.3	28.9 / 56.9
lt_en	35.5 / 61.1	35.1 / 61.4	36.8 / 62.2	36.2 / 62.1	4.5 / 21.9	28.9 / 56.4	30.1 / 57.3	30.1 / 57.5
ltg_en	40.4 / 65.3	35.3 / 62	30.3 / 57.8	36.5 / 62.9	4.4 / 26	25.8 / 52.4	25.6 / 52.1	26.6 / 53.4
lua_en	19.9 / 43.1	6.3 / 27.8	6.7 / 28	7.9 / 30	0.2 / 7.9	4.3 / 21.3	4.2 / 21.9	4.3 / 23.8
luo_en	22 / 45.4	4.1 / 23.6	4.4 / 24.3	5.4 / 26.4	0.2 / 9	1.6 / 19.4	2.8 / 19.1	2.9 / 18.8
lus_en	18.4 / 43.6	13.1 / 37.7	18.5 / 43.2	18.4 / 43.8	1.1 / 15.1	9.8 / 32.1	9.9 / 31.9	10.9 / 34.4
lv_en	37.1 / 62.9	39 / 64.7	40.7 / 65.7	40.1 / 65.5	3.4 / 20	32.9 / 60.1	33.3 / 60.2	33.3 / 60
mag_en	51.6 / 73.7	40 / 65.8	35.8 / 62.5	42.1 / 67.3	0.5 / 4.6	24.2 / 53.5	26.6 / 55.7	26.8 / 57.2
mai_en	46.7 / 70.2	35.4 / 62.4	34.1 / 60.9	38.1 / 64.4	1 / 7.4	21.5 / 50.4	23.3 / 52.4	25 / 54.9
mg_en	35.1 / 59.1	30.4 / 55	33.8 / 57.7	34 / 58	1.7 / 18.5	15.6 / 39.5	19.1 / 44.7	20 / 45.9
mi_en	31 / 54.1	20.8 / 45.2	18 / 43.1	21.6 / 46.8	1.9 / 18.7	10.1 / 32	13.4 / 39.1	12.6 / 39.3

#N/A min_en	41.7 / 64	27.3 / 52.9	25 / 51.2	30.6 / 55.9	0.6 / 12.5	19.4 / 43.4	23.4 / 47.7	21.7 / 48.7
mk_en	45.4 / 68.7	44.7 / 68.4	45.9 / 69.1	46 / 69.2	7.7 / 28	37.7 / 62.8	39.9 / 64.9	39.7 / 64.9
ml_en	39.1 / 64.9	33 / 59.4	34.3 / 59.9	35 / 61.1	0.9 / 4.8	19.2 / 47	23.8 / 52.6	23.9 / 53
mn_en	28.9 / 56.3	28.7 / 55.9	32.2 / 58.9	31.9 / 58.8	0.8 / 8	18.5 / 45.5	20.5 / 48	20.1 / 47.9
mni_en	27.8 / 53.5	23.8 / 51.1	22.6 / 49.5	24.1 / 51.2	0.1 / 2.2	1.9 / 20.5	3.3 / 22.3	2.2 / 21
mos_en	12.2 / 34.3	3.4 / 23	3.4 / 22.4	3.7 / 24.1	0.3 / 9.9	1.4 / 15	1.4 / 18	1.6 / 17.5
mr_en	40.3 / 65.8	35.2 / 61.3	36.3 / 61.6	36.9 / 62.4	1.7 / 7.8	24.8 / 53.7	27.8 / 56.3	28 / 56.4
ms_en	47.7 / 69.7	43.9 / 67.1	46 / 68.7	45.7 / 68.6	2.7 / 18.7	38.5 / 63.4	39.9 / 64.6	40.3 / 64.8
mt_en	59.2 / 77.6	57.6 / 77.1	59.2 / 78.1	59.4 / 78.4	4.6 / 22	44.8 / 67.3	46.1 / 68.8	47 / 70.2
my_en	31.5 / 58.4	28.7 / 55.1	30.9 / 56.7	31 / 57.2	0.2 / 4.2	16.1 / 45.6	16 / 43.7	17.7 / 45.9
ne_en	44.5 / 68.8	39.8 / 65.6	41 / 66.2	41.8 / 67.2	1.1 / 7.5	25 / 54.4	28.2 / 56.7	27.1 / 55.7
nl_en	34.4 / 61.2	34.3 / 61.2	34.3 / 61.3	34.3 / 61.4	6.5 / 28.8	27.1 / 55.2	28.8 / 58.1	29.1 / 57.7
nn_en	46.4 / 68.8	47 / 69.7	48.3 / 70.5	47.8 / 70.4	4.8 / 26.9	42 / 65.8	42.3 / 66.5	43.1 / 66.9
no_en	45 / 68	45.1 / 68.4	46.6 / 69.5	45.9 / 69	5.5 / 26.2	40.5 / 65	40.7 / 65.2	39.9 / 65.7
nso_en	42.6 / 63	26.5 / 48.3	31.8 / 53.2	31.9 / 53.2	0.4 / 11.4	9.1 / 26.9	11.3 / 33.8	12.7 / 36.1
nus_en	18.6 / 41.2	12.9 / 36.1	11.9 / 35.2	14.8 / 38.3	0.1 / 6.9	0.5 / 11.9	1 / 16.1	0.6 / 16.3
ny_en	29.2 / 52.9	24.3 / 47.2	27.2 / 50.1	27.2 / 50.5	0.6 / 12	8.4 / 27.7	12.2 / 35.4	13.9 / 37.2
oc_en	58.4 / 77.2	55 / 75.4	58.9 / 77.6	57.4 / 76.8	7.8 / 27.7	42.5 / 66.5	43.8 / 67.3	42.9 / 68.2
om_en	27.2 / 52.1	11.1 / 35.6	17.3 / 42.1	17 / 42.6	0.4 / 10.5	4.1 / 22.4	5 / 27.1	5.9 / 29
or_en	41.6 / 66.2	34.9 / 61	36.1 / 61.5	36.1 / 61.7	1 / 8.6	19.1 / 47.4	20.6 / 49.1	22.5 / 50.7
pa_en	44.8 / 67.9	39 / 63.7	42 / 65.8	41.1 / 65.2	1.5 / 11.5	24.9 / 52.8	26.3 / 53.7	27.2 / 55.2
pag_en	27.9 / 52.3	22 / 46.4	22.9 / 46.2	24.4 / 48.5	0.5 / 11	17.6 / 40.7	17.9 / 42.2	17.7 / 42.8
pap_en	53 / 73.4	48.2 / 70.8	49.7 / 71.7	53.4 / 73.9	1.4 / 15.8	33.1 / 58.1	37.4 / 61.9	37.6 / 62.8
pl_en	32.1 / 59.5	30.5 / 58.6	31.8 / 59.4	31.5 / 59.3	8.5 / 32.3	25.7 / 54.6	26.2 / 55.4	26 / 55.4
ps_en	36.6 / 61.8	30.1 / 57.1	30.6 / 57.2	32.6 / 59.1	1.2 / 11.8	15.7 / 39.4	22.9 / 49	23.2 / 50.7
pt_en	51.7 / 72.7	50.7 / 72.7	52.3 / 73.6	51.7 / 73.2	5.5 / 24	43.4 / 67.8	44.2 / 68.4	44.3 / 68.3
quy_en	13.6 / 36.6	8.7 / 31.5	10.3 / 32.7	11.4 / 34.1	0.3 / 8.5	2.8 / 23.2	2.7 / 21.7	3.5 / 22.8
rn_en	27.4 / 51.2	19.9 / 43.2	23.5 / 46.6	23.6 / 46.9	0.2 / 7.1	10.1 / 30.6	12.3 / 35.4	11.6 / 35.3
ro_en	46.9 / 70.4	45.1 / 69.6	46.2 / 70.3	46.1 / 70.2	6.3 / 27.3	37.6 / 62.9	38.2 / 64.9	39 / 64.9
ru_en	38.5 / 63.7	37.5 / 63.1	38.8 / 64.1	38.3 / 63.8	3.2 / 15.8	29.3 / 55.7	31.1 / 58.9	30.5 / 59
rw_en	34.8 / 57.4	29.1 / 52.1	33.5 / 55.9	33.7 / 56.2	1.9 / 18.2	19.8 / 43.2	19.1 / 42.5	17.3 / 44.9
sa_en	26.1 / 52.9	20.7 / 47.4	21.5 / 48	16.7 / 41.8	1.3 / 12.3	11.8 / 37.9	13.6 / 42.3	11.4 / 42.5
#N/A sc_en	47.8 / 69.3	37.1 / 62.1	30.1 / 56.6	36.9 / 62.3	3 / 22.8	18.4 / 45.6	20.6 / 48	20.5 / 49.2
scn_en	41.3 / 64.5	33.5 / 59.8	27.4 / 54.8	33.3 / 59.6	3.8 / 24.5	24.3 / 50.5	26.7 / 53.6	25.1 / 53.9
sd_en	45 / 67.9	39 / 62.9	42.2 / 65.6	41.7 / 65	1.1 / 9.8	24.2 / 50.5	25.3 / 51.8	26.4 / 53
sg_en	14.4 / 36.7	8.2 / 31.1	9 / 31.7	10 / 32.8	0.2 / 9.7	3.5 / 19.2	2.7 / 19.3	2.7 / 22.1
shn_en	26.5 / 51.5	18.6 / 45.3	17.3 / 43.5	20.2 / 47	0.1 / 3.3	1.9 / 17.3	2 / 18.4	1.8 / 17.4
si_en	37.9 / 63.7	34.1 / 60.4	36 / 61.7	35.9 / 62.2	0.7 / 6.3	17.2 / 45.6	21.6 / 50.2	21.9 / 50.6
sk_en	41.1 / 66.1	41.4 / 66.9	42.2 / 67.5	42.3 / 67.7	7.3 / 29.5	34.3 / 61.4	35.7 / 62.5	35.5 / 62.4
sl_en	36.5 / 63	37.1 / 63.2	37.8 / 63.9	37.9 / 63.9	4.8 / 25.4	31.5 / 58.8	32.1 / 59.4	31.7 / 59.1
sm_en	35.8 / 58.3	28 / 52.3	31.6 / 55.9	33.4 / 56.4	0.7 / 13.1	14.2 / 36.3	18.1 / 42	15.4 / 41.8
sn_en	28.9 / 51.9	23.7 / 46.6	27.2 / 49.9	26.9 / 49.9	0.6 / 11.4	12.4 / 33.2	13.1 / 37.5	14.7 / 37.7
so_en	30.2 / 54.4	27.8 / 51.6	30.8 / 54.6	31.2 / 55	1 / 11.6	17.5 / 40.6	21.1 / 45.1	20.1 / 45.7
sq_en	44.9 / 68.4	41.6 / 66.9	43.7 / 68.2	43.5 / 68	11.3 / 34.5	35.8 / 62	36.5 / 62.4	37.1 / 63.4
sr_en	46.3 / 69.4	44.1 / 68	46.3 / 69.4	45.7 / 69.2	6.1 / 22.2	38.7 / 63.8	39.1 / 65.4	40.7 / 66
ss_en	29.2 / 52.3	21.8 / 43.8	25.3 / 47.5	25 / 47.7	0.4 / 11	6.9 / 25.1	8.2 / 29.2	8.9 / 32.3
st_en	41.2 / 62.9	27.9 / 51.2	34.2 / 57	34 / 56.8	0.6 / 12	10.1 / 30.2	15.5 / 38.9	13.2 / 40.1
su_en	40.2 / 63.6	34.3 / 59.1	32.6 / 58.1	35.8 / 60.7	1.8 / 16.4	26.4 / 51.8	26.6 / 52.3	29.2 / 54.9
sv_en	49.4 / 71.2	49.8 / 71.6	50.4 / 72.1	50.4 / 72.2	7.6 / 30.5	44.7 / 67.8	45.3 / 68.1	45.5 / 68.4
sw_en	46.2 / 67.4	43.3 / 64.9	46.5 / 67.1	46.1 / 66.9	1.8 / 15.3	30.8 / 54.3	34.3 / 57.9	36 / 59.5
szl_en	45.8 / 69	39.4 / 64.4	34 / 60.4	40.3 / 65.2	6.9 / 29	29.6 / 54.9	29.2 / 55.6	28.8 / 56.2
ta_en	36.8 / 62.8	30.9 / 57.4	32.3 / 58	33.1 / 59.3	1 / 5.2	22.9 / 51	22.7 / 50.8	24.1 / 52.4
taq_Tfng_en	8.8 / 30.1	4.9 / 27.3	6.7 / 28.8	6.5 / 29.6	0.1 / 5.4	0.2 / 12.9	0.4 / 14.7	0.3 / 13.7
taq_en	13.4 / 35.8	10.2 / 32.8	9.6 / 32.6	11.5 / 34.7	0.3 / 9.4	1.1 / 18.7	2.1 / 18.6	3.3 / 20.1
te_en	43.6 / 67.3	37.4 / 62.4	38.2 / 62.5	39.5 / 63.9	1.1 / 3.3	23.8 / 51.5	27.5 / 55.9	27.2 / 55.4
tg_en	36.5 / 61.7	13.7 / 38.2	24.8 / 50.5	22.5 / 47.3	2.3 / 16.1	23.4 / 49.9	26.5 / 54.7	27.3 / 54.3
th_en	33 / 60	31.4 / 57.4	33.3 / 59.2	33.3 / 59.6	2.1 / 6.7	24.1 / 53.1	24.1 / 54.7	24.8 / 54.5
ti_en	26.4 / 52.4	15.2 / 41.5	19.8 / 46	20.6 / 47.1	0.6 / 10.2	8 / 29.8	8.8 / 34.6	9.3 / 35
tk_en	34.9 / 61.2	31.3 / 57.7	33 / 58.9	33.5 / 58.8	2.4 / 18.5	19.1 / 45.6	20 / 47	20.2 / 49.2
tn_en	29.7 / 53.4	18.7 / 42.6	21.9 / 46.7	23.4 / 46.8	0.3 / 10.8	7.4 / 25.9	9.9 / 31.8	7.4 / 31.1
tpi_en	30.4 / 54.6	10.7 / 37.8	10.5 / 37.3	14.2 / 42.2	0.9 / 15.8	7.3 / 31.1	8.5 / 37.3	8.9 / 29.3
tr_en	41.5 / 66.1	39.1 / 63.8	41.4 / 65.5	40.9 / 65.3	3.4 / 20.4	25 / 51.8	28.1 / 55.5	29.1 / 56.7
ts_en	32.1 / 54.9	19.6 / 42.3	24.3 / 47.3	25.4 / 47.7	0.4 / 10.3	7.4 / 25.9	8.8 / 28.1	7.8 / 30.7
tt_en	31.8 / 58.3	10.4 / 30.4	10.3 / 29.4	17.5 / 38.5	1.2 / 9.9	16.5 / 42.1	21.3 / 48.5	21.3 / 48.5
tum_en	20.5 / 44.9	12.2 / 37	15.2 / 40	16.9 / 40.5	0.2 / 6.9	7.2 / 27.2	7 / 27.3	7.2 / 28.7
ug_en	27 / 54.6	8.6 / 29	14.1 / 36	10.9 / 30.6	1.6 / 14.4	13.4 / 39.4	17.3 / 44.9	17.3 / 44.9
uk_en	42.4 / 66.7	42.1 / 66.4	43 / 66.8	42.5 / 66.7	6.6 / 24.8	34.6 / 60.5	35.9 / 61.7	34.5 / 62
umb_en	11.4 / 33.3	4.4 / 24.2	4.7 / 24.2	5.5 / 25.9	0.2 / 9.6	1.1 / 17.2	2.3 / 18.3	1.6 / 17.1
ur_en	39.6 / 64.8	33.3 / 59.6	36.3 / 62.1	35.9 / 61.7	2.5 / 17.4	24.8 / 52.8	26.7 / 54.1	28.7 / 56.2
uz_en	35.2 / 61.6	33.9 / 59	37.2 / 62.1	37.8 / 63.2	1.8 / 15.6	23.5 / 51.2	24.6 / 52.3	24.9 / 52.9
vec_en	45.4 / 68	39.4 / 64.6	33.4 / 59.9	39.4 / 64.7	4 / 23.6	31 / 56.5	34.1 / 60	35.1 / 60.2
vi_en	40 / 64.2	37.4 / 62.5	39.2 / 63.9	39.3 / 63.8	4.1 / 19.7	28 / 53.5	31.7 / 57.3	32.1 / 57.9
war_en	51 / 71.1	32.1 / 58.6	32.5 / 58.8	35.9 / 60.9	1.1 / 15.5	25 / 50	27.4 / 55.3	31.8 / 56.4
wo_en	19.8 / 42.9	6.6 / 28.4	6.7 / 29.3	7.1 / 29.8	0.3 / 9	1.8 / 16.9	3 / 18.2	3.2 / 19.7
xh_en	39.7 / 61.1	32.1 / 54.3	36.5 / 58.2	35.5 / 57.7	1 / 15.2	17.2 / 39.3	21 / 43.9	21.1 / 44
yi_en	53.6 / 72.4	38.8 / 62.6	48.8 / 69	45.5 / 67.4	1.2 / 8.5	34.2 / 56	37.6 / 59.6	39.1 / 62.2
yo_en	23.9 / 47.9	11.9 / 34.9	17.4 / 40.8	17.8 / 40.7	0.4 / 12.5	5.1 / 23.5	4 / 24.1	6.3 / 26
yue_en	30.8 / 58.5	30.4 / 57.9	31.7 / 58.7	32 / 59.3	0.3 / 1.3	21.5 / 49.9	22.5 / 51.3	23.3 / 52.5
zh_Hant_en	28.8 / 56.2	28.1 / 55.7	29.6 / 56.8	30 / 57.5	0.6 / 2.7	19.6 / 47.3	21.2 / 49.6	21.6 / 50.5
zh_en	31.9 / 59.5	29 / 57.9	30.4 / 59	30.5 / 59.2	0.3 / 1.9	21.8 / 50.2	22.5 / 51.5	23.4 / 52.1

zu_en	41.3 / 62.7	33 / 55.1	37.7 / 59.1	37.1 / 58.9	0.8 / 13.4	17.5 / 40	20.3 / 44	20.2 / 45.5
xx2en	**35.5 / 59.6**	29.7 / 54.4	30.9 / 55.4	31.9 / 56.4	2.0 / 13.3	20.5 / 44.1	22.3 / 46.9	22.4 / 47.6
en2xx	**20.7 / 50.**1	17.3 / 44.1	17.8 / 44.7	18.6 / 45.7	0.4 / 5.7	8.1 / 26.7	8.7 / 29.0	8.7 / 28.8
Mean	**28.2 / 54.9**	23.5 / 49.2	24.4 / 50.0	25.3 / 51.1	1.2 / 9.6	14.3 / 35.5	15.6 / 38.0	15.6 / 38.2
xx2yy	**13.7 / 40.5**	8.8 / 31.2	8.4 / 30.9	10.1 / 34.0	0.3 / 4.1	4.0 / 16.1	4.4 / 17.3	4.2 / 17.1

Table 18: Evaluation scores on Flores-200 direct pairs (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against NLLB-54B. All metrics are computed with the sacrebleu reference implementation.

	NLLB	MT-3B	MT-7.2B	MT-10.7B	LM-8B			
					0-shot	1-shot	5-shot	10-shot
ckb_cs	20.7 / 47.3	15.4 / 39.4	18.5 / 44.9	19.1 / 45.1	0 / 0.8	8.1 / 30.2	10.4 / 35.5	9.7 / 36.6
ckb_cy	26.9 / 53.6	19.3 / 41.4	23.6 / 47	23.9 / 47.8	0 / 0.7	0.3 / 8.8	0.7 / 15.1	0.3 / 12.4
ckb_en	37.5 / 61.6	28.3 / 53.1	34.4 / 58.9	34.2 / 59	1 / 9.7	17.9 / 42.5	22.4 / 48.4	22.7 / 49.4
ckb_et	16.4 / 48.6	13 / 40.8	15.3 / 45.6	16.3 / 47	0 / 1	1.9 / 12.9	6.7 / 36.6	7.3 / 38.2
ckb_eu	11.3 / 47.4	7.2 / 38.6	10 / 44.2	11.5 / 46	0 / 0.5	1.3 / 18.4	1.9 / 30.8	2.1 / 33.5
ckb_fon	2.1 / 19.9	1 / 14.7	0.4 / 10.8	1 / 14.4	0 / 0.2	0.3 / 8.5	0 / 1.8	0 / 3.2
ckb_fr	31.2 / 56.9	23.8 / 45.4	30.5 / 53.5	28.7 / 51.9	0.1 / 2.5	13.5 / 38.4	18.7 / 45.2	18.8 / 45.6
ckb_ln	15.5 / 47.5	1.3 / 16	0.5 / 14.4	1.2 / 17.4	0 / 0.3	0.1 / 6.2	0.1 / 10.3	0.2 / 11.4
ckb_mr	11 / 43.3	3.3 / 22.5	1.4 / 22.4	4.7 / 27.9	0 / 0.4	0.6 / 4.7	0.6 / 21.5	0.8 / 24.8
ckb_ny	10.4 / 44.7	3.5 / 29.7	2.7 / 31	6.8 / 35.9	0.1 / 0.4	0.3 / 13.1	0.1 / 9.9	0.1 / 8.5
ckb_or	8.6 / 41.8	7 / 36	7.3 / 38.5	8.5 / 40.1	0 / 0.1	0 / 0.2	0 / 0.3	0 / 0.3
ckb_so	8.8 / 42.2	5 / 32.4	4.1 / 34.4	6.9 / 37.2	0 / 0.3	0.3 / 6.6	0.1 / 5.8	0.1 / 7.4
ckb_ss	6.5 / 44.3	2 / 27.4	0.9 / 23.5	3.1 / 30.9	0 / 0.2	0.1 / 7.7	0.1 / 9.8	0 / 9.3
ckb_ti	4 / 24.2	1.1 / 12.8	0.3 / 10.5	1.7 / 16	0 / 0.1	0 / 0.4	0 / 0.1	0 / 0.1
ckb_yo	5.5 / 27	1.2 / 15.2	1.2 / 16.6	1.8 / 18.2	0 / 0.3	0 / 4.1	0 / 3.3	0 / 4
ckb_zh	27.6 / 25.2	3 / 18.9	2.2 / 22.1	4.1 / 22.1	0.4 / 0.9	1.5 / 3.4	15.7 / 15.7	14.6 / 16
cs_ckb	8.8 / 45.4	5.8 / 37.6	1.3 / 30.8	6 / 37.8	0 / 0.2	0.1 / 8	0.1 / 9.9	0.1 / 8.8
cs_cy	29.7 / 57.6	24.3 / 48	28.4 / 52.4	27.4 / 51.9	0.3 / 7.4	2.5 / 19.3	3.3 / 29.4	2.2 / 28.5
cs_en	41.2 / 66.4	41.2 / 66.6	42.3 / 67.4	42.3 / 67.3	7.9 / 28.9	34.7 / 61.4	35.9 / 62.6	36.2 / 62.9
cs_et	20.4 / 53.9	22.8 / 54.9	22.3 / 54.5	23.5 / 56	1.8 / 14.1	15.2 / 45.8	17.9 / 51.1	17.6 / 51.3
cs_eu	11.8 / 47.8	11.9 / 45.3	8.9 / 44.7	12.6 / 47.5	0.2 / 7.6	7.3 / 40.6	6.3 / 44.6	7 / 46
cs_fon	2.5 / 21.6	1.2 / 14.3	0.7 / 11.9	1 / 14	0 / 2.3	0.1 / 4.3	0 / 5	0 / 1.7
cs_fr	35.3 / 60.9	38.7 / 62.3	39.5 / 62.6	40.1 / 63.2	1.2 / 10.2	24.5 / 51.6	24.2 / 54	25.6 / 54.6
cs_ln	15.6 / 47.8	1.6 / 17.6	1.1 / 17.1	2.3 / 20.9	0.2 / 6.2	0.3 / 10.6	0.1 / 8.9	0.1 / 7.2
cs_mr	10.8 / 43.1	3.6 / 24.9	1.6 / 22.9	4.5 / 26.8	0.2 / 2.7	3.7 / 28.8	3.5 / 33.8	2.9 / 35.2
cs_ny	10.1 / 44.7	7.3 / 38.3	3.9 / 36.2	7.9 / 39.3	0.2 / 5.3	0.2 / 16	0.3 / 13.6	0.1 / 12.1
cs_or	9.1 / 42.1	8.7 / 40.2	9.3 / 41.3	9.9 / 42.5	0.1 / 0.2	0 / 4.9	0.2 / 0.5	0.1 / 0.5
cs_so	9.1 / 42.7	7.7 / 39	7.3 / 39.3	7.7 / 39.6	0.2 / 5	0.4 / 14.3	0.2 / 13.5	0.1 / 10.9
cs_ss	7.3 / 45.1	2.4 / 26.2	1.2 / 25.4	3.2 / 30.4	0.2 / 6.3	0.2 / 20.7	0 / 6.3	0 / 7.4
cs_ti	4.3 / 24.9	1.4 / 12.7	0.3 / 9.8	1.6 / 16.1	0 / 0.3	0 / 0.7	0 / 0.7	0 / 0.4
cs_yo	4.5 / 25.1	2 / 18.4	1.4 / 16.3	2 / 17.7	0.1 / 4.8	0.1 / 11.7	0 / 2.1	0 / 7.1
cs_zh	23.6 / 23.3	6.4 / 31.1	7.3 / 31.8	6.8 / 32.7	2 / 2.3	20.2 / 19.9	19.7 / 20	21.6 / 20.5
cy_ckb	10.5 / 48.3	8 / 43.1	5.2 / 41.6	8.4 / 42.7	0 / 0.2	0 / 5.6	0 / 5.2	0 / 2.1
cy_cs	27.2 / 54.1	28.9 / 55.6	29.8 / 56.6	29.7 / 56.4	0.3 / 4.7	16.1 / 41.8	16 / 43.4	12.8 / 43.4
cy_en	60 / 77.1	57.6 / 75.6	60.7 / 77.7	60.8 / 77.7	5.4 / 24.3	43.9 / 65.6	48.5 / 69.3	47.7 / 68.7
cy_et	22.3 / 55	24.2 / 56.4	25 / 57.5	25.8 / 57.9	0.1 / 4.8	5.6 / 31.3	7.6 / 40.8	7.5 / 42.2
cy_eu	14.4 / 51.6	17.1 / 54.9	19 / 56.7	18.5 / 56.3	0 / 4.8	0.6 / 16.8	2.8 / 36.2	3.3 / 37
cy_fon	2.2 / 18.6	1.3 / 14.9	0.6 / 11.7	1.3 / 14.9	0 / 0.9	0.5 / 7.1	0 / 1.7	0 / 5.5
cy_fr	40.9 / 64.2	44 / 65.6	45.8 / 66.7	45.3 / 66.7	0.7 / 9.3	27.7 / 53.8	28.7 / 54.9	27.4 / 55.7
cy_ln	17.4 / 49.1	2 / 18	1.1 / 17.5	2 / 20.1	0.1 / 3.8	0.3 / 11.4	0.1 / 8.1	0.1 / 8.8
cy_mr	13.9 / 47.5	10.2 / 41.3	6.4 / 39.1	11.1 / 42.4	0.1 / 1.5	2.8 / 26	2 / 29.7	1 / 26.5
cy_ny	12.4 / 46.5	6.1 / 36.2	5.6 / 40.4	9.3 / 41.9	0.1 / 3	0.8 / 13.6	0.2 / 11	0.1 / 9.1
cy_or	11.5 / 45.1	11.2 / 44.4	12.1 / 46	12.3 / 46.2	0 / 0.3	0 / 0.4	0.1 / 0.4	0.1 / 0.4
cy_so	10.8 / 44.8	8.6 / 41.3	8.2 / 42.4	9.6 / 43	0.1 / 3.4	1 / 13.3	0.4 / 14.5	0.2 / 12.9
cy_ss	9 / 46.7	3.2 / 31.3	1.4 / 28.3	4.1 / 34	0.1 / 3	0.2 / 12.3	0.4 / 11.3	0.2 / 11.4
cy_ti	4.8 / 25.5	1.5 / 14.2	0.4 / 12.3	2.1 / 17.9	0 / 0.3	0 / 0.8	0 / 0.5	0 / 0.2
cy_yo	5.4 / 26.3	2.1 / 17.7	1.7 / 18.3	2.2 / 19.4	0.1 / 2.5	0 / 2.9	0 / 4.1	0 / 6.4
cy_zh	30.4 / 28.1	5.4 / 31.5	5.7 / 33.1	5.3 / 32.9	0.8 / 1.4	8.4 / 9	19.5 / 20.1	15.3 / 19.3
en_ckb	13.2 / 52.5	9.1 / 44.9	4.5 / 42.8	9.4 / 44.4	0.1 / 0.3	0.3 / 10.2	0.1 / 13.8	0.1 / 13.4
en_cs	33.6 / 59.8	34.8 / 61.2	34.8 / 61.1	35.6 / 61.5	1.1 / 11.1	25.3 / 53.1	26.2 / 54.5	25.6 / 54.4
en_cy	51.6 / 72.5	41.6 / 62.4	45.6 / 66.3	44.7 / 65.6	0.5 / 9	6.4 / 29.4	8.2 / 38	4.8 / 35.4
en_et	27.1 / 59.9	28.9 / 61.3	28.1 / 61.2	29.8 / 61.8	0.9 / 11.9	22.2 / 54.7	22.8 / 55.6	22.2 / 55.3
en_eu	17.2 / 54.9	18.3 / 55.5	16.8 / 55.4	19.3 / 57.2	0.2 / 11.1	12.3 / 49.3	12.9 / 51	12.4 / 51.3
en_fon	3.1 / 23.5	1.6 / 15.6	1.3 / 14.6	1.6 / 15.9	0 / 0.3	0.1 / 4.2	0 / 1.9	0 / 1.6
en_fr	51.4 / 71.4	52.4 / 72	53.3 / 72.4	53.2 / 72.5	1.7 / 15.3	37.1 / 61.9	38.9 / 63.5	38.8 / 63.1
en_ln	19.1 / 50.8	2.2 / 18.3	1.5 / 18.2	2.7 / 20.8	0.4 / 9.3	0.7 / 11.3	0.1 / 9.2	0.2 / 10.7
en_mr	17.6 / 52.1	10.1 / 39	5.8 / 36.4	11.8 / 42	0.8 / 12	10.5 / 42.8	9 / 43.2	8.1 / 43.7
en_ny	13.6 / 48.7	8.2 / 38.7	6.6 / 43.3	10.6 / 43.5	0.4 / 8	0.7 / 16.4	0.4 / 16	0.4 / 17.6
en_or	15.1 / 50.4	12.4 / 46.8	13.2 / 47.4	13.1 / 47.8	0.1 / 0.2	0.4 / 0.9	0.3 / 0.8	0.3 / 0.8
en_so	12.6 / 47.3	9.4 / 41.8	9.9 / 43.2	10.2 / 43	0.2 / 6.9	0.6 / 15.2	0.2 / 13	0.2 / 13.3
en_ss	10.7 / 49.2	4.1 / 33.5	1.9 / 31.9	5.3 / 36	0.5 / 7.2	0.6 / 15	0.1 / 11.6	0.1 / 9.5
en_ti	6 / 27.9	1.9 / 15.7	0.6 / 14.6	2.5 / 18.9	0.1 / 0.3	0 / 0.9	0 / 0.8	0 / 0.6

en_yo	6 / 27.4	2.6 / 19.7	1.9 / 19.6	2.9 / 20.7	0.3 / 6.3	0.1 / 10.6	0.1 / 5.3	0 / 3.3
en_zh	31.2 / 29.3	5.9 / 35.7	6 / 36.5	5.8 / 36.5	2.9 / 3.3	29.1 / 26.1	29.9 / 26.6	29.9 / 26.3
et_ckb	8.7 / 44.9	4.9 / 34.9	2.8 / 34.8	5 / 34.7	0.1 / 0.4	0.1 / 10.4	0 / 8.7	0 / 5.9
et_cs	24.1 / 51.6	25.3 / 52.3	24.9 / 51.8	25.3 / 52.6	1.8 / 14.1	15.8 / 42	18.2 / 46	17.4 / 46
et_cy	27.9 / 56.1	23.2 / 47.2	25.4 / 49.3	25.9 / 49.9	0.4 / 10.2	2.5 / 22.3	1.5 / 25	1.2 / 23.3
et_en	38.8 / 64.6	39.4 / 64.8	40.1 / 65.5	39.6 / 65.5	7.7 / 27.9	31.8 / 59.1	32.5 / 59.8	32.6 / 59.7
et_eu	11.4 / 47	13.4 / 48.5	13.5 / 49.1	14 / 50	0.3 / 12.2	5.9 / 37.8	5.7 / 41.2	3.9 / 41.1
et_fon	2.5 / 22.4	1 / 13.2	0.5 / 11.3	0.9 / 12.7	0 / 2.6	0.1 / 4.8	0 / 3.5	0 / 3.5
et_fr	33.4 / 59.2	35.1 / 59.3	35.7 / 59.3	36 / 60.1	1.4 / 14.2	23 / 50.2	24.8 / 52.1	25.3 / 52.6
et_ln	14.8 / 47.6	1.7 / 17.3	0.8 / 16.1	2 / 20.8	0.3 / 10.7	0.2 / 9.5	0.1 / 9.3	0.1 / 10.5
et_mr	10.8 / 42.8	5.4 / 29.3	2.4 / 25.8	5 / 28.5	0.3 / 1.6	0.7 / 2.7	3.9 / 33.5	2.8 / 35.3
et_ny	9.7 / 43.8	6.1 / 34.2	3 / 33.2	7.8 / 37.4	0.4 / 9.9	0.1 / 7	0.1 / 11.4	0.1 / 7.9
et_or	9 / 41.8	8.2 / 39.5	7.7 / 39.9	9 / 41	0 / 0.3	0.1 / 1.8	0.3 / 0.5	0.3 / 0.5
et_so	8.6 / 42.4	7.6 / 37.8	6.6 / 38.4	8.1 / 39.5	0.3 / 9	0.5 / 15	0.4 / 14.5	0.1 / 12.2
et_ss	6.6 / 44.8	2.5 / 26.3	0.9 / 23.6	3.1 / 29.3	0.1 / 10.7	0.1 / 11.8	0 / 7.4	0 / 7.8
et_ti	4 / 24.1	1.2 / 11.6	0.3 / 8.9	1.3 / 13.8	0 / 0.3	0 / 0.8	0 / 0.7	0 / 1.2
et_yo	4.1 / 24.6	2 / 17.4	1 / 15	1.6 / 16.2	0.2 / 7.3	0 / 4.1	0 / 5.3	0 / 3.2
et_zh	22.9 / 22.6	6.3 / 30.9	6.1 / 31.7	5.7 / 31.6	2.1 / 2.8	21.2 / 20.1	18.9 / 21.3	22.7 / 22.8
eu_ckb	7.3 / 43.7	4.6 / 34.2	1 / 27.8	4.3 / 32.4	0 / 0.2	0.1 / 8.3	0 / 8.6	0 / 5.3
eu_cs	19.2 / 46.9	16.7 / 42.2	14.4 / 41.9	18.2 / 44.4	0.9 / 12.2	13 / 40.6	13.8 / 41.6	13.2 / 41.2
eu_cy	24 / 53.1	22 / 46.1	25.6 / 50.5	24.5 / 49.7	0.2 / 10.6	1.2 / 18.7	1.5 / 22.7	0.9 / 21.6
eu_en	34.4 / 61.2	32.6 / 58.6	34.1 / 59.8	34.4 / 60.4	4.6 / 23.3	25.5 / 53.8	24.7 / 52.9	26.2 / 54.4
eu_et	16.8 / 49.6	16.4 / 47.7	17.9 / 49.4	18.7 / 50.2	0.1 / 12.2	7.1 / 35.2	9.9 / 43.9	9.6 / 43.6
eu_fon	2.5 / 20.7	1 / 13.4	0.4 / 10.1	1 / 13	0.2 / 7.3	0.1 / 9.1	0 / 2.8	0 / 1.6
eu_fr	29.4 / 56.2	28.8 / 53	30.3 / 54	30.3 / 54.4	1.2 / 14	20.3 / 48.3	21.3 / 49.4	21.1 / 49.5
eu_ln	14.5 / 47	1.6 / 17	0.6 / 15.8	1.9 / 19	0.1 / 12.5	0.4 / 16.5	0.1 / 8.9	0.1 / 8.5
eu_mr	9.6 / 42.6	2.8 / 22.6	1.4 / 21	3.7 / 24.6	0.1 / 0.6	3.3 / 31	2.7 / 31.1	2.4 / 32.1
eu_ny	9.3 / 44.2	4.3 / 30.7	2.8 / 31.9	6.4 / 35.1	0.4 / 11.2	0.2 / 12.8	0.1 / 11.5	0.1 / 11.3
eu_or	7.9 / 40.3	8.1 / 39.6	7.4 / 40	8.6 / 41	0 / 0.3	0 / 3.3	0.2 / 0.5	0.1 / 0.5
eu_so	8.3 / 41.7	6.4 / 35.4	4.8 / 35.8	7.1 / 37.8	0.2 / 11.4	0.4 / 12.8	0.1 / 12	0.1 / 10.9
eu_ss	5.9 / 43.7	1.9 / 25	0.9 / 22.6	2.8 / 29.4	0.1 / 11.3	0.1 / 8.1	0 / 6	0 / 8.7
eu_ti	3.8 / 24.1	0.8 / 11	0.3 / 9.3	1.5 / 15	0 / 0.3	0 / 1.9	0 / 0.6	0 / 0.7
eu_yo	5 / 26.3	1.7 / 16.8	1 / 15.8	1.7 / 16.8	0.1 / 7.6	0.1 / 7.5	0 / 2.8	0 / 4.2
eu_zh	23.2 / 22.4	5.6 / 22.6	2.3 / 20.3	5.9 / 24.9	1.8 / 2.6	17.5 / 17	20.2 / 21	14.3 / 19.4
fon_ckb	2.8 / 28.6	0.9 / 20.6	0.3 / 16.8	1.6 / 24	0 / 0.2	0 / 0.2	0 / 2	0 / 1.5
fon_cs	7.6 / 27.8	2.8 / 20.2	2.1 / 19.3	4.3 / 22.3	0 / 1.3	0.5 / 13	0.8 / 13.9	0.3 / 13.5
fon_cy	8.8 / 31.5	4 / 21.8	2.9 / 21.2	6 / 25.6	0 / 2.2	0 / 7.3	0.1 / 10.4	0.1 / 7.1
fon_en	12.9 / 35.4	3.9 / 25	2.2 / 23.4	6.4 / 27.8	0.1 / 7.8	0.8 / 12.5	1.4 / 17.7	1.9 / 18.3
fon_et	6.7 / 30.6	2.2 / 22.3	1.2 / 20.4	3.4 / 24.9	0 / 1.3	0.7 / 15.5	0.4 / 15.8	0.6 / 16.1
fon_eu	4.6 / 31.3	1.4 / 22.5	0.9 / 19.8	2.9 / 27.2	0 / 2	0.5 / 17.6	0.1 / 12.4	0 / 14.3
fon_fr	10.6 / 33.2	5.3 / 24.4	4.4 / 24.3	7.6 / 26.8	0.1 / 3.7	0.9 / 11.2	1.3 / 17.1	1.3 / 16.4
fon_ln	8.2 / 36.8	0.6 / 11	0.2 / 7.6	0.5 / 11.8	0.1 / 3	0.1 / 6.6	0 / 5	0 / 1.5
fon_mr	3.8 / 27	0.8 / 16.5	0.2 / 13.4	1.5 / 18.7	0 / 0.4	0.3 / 8.3	0.1 / 8.7	0 / 7
fon_ny	5.6 / 33.3	1.3 / 20.6	0.7 / 18.7	3 / 26.5	0 / 1.9	0.1 / 12.8	0 / 4.4	0 / 2.7
fon_or	2.7 / 25.1	1.1 / 18.5	0.7 / 17	2 / 22	0 / 0.2	0 / 0.2	0 / 0.4	0 / 0.3
fon_so	4.3 / 31.2	1.6 / 23	0.8 / 19.6	2.4 / 26.3	0 / 2	0.1 / 5.6	0 / 5.5	0 / 4.1
fon_ss	3 / 32.5	0.8 / 16.7	0.3 / 14	1.8 / 23.2	0 / 2.4	0 / 4.5	0 / 3.9	0 / 1.8
fon_ti	1.7 / 15.5	0.3 / 6.5	0.1 / 5.5	0.7 / 10.2	0 / 0.2	0 / 0.2	0 / 0.1	0 / 0.1
fon_yo	3.4 / 21.3	0.7 / 12.3	0.4 / 10.8	1.1 / 14.9	0 / 2.3	0 / 3.2	0 / 3.7	0 / 1
fon_zh	11.8 / 12.9	1.9 / 8.7	0.5 / 6.2	2.2 / 10.2	0.1 / 0.6	1.6 / 4.3	1.8 / 5.1	0.7 / 3.5
fr_ckb	9.2 / 46.9	6 / 39.7	3.3 / 38.4	6.1 / 39.1	0 / 0.3	0.1 / 7.8	0.1 / 13.8	0.1 / 13.9
fr_cs	26 / 53.6	27.3 / 54.9	27.8 / 55.3	27.8 / 55.2	1.8 / 14.2	19.3 / 46.8	20.9 / 49.1	20.4 / 49.4
fr_cy	33.7 / 60.1	28 / 51.6	31.7 / 56	30.7 / 55	0.3 / 9.5	4.1 / 27.8	4.2 / 32.8	3.7 / 34.1
fr_en	47.9 / 70.1	46.1 / 69.6	47.3 / 70.3	47.1 / 70.1	2.7 / 21.4	39.2 / 64.5	39.9 / 64.9	40.1 / 65.1
fr_et	20.9 / 54.3	22.2 / 55.2	18.5 / 54.5	23.6 / 56.3	1.7 / 15.8	11.1 / 44.6	16.9 / 50.6	15.8 / 51
fr_eu	14 / 51.2	13.1 / 50.8	11.6 / 51.3	16.1 / 53.5	0.3 / 9.9	10.2 / 47.7	9.5 / 48.8	9.6 / 49.4
fr_fon	2.5 / 22.6	1.1 / 14.7	0.7 / 12.3	1.2 / 14.5	0.2 / 2.4	0 / 1.7	0 / 3.8	0 / 1.8
fr_ln	16.8 / 49.3	1.7 / 17.9	1.2 / 17.3	2.1 / 20.2	0.2 / 7.3	0.1 / 8.7	0 / 6.3	0.2 / 10.6
fr_mr	12 / 45.5	7.1 / 34.8	2.2 / 27	6.7 / 33.2	0.5 / 8.8	5.5 / 35.9	5.3 / 38.3	4.5 / 38.4
fr_ny	10.8 / 45.5	5.4 / 34.9	4.1 / 38.3	7.8 / 40	0.2 / 6.6	0.5 / 16.1	0.2 / 13.8	0.2 / 13.8
fr_or	10.2 / 43.8	9.3 / 41.7	10.1 / 43.5	10.1 / 43.6	0 / 0.2	0.1 / 1.1	0.1 / 0.6	0.2 / 0.6
fr_so	9.7 / 43.8	7.5 / 39.5	6 / 39.9	7.7 / 40.1	0.1 / 5	0.5 / 15.9	0.3 / 15	0.1 / 11.1
fr_ss	7.9 / 45.5	2.4 / 28.5	1 / 26.5	3.4 / 31.9	0.1 / 6.9	0.1 / 10.3	0.1 / 10.2	0.1 / 8.9
fr_ti	4.6 / 25.3	1 / 12.9	0.5 / 11.7	1.8 / 16.9	0 / 0.3	0 / 1.1	0 / 0.8	0 / 0.5
fr_yo	4.9 / 26.2	2.1 / 18.7	1.3 / 17.6	1.9 / 18.8	0.1 / 4.6	0.1 / 6.6	0 / 3.8	0 / 10.2
fr_zh	25.5 / 24.4	7.4 / 33	7.2 / 34.1	6.8 / 33.6	4 / 5.5	16.2 / 18.1	22.8 / 23.6	19.3 / 21.8
ln_ckb	6.6 / 40	1.1 / 22.1	0.3 / 18	1.4 / 22.8	0 / 0.2	0 / 3	0 / 3.6	0 / 3.8
ln_cs	15.6 / 40.7	3.6 / 22.1	1.4 / 18.1	4.7 / 23.6	0.2 / 4.7	2.6 / 19.2	2.5 / 21.2	1.9 / 20.4
ln_cy	20.2 / 45.8	4.9 / 23.2	2.6 / 21	6.4 / 26.6	0.1 / 5.8	0.1 / 7.8	0.1 / 6.7	
ln_en	28.9 / 52.1	5.5 / 27.2	1.7 / 23.4	6.8 / 29.5	0.3 / 11.1	6.5 / 27.2	6.6 / 25.5	6.7 / 29.9
ln_et	12.8 / 42.6	3.2 / 24.8	1.3 / 20	3.7 / 26.3	0.2 / 5.2	0.3 / 12.9	2.3 / 23.7	1.9 / 22.9
ln_eu	9.3 / 42.1	2.1 / 25.3	1.3 / 22	3.2 / 28.3	0.1 / 5.9	0.7 / 17.7	1.4 / 25.3	0.6 / 22.3
ln_fon	2.6 / 22.6	1.1 / 13.1	0.3 / 8.4	0.8 / 13.3	0 / 0.5	0.1 / 5.4	0 / 3	0 / 1.8
ln_fr	23.8 / 48.9	6.5 / 25.5	2.8 / 24	7.6 / 28	0.4 / 9.9	4 / 23.1	6.5 / 30.9	4.1 / 28
ln_mr	8.1 / 37.1	1.2 / 16.8	0.3 / 12.8	1.5 / 18.7	0.1 / 0.7	0.6 / 16.4	0.1 / 10.1	0.2 / 13.6
ln_ny	9.4 / 42.1	1.6 / 20.5	0.6 / 17.3	2.6 / 25.9	0.2 / 6.4	0.1 / 8.2	0.1 / 9.6	0.1 / 8.9
ln_or	6.8 / 36.6	1.4 / 18.9	0.5 / 15.9	1.8 / 21.7	0 / 0.3	0 / 0.4	0 / 0.4	
ln_so	8.6 / 40	2.1 / 24	0.7 / 19.4	2.6 / 26.6	0.1 / 5.9	0.4 / 12.9	0.1 / 9.8	0.1 / 8.9
ln_ss	7.1 / 43	1.2 / 18.5	0.4 / 13.6	2 / 22.5	0.1 / 5.2	0.1 / 9.5	0.1 / 8.3	0 / 7.2
ln_ti	3.4 / 20.6	0.3 / 4.5	0.1 / 5.7	0.6 / 10	0 / 0.3	0 / 0.2	0 / 0.2	0 / 0.2
ln_yo	4.3 / 24.5	0.8 / 12.9	0.4 / 11	1.1 / 14.9	0.1 / 4	0 / 1.4	0.1 / 7	0.1 / 7.4

43

ln_zh	20 / 19.9	1.7 / 8.9	0.3 / 4.3	2.2 / 10.7	0.3 / 1.2	1.5 / 5.1	4.2 / 8.6	2.9 / 7.9
mr_ckb	8.1 / 45.2	4.4 / 35.5	1.1 / 28.5	4.9 / 34.8	0.1 / 0.3	0 / 8.8	0 / 8.7	0 / 8
mr_cs	21.8 / 49.3	9.5 / 31.4	3.4 / 29.2	14.4 / 37.7	0.2 / 0.8	11.7 / 36.7	12.5 / 38.7	10.8 / 38.9
mr_cy	28.1 / 56.1	22.3 / 47	25.6 / 51.2	26 / 51.1	0.1 / 1	2.1 / 21.1	1.3 / 23.6	0.9 / 21.2
mr_en	40.3 / 65.8	35 / 61.2	35.4 / 61.3	36.9 / 62.4	1.5 / 7.6	24.8 / 53.7	27.8 / 56.4	27.9 / 56.3
mr_et	18 / 51.3	7.5 / 34	7.6 / 41	15.6 / 45.7	0.2 / 1.7	10 / 41.6	8.7 / 43	9.7 / 44.2
mr_eu	11.3 / 48.3	6.3 / 35.8	3.7 / 35.6	9.6 / 42	0 / 0.8	4.4 / 36.5	3.4 / 39	2.3 / 37.6
mr_fon	2.3 / 22.2	0.9 / 13.2	0.3 / 8.9	0.8 / 12.6	0 / 0.2	0 / 3.6	0 / 5.1	0 / 1.2
mr_fr	32.2 / 58.7	18.5 / 39.8	10.7 / 39.2	24.7 / 47.7	0.5 / 1.4	17.2 / 44.8	14.3 / 45	18.2 / 47.3
mr_ln	15.3 / 47.8	1 / 14	0.3 / 13.5	1.7 / 19	0 / 0.3	0 / 6.5	0.1 / 8.2	0.1 / 6.9
mr_ny	9.9 / 44.7	2.9 / 28.3	2.9 / 34.6	7.1 / 38	0.1 / 1.3	0.2 / 11.6	0.1 / 10.1	0 / 7.8
mr_or	11 / 45.6	9.2 / 42.3	9.7 / 43.2	9.5 / 43.4	0.1 / 0.3	0.2 / 0.7	0.2 / 1.2	0 / 1
mr_so	8.8 / 42.8	6.2 / 36.7	3.5 / 36.3	7 / 39.1	0.1 / 1	0.2 / 10	0.1 / 7.9	0 / 7.3
mr_ss	7.1 / 44.9	1.8 / 24.7	0.6 / 20.8	3.2 / 30.8	0.1 / 0.6	0.1 / 11.7	0 / 6.6	0 / 5.8
mr_ti	4.5 / 25.2	0.7 / 10.6	0.4 / 11.1	1.7 / 16.2	0 / 0.2	0 / 1.4	0 / 0.8	0 / 0.6
mr_yo	5.1 / 26.5	1.8 / 17.5	0.9 / 16.4	1.7 / 18.1	0.1 / 0.4	0.1 / 7.1	0 / 3.1	0 / 3.9
mr_zh	25.4 / 24	4.8 / 19.3	1 / 13.6	5.6 / 23.3	0.1 / 0.4	17.7 / 17	19.9 / 19.4	14.8 / 18.9
ny_ckb	6.6 / 39	4.5 / 33.5	1.4 / 29.5	5.2 / 35.5	0 / 0.2	0 / 0.5	0 / 1.6	0 / 2.9
ny_cs	15.2 / 40.3	14.2 / 37.4	15.2 / 39.3	15.3 / 39.2	0.2 / 4.2	0.6 / 15.9	3.5 / 23.3	3.1 / 23.2
ny_cy	20.7 / 46	17.4 / 39.1	20.3 / 42.2	20 / 42.7	0.1 / 4.2	0.2 / 8.6	0.1 / 7.8	0.1 / 6.3
ny_en	29.2 / 52.9	24.2 / 47.2	24 / 49.7	27.2 / 50.5	0.6 / 12.2	8.4 / 27.7	12.4 / 35.5	13.9 / 37.1
ny_et	12.7 / 42.6	11.8 / 38.6	10.9 / 40.2	13.5 / 41.9	0.1 / 4.7	1.5 / 20.7	1.6 / 24.5	2 / 26.7
ny_eu	8.9 / 41.1	8.6 / 39	5.9 / 36.9	9.8 / 42.7	0 / 4.5	0.6 / 20.4	0.8 / 25.4	0.6 / 23
ny_fon	2.5 / 21.9	1.3 / 14.6	0.6 / 12.1	1.4 / 15.6	0 / 0.3	0 / 4.4	0 / 1.4	0 / 3.7
ny_fr	22.5 / 47.4	19.8 / 42.1	22.4 / 45.2	23.8 / 46.3	0.2 / 5.5	8.6 / 31.6	5.6 / 32.2	4.5 / 32.2
ny_ln	13.6 / 44.7	1 / 13.7	0.5 / 13	1.8 / 19.2	0.1 / 5.2	0.5 / 13.4	0.1 / 10.8	0.1 / 9.4
ny_mr	7.4 / 36.1	4.3 / 27.3	1.4 / 21.6	5.3 / 29.9	0 / 0.5	0.3 / 13.6	0.5 / 19.6	0.3 / 15.8
ny_or	6.2 / 35.9	5.3 / 33.9	6.6 / 35.4	6.7 / 36.4	0 / 0.3	0.1 / 0.2	0 / 0.3	0.1 / 0.5
ny_so	8.2 / 39.6	6.2 / 35.3	4.5 / 35	6.9 / 37.1	0.1 / 5.5	0.4 / 12.8	0.2 / 12.3	0.1 / 9.5
ny_ss	7.3 / 42.5	2.5 / 27.2	0.9 / 22.1	4.2 / 32.2	0.1 / 4	0.1 / 10.5	0.2 / 13.5	0.1 / 9.5
ny_ti	3.3 / 19.4	0.8 / 10.8	0.3 / 9.3	1.7 / 15.4	0 / 0.3	0 / 0.3	0 / 0.2	0 / 0.1
ny_yo	4 / 23.3	2 / 17.7	1.4 / 16.6	2.3 / 19	0.1 / 3.5	0.1 / 4.1	0 / 3.8	0 / 4.4
ny_zh	18.8 / 18.9	5 / 20.7	1.3 / 14.9	4.7 / 21.9	0.3 / 1.1	3.9 / 6.7	6.2 / 11.3	6 / 11.5
or_ckb	8.1 / 45.1	6 / 38.9	5.7 / 40.4	7.5 / 42	0 / 0.2	0 / 0.2	0 / 0.3	0 / 0.3
or_cs	21.3 / 49.1	20.3 / 47.5	21.6 / 47.9	21.7 / 48.9	0 / 0.7	8.1 / 32.7	9.5 / 36.9	10.6 / 36.7
or_cy	28.6 / 56.4	22.4 / 48	27.4 / 52.1	26.3 / 51.6	0.1 / 0.9	0.5 / 8.6	0.3 / 5.6	0.8 / 10.5
or_en	41.6 / 66.2	35 / 61	36.3 / 61.7	36.1 / 61.7	1 / 8.6	18.9 / 47.3	20.6 / 49.1	22.5 / 50.7
or_et	17.1 / 50.7	17.6 / 49.6	18.2 / 50.4	18.7 / 51.1	0.1 / 0.9	6.8 / 35	9.1 / 41.1	7.9 / 38.3
or_eu	11.9 / 48.8	13.3 / 49.9	14.1 / 51.1	13.9 / 51.4	0 / 0.5	2.1 / 24.3	1.9 / 28.8	2.2 / 36.6
or_fon	2.3 / 21.4	1 / 13.5	0.5 / 10.7	1 / 13.9	0 / 0.5	0 / 2.3	0 / 1.7	0 / 1
or_fr	32.3 / 58.7	29.1 / 54.1	31.3 / 55.7	32.6 / 57	0.1 / 1	12.8 / 39.4	13.8 / 42.6	16.5 / 44.6
or_ln	15.9 / 47.8	1.4 / 14.8	0.7 / 14.7	1.6 / 16.3	0 / 0.4	0.3 / 5.1	0.1 / 6.4	0.1 / 7.3
or_mr	12.8 / 47	9.1 / 42.1	9.9 / 42.8	10.3 / 43.2	0.2 / 4.2	4.5 / 27.6	2.4 / 34.6	6.4 / 40.1
or_ny	10.8 / 45.7	5.3 / 34.9	5.4 / 38.7	8 / 39.6	0.1 / 0.7	0.1 / 10	0.1 / 5.8	0.1 / 7.7
or_so	8.8 / 42.5	6.3 / 36.8	7.2 / 38.5	7.5 / 40	0.1 / 0.5	0.3 / 2.5	0 / 6.7	0.1 / 6.9
or_ss	7.1 / 44.6	2.3 / 26.6	1.5 / 26.3	3.4 / 32.2	0 / 0.4	0 / 3.7	0 / 4.7	0.1 / 7.6
or_ti	4.4 / 25.3	0.8 / 10.5	0.5 / 12.6	1.8 / 16.2	0 / 0.2	0 / 0.3	0 / 0.3	0 / 0.2
or_yo	5.6 / 27.3	1.6 / 17.2	1.4 / 17.4	1.9 / 18.7	0 / 0.4	0 / 3.3	0 / 2.9	0 / 2.8
or_zh	26 / 24.3	5.2 / 26.7	4.2 / 26.8	6.6 / 29.5	0.4 / 0.6	8.6 / 8.4	18.2 / 16.7	18 / 17.9
so_ckb	6.3 / 40.7	3.5 / 30	2 / 31.4	4.5 / 33.7	0 / 0.5	0.1 / 5.9	0 / 1.2	0 / 2.6
so_cs	15.6 / 41	14.6 / 40.1	16.4 / 41.9	16.4 / 42.2	0.1 / 3.4	5.6 / 24.5	6.5 / 29.2	5.8 / 31.1
so_cy	21.2 / 47	20.1 / 43	23.1 / 46	22.6 / 46.1	0.2 / 4.4	0.7 / 11.5	0.2 / 10.6	0.2 / 9.6
so_en	30.2 / 54.4	27.8 / 51.7	30.7 / 54.5	31.2 / 55	1 / 11.4	17.5 / 40.5	21.1 / 45.2	19.5 / 45.7
so_et	13.1 / 43.3	14 / 43	13.9 / 43.4	15 / 44.5	0.3 / 7.2	2.5 / 22	3.7 / 30.8	2.9 / 30.4
so_eu	9.1 / 42.4	9.8 / 42.2	9.4 / 42.1	11.4 / 45.4	0.1 / 4.8	0.7 / 18.3	0.5 / 21.5	0.1 / 13.3
so_fon	2.1 / 20	1 / 13.6	0.5 / 10.6	0.9 / 13.8	0 / 0.6	0.1 / 7.4	0 / 5.7	0 / 1.8
so_fr	24.5 / 49.8	24 / 47.8	26.4 / 49.7	26.1 / 49.7	0.4 / 7.1	13.8 / 38.9	11.3 / 39.6	11.3 / 40.2
so_ln	15.3 / 45.9	1.4 / 15.7	0.6 / 13.5	1.8 / 18.9	0.1 / 4.8	0.2 / 11.8	0.1 / 9.4	0.1 / 8.7
so_mr	8.7 / 38.8	4.8 / 28.9	1.3 / 21.5	5.1 / 28.5	0.2 / 6.1	1.8 / 23.7	1.1 / 24	0.7 / 22.6
so_ny	10.5 / 43.4	4.7 / 31.9	2.5 / 31.9	7 / 37.2	0.2 / 5	0.5 / 17.3	0.2 / 12.8	0.1 / 10.6
so_or	7 / 37.3	6.2 / 35	7.1 / 36.9	7.5 / 37.8	0.1 / 0.3	0.1 / 0.2	0.1 / 0.4	0.1 / 0.4
so_ss	6.6 / 42.4	2 / 25.5	0.8 / 21.4	3.5 / 31.2	0 / 3.6	0 / 12.9	0.2 / 12.3	0 / 6.5
so_ti	3.6 / 22.5	1 / 11.3	0.3 / 9.6	1.4 / 15.2	0 / 0.3	0 / 0.4	0 / 0.3	0 / 0.2
so_yo	6.1 / 27	1.5 / 16.2	1 / 15.7	1.8 / 17.9	0.1 / 3.2	0.1 / 11.9	0.1 / 9.2	0 / 6
so_zh	20.3 / 20.5	3.6 / 21.4	4.3 / 22.9	3.5 / 23	0.6 / 1.5	8.5 / 12.4	10.1 / 14.6	10.2 / 14.4
ss_ckb	6.2 / 39.2	4 / 32.4	1.8 / 30.2	4.5 / 33.3	0 / 0.2	0 / 3	0 / 1.7	0 / 1.9
ss_cs	14.9 / 39.1	11.1 / 33.3	13 / 36	12.8 / 36.2	0.1 / 3.6	0.7 / 13.5	1.7 / 20.4	1.3 / 20
ss_cy	20.1 / 45.4	15.8 / 36.8	16.7 / 39.1	18.8 / 40.7	0.1 / 4.5	0.4 / 11	0.1 / 8.6	0.1 / 6.9
ss_en	29.2 / 52.3	21.6 / 43.8	22.9 / 47	25 / 47.7	0.4 / 11	7 / 25.1	8.4 / 29.3	9.2 / 32.5
ss_et	12.1 / 41.6	9.6 / 35.5	8.8 / 37.2	11.3 / 39.1	0.1 / 4	0.2 / 14.9	1.2 / 20.7	1 / 20.3
ss_eu	8.2 / 39.7	7.7 / 36.6	7.1 / 37.4	8.9 / 40.5	0 / 4.9	0.1 / 10.7	0.4 / 20.9	0.3 / 18.7
ss_fon	2.7 / 22	1.4 / 14.8	0.6 / 11.5	1.4 / 14.9	0 / 0.3	0 / 3.4	0 / 3.9	0 / 1.5
ss_fr	20.7 / 45.4	18.3 / 40.1	21.3 / 43.1	20.9 / 43.3	0.2 / 5.9	4.4 / 25.5	4.1 / 27.3	2.5 / 26.8
ss_ln	12.1 / 42.8	1 / 14.4	0.5 / 11.6	1.5 / 18	0.1 / 6.4	0.1 / 10.3	0.1 / 9.9	0.1 / 8.7
ss_mr	6.7 / 34.7	3.4 / 24.7	1.3 / 20.4	4.4 / 27.4	0.1 / 0.9	0.4 / 13.5	0.3 / 16.6	0.2 / 13.3
ss_ny	7.6 / 38.4	5.1 / 31.9	3.2 / 31.8	7.7 / 36.9	0.2 / 6.8	0.1 / 9.2	0.1 / 9.6	0.1 / 9.6
ss_or	6.1 / 34.7	4.9 / 31.1	4.9 / 32	6.2 / 34	0.1 / 0.3	0 / 0.2	0 / 0.4	0 / 0.3
ss_so	7.7 / 38.2	6 / 33.6	4.2 / 33	6.9 / 36.2	0.1 / 6	0.3 / 11.1	0.1 / 9.9	0.1 / 8.8
ss_ti	2.6 / 18.3	0.8 / 11	0.4 / 10	1.5 / 15	0 / 0.3	0 / 0.3	0 / 0.2	0 / 0.1
ss_yo	3.6 / 21.7	1.8 / 16.7	1.2 / 15.9	2.2 / 18.3	0.1 / 4.2	0 / 3.1	0.1 / 7.6	0 / 3.4
ss_zh	19.9 / 20	4.1 / 17.8	4 / 19.3	4.2 / 19.5	0.1 / 0.7	2.5 / 5.3	3.4 / 8.3	3 / 7.9

ti_ckb	5.7 / 39.5	3.4 / 33	1.3 / 26.9	4.4 / 36.3	0 / 0.2	0 / 1.9	0 / 0.3	0 / 0.1
ti_cs	14.5 / 40.9	9.1 / 32.8	11.1 / 34.6	11.8 / 37.2	0.1 / 1.7	0.8 / 11.5	2.4 / 23.2	2.9 / 25.6
ti_cy	18.5 / 45.8	12.5 / 34.9	15.5 / 37.2	16.1 / 40.1	0 / 1.8	0.3 / 14.4	0.1 / 5.6	0.1 / 7.8
ti_en	26.4 / 52.4	15.2 / 41.5	17.2 / 45	20.6 / 47.1	0.6 / 10.2	8 / 29.9	9.4 / 34.6	9.3 / 35
ti_et	12 / 42.8	7.5 / 34.9	7.4 / 34.9	9.3 / 37.6	0.1 / 3.5	0.3 / 10.5	1.6 / 25.8	2.2 / 26.7
ti_eu	8.1 / 41.7	5.8 / 36.1	4.5 / 34.4	7.6 / 40.4	0 / 2.3	0.8 / 24.9	1.3 / 25.2	0.5 / 22.9
ti_fon	1.9 / 20.8	0.8 / 14.2	0.3 / 8.8	0.9 / 14.6	0 / 0.2	0 / 0.3	0 / 1.4	0 / 3
ti_fr	22.1 / 49	15.6 / 39.6	19.5 / 42.6	20.2 / 44.4	0.2 / 3.6	4.7 / 26.2	6.1 / 31.5	3.9 / 31
ti_ln	13 / 44.3	0.5 / 13.5	0.2 / 8.8	0.2 / 0.9	0 / 0.4	0.3 / 10.1	0 / 3.9	0.1 / 6.5
ti_mr	8.2 / 38.6	3.4 / 26.2	1.9 / 23.8	4.6 / 30.3	0 / 1.2	0.7 / 18.8	0.6 / 21.1	0.3 / 18.4
ti_ny	8.4 / 41.2	3.4 / 30.7	1 / 22.7	5.3 / 34.7	0 / 0.4	0 / 0.6	0 / 2.5	0 / 1.1
ti_or	6.7 / 38	4.5 / 31.2	5.1 / 32	5.5 / 34.7	0 / 0.2	0 / 0.2	0 / 0.7	0 / 0.3
ti_so	7.2 / 39.3	4.1 / 32.6	2.3 / 28	5.1 / 35.6	0.1 / 0.4	0.1 / 2.5	0 / 3.5	0 / 3.8
ti_ss	4.8 / 40.5	1.8 / 25.8	0.5 / 17.1	2.5 / 29.7	0.1 / 0.4	0 / 0.9	0 / 0.8	0 / 1.7
ti_yo	4.3 / 24.4	1.4 / 16.7	0.6 / 12.9	1.6 / 17.7	0 / 0.6	0.2 / 7.3	0 / 1.1	0 / 4.9
ti_zh	22.2 / 20.9	2.6 / 16.9	3 / 18.5	4.5 / 21.4	0.3 / 0.7	1.5 / 3.5	3.9 / 5.7	5.2 / 9.4
yo_ckb	5.5 / 36.6	2.4 / 27.5	1.4 / 27.3	3.5 / 31.1	0 / 0.2	0 / 2	0 / 3.2	0 / 2.8
yo_cs	12.7 / 36.6	7.3 / 27.1	9.9 / 31.4	9.7 / 31.7	0.1 / 3.3	0.5 / 18.1	1.6 / 15.1	0.6 / 16.7
yo_cy	16.9 / 42.4	10.3 / 30.1	12.7 / 34.7	13.9 / 35.5	0.1 / 3.7	0.1 / 9.8	0.1 / 6.9	
yo_en	23.9 / 47.9	11.8 / 34.9	12.7 / 40.3	17.8 / 40.7	0.4 / 12.5	5.2 / 23.5	4.2 / 24.3	6.5 / 26.1
yo_et	10.8 / 38.8	5.3 / 29	7.4 / 33.7	8.5 / 34.3	0.1 / 4.5	1.7 / 18.9	1.7 / 20.1	1.3 / 20.8
yo_eu	7.2 / 38.8	3.2 / 29.6	4.9 / 33.9	6.7 / 37	0 / 3.9	0.3 / 19.4	0.4 / 18.2	0.3 / 17.2
yo_fon	1.8 / 19.7	1 / 13.7	0.5 / 11.2	1.1 / 14.9	0 / 0.4	0.1 / 5.2	0 / 4.1	0 / 3.1
yo_fr	19.1 / 44.1	11.5 / 31.5	16.2 / 38	15.9 / 38.4	0.3 / 7	3.2 / 21.8	1.5 / 20.2	1.9 / 22.6
yo_ln	12.4 / 42.8	0.5 / 11.4	0.4 / 11.1	1 / 16.2	0.1 / 4.3	0.3 / 9.1	0.1 / 8	0.1 / 7.7
yo_mr	6.9 / 34.9	1.7 / 20.9	1 / 21.1	3.8 / 27.2	0.1 / 2.5	0.3 / 13.7	0.2 / 12.9	0.1 / 10.3
yo_ny	8.9 / 40.2	2.4 / 25.5	2 / 28.4	6 / 33.9	0.1 / 3.9	0.5 / 9.4	0.1 / 6.2	0 / 5.3
yo_or	5.2 / 33	2.9 / 26.2	2.9 / 28.2	4 / 30.5	0 / 0.3	0 / 0.3	0 / 0.2	0 / 0.2
xx2en	**35.5 / 59.6**	29.7 / 54.4	30.9 / 55.4	31.9 / 56.4	2.0 / 13.3	20.5 / 44.1	22.3 / 46.9	22.4 / 47.6
en2xx	**20.7 / 50.1**	17.3 / 44.1	17.8 / 44.7	18.6 / 45.7	0.4 / 5.7	8.1 / 26.7	8.7 / 29.0	8.7 / 28.8
Mean	**28.2 / 54.9**	23.5 / 49.2	24.4 / 50.0	25.3 / 51.1	1.2 / 9.6	14.3 / 35.5	15.6 / 38.0	15.6 / 38.2
xx2yy	**13.7 / 40.5**	8.8 / 31.2	8.4 / 30.9	10.1 / 34.0	0.3 / 4.1	4.0 / 16.1	4.4 / 17.3	4.2 / 17.1

Table 19: Evaluation scores on the recently introduced NTREX test set (depicted as `<bleu>` / `<chrf>`) for the MT models and language models described in Section 4.1 and Section 4.2 compared against unsupervised baselines [10]. Note that LM-8B is evaluated on a 50% split of the NTREX data and is not comparable to the MT-model evaluations.

	Baziotis et al. [10]	MT-3B	MT-7.2B	MT-10.7B	LM-8B			
					0-shot	1-shot	5-shot	10-shot
af_en	- / -	57.1 / 75.4	58.5 / 76.5	58.4 / 76.4	7.6 / 30.6	49 / 69.9	49.2 / 69.6	51.8 / 71.9
am_en	- / -	24.3 / 50.3	27.2 / 52.5	27.2 / 52.7	1 / 10.9	13.4 / 37.9	14.6 / 40.4	13.8 / 40.3
ar_en	- / -	36 / 61.9	37.9 / 63.1	37.8 / 63.1	1.1 / 10	23.7 / 51.6	28.6 / 53.9	28.8 / 54.1
az_en	- / -	26.3 / 52.7	29.1 / 54.9	30.1 / 55.8	4.7 / 26.3	15.5 / 40.8	20.6 / 47	21.8 / 48.6
ba_en	- / -	8 / 28.2	9 / 28.4	9.7 / 28.8	0.5 / 7.4	11.1 / 37	9.5 / 34.4	13.2 / 38.7
be_en	- / -	31.5 / 57.6	32.8 / 58.5	35.3 / 59.7	4 / 19.4	18.4 / 40.7	29.1 / 56	30.7 / 56.3
bem_en	- / -	10 / 32.6	12.1 / 33.9	13.3 / 34.7	0.1 / 5.3	4.8 / 20.7	2.7 / 21.7	2.6 / 21.5
bg_en	- / -	38.2 / 63.3	39.3 / 64	39.4 / 64.1	4.3 / 25.4	31.6 / 58.3	31.6 / 58.7	32.6 / 58.3
bn_en	- / -	35.4 / 60.7	37.5 / 61.9	38 / 62.3	0.8 / 6	23.5 / 51.4	22.9 / 50.1	24.4 / 51.9
bo_en	- / -	12.1 / 37.8	13.3 / 38.8	14.5 / 40	0.1 / 2.7	5.9 / 28.4	2.9 / 25.8	4.3 / 27.8
bs_en	- / -	40.7 / 65.1	42.6 / 66.2	41.9 / 66	4.6 / 24.2	27.2 / 52.2	33.6 / 59.4	35.3 / 60.4
ca_en	- / -	41.6 / 66	43.4 / 66.9	43.1 / 66.8	5.4 / 22.9	31.3 / 56.6	34.5 / 61	36.1 / 61.4
ckb_en	- / -	28.3 / 53.4	33.9 / 58	33.5 / 57.9	1.1 / 11.4	7.8 / 27.4	18.8 / 43.6	20.2 / 45.3
cs_en	- / -	39.4 / 64.8	41.1 / 65.7	41.4 / 65.8	5.8 / 29.1	26 / 51.5	33.5 / 59.3	34.1 / 59.7
cy_en	- / -	43.2 / 66.6	45 / 68.1	45.2 / 68.2	3.9 / 24.2	35.2 / 58.8	37.5 / 61.1	37.2 / 60.7
da_en	- / -	42.5 / 65	43.7 / 65.8	43.7 / 65.8	6.3 / 28.6	36.1 / 60.2	37.6 / 61.2	37.5 / 61.2
de_en	- / -	38.9 / 64.6	39.8 / 65.4	40.2 / 65.5	4.3 / 26.4	31.6 / 59.4	33 / 59.1	34 / 60.4
dv_en	- / -	22.2 / 48.8	24.6 / 50.5	25 / 50.8	0.6 / 6.8	7.9 / 29.6	11.1 / 36.9	12.6 / 39.5
dz_en	- / -	6.4 / 28.2	6.4 / 27.9	6.7 / 28.7	0 / 1.6	0.9 / 13.9	1.1 / 17.5	0.9 / 15
ee_en	- / -	13.2 / 35.1	16.3 / 38.4	16.7 / 38.5	0.3 / 7.9	3.2 / 22.1	1 / 15.2	2.8 / 19.6
el_en	- / -	43 / 65.8	43.3 / 66.1	44.6 / 66.7	5.2 / 23.8	33.9 / 58.7	31.7 / 58	32.3 / 59
en_GB_en	- / -	89.3 / 94.4	90.3 / 94.6	90.5 / 94.9	7.9 / 26	97.5 / 98.7	99.4 / 99.8	99.4 / 99.7
en_IN_en	- / -	87.1 / 93.6	86.4 / 93	86.9 / 93.8	10.1 / 27	35.1 / 45.3	93.7 / 98.3	95.6 / 98.7
en_af	- / -	42.3 / 66.7	44.5 / 68.4	44.6 / 68.3	2.9 / 16.5	35 / 61.4	37.7 / 63.3	37.8 / 63.4
en_am	- / -	3.8 / 23	4.5 / 23.8	4.2 / 24.3	0.1 / 0.7	0.2 / 0.8	0 / 0.6	0 / 0.4
en_ar	- / -	24.7 / 54.2	24.6 / 54.3	24.9 / 54.7	0.4 / 2.9	6.7 / 38.1	15.4 / 45.3	12.1 / 44
en_az	- / -	14.6 / 46.7	15.2 / 47.5	15.5 / 48.2	0.4 / 8.6	10.4 / 41.6	10.6 / 42.9	7.4 / 40.9
en_ba	- / -	3.3 / 24.3	4 / 26.3	5.2 / 28.9	0 / 0.4	0.3 / 13.4	0.1 / 9.8	0.1 / 10.5
en_be	- / -	21.9 / 44.8	24.2 / 47.3	26 / 50.2	0.7 / 6	20.6 / 49.4	21.6 / 50.3	21.9 / 50.6
en_bem	- / -	2.4 / 4	3.9 / 19.5	2.1 / 3.4	0.1 / 6.7	0.1 / 8.7	0.2 / 10.6	0.1 / 5
en_bg	- / -	34.1 / 59.5	34.8 / 59.9	34.6 / 59.7	1.4 / 8.8	21.1 / 48.7	27.3 / 53.4	29.1 / 55.1
en_bn	- / -	13.8 / 48.5	14 / 49.2	14.6 / 49.8	0.4 / 7.4	8.6 / 40.8	7.4 / 41.5	5.8 / 42
en_bo	- / -	12 / 25.2	14.7 / 29.1	14 / 28.6	0 / 0.9	0 / 1.8	0 / 1.6	0 / 1.1
en_bs	- / -	29.4 / 58.6	30.3 / 59.4	30.2 / 59.3	0.7 / 10.5	23.6 / 53	24.9 / 54.2	25.3 / 54.3

en_ca	- / -	39.9 / 63	40.9 / 63.7	40.5 / 63.4	2.3 / 15.1	30.1 / 55.8	31.6 / 57.7	32.1 / 58.1
en_ckb	- / -	8.5 / 42.4	9.2 / 42.5	9.2 / 42.2	0 / 0.2	0.1 / 10.7	0.2 / 10.9	0.1 / 9.3
en_cs	- / -	32.4 / 59.4	32.9 / 59.6	32.6 / 59.7	1 / 10.8	22.2 / 50.2	22.7 / 51.2	20.9 / 51.5
en_cy	- / -	29.6 / 56.4	33 / 59.7	33.3 / 59.8	0.3 / 9.3	3.4 / 25.2	2.6 / 24.2	3 / 29.1
en_da	- / -	40.4 / 63.9	40.9 / 64.3	40.7 / 64.1	2 / 13.5	34.8 / 59.2	35.5 / 59.9	36.6 / 60.6
en_de	- / -	34.5 / 61.8	35.2 / 62.1	34.7 / 61.8	2 / 16.2	21.3 / 49.9	23.5 / 53.1	22.1 / 52.7
en_dv	- / -	3.5 / 40.7	4.7 / 44.4	4.7 / 44.7	0 / 0.2	0.3 / 0.4	0.2 / 0.4	0.1 / 0.4
en_dz	- / -	22 / 35.8	22 / 35.5	22.7 / 37.2	0 / 0.1	0 / 2.1	0 / 0.3	0 / 1.1
en_ee	- / -	6.1 / 29.1	7.4 / 31.6	7.2 / 30.5	0.2 / 6.2	0.4 / 13.5	0.2 / 6.9	0.1 / 4.5
en_el	- / -	37.4 / 61.5	37.4 / 61.6	37.6 / 61.6	0.9 / 3.7	26.7 / 50.8	28.2 / 52.4	28 / 52.6
en_en_GB	- / -	6.5 / 9.1	34.4 / 48.4	5.8 / 7.1	8.3 / 21.8	99.1 / 99.7	99.4 / 99.8	99.5 / 99.8
en_en_IN	- / -	5.7 / 8.7	21.2 / 28	4.1 / 5.5	4.4 / 15.4	91.2 / 97.4	92.3 / 98	92.1 / 97.9
en_es	- / -	42 / 65.4	42.3 / 65.6	42.2 / 65.5	1.4 / 15.4	28.6 / 53.7	34.1 / 59	33.5 / 58.5
en_es_MX	- / -	2.4 / 5.7	7.6 / 28.1	1.7 / 4	0.8 / 9.7	34.1 / 58.8	36.9 / 60.7	36.5 / 60.9
en_et	- / -	26.4 / 59	26.7 / 59.1	27.3 / 59.4	0.5 / 10.2	11.2 / 42.8	20.2 / 52.9	21.8 / 53.7
en_eu	- / -	14.8 / 51.3	15 / 51.2	15.4 / 52.3	0.2 / 9.4	9.9 / 45.6	9.8 / 45.7	7.4 / 45.7
en_fa	- / -	19.1 / 45	19.5 / 44.9	19.5 / 44.9	0.5 / 3.1	14.3 / 40.7	14.9 / 42.4	14.8 / 43
en_fa_AF	- / -	0.3 / 0.9	0.2 / 0.8	0.2 / 0.8	0 / 0.2	12.4 / 39.6	13.5 / 41.1	11.4 / 40.1
en_ff	- / -	4.8 / 27.6	5.3 / 28.1	5.1 / 28.8	0.2 / 5.5	0.1 / 7.9	0.1 / 5.5	0.1 / 4.3
en_fi	- / -	21.5 / 57.1	21.7 / 57.4	22 / 57.3	0.5 / 11	14.5 / 47.5	16.4 / 50.5	17.2 / 50.4
en_fil	- / -	25.3 / 55.4	25.8 / 55.6	25.3 / 55.4	1.6 / 14.6	26.5 / 54	30 / 57.6	28.6 / 55.8
en_fj	- / -	6.4 / 27.5	7.3 / 28.6	7.7 / 29	0.3 / 6.8	0 / 4.6	0.2 / 7.3	0.1 / 5
en_fo	- / -	16.4 / 37.9	18.6 / 40.8	16.6 / 38.2	0.4 / 9	5.9 / 32.1	7.5 / 32.5	7.2 / 32.7
en_fr	- / -	38.3 / 62.9	39.2 / 63.5	39.2 / 63.5	0.8 / 12.7	28.8 / 54.8	30.2 / 56.2	26.7 / 56.6
en_fr_CA	- / -	2.1 / 5.7	4.2 / 27.8	2.5 / 7.6	0.6 / 8.6	29.6 / 55.8	29.7 / 56.5	30 / 57.6
en_ga	- / -	26.8 / 54.9	27.5 / 55.5	27.1 / 55.2	0.4 / 10.2	1.2 / 16.2	0.9 / 15.4	0.8 / 15.9
en_gl	- / -	39.9 / 64.5	40.6 / 65	40.5 / 64.8	1.3 / 13.2	31.3 / 57.5	32.6 / 58.6	30.6 / 58.1
en_gu	- / -	14.9 / 47.5	15.3 / 48	15.4 / 48.2	0.1 / 0.3	0.4 / 1.2	0.1 / 1.7	0.1 / 1.3
en_ha	- / -	21 / 49	21.8 / 50.1	22.8 / 51.1	0.2 / 4.2	0.4 / 11.4	0.3 / 9.9	0.3 / 9
en_hi	- / -	25.5 / 50.2	25.7 / 50.2	25.9 / 50.6	0.9 / 7.8	16.7 / 42.9	15.6 / 42.8	12.6 / 42.8
en_hmn	- / -	16.6 / 42.1	17.5 / 42.9	17.7 / 43.3	0.2 / 6.1	1.1 / 12.4	0.6 / 10.3	0.5 / 9.4
en_hr	- / -	34.9 / 62	35.5 / 62.7	35.6 / 62.8	3.7 / 21.3	25.7 / 54	26.7 / 55.3	25.1 / 55.3
en_hu	- / -	21 / 50.8	21.4 / 51.2	21.7 / 51.4	0.6 / 10.8	10.6 / 36.9	11.1 / 42.3	12.3 / 42.5
en_hy	- / -	15.7 / 46.5	18.5 / 51	19.1 / 51.7	0.1 / 0.5	0.4 / 0.8	0.5 / 1	0.5 / 1.2
en_id	- / -	38.7 / 65.2	39.6 / 65.8	39.8 / 65.8	0.7 / 9	32.8 / 60.5	35 / 62.7	34.8 / 62.7
en_ig	- / -	13.5 / 37.9	16.4 / 43.2	16.8 / 42	0.2 / 5.8	0.2 / 9.7	0.1 / 5.3	0.2 / 5.5
en_is	- / -	25.1 / 52.8	25.3 / 53	25.3 / 53.3	2.6 / 16.8	22.5 / 48.9	26.3 / 52.3	26 / 51.9
en_it	- / -	38.8 / 64	39.2 / 64.1	39 / 64.1	1.2 / 14.7	28.7 / 55.8	29.7 / 56.7	30.2 / 57
en_iw	- / -	24.3 / 53	22.6 / 48.5	25.4 / 54.2	0.5 / 2.6	14 / 42.3	15.9 / 44.6	15.7 / 44.8
en_ja	- / -	6.3 / 33.6	6.8 / 34.3	5.9 / 33.9	0 / 3.2	0.1 / 26.5	0.1 / 26.5	0.2 / 24.8
en_ka	- / -	2.7 / 15.3	1.6 / 11.9	3.1 / 15.5	0.6 / 6.4	10.2 / 42.1	11.5 / 44.8	9.7 / 46
en_kk	- / -	12.3 / 45.5	13.2 / 47.1	13.7 / 47.3	0.3 / 5.9	8.4 / 41.2	7.7 / 40.8	6.7 / 41.2
en_km	- / -	6 / 40.8	6 / 41.3	4.8 / 43.6	0.1 / 1.1	1.6 / 27.4	0.7 / 32.3	0.3 / 29.3
en_kn	- / -	10.8 / 48.4	12.1 / 50	11.9 / 49.8	0.1 / 0.5	0.2 / 4.1	0.1 / 4.9	0.1 / 4.9
en_ko	- / -	10.9 / 31.7	11.6 / 32.4	11.9 / 32.7	0.2 / 2.8	5.6 / 22.1	3.5 / 22.8	2.9 / 22.8
en_ku	- / -	0.2 / 0.5	0.2 / 0.6	0.3 / 0.8	0.1 / 6.4	0.6 / 15.8	0.5 / 16.3	0.3 / 14.3
en_ky	- / -	9 / 42.1	10.6 / 45	10.4 / 44.2	0.1 / 1.1	1.3 / 22.7	0.9 / 24.5	0.8 / 24.9
en_lb	- / -	8.5 / 29.5	8.9 / 29.8	9.6 / 31	0.4 / 10	3.5 / 32.4	4.1 / 32.7	4.6 / 33.9
en_lo	- / -	11.1 / 38	11.1 / 38.4	11.7 / 39.1	0.2 / 1.4	1.3 / 19.4	2.7 / 31.6	1.9 / 32.6
en_lt	- / -	24.3 / 56.1	26 / 56.7	25 / 56.3	0.6 / 11.8	15.8 / 46.8	17.8 / 50	17.4 / 50.3
en_lv	- / -	22.6 / 54.1	22.9 / 54.1	23.4 / 54.6	1 / 10.2	17.6 / 48.1	18.8 / 49.4	19.1 / 50.6
en_mey	- / -	0.1 / 0.6	0.1 / 0.5	0.1 / 0.6	0 / 0.2	2.9 / 19.9	0.7 / 21	0.8 / 23.2
en_mg	- / -	16.8 / 48.5	17.7 / 50.1	17.6 / 49.6	0.4 / 6.7	1.3 / 19.4	0.6 / 17.1	0.3 / 14
en_mi	- / -	20.9 / 46.4	19.7 / 45.8	21.5 / 47.1	0.5 / 7.9	0.8 / 13.6	0.4 / 11.2	0.4 / 10
en_mk	- / -	37 / 63.9	37.6 / 64.1	37.6 / 64.1	1 / 4	27.2 / 55.3	28.9 / 57.1	30.4 / 58.5
en_ml	- / -	7.1 / 44.2	8 / 44.4	8.3 / 45.3	0.3 / 8.8	5.4 / 37	4.6 / 39.7	2.1 / 37.9
en_mn	- / -	10.7 / 41.6	12 / 44	12.4 / 45	0.1 / 0.5	0.6 / 1.6	0.4 / 3.5	0.4 / 4.1
en_mr	- / -	7.5 / 36	7.3 / 34.2	8.4 / 37.3	1.2 / 14.1	7.8 / 39.6	7.4 / 40	6.8 / 40.3
en_ms	- / -	33.6 / 61.8	35.1 / 62.8	35.3 / 62.9	1.8 / 14.2	29.1 / 56.6	31.6 / 62	33 / 62.2
en_mt	- / -	45.7 / 66.6	47.1 / 67.3	47.6 / 67.5	0.4 / 10	3.7 / 25.6	3.7 / 34.2	3.3 / 33.7
en_my	- / -	1.7 / 16.7	1.5 / 16.2	1.4 / 16.1	0 / 0.5	0 / 5.4	0 / 5.1	0 / 6.4
en_nd	- / -	1.3 / 3	1.8 / 18.2	1 / 2.2	0.1 / 2.5	0.3 / 20.2	0.2 / 13.3	0.2 / 13
en_ne	- / -	7.5 / 35.9	7.9 / 37	8.1 / 37.8	0.1 / 0.5	1.4 / 23.9	1.7 / 30.3	1 / 26.5
en_nl	- / -	36.7 / 62.9	37.5 / 63.4	37.4 / 63.3	2 / 15.7	25 / 51.7	28.8 / 56.6	29.8 / 57.8
en_nn	- / -	34.6 / 60.9	35.8 / 61.6	35.8 / 61.4	4.5 / 14.4	24.9 / 53.2	29.9 / 56.1	30.6 / 57
en_no	- / -	38.7 / 63.6	39 / 63.7	38.9 / 63.6	1.9 / 12.7	33.1 / 59	34.9 / 60.3	34.8 / 60.3
en_nso	- / -	7.9 / 31.2	9.1 / 33.5	9.2 / 33.7	0.3 / 4.6	0.9 / 13.8	0.5 / 13.5	0.4 / 12.4
en_ny	- / -	12 / 41.6	14.8 / 45.5	14.4 / 44.6	0.7 / 8	1.1 / 18.3	0.7 / 17.8	0.7 / 18.3
en_om	- / -	1.1 / 23.2	1.8 / 30.4	2 / 30.3	0.1 / 6.5	0.1 / 9.7	0.1 / 7.3	0.1 / 7.6
en_pa	- / -	18.2 / 44.1	18.9 / 45.2	19.2 / 45.6	0.1 / 0.3	1 / 9	0.6 / 2.6	0.2 / 1.4
en_pl	- / -	27.6 / 55.5	28.1 / 55.8	28.2 / 55.9	1.4 / 12.2	18.1 / 45.3	15.2 / 46.7	14.9 / 45.4
en_ps	- / -	10.5 / 33.6	10.8 / 34.3	10.8 / 34.4	0.1 / 0.5	0.5 / 10.3	0.3 / 8.6	0.3 / 7.6
en_pt	- / -	41.7 / 64.9	42.3 / 65.3	42.3 / 65.3	3.3 / 18.3	30 / 55.8	33.4 / 58.8	34 / 59.7
en_pt_PT	- / -	2.7 / 5.9	8.9 / 34.5	3 / 18	2.9 / 13.4	23.9 / 49.3	31.7 / 57.4	32.7 / 57.9
en_ro	- / -	34.5 / 59	35.3 / 59.4	35 / 59.2	4.4 / 19.8	28.1 / 52.8	30.2 / 55	30.8 / 55.4
en_ru	- / -	30.7 / 55.8	31.9 / 56.7	31.8 / 56.7	1 / 2.9	18 / 41.8	22.3 / 48.5	23 / 48.9
en_rw	- / -	3.2 / 18.6	0.3 / 8.3	0.9 / 12	1 / 9.5	1.1 / 18	0.8 / 17.5	0.5 / 16.5
en_sd	- / -	10 / 35.8	11.4 / 37.1	11.2 / 37.4	0.1 / 0.6	0.3 / 8.7	0.2 / 8.8	0.3 / 10.9
en_shi	- / -	0.3 / 0.7	0.2 / 0.7	0.2 / 0.7	0 / 0.3	0.1 / 4.3	0 / 3.4	0 / 3.3
en_si	- / -	11 / 42.6	10.9 / 42.2	11.4 / 44.2	0.1 / 0.5	0.4 / 1.1	0.6 / 1	0.4 / 1.2
en_sk	- / -	33.9 / 60.3	34.2 / 60.4	34.3 / 60.7	2 / 14.3	26.4 / 53.1	25.6 / 53.2	27.5 / 54.1

en_sl	- / -	32.4 / 59.6	33.2 / 60	33.4 / 60.1	1.1 / 12.4	21.1 / 50.5	23.9 / 52.5	24.9 / 53
en_sm	- / -	23.4 / 48.7	25.4 / 51.2	27 / 51.9	0.4 / 7.5	1 / 16.6	0.5 / 12.6	0.4 / 11.8
en_sn	- / -	8.9 / 38.5	10.6 / 41.4	11.4 / 43.5	0.3 / 6	0.5 / 15.3	0.5 / 16.8	0.5 / 17
en_so	- / -	14.2 / 46.9	14.5 / 48	14.8 / 48.1	0.3 / 7.6	2.1 / 14.7	0.3 / 12.5	0.4 / 14.3
en_sq	- / -	31.8 / 57.9	32.3 / 58.3	31.9 / 58	1.9 / 11.8	30.4 / 56.3	31.4 / 56.8	31.9 / 57
en_sr	- / -	21.3 / 45	21.7 / 45.4	21.8 / 45.5	0.2 / 1.3	4.2 / 21.3	14.9 / 39.3	9.3 / 34.3
en_sr_Latn	- / -	0.9 / 3.6	0.9 / 19	0.8 / 2.5	1.1 / 5	21.4 / 50.1	22.9 / 51.1	23 / 51.5
en_ss	- / -	5.7 / 35.4	6.6 / 36.7	6.9 / 38	0.2 / 6.7	0.1 / 6.1	0.2 / 12.9	0.2 / 11.4
en_sv	- / -	43.3 / 67.5	43.7 / 67.6	43.2 / 67.3	2 / 13.7	35 / 60.4	36 / 62.5	35.8 / 61.8
en_sw	- / -	31.7 / 57.2	30.9 / 56.2	29 / 54.7	0.8 / 9.5	2.4 / 23	1.7 / 25	2.8 / 31.2
en_ta	- / -	7.8 / 45.1	8.3 / 45.3	8.4 / 45.8	0.4 / 11.7	2.1 / 34.1	4.6 / 40.3	2.6 / 40.1
en_te	- / -	9.2 / 44.3	9.8 / 45.1	10 / 45	0.5 / 9.6	5.4 / 35.8	5.4 / 39.8	3.6 / 38.5
en_tg	- / -	3.2 / 21	5.5 / 24.4	3.4 / 19.5	0.1 / 0.5	0.8 / 15.3	0.8 / 19.7	0.7 / 20.6
en_th	- / -	6.6 / 40.9	5.6 / 40.5	5.8 / 39.4	0.2 / 10.1	11.8 / 47.4	9 / 48.3	12.6 / 49.1
en_ti	- / -	2.3 / 15.7	3.3 / 19.6	3.9 / 20.4	0.2 / 0.5	0 / 1.1	0 / 0.9	0 / 1.1
en_tk	- / -	12.2 / 42	14.2 / 46.2	13.8 / 45.6	0.2 / 6.7	1.1 / 18.3	0.5 / 19.2	0.6 / 19.4
en_tn	- / -	16.3 / 36.9	19.9 / 41.5	19.1 / 40.9	0.5 / 7.3	0.3 / 9.1	0.3 / 10.5	0.4 / 11.1
en_to	- / -	3.9 / 25.5	3.3 / 26.4	4.9 / 27.8	0.1 / 3.6	0.3 / 11.2	0.2 / 9.3	0.2 / 8.3
en_tr	- / -	25 / 55.1	25.4 / 55.4	25.9 / 55.7	0.8 / 11.6	11.6 / 43.4	11.2 / 44.4	10.4 / 44.7
en_tt	- / -	5 / 27.3	8 / 32.4	9.7 / 36	0.1 / 0.5	0.7 / 19.7	0.7 / 22.2	0.4 / 20.7
en_ty	- / -	0.6 / 2.4	1.3 / 12.8	0.4 / 2.1	0.4 / 9.2	0.6 / 14.1	0.4 / 12.6	0.4 / 11.3
en_ug	- / -	4.7 / 29.9	5.4 / 31.3	5.8 / 31.5	0.1 / 0.3	0.1 / 1.4	0.2 / 2.3	0 / 1.2
en_uk	- / -	24.3 / 51.4	25.5 / 52.6	25.6 / 52.5	1.4 / 5.6	18.5 / 45.9	20.4 / 48.2	18.1 / 46.9
en_ur	- / -	2.3 / 16.3	2.3 / 16.3	2.4 / 16.4	0.2 / 1.4	7.1 / 32	4.3 / 31.5	2.5 / 28.2
en_uz	- / -	0.7 / 1.5	0.7 / 1.4	0.6 / 1.3	0.1 / 7.3	1.3 / 26.8	1.8 / 31.9	2 / 33.9
en_ve	- / -	7 / 31.1	7.8 / 32	8.5 / 32.9	0.2 / 4.2	0.3 / 11.9	0.1 / 8.1	0.1 / 8.1
en_vi	- / -	0.1 / 12.5	0.1 / 12.4	0.1 / 12.4	1.4 / 9.2	34.4 / 53.4	34.7 / 53.8	34.6 / 54
en_wo	- / -	0.4 / 9.8	0.5 / 10	0.5 / 12.1	0.3 / 6.4	0.4 / 11.4	0.2 / 8.9	0 / 5.3
en_xh	- / -	10.3 / 45.1	10.9 / 47.1	11.3 / 47.5	0.2 / 6.8	0.3 / 14	0.2 / 12.5	0.2 / 13.7
en_yo	- / -	5.4 / 20.9	5.5 / 21.6	5.7 / 21.2	0.2 / 4.2	0.1 / 4.6	0 / 6.1	0.2 / 10.5
en_yue	- / -	0 / 1.3	0 / 1.2	0 / 1.2	0 / 1.9	0.1 / 13.2	0 / 14.6	0 / 15.7
en_zh	- / -	3.8 / 29.7	3.9 / 30.1	3.9 / 30.1	1.9 / 2.7	19.5 / 21.2	23.6 / 21.3	23.1 / 23.2
en_zh_Hant	- / -	1 / 8.2	0.9 / 8.8	0.7 / 5.3	0.4 / 4	6 / 23.1	6.5 / 22.9	3.8 / 22.7
en_zu	- / -	2.7 / 24.6	2.6 / 25.2	2.6 / 24.7	0.5 / 7.3	0.5 / 15.2	0.2 / 13.9	0.2 / 12.6
es_MX_en	- / -	50.4 / 71.7	51.9 / 72.7	52.3 / 72.7	6.1 / 24	40.5 / 64.9	41.3 / 65.4	41.1 / 65.3
es_en	- / -	41.1 / 66.4	42.4 / 67.1	42.9 / 67.3	5.9 / 26.2	33.1 / 60	35.2 / 61.9	35.8 / 62
et_en	- / -	35.1 / 61.8	36.8 / 62.8	36.8 / 62.8	8.6 / 31.2	28.2 / 55.8	30.3 / 56.7	30.3 / 56.6
eu_en	- / -	31.8 / 56.8	34 / 58.3	34 / 58.2	5.5 / 25.7	22.4 / 48.8	23.4 / 49.6	23.8 / 50.1
fa_AF_en	- / -	32.3 / 58.6	33 / 59	34.1 / 59.8	2.4 / 14.8	18.2 / 42.1	24.6 / 51.1	25.6 / 52
fa_en	- / -	32.2 / 58.6	34 / 59.7	33.7 / 59.5	3.7 / 18.7	16.3 / 37.6	24.1 / 50.2	25.4 / 51.6
ff_en	- / -	14.4 / 35.8	14.2 / 36	15.8 / 37.5	0.3 / 9.6	3.3 / 20.5	4 / 18.7	2.4 / 18.8
fi_en	- / -	30.3 / 57.8	31.7 / 58.8	31.5 / 58.6	4.2 / 24.6	24.3 / 52.5	26.4 / 52.8	28.1 / 55.1
fil_en	- / -	45.7 / 66.9	48.2 / 68.5	48.1 / 68.7	4 / 19.3	38.3 / 61.7	36.2 / 59.5	39.9 / 62.6
fj_en	- / -	6.6 / 26.6	8.4 / 28.5	8.2 / 28.4	0.5 / 10.3	4.7 / 18.7	6.2 / 27.1	3.7 / 21.7
fo_en	- / -	32.9 / 56.7	37 / 59.8	38.6 / 61	8 / 28.7	28.6 / 52.8	33.2 / 57.1	33.6 / 56.9
fr_CA_en	- / -	43.2 / 66.8	44.1 / 67.4	43.8 / 67.4	5 / 25.8	26.6 / 56	37.3 / 62.8	36.7 / 62.5
fr_en	- / -	38.8 / 63.5	39.5 / 64.1	39.2 / 63.9	4.5 / 26.1	31.1 / 57.6	32.6 / 57.8	32.6 / 58.8
ga_en	- / -	38.7 / 64.1	41 / 65.7	41.6 / 65.7	4.2 / 23	24.6 / 48.7	29.2 / 53.5	31.5 / 55.3
gl_en	- / -	43.7 / 66.8	45.3 / 67.9	45.1 / 67.8	6 / 19.5	33.9 / 59.7	35.3 / 60.3	36.9 / 62.3
gu_en	- / -	34.9 / 62	38.3 / 64	38 / 64.1	2.2 / 16.6	21.1 / 48	24.2 / 52.1	25.4 / 53.6
ha_en	- / -	35 / 56.9	39.2 / 59.9	38.7 / 60	1.1 / 14.7	12.5 / 33	21 / 43.6	18.9 / 43.3
hi_en	- / -	35.7 / 61.8	38.7 / 63.4	38.2 / 63.1	2.7 / 14.7	20 / 44.9	24.6 / 52.3	26.7 / 54.3
hmn_en	- / -	23.4 / 47.5	25.5 / 49.6	27 / 50.2	1 / 12.3	10.8 / 30.5	13.4 / 38.2	14.3 / 37.7
hr_en	- / -	41.3 / 65.5	42.4 / 66.5	42.3 / 66.4	6.6 / 26.9	29.9 / 55.6	31.7 / 57.6	35.2 / 60.6
hu_en	- / -	27.8 / 55.6	27.6 / 55.8	28.1 / 55.8	3.5 / 25.6	20.1 / 47	21.6 / 49	21.3 / 49.2
hy_en	- / -	30.7 / 55.8	34.8 / 59.3	34.1 / 58.9	3.2 / 18.7	17.8 / 44.4	22.9 / 48.8	23.7 / 50.7
id_en	- / -	43 / 66.4	45.1 / 67.8	45 / 67.8	3.8 / 18.4	34.8 / 59.9	37.3 / 61.5	38 / 61.9
ig_en	- / -	27.5 / 51.1	31.9 / 55.3	32.7 / 55.8	1.1 / 14.4	9.4 / 28.1	11.4 / 33.4	11.8 / 33.1
is_en	- / -	35.3 / 60.5	37.3 / 61.8	37.7 / 61.8	9.1 / 31.5	29 / 54.9	30.5 / 55.3	33 / 57.9
it_en	- / -	42.3 / 66.2	43.2 / 66.8	43.2 / 66.9	7.5 / 28.6	36.8 / 61.5	36 / 60.5	38.5 / 62.4
iw_en	- / -	40.5 / 63.8	42.9 / 65.7	42.9 / 65.6	4.3 / 19.1	29.2 / 55.7	31 / 56.9	31.1 / 57.4
ja_en	- / -	27.1 / 54.5	28.7 / 55.1	29.1 / 55.5	0.3 / 1.2	15 / 40.9	19.2 / 46.6	18.7 / 45.9
ka_en	- / -	28.8 / 53.9	31.8 / 56.1	32 / 56.3	2.6 / 14.1	20.1 / 45	26.3 / 52.4	25.3 / 52.6
kk_en	- / -	24.1 / 52.1	26.4 / 53.6	25.7 / 53.3	3.7 / 18.6	16.4 / 42.9	18.3 / 44.3	18 / 44
km_en	- / -	33.6 / 59.6	37.8 / 61.4	37.3 / 61.7	1.9 / 16.1	21.1 / 47.2	26.4 / 52.2	27.2 / 53.5
kn_en	- / -	29.2 / 56.8	31.4 / 57.9	31.1 / 58.3	1.3 / 11.5	13.7 / 38.9	18.8 / 45.8	20.4 / 48.2
ko_en	- / -	30.9 / 57.1	33.1 / 58.6	33.2 / 58.8	1.1 / 4.5	19 / 45.8	18.7 / 45.2	19 / 47
ku_en	- / -	27.6 / 52.5	30.5 / 54.4	30.7 / 54.9	2.9 / 18.3	17.2 / 41.7	16.5 / 43.2	20.2 / 44.2
ky_en	- / -	23.8 / 50.5	27.5 / 53.6	26.2 / 52.6	2.6 / 16.1	15.4 / 41.5	15.9 / 41.1	17 / 43.2
lb_en	- / -	21.9 / 49.8	24.4 / 51.6	26 / 52	4.2 / 23.8	29.5 / 53.3	32.3 / 56.6	30.6 / 56.1
lo_en	- / -	34.9 / 58.2	37.5 / 59.7	37.9 / 60.9	1.2 / 11.8	23.4 / 49	28.5 / 53.9	28.1 / 53.5
lt_en	- / -	32 / 59.6	33.9 / 60.6	34.1 / 60.6	4.9 / 25.7	24.3 / 52.3	25.7 / 52.9	26.4 / 52.9
lv_en	- / -	34.6 / 61.2	36.2 / 62.3	36.6 / 62.3	3.4 / 22.7	26.1 / 53.5	29.5 / 55.4	30.6 / 57.1
mey_en	- / -	18 / 45.5	19.7 / 47	20.2 / 46.9	0.3 / 4.2	4.5 / 22.6	11.8 / 38.8	10.4 / 38.8
mg_en	- / -	25.8 / 50.8	28.3 / 52.7	28.7 / 52.9	1.7 / 18.6	14 / 37.6	14.8 / 39.1	16 / 39.5
mi_en	- / -	22.1 / 45.3	20.5 / 44.1	22.5 / 46.3	2.2 / 19.2	10.4 / 35.6	10.8 / 35.7	17.7 / 41.1
mk_en	- / -	44.6 / 67.4	46.3 / 68.5	46.4 / 68.4	8.5 / 28.5	29.3 / 55.2	36.9 / 61.3	37.7 / 62.6
ml_en	- / -	30.3 / 56.8	31.4 / 57.1	32.4 / 58.2	0.8 / 5.7	11.5 / 34.3	17.8 / 45.8	18.8 / 46.5
mn_en	- / -	21.8 / 48.4	24 / 50.4	24.1 / 50.2	1.3 / 10.1	12.9 / 38.5	13.6 / 38.4	14.3 / 40.8
mr_en	- / -	32.5 / 59.3	34 / 60.2	34.9 / 60.9	1.7 / 9.8	12.7 / 35.2	22.6 / 50.7	23.4 / 50.4
ms_en	- / -	40.4 / 63.7	42.7 / 65.4	42.7 / 65.3	3.9 / 20.7	31.3 / 55.8	36 / 60.1	36.4 / 60.3

47

mt_en	- / -	50.9 / 72.9	52.4 / 73.9	53.5 / 74.3	5.6 / 25	40.3 / 63.2	40.1 / 62.5	41.5 / 65.1
my_en	- / -	14.3 / 40.3	15.7 / 40.9	18.1 / 44.5	0.2 / 5.7	2.8 / 20.2	7.5 / 32.2	9.7 / 34.2
nd_en	- / -	18.8 / 43.1	21.6 / 45.6	21.8 / 45.8	0.2 / 8	8 / 27.2	9 / 32.6	9.1 / 32.1
ne_en	- / -	35.9 / 62	38.1 / 63.3	38.6 / 63.9	1.4 / 9	15.6 / 40.3	22.3 / 48.8	23.5 / 50.9
nl_en	- / -	41.2 / 66.1	42.5 / 66.7	42.5 / 66.6	8.3 / 31.4	35.1 / 60.3	36.5 / 61.4	36.6 / 62.3
nn_en	- / -	46 / 67.3	47.1 / 68.1	47 / 68.1	5.4 / 26.9	39 / 63.2	40.5 / 63.9	41 / 63.3
no_en	- / -	44 / 67	45.1 / 67.7	45 / 67.7	6.1 / 25.6	38.8 / 61.7	38.8 / 63.5	39.7 / 63.5
nso_en	- / -	23.6 / 47.6	27.5 / 51.3	28.1 / 51.7	0.6 / 10.9	3.7 / 26.1	10.1 / 31.4	11.1 / 34.9
ny_en	- / -	28.1 / 49.5	31.6 / 52.9	31.9 / 53.2	1.1 / 13	15.3 / 36.4	17.6 / 38.8	15.4 / 39.4
om_en	- / -	8.4 / 29.2	11.2 / 33.6	11.2 / 33.6	0.5 / 9.8	1.9 / 21.2	4.6 / 24.3	5.2 / 23.2
pa_en	- / -	34.6 / 60.8	38.5 / 62.9	38.2 / 63.1	2.4 / 16.1	16.1 / 42.3	24 / 51	25.4 / 51.8
pl_en	- / -	31.9 / 58.9	32.6 / 59.2	33.3 / 59.7	9.3 / 34.9	24.4 / 52.1	27.4 / 54.4	27.3 / 53.8
ps_en	- / -	22.6 / 49.5	23.9 / 50.5	24.5 / 50.8	1.9 / 14.2	14.1 / 38.8	15.6 / 40.3	16.3 / 42.1
pt_PT_en	- / -	44.7 / 67.4	45.7 / 68.2	45.9 / 68.2	5.2 / 23.6	35.2 / 60.3	36 / 60.8	36.8 / 61.4
pt_en	- / -	43.1 / 65.7	43.9 / 66.2	44.1 / 66.2	6.4 / 24.9	34.4 / 59.3	35.8 / 60.8	36.8 / 61.1
ro_en	- / -	37.7 / 63.9	38.5 / 64.6	39 / 64.7	6.1 / 28.5	22.8 / 46.9	32.3 / 58.6	33.4 / 59.5
ru_en	- / -	30.8 / 57.9	32.3 / 58.8	32.1 / 58.7	3.7 / 19.2	24 / 50.2	26.1 / 53.4	25.3 / 52.9
rw_en	- / -	27.6 / 52.4	30.9 / 55.2	32.3 / 55.8	1.9 / 18.2	15.8 / 37.9	17.2 / 42.3	16.3 / 42.3
sd_en	- / -	30.6 / 54.2	34 / 57	34.1 / 56.9	1.5 / 12.1	15.8 / 40.8	14.6 / 40.8	13.3 / 42.1
shi_en	- / -	3.3 / 23.3	4.4 / 25.8	5.8 / 27.6	0.1 / 3.1	1.5 / 15.9	2.9 / 24	2.5 / 23.5
si_en	- / -	31.7 / 58	34 / 59.4	34.3 / 60	1.1 / 10.1	16.2 / 44.1	18.1 / 45.5	17.3 / 43.8
sk_en	- / -	40.7 / 65.6	42.5 / 66.6	42.5 / 66.5	8.7 / 31.5	26.6 / 52.2	33.1 / 58.4	35.1 / 61
sl_en	- / -	36.5 / 62.4	38.2 / 63.4	38.3 / 63.3	6.5 / 28.7	29.7 / 56.3	32.2 / 58.2	30.8 / 56.6
sm_en	- / -	25.6 / 50.5	28.9 / 53.6	28.5 / 53.5	0.6 / 9	6 / 24.1	14.2 / 39.9	14 / 37.7
sn_en	- / -	28.6 / 50.6	33.5 / 54.4	34.5 / 55	0.8 / 10.9	8.6 / 25.6	16.6 / 38.8	15.1 / 37.7
so_en	- / -	36.3 / 59.1	40.7 / 62.8	41.1 / 63.3	1.9 / 13.1	20.5 / 42.3	20.3 / 43.8	21.3 / 49
sq_en	- / -	41.9 / 65.8	43.5 / 66.8	43.5 / 66.9	12.6 / 35.4	35.4 / 60.4	35.6 / 60	36.9 / 62
sr_Latn_en	- / -	37 / 62.3	39.4 / 63.9	39 / 63.8	4.1 / 22.8	26.7 / 53.1	31.1 / 56.9	30.7 / 56
sr_en	- / -	37.3 / 62	39.2 / 63	39.6 / 63.5	5.4 / 24	27.7 / 53.6	31.3 / 57	33 / 58.6
ss_en	- / -	23.9 / 46.4	28.4 / 50.6	29.6 / 51.7	0.4 / 10	6.3 / 22.8	8.5 / 31.5	6.7 / 31.4
sv_en	- / -	45.5 / 68.1	46.9 / 69	46.8 / 68.9	8.2 / 31.4	40.7 / 64.3	41.7 / 64.9	42 / 65
sw_en	- / -	41.8 / 62.7	44.1 / 64.5	44.2 / 64.5	3.8 / 17.9	31 / 54.3	32.2 / 55.1	33.3 / 56.6
ta_en	- / -	27.3 / 53.5	28.4 / 54	29.4 / 54.9	1.3 / 7.4	15.9 / 42	15.9 / 43.5	18.2 / 45.6
te_en	- / -	27.5 / 53.7	28.6 / 54.4	29.6 / 55.1	1 / 4.8	12.5 / 36.6	18 / 44.4	19.2 / 46.4
tg_en	- / -	9.6 / 32.2	19.9 / 43.8	16.6 / 39	2.3 / 17.1	16.7 / 42	20.4 / 46.8	20.6 / 47.5
th_en	- / -	37.2 / 60.3	39.7 / 61.9	39.9 / 62.4	3.9 / 12	20 / 44.3	27.8 / 54.5	30.2 / 56.3
ti_en	- / -	17.5 / 42.2	22.2 / 46.7	24.1 / 48.4	0.7 / 10.2	8 / 29.9	8 / 31.9	9.4 / 31.8
tk_en	- / -	28.5 / 54.8	31.6 / 57	31 / 56.5	2.1 / 18.3	4.4 / 26.3	15.7 / 40.3	16 / 44
tn_en	- / -	24.2 / 48	29 / 52.8	30.9 / 53.8	0.3 / 9.2	7.6 / 29.1	9.6 / 32	10.8 / 34.9
to_en	- / -	15.9 / 39.9	21.2 / 45	21.4 / 44.7	0.3 / 6.8	4.7 / 25.8	7.6 / 26.3	3.2 / 26.5
tr_en	- / -	32.5 / 58.7	34.3 / 59.9	34.6 / 60	4.3 / 23.6	14.7 / 36.6	21.3 / 48.3	22.4 / 49.4
tt_en	- / -	14.4 / 36	14.4 / 34.9	19.3 / 41.7	1.1 / 9.7	9.5 / 38	16.8 / 42.6	16.9 / 43.7
ty_en	- / -	5.5 / 28.9	5.5 / 28.6	6.3 / 29.5	0.5 / 10.3	6 / 27.7	5.3 / 27	3.5 / 26.3
ug_en	- / -	9.1 / 32.2	14.7 / 39.9	13.4 / 35.6	1.2 / 13.8	10.5 / 35.6	12.6 / 39.4	11.6 / 37.7
uk_en	- / -	34 / 59.4	35.2 / 60.1	35.1 / 60.1	6.6 / 26.8	26.7 / 54.1	27.4 / 53.6	28.1 / 54.1
ur_en	- / -	3.4 / 18.9	3.8 / 19	3.7 / 19.1	4.3 / 20	22.2 / 49.7	23.9 / 50.5	25.6 / 53
uz_en	- / -	24.5 / 52.2	27.2 / 54.5	26.9 / 54.4	2.8 / 17.8	16.4 / 44.4	16.5 / 42.7	16.9 / 42.8
ve_en	- / -	19.1 / 41.9	21.2 / 44.6	24.3 / 46.7	0.2 / 9.3	5.4 / 21.9	4.7 / 25	3.3 / 22.2
vi_en	- / -	0.4 / 16	0.3 / 15.9	0.3 / 15.9	5.5 / 24.9	13.8 / 34.5	27.1 / 52.8	30.6 / 55.4
wo_en	- / -	2.1 / 18.4	2.4 / 19.3	2.8 / 19.4	0.1 / 7.3	2.2 / 20.9	2.2 / 20.3	2.2 / 20.2
xh_en	- / -	29.9 / 52.5	34.2 / 56.1	34.1 / 56.2	1 / 14.8	13.7 / 33.4	16.2 / 37.8	14.5 / 39.6
yo_en	- / -	13.3 / 37	14.5 / 37.4	20.9 / 43.5	0.4 / 11.1	3.8 / 23.9	3.4 / 21.5	4.6 / 23
yue_en	- / -	26.7 / 54.4	29.1 / 56.2	29.3 / 56.2	0.3 / 1.8	16.3 / 44.1	18.1 / 46	17.1 / 45.9
zh_Hant_en	- / -	27.1 / 54	29.1 / 55.5	29.1 / 55.6	1.6 / 7.7	10 / 29.8	19.2 / 46.4	19.5 / 46.6
zh_en	- / -	24.3 / 53.4	26.8 / 54.9	26.3 / 54.6	0.4 / 3	17.8 / 45.4	18.8 / 46.4	19.1 / 46.6
zu_en	- / -	6.5 / 24.3	7.5 / 25	7.5 / 25.1	0.9 / 13.2	13.1 / 32.6	17 / 38.6	16.7 / 40.4
xx2en	- / -	30.6 / 54.5	32.7 / 56.2	**33.6 / 57.6**	3.2 / 17.3	20.4 / 43.8	23.8 / 48.2	24.4 / 49.0
en2xx	- / -	16.5 / 39.6	17.6 / **41.9**	17.9 / **41.9**	0.8 / 7.3	11.7 / 31.2	12.6 / 32.4	12.3 / 32.3
Average	19.8 / -	23.5 / 47.0	25.1 / 49.0	**25.7 / 49.7**	2.0 / 12.3	16.0 / 37.4	18.1 / 40.2	18.3 / 40.6

A.11 Canaries

We design and generate different types of canaries for each dataset. We treat the `MADLAD-400` dataset as a large unlabeled pretraining corpus and for each language with sufficient size ($> 50,000$ samples), we generate no more than 0.05% canaries per language, leading to a total of $1,279,635$ canaries across all languages. For parallel data, we design and generate different canaries specific to its usage for translation. We generate $585,596$ canaries in total for all target languages with $> 50,000$ samples. In both cases, we scale the proportion of canaries based on the size of each language to minimize their impact to utility in model training. Finally, we also generate $80,400$ "generic" canaries that share no resemblance to natural data. In total, we generate $1,945,631$ canaries ($\approx 0.0026\%$ of the training data).

A.11.1 `MADLAD-400` Canaries

Because `MADLAD-400` contains only monolingual data, i.e., each example relates to only one language, we treat it as a large unlabeled pretraining corpus. Similar to Anil et al. [6], we aim to generate canaries that share characteristics of the underlying training data but are still outliers. For this, we design three types of canaries: `shuffle`, `interleave` and `training_prefix`. `interleave` canaries can be viewed as the closest to natural data, where all tokens are sampled from the underlying distribution and most sequence-level correlations are kept intact. We generate these canaries by sampling two real documents from a language, and interspersing chunks of 20 tokens in their same relative ordering. On the other hand, `shuffle` canaries can be viewed as the farthest from natural data, sharing only the average token frequencies of the language but with no sequence-level correlations. These are generated by sampling a real document and uniformly sampling its tokens without replacement. In addition, we also propose `training_prefix` canaries which can be viewed as something in between. Here, each canary is generated by sampling 100 tokens from a real sample and then completing the sequence with random tokens (i.e, taken uniformly with replacement from the vocabulary).

We take care to adjust the number and type of canaries based on the resources of the language, in order to minimize any harm to model utility. We group languages based on their relative size. Then, prior to generation we fix a target canary rate based on this resource level - this determines the total number of canaries that can be added per language. We choose a smaller proportion of canaries (relative to the total number of sequences in the language) for lower-resource languages based on the intuition that these languages can tolerate less noisy data before utility is altered. With the number of canaries fixed, we then choose how many times each canary will be repeated, as this has a significant impact on memorization [44, 6]. Note that repeating canaries may be beneficial to study the relative vulnerability of repeated data, but also reduces to the total number of unique canaries that can be added within that language's canary budget. We choose the distribution of repeats heuristically aiming to maximize the support of the distribution while also ensuring that each bucket has enough unique canaries to achieve meaningful results. Finally, as the language size grows, (and thus the canary budget as well) we also introduce more canary types. We describe the full distribution of canaries generated in Table 20.

Table 20: `MADLAD-400` distribution of (the $1,279,635$ in total) canaries across languages. For legibility, we omit 0 entries. *Uses the codes: I=interleave, S=shuffle, TP=training_prefix.

Dataset Size (# Samples)	Languages Included	Target Canary Rate	Canary Types*	Canaries per Language	Canaries per # of Repetitions									
					1	2	3	4	5	8	10	25	50	100
X-Large (200e6+)	sw, kaa, si, gu, kn, ne, uz, gl, mn, fil, mk, eu, ka, be, af, bn, te, is, mr, ml, hr, kk, ms, az, ta	0.016%	I,S,TP	31500	600	600	600	600	600		600	300	60	60

Category	Languages	%	Codes								
Large (20e6 to 200e6)	sw, kaa, si, gu, kn, ne, uz, gl, mn, fil, mk, eu, ka, be, af, bn, te, is, mr, ml, hr, kk, ms, az, ta	0.035%	I,S,TP	7020	195	150		60	60	45	30	30
Medium (6e6 to 20e6)	lo, dv, lb, fy, so, am, ps, zh, ku, km, pa, mt, tt, ga, tg, cy, ky, hy, my, eo	0.02%	I,S,TP	1200	150	75		60	30	12		
Small (600e3 to 6e6)	ilo, os, cnh, ctd_Latn, ti, udm, om, se, rm, tet, bo, ro, br, sa, lus, gsw, sah, kaa_Latn, st, haw, pap, oc, cv, zu, sn, yo, as, sm, co, xh, ig, ny, kl, su, ceb, tk, fo, yi, hmn, el_Latn, ba, jv, grc, or, sd, gd, ug, ckb, mg, ht, ha, rw	0.02%	I,S	120	12	8	8		3			
XSmall-5 (500e3 to 600e3)	hil	0.02%	I,S	100	12	8	6	6				
XSmall-4 (400e3 to 500e3)	te_Latn, tyv, vec, kbd, lg	0.02%	I,S	80	8	8	6	4				
XSmall-3 (300e3 to 400e3)	iba, ak, av, ber_Latn, zza, ts, ee, ru_Latn	0.02%	I,S	60	8	6	6	2				
XSmall-2 (200e3 to 300e3)	ta_Latn, cfm, otq, syr, bua, gn, to, az_RU, wa, chm, tn, ada, krc, fj, nso	0.02%	I,S	40	8	4	2	2				
XSmall-1 (100e3 to 200e3)	emp, pck, meu, nnb, meo, nzi, tlh, tzo, iu, ksd, hui, tiv, sq, new, bci, bbc, min, sr, nan_Latn_TW, ve, ang, ml_Latn, kac, ngu, pag, abt, kum, tyz, zap, kv, bik, nv, gom, ltg, qu, ay, rom, sg, ady, iso, yua, war, bho, hif, kbp, srn, myv, kha	0.02%	I,S	20	4	4	2					
XXSmall-5 (90,000 to 100e3)	mrj, zxx_xx_dtynoise, kw, mgh, bew, crh, alt, nhe, fon	0.01%	I	9	2	2	1					
XXSmall-4 (80,000 to 90,000)	mam, dov, ho, mai, bgp	0.01%	I	8	3	1	1					
XXSmall-3 (70,000 to 80,000)	gym, rcf, shn, tvl, mbt, qub, pon	0.01%	I	7	2	1	1					

XXSmall-2 (60,000 to 70,000)	ium, gag, tbz, gv, crs, quc, zh_Latn, chk, btx, ace, bru, ubu, ape, mdf, tuc	0.01%	I	6	2	2
XXSmall-1 (50,000 to 60,000)	tzh, kek, bum, bts, ibb, tcy, enq, kj, seh, xal, kmb, rwo, cab, wo, ppk, ach, kri, ss, cuk	0.01%	I	5	3	1

A.11.2 Parallel Canaries

Unlike MADLAD-400, the parallel data consists of source-target pairs from different languages corresponding to the source and target languages for translation. This leads to new intricacies not present in the monolingual setting, e.g., because languages have different grammatical structure, it may be difficult to tailor modifications to both the inputs and outputs simultaneously that maintain linguistic structure.

Rather than design canaries for all N^2 combinations of language pairs, where many pairs may have insufficient resource levels to incorporate canaries, we instead focus on the multiway setting where languages are grouped by the target language for translation. To minimize impact on the source languages (which may include very low-resource languages), we opt to not use any real training data from the source as inputs to the model. Instead, we generate canary data following one of two methodologies for the source: random_prefix corresponds to cases where all canaries for a given target language share the same prefix of 100 tokens but have unique uniformly random (w.r.t. the token vocabulary) suffixes following it and full_random canaries are analogous with no shared prefix. The shared prefix of random_prefix canaries is designed to align with cases where data may share common subsequences. For the targets, we either interleave or shuffle them as done in the MADLAD-400 case above (Appendix A.11.1), except interleaving in batches of 50. Taking the outer product of these options, we get four possible canaries, e.g., random_prefix_interleave and so forth. The resource level groups and distribution of canaries is the same as for the MADLAD-400 canaries described in Table 20; the mapping for parallel languages to these resource level groups is shown in Table 21. In total, $565,476$ canaries are generated this way across all languages.

Finally, we also design two additional types of canaries that use natural data from the source. Because this might impact utility more, we restrict these canaries to only the largest language pairs that have at least $500,000$ examples. The set of language pairs and languages satisfying this threshold are shown in Figure 3 and Figure 4. These two canary types are interleaved_both and interleaved_mislabeled_to. The former performs the same interleaving operation on the source and targets for a language pair, interleaving in batches of 50 tokens. The latter does the same, with the addition of also select a new target language label, uniformly at random, from all qualifying high resource languages. For each language pair listed in Figure 3, we generate 60 canaries in total, split evenly across the two canary types, and in the following distribution: 10 canaries are repeated once, 5 are repeated twice, and 2 are repeated 5 times. This gives a total of $21,120$ canaries in total across all language-pairs. Combined with the $565,476$ canaries from the prior 4 canary types, there are a total of $585,596$ canaries.

Table 21: Distribution of (the $565,476$ in total) canaries across languages for parallel data. Distribution of canaries across repeats matches that in Table 20. *Uses the codes: RPI=random_prefix_interleave, RPS=random_prefix_shuffle, FRI=fully_random_interleave, FRS=fully_random_shuffle. **includes 4 canary types instead of 3; so the canary distribution can be obtained by multiplying the values in Table 20 by $4/3$.

Dataset Size (# Samples)	Languages Included	Target Canary Rate	Canary Types*	Canaries per Language
X-Large** (200e6+)	nl, it, pt, fr, de, es, en	0.016%	I,S,TP	42000

Large** (20e6 to 200e6)	fa, is, uk, tr, hr, ca, ko, ja, et, no, lv, sl, lt, bg, ar, el, fi, sk, ro, ru, hu, da, zh, pl, cs, sv	0.035%	RPI,RPS,FRS,FRI	9360
Medium (6e6 to 20e6)	th, si, bn, sh, bs, hi, eo, mt, eu, sq, sr, gl, ga, mk, he, vi, id	0.02%	RPI,RPS,FRS	1200
Small (600e3 to 6e6)	hy, ps, as, lb, uz, wa, my, iu, la, ha, pa, mg, xh, cy, ceb, gu, km, en_xx_simple, br, af, fy, tt, be, ka, oc, nds, tg, kk, az, nn, ne, sw, zh_Hant, ur, fil, ms, te, mr, ta, ml	0.02%	RPI,RPS	120
XSmall-5 (500e3 to 600e3)	dv, so, am, ba, se, sd	0.02%	RPI,RPS	100
XSmall-4 (400e3 to 500e3)	kn, fo, or, fr_CA, ku	0.02%	RPI,RPS	80
XSmall-3 (300e3 to 400e3)	li, ug, arz, lmo, wuu, rw	0.02%	RPI,RPS	60
XSmall-2 (200e3 to 300e3)	ltg, gn, bug, ks_Deva, szl, fuv, ary, ban, bm, ace, bjn_Arab, taq, ace_Arab, bjn, prs, taq_Tfng, tzm, lij, hne, vec, din, kr_Arab, sc, ks, fur, shn, bho, mag, nus, mi, mni, dz, scn, an	0.02%	RPI,RPS	40
XSmall-1 (100e3 to 200e3)	nds_NL, ky, zu, mn, jv, bar, gd, kr, crh_Latn	0.02%	RPI,RPS	20
XXSmall-5 (90,000 to 100e3)	mwl	0.01%	RPI	9
XXSmall-3 (70,000 to 80,000)	io	0.01%	RPI	7

A.11.3 Generic Canaries

Finally, we also designed and generated $80,400$ `generic` canaries. Unlike the canaries of the prior two sections (A.11.1 and A.11.2), these canaries share minimal resemblance to natural data. These canaries may be useful for understanding memorization of highly outlier data. Here, we generate monolingual canaries where the source and targets are the same. We propose two types of canaries: `random_prefix` and `fully_random` canaries. These are the same as the canaries described in Section A.11.2 but with the source matching the target. We generated $80,400$ canaries in total split evenly among 4 types of canaries: `fully_random` canaries and `random_prefix` canaries with shared prefixes of length 50, 100, and 200.

```
ar-es, ar-fr, ar-ru, ar-zh, bg-cs, bg-da, bg-de, bg-el, bg-es, bg-fi, bg-fr, bg-
hu, bg-it, bg-lt, bg-nl, bg-pl, bg-pt, bg-ro, bg-sk, bg-sl, bg-sv, cs-bg, cs-da,
 cs-de, cs-el, cs-es, cs-fi, cs-fr, cs-hu, cs-it, cs-lt, cs-nl, cs-pl, cs-pt, cs-
ro, cs-ru, cs-sk, cs-sl, cs-sv, cs-zh, da-bg, da-cs, da-de, da-el, da-es, da-fi,
 da-fr, da-hu, da-it, da-lt, da-nl, da-pl, da-pt, da-ro, da-sk, da-sl, da-sv, da-
zh, de-bg, de-cs, de-da, de-el, de-es, de-fi, de-fr, de-hu, de-it, de-lt, de-nl,
 de-pl, de-pt, de-ro, de-ru, de-sk, de-sl, de-sv, de-zh, el-bg, el-cs, el-da, el-
de, el-es, el-fi, el-fr, el-hu, el-it, el-lt, el-nl, el-pl, el-pt, el-ro, el-sk,
 el-sl, el-sv, es-ar, es-bg, es-cs, es-da, es-de, es-el, es-fi, es-fr, es-hu, es-
it, es-lt, es-nl, es-pl, es-pt, es-ro, es-ru, es-sk, es-sl, es-sv, es-zh, fi-bg,
 fi-cs, fi-da, fi-de, fi-el, fi-es, fi-fr, fi-hu, fi-it, fi-lt, fi-nl, fi-pl, fi-
pt, fi-ro, fi-sk, fi-sl, fi-sv, fr-ar, fr-bg, fr-cs, fr-da, fr-de, fr-el, fr-es,
 fr-fi, fr-hu, fr-it, fr-lt, fr-nl, fr-pl, fr-pt, fr-ro, fr-ru, fr-sk, fr-sl, fr-
sv, fr-zh, hu-bg, hu-cs, hu-da, hu-de, hu-el, hu-es, hu-fi, hu-fr, hu-it, hu-lt,
 hu-nl, hu-pl, hu-pt, hu-ro, hu-sk, hu-sl, hu-sv, it-bg, it-cs, it-da, it-de, it-
el, it-es, it-fi, it-fr, it-hu, it-lt, it-nl, it-pl, it-pt, it-ro, it-ru, it-sk,
 it-sl, it-sv, it-zh, lt-bg, lt-cs, lt-da, lt-de, lt-el, lt-es, lt-fi, lt-fr, lt-
hu, lt-it, lt-nl, lt-pl, lt-pt, lt-ro, lt-sk, lt-sl, lt-sv, nl-bg, nl-cs, nl-da,
 nl-de, nl-el, nl-es, nl-fi, nl-fr, nl-hu, nl-it, nl-lt, nl-pl, nl-pt, nl-ro, nl-
ru, nl-sk, nl-sl, nl-sv, nl-zh, pl-bg, pl-cs, pl-da, pl-de, pl-el, pl-es, pl-fi,
 pl-fr, pl-hu, pl-it, pl-lt, pl-nl, pl-pt, pl-ro, pl-ru, pl-sk, pl-sl, pl-sv, pl-
zh, pt-bg, pt-cs, pt-da, pt-de, pt-el, pt-es, pt-fi, pt-fr, pt-hu, pt-it, pt-lt,
 pt-nl, pt-pl, pt-ro, pt-ru, pt-sk, pt-sl, pt-sv, pt-zh, ro-bg, ro-cs, ro-da, ro-
de, ro-el, ro-es, ro-fi, ro-fr, ro-hu, ro-it, ro-lt, ro-nl, ro-pl, ro-pt, ro-sk,
 ro-sl, ro-sv, ru-ar, ru-cs, ru-de, ru-es, ru-fr, ru-it, ru-nl, ru-pl, ru-pt, ru-
zh, sk-bg, sk-cs, sk-da, sk-de, sk-el, sk-es, sk-fi, sk-fr, sk-hu, sk-it, sk-lt,
 sk-nl, sk-pl, sk-pt, sk-ro, sk-sl, sk-sv, sl-bg, sl-cs, sl-da, sl-de, sl-el, sl-
es, sl-fi, sl-fr, sl-hu, sl-it, sl-lt, sl-nl, sl-pl, sl-pt, sl-ro, sl-sk, sl-sv,
 sv-bg, sv-cs, sv-da, sv-de, sv-el, sv-es, sv-fi, sv-fr, sv-hu, sv-it, sv-lt, sv-
nl, sv-pl, sv-pt, sv-ro, sv-sk, sv-sl, sv-zh, zh-ar, zh-cs, zh-da, zh-de, zh-es,
 zh-fr, zh-it, zh-nl, zh-pl, zh-pt, zh-ru, zh-sv
```

Figure 3: All language pairs satisfying the minimum $500,000$ example threshold.

```
da, cs, fi, el, ar, de, ru, fr, zh, nl, bg, lt, es, sv, pl, hu, pt, it, sk, ro,
sl
```

Figure 4: Unique languages from Figure 3

A.12 Additional Memorization Figures
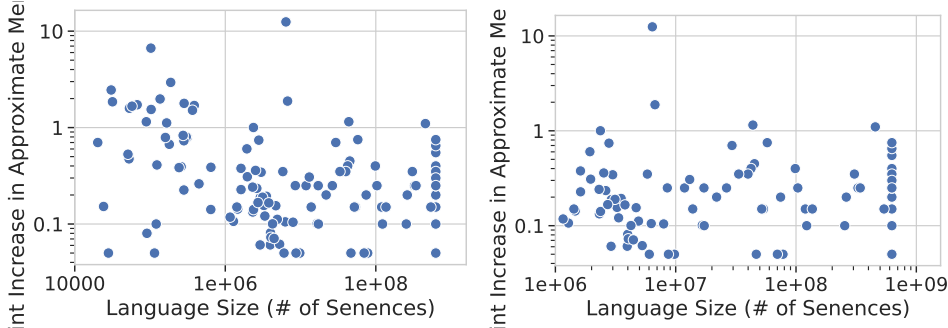
Figure 5: **Translate models may also paraphrase memorizations.** Training data extraction rates under approimate memorization for both **(left)** monolingual (translate_copy) and **(right)** multiway (`translate_diff`) data. Extraction performed on the 3B parameter model using a $S = P + 50$. We use a Levenshtein similarity of 90% on the additioanl leakage. After accounting for this, a fewer 208/370 and 119/146 had no memorization detected.

A.13 Datasheet

Datasheet - `MADLAD-400`

Motivation

1. For what purpose was the dataset created? (Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.) *We create `MADLAD-400` as a general purpose monolingual document level dataset covering 419 languages for the purpose of providing general training data for multilingual NLP tasks such as MT and language modeling. One of the goals of the Language Inclusivity Moonshot (LIM)* [13] *is to scale our language support to 1,000 languages and to support speech recognition for 97% of the global population. A core objective associated with this goal is to open source data and models. Our expectation is that releasng `MADLAD-400` will foster progress on the language research, especially on medium and low resource languages. An estimate of over 1B people globally speak languages that are not covered by mainstream models at Google or externally.*

2. Who created this dataset and on behalf of which entity? *Sneha Kudugunta[†], Isaac Caswell[◇], Biao Zhang[†], Xavier Garcia[†], Derrick Xin[†], Aditya Kusupati[◇], Romi Stella[†], Ankur Bapna[†], Orhan Firat[†] ([†]Google DeepMind, [◇]Google Research)*

3. Who funded the creation of the dataset? *Google Research and Google DeepMind*

4. Any other comments? *None*

Composition

1. What do the instances that comprise the dataset represent? *Each instance is a preprocessed web-crawled document whose language that we annotated using a LangID model described by [15]. For the sentence level version, we used a sentence-splitter to split the documents into sentences and then deduplicated the resulting dataset.*

2. How many instances are there in total? *`MADLAD-400` has 4.0B documents (100B sentences, or 2.8T tokens) total across 419 languages with the median language containing 1.7k documents (73k sentences of 1.2M tokens.)*

3. Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? (If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).) *`MADLAD-400` are created from CommonCrawl documents that have been annotated by language, filtered and preprocessed. To maintain high precision, we filtered out data aggressively, and may not have captured every document of a given language in CommonCrawl. Moreover, there may also be languages in CommonCrawl that we may not have mined.*

4. What data does each instance consist of? *Each instance is raw text in either document form for the document level data, or in sentence form for the sentence level data.*

5. Is there a label or target associated with each instance? If so, please provide a description. *No.*

6. Is any information missing from individual instances? *No.*

7. Are relationships between individual instances made explicit? *No.*

8. Are there recommended data splits (e.g., training, development/validation, testing)? *No.*

9. Are there any errors, sources of noise, or redundancies in the dataset? *While we have taken extensive care to audit and filter `MADLAD-400`, there may still be documents annotated with the wrong language or documents of low quality.*

10. Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? (If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.) *Yes*

11. Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? (If so, please provide a description.) *Given that `MADLAD-400` is a general web-crawled dataset it is possible that documents in the dataset may contain such information.*

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[13] https://blog.google/technology/ai/ways-ai-is-scaling-helpful/

12. Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? (If so, please describe why.) *Given that* `MADLAD-400` *is a general web-crawled dataset, even after filtering, it is possible that there are documents containing offensive content, etc.*

13. Does the dataset relate to people? *It is likely that some documents in* `MADLAD-400` *contain sentences referring to and describing people.*

14. Does the dataset identify any subpopulations (e.g., by age, gender)? *It is likely that some documents in* `MADLAD-400` *contain sentences referring to and describing people of certain subpopulations.*

15. Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? *Yes, it is possible that their names are mentioned in certain documents.*

16. Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? *Given that* `MADLAD-400` *is a general web-crawled dataset, even after filtering, it is possible that there are documents containing sensitive data.*

17. Any other comments? *None.*

Collection

1. How was the data associated with each instance acquired? *Each instance was acquired by performing transformations on the documents in all available snapshots of CommonCrawl as of August 20, 2022.*

2. What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? *We annotated the CommonCrawl data using a LangID model trained using the procedure described by [15]. Then, we manually inspected the data and then filtered or preprocessed the documents to create* `MADLAD-400`.

3. If the dataset is a sample from a larger set, what was the sampling strategy? `MADLAD-400` *is a subset of CommonCrawl documents determined using LangID annotations and filtering/preprocessing steps.*

4. Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)? *For the audit, the authors inspected the dataset. In some cases native speaker volunteers provided advice on the quality of the dataset.*

5. Over what timeframe was the data collected? (Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.) *We do not annotate timestamps. The version of CommonCrawl that we used has webcrawls ranging from 2008 to August 2022.*

6. Were any ethical review processes conducted (e.g., by an institutional review board)? *No.*

7. Does the dataset relate to people? *It is likely that some documents in* `MADLAD-400` *contain sentences referring to and describing people.*

8. Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)? *We collected this data via webpages crawled by CommonCrawl.*

9. Were the individuals in question notified about the data collection? *No.*

10. Did the individuals in question consent to the collection and use of their data? *No.*

11. If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? *No.*

12. Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? *No.*

13. Any other comments? *None.*

Preprocessing/cleaning/labeling

1. Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? (If so, please provide a description. If not, you may skip the remainder of the questions in this section.) *Various types of preprocessing were done: deduplication of 3 sentence spans, filtering substrings according to various heuristics associated with low quality, Virama encoding correction, converting Zawgyi encoding to Unicode encoding for Myanmar script characters and a Chinese pornographic content filter heuristic. In addition, 79 annotated language datasets were removed on inspection due to low quality or mislabeling.*

2. Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? *No, this raw data is hosted by CommonCrawl.*

3. Is the software used to preprocess/clean/label the instances available? *As of June 13, 2023, no.*

4. Any other comments? *None.*

Uses

1. Has the dataset been used for any tasks already? (If so, please provide a description.) `MADLAD-400` *has been used for MT and language modeling.*

2. Is there a repository that links to any or all papers or systems that use the dataset? *No*

3. What (other) tasks could the dataset be used for? *This dataset could be used as a general training dataset for any of the languages in* `MADLAD-400`.

4. Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? (For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?) *While steps have been taken to clean* `MADLAD-400`, *content containing sensitive content about individuals or groups could affect the performance of some downstream NLP tasks. Moreover, while building applications for (a) given language(s), we urge practitioners to assess the suitability of* `MADLAD-400` *for their usecase.*

5. Are there tasks for which the dataset should not be used? (If so, please provide a description.) *N/A.*

6. Any other comments? *None.*

Distribution

1. How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? `MADLAD-400` *is made available through a GCP bucket.*

2. When will the dataset be distributed? *June 2023*

3. Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? (If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.) *AI2 has made a version of this data available under the ODC-BY license. Users are also bound by the CommonCrawl terms of use in respect of the content contained in the dataset.*

4. Have any third parties imposed IP-based or other restrictions on the data associated with the instances? *Users are bound by the CommonCrawl terms of use in respect of the content contained in the dataset.*

5. Any other comments? *None.*

Maintenance

1. Who is supporting/hosting/maintaining the dataset? *An external organization, AI2 is hosting the dataset.*

2. How can the owner/curator/manager of the dataset be contacted (e.g., email address)? *Sneha Kudugunta* `snehakudugunta@google.com` *or Isaac Caswell (*`icaswell@google.com`*) for questions about the dataset contents, or Dirk Groeneveld* `dirkg@allenai.org` *for questions related to the hosting of the dataset.*

3. Is there an erratum? (If so, please provide a link or other access point.) https://github.com/google-research/google-research/tree/master/madlad_400

4. Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances')? (If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?) *There are no such plans, but major issues may be corrected when reported through email or the Github page (*https://github.com/google-research/google-research/tree/master/madlad_400*).*

5. If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? (If so, please describe these limits and explain how they will be enforced.) *N/A*

6. Will older versions of the dataset continue to be supported/hosted/maintained? (If so, please describe how. If not, please describe how its obsolescence will be communicated to users.) *No*

7. If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? (If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.) *A relatively unprocessed version of* `MADLAD-400`, `MADLAD-400`-`noisy` *is made available for others to build upon using superior cleaning/preprocessing techniques for their specific usecases.*

8. Any other comments? *None*

A.14 Model Card

Model Card

Model Details

- Person or organization developing model: *Google DeepMind and Google Research*

- Model Date: *June 13, 2023*

- Model Types: *Machine Translation and Language Modeling Models.*

- Information about training algorithms, parameters, fairness constraints or other applied approaches, and features: *Provided in the paper.*

- Paper: *Kudugunta et al, `MADLAD-400`: Monolingual And Document-Level Large Audited Dataset, Under Review, 2023*

- License: *ODC-BY*

- Contact: *snehakudugunta@google.com*

Intended Use

- Primary intended uses: *Machine Translation and multilingual NLP tasks on over 400 languages.*

- Primary intended users: *Research community.*

- Out-of-scope use cases: *These models are trained on general domain data and are therefore not meant to work on domain-specific models out-of-the box. Moreover, these research models have not been assessed for production usecases.*

Factors

- *The translation quality of this model varies based on language, as seen in the paper, and likely varies on domain, though we have not assessed this.*

Metrics

- *We use SacreBLEU and chrF, two widely used machine translation evaluation metrics for our evaluations.*

Ethical Considerations

- *We trained these models with `MADLAD-400` and publicly available data to create baseline models that support NLP for over 400 languages, with a focus on languages underrepresented in large-scale corpora. Given that these models were trained with web-crawled datasets that may contain sensitive, offensive or otherwise low-quality content despite extensive preprocessing, it is still possible that these issues to the underlying training data may cause differences in model performance and toxic (or otherwise problematic) output for certain domains. Moreover, large models are dual use technologies that have specific risks associated with their use and development. We point the reader to surveys such as those written by Weidinger et al. [67] or Bommasani et al. [11] for a more detailed discussion of these risks, and to Liebling et al. [46] for a thorough discussion of the risks of machine translation systems.*

Training Data

- *For both the machine translation and language model, `MADLAD-400` is used. For the machine translation model, a combination of parallel datasources covering 157 languages is also used. Further details are described in the paper.*

Evaluation Data

- *For evaluation, we used WMT, NTREX, Flores-200 and Gatones datasets as described in Section 4.3.*

Caveats and Recommendations

- *We note that we evaluate on only 204 of the languages supported by these models and on machine translation and few-shot machine translation tasks. Users must consider use of this model carefully for their own usecase.*

Canaries Datasheet

Motivation

1. For what purpose was the dataset created? (Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.) *We create these canaries with the goal of enabling the study of memorization in the multilingual and translate settings. Models can be trained on these canaries and then their risk of memorization assessed.*

2. Who created this dataset and on behalf of which entity? *Christopher A. Choquette-Choo[†], Katherine Lee[†] ([†]Google DeepMind)*

3. Who funded the creation of the dataset? *Google DeepMind*

4. Any other comments? *None*

Composition

1. What do the instances that comprise the dataset represent? *Each instance is constructed from a* `MADLAD-400` *sentence-level example. Careful modifications are used, e.g., shuffling the tokens, to make the sample outlier to the natural distribution.*

2. How many instances are there in total? *There are* $1,945,631$ *in total.*

3. Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? (If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).) *The canary dataset itself is a subsampling from* `MADLAD-400`*. However, all described canaries are included in the release.*

4. What data does each instance consist of? *Each instance consists of the original text as well as the modified instance in tokens.*

5. Is there a label or target associated with each instance? If so, please provide a description. *No.*

6. Is any information missing from individual instances? *No.*

7. Are relationships between individual instances made explicit? *No.*

8. Are there recommended data splits (e.g., training, development/validation, testing)? *No.*

9. Are there any errors, sources of noise, or redundancies in the dataset? *Some canaries are duplicated for the purposes of studying repetition in memorization.*

10. Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? (If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.) *Yes*

11. Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? (If so, please provide a description.) *This may be possible given the underlying* `MADLAD-400` *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

12. Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? (If so, please describe why.) *This may be possible given the underlying* `MADLAD-400` *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

13. Does the dataset relate to people? *This may be possible given the underlying* `MADLAD-400` *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

14. Does the dataset identify any subpopulations (e.g., by age, gender)? *This may be possible given the underlying* `MADLAD-400` *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

15. Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? *This may be possible given the underlying* `MADLAD-400` *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

16. Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? *This may be possible given the underlying* MADLAD-400 *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

17. Any other comments? *None.*

Collection

1. How was the data associated with each instance acquired? *Each instance was acquired by performing transformations on the documents in all available snapshots of CommonCrawl as of August 20, 2022.*

2. What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? *We randomly subsampled* MADLAD-400 *and then applied random*

3. If the dataset is a sample from a larger set, what was the sampling strategy? *A predefined number of sentences were uniformly sampled from each language.*

4. Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)? *The authors created the canary dataset.*

5. Over what timeframe was the data collected? (Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.) *We do not annotate timestamps.*

6. Were any ethical review processes conducted (e.g., by an institutional review board)? *No.*

7. Does the dataset relate to people? *This may be possible given the underlying* MADLAD-400 *may contain such data. However, the modifications used for generating canaries reduce the chance of this.*

8. Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)? *Obtained second-hand through* MADLAD-400*, a CommonCrawl based dataset.*

9. Were the individuals in question notified about the data collection? *No.*

10. Did the individuals in question consent to the collection and use of their data? *No.*

11. If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? *No.*

12. Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? *No.*

13. Any other comments? *None.*

Preprocessing/cleaning/labeling

1. Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? (If so, please provide a description. If not, you may skip the remainder of the questions in this section.) *Various types of processing were applied on top of* MADLAD-400*. Sentences were either interleaved in batches of* $20 - 50$ *tokens or shuffled at the token-level.*

2. Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? *The raw* MADLAD-400 *data is saved.*

3. Is the software used to preprocess/clean/label the instances available? *As of June 13, 2023, no.*

4. Any other comments? *None.*

Uses

1. Has the dataset been used for any tasks already? (If so, please provide a description.) MADLAD-400 *has been used for MT.*

2. Is there a repository that links to any or all papers or systems that use the dataset? *No*

3. What (other) tasks could the dataset be used for? *This dataset can be used to study memorization in broad language modelling scenarios.*

4. Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? (For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?) *We urge users to read the datasheet for* MADLAD-400 *to understand the underlying risk for the canaries.*

5. Are there tasks for which the dataset should not be used? (If so, please provide a description.) *N/A*.

6. Any other comments? *None.*

Distribution

1. How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? `MADLAD-400` *is made available through a GCP bucket.*

2. When will the dataset be distributed? *June 2023*

3. Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? (If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.) *AI2 has made a version of this data available under the ODC-BY license. Users are also bound by the CommonCrawl terms of use in respect of the content contained in the dataset.*

4. Have any third parties imposed IP-based or other restrictions on the data associated with the instances? *Users are bound by the CommonCrawl terms of use in respect of the content contained in the dataset.*

5. Any other comments? *None.*

Maintenance

1. Who is supporting/hosting/maintaining the dataset? *An external organization, AI2 is hosting the dataset.*

2. How can the owner/curator/manager of the dataset be contacted (e.g., email address)? *Christopher A. Choquette-Choo* `cchoquette@google.com` *for questions about the dataset contents or Dirk Groeneveld* `dirkg@allenai.org` *for questions related to the hosting of the dataset.*

3. Is there an erratum? (If so, please provide a link or other access point.) *No*

4. Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances')? (If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?) *There are no such plans, but major issues may be corrected when reported through email or the Github page.*

5. If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? (If so, please describe these limits and explain how they will be enforced.) *N/A*

6. Will older versions of the dataset continue to be supported/hosted/maintained? (If so, please describe how. If not, please describe how its obsolescence will be communicated to users.) *No*

7. If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? (If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.) *Others may build upon this by similarly generating canaries from* `MADLAD-400` *which is made available.*

8. Any other comments? *None*