Quality at a Glance: An Audit of Web-Crawled Multilingual Datasets

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Abstract

With the success of large-scale pre-training and multilingual modeling in Natural Language Processing (NLP), recent years have seen a proliferation of large, web-mined text datasets covering hundreds of languages. However, to date there has been no systematic analysis of the quality of these publicly available datasets, or whether the datasets actually contain content in the languages they claim to represent. In this work, we manually audit the quality of 205 languagespecific corpora released with five major public datasets (CCAligned, ParaCrawl, WikiMatrix, OSCAR, mC4), and audit the correctness of language codes in a sixth (JW300). We find that lower-resource corpora have systematic issues: at least 15 corpora are completely erroneous, and a significant fraction contains less than 50% sentences of acceptable quality. Similarly, we find 83 corpora that are mislabeled or use nonstandard/ambiguous language codes. We demonstrate that these issues are easy to detect even for non-speakers of the languages in question, and supplement the human judgements with automatic analyses. Inspired by our analysis, we recommend techniques to evaluate and improve multilingual corpora and discuss the risks that come with low-quality data releases.

1 Introduction

Access to multilingual datasets for NLP research has vastly improved over the past years. A variety of web-derived collections for hundreds of languages is available for anyone to download, such as ParaCrawl (Esplà et al., 2019; Bañón et al., 2020), WikiMatrix (Schwenk et al., 2019) CCAligned (El-Kishky et al., 2020), OSCAR (Ortiz Suárez et al., 2019, 2020), and several others. These have in turn enabled a variety of highly multilingual models, like mT5 (Xue et al., 2020), M2M-100 (Fan et al., 2020), M4 (Arivazhagan et al., 2019).

Curating such datasets relies on the websites giving clues about the language of their contents (e.g. a language identifier in the URL) and on automatic language classification (LangID). It is commonly known that these automatically crawled and filtered datasets tend to have overall lower quality than hand-curated collections (Koehn et al., 2020), but their quality is rarely measured directly, and is rather judged through the improvements they bring to downstream applications (Schwenk et al., 2019).

Building NLP technologies with automatically crawled datasets is promising. This is especially true for low-resource languages, because data scarcity is one of the major bottlenecks for deep learning approaches. However, there is a problem: There exists very little research on evaluating both data collections and automatic crawling and filtering tools for low-resource languages. As a result, although many low-resource languages are covered by the latest multilingual crawl data releases, their quality and thus usability is unknown.

To shed light on the quality of data crawls for the lowest resource languages, we perform a manual data audit for 230 per-language subsets of five major crawled multilingual datasets: CCAligned (El-Kishky et al., 2020), ParaCrawl (Esplà et al., 2019; Bañón et al., 2020), WikiMatrix (Schwenk et al., 2019), OSCAR (Ortiz Suárez et al., 2019, 2020) and mC4 (Xue et al., 2020). We propose solutions for effective, low-effort data auditing (section 4), including an error taxonomy. Our quantitative analysis reveals surprisingly low amounts of valid in-language data, and identifies systematic issues across datasets and languages. In addition, we find that a large number of datasets is labeled with nontransparent or incorrect language codes (section 5). This leads us to reflect on the potential harm of low-quality data releases for low-resource languages (section 6), and provide a set of recommendations for future multilingual data releases (section 8).

2 Related Work

Corpora collected by web crawlers are known to be noisy (Junczys-Dowmunt, 2019; Caswell et al., 2020). In highly multilingual settings, past work has found that web-crawls of lower-resource languages have serious issues, especially problems with segment-level LangID (Caswell et al., 2020). Repeated studies have shown that cleaning and filtering web-crawls significantly boosts both general language modeling (Gao et al., 2020; Brown et al., 2020; Raffel et al., 2020) and downstream task performance (Moore and Lewis, 2010; Xu and Koehn, 2017; Khayrallah and Koehn, 2018; Brown et al., 2020).

As the scale of ML research grows, it becomes increasingly difficult to validate automatically collected and curated datasets (Biderman and Scheirer, 2020; Prabhu and Birhane, 2020; Bender et al., 2021). Several works have focused on advancing methodologies and best practices to address these challenges. Bender and Friedman (2018) introduced data statements, a documentary framework for NLP datasets that seeks to provide a universal

minimum bar for dataset description. Similar work has focused on online news (Kevin et al., 2018), data ethics (Sun et al., 2019), and data exploration (Holland et al., 2018), as well as generalist work such as (Gebru et al., 2018). And there is a large literature on filtering text data, e.g. (Axelrod et al., 2011; Moore and Lewis, 2010; Wang et al., 2018; Kamholz et al., 2014; Junczys-Dowmunt, 2018; Caswell et al., 2020).

Perhaps the closest work to the present work is by Caswell et al. (2020), who perform a highly multilingual web-crawl and then systematically analyze the LangID related quality issues their dataset has. However, though they perform a brief analysis of the quality of OSCAR in appendix E, they omit analyses of any other public datasets, and focus only on the presence of in-language content.

3 Multilingual Corpora

Table 1 provides an overview of the corpora of interest in this work. We selected the corpora for their multilinguality and the inclusion of understudied languages in NLP. With the exception of WikiMatrix and Paracrawl, all corpora are derived from CommonCrawl, and distinguish themselves by the choice of filtering methods, LangID and automatic alignment technology.

CCAligned (El-Kishky et al., 2020) is a 119language¹ parallel dataset built off 68 snapshots of Common Crawl. Documents are aligned if they are in the same language according to FastText LangID (Joulin et al., 2016, 2017), and have the same URL but for a differing language code. These alignments are refined with cross-lingual LASER embeddings (Artetxe and Schwenk, 2019). For sentence-level data, they split on newlines and align with LASER, but perform no further filtering. Human annotators evaluated the quality of document alignments for six languages (de, zh, ar, ro, et, my) selected for their different scripts and amount of retrieved documents, reporting precision of over 90%. The quality of the extracted parallel sentences is evaluated in a machine translation (MT) task on six European (da, cr, sl, sk, lt, et) languages of the TED corpus(Qi et al., 2018), where it compares favorably to systems built on crawled sentences from WikiMatrix and ParaCrawl

¹Although 137 language pairs are reported in El-Kishky et al. (2020), only 119 sentence-level corpora were available to download on statmt.org as of February 2021.

		Parallel		Monoli	ngual
	CCAligned	ParaCrawl v7.1	WikiMatrix	OSCAR	mC4
#languages	137	41	85	166	101
Source	CC 2013-2020	selected websites	Wikipedia	CC 11/2018	CC all
Filtering level	document	sentence	sentence	document	document
Langid	FastText	CLD2	FastText	FastText	CLD3
Alignment	LASER	Vec/Hun/BLEU-Align	LASER	-	-
Evaluation	TED-6	WMT-5	TED-45	POS/DEP-5	XTREME

Table 1: Comparison of parallel and monolingual corpora extracted from web documents, including their downstream evaluation tasks. All parallel corpora are evaluated through machine translation evaluation with BLEU. CC: CommonCrawl; TED-6: da, cr, sl, sk, lt, et; TED-45: 45-language subset of (Qi et al., 2018); WMT-5: cs, de, fi, lv, ro. POS/DEP-5: part-of-speech labeling and dependency parsing for bg, ca, da, fi, id.

v6, yielding BLEU scores in a range between 15 and 38.

Multilingual C4 (mC4) (Xue et al., 2020) is a document-level dataset used for training the mT5 language model. It consists of monolingual text in 101 languages and is generated from 71 CommonCrawl snapshots. It filters out pages that contain less than three lines of at least 200 characters and pages that contain bad words (Emerick, 2018). Since this is a document-level dataset, we split it by sentence and deduplicate it before rating. For language identification, it uses CLD3 (Botha et al., 2017), a small feed-forward neural network that was trained to detect 107 languages. The mT5 language model pre-trained on mC4² is evaluated on 6 tasks of the XTREME benchmark (Hu et al., 2020) covering a variety of languages and outperforms other multilingual pre-trained language models such as mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020).

oscar (Ortiz Suárez et al., 2019, 2020) is a set of monolingual corpora extracted from Common Crawl snapshots, specifically from the plain text *WET* format distributed by Common Crawl which removes all the HTML tags and converts the text formatting to UTF-8. It is deduplicated and follows the same approach as Grave et al. (2018) by using FastText LangID (Joulin et al., 2016, 2017) on a line-level. No other filtering was applied. For five languages (bg, ca, da, fi, id) OSCAR corpora were used to train ELMo (Peters et al., 2018) embeddings for POS tagging and dependency parsing, outperforming Wikipedia-sourced embeddings (Ortiz Suárez et al., 2020).

ParaCrawl v7.1 is a parallel dataset with 41 language pairs primarily aligned with English (39 out of 41) and mined using the parallel-data-crawling tool Bitextor (Esplà et al., 2019; Bañón et al., 2020) which includes downloading documents, preprocessing and normalization, aligning documents and segments, and filtering noisy data via Bicleaner. ParaCrawl focuses on European languages, but also includes 9 lower-resource, non-European language pairs in v7.1. Sentence alignment and sentence pair filtering choices were optimized for five languages (mt, et, hu, cs, de) by training and evaluating MT models on the resulting parallel sentences. ParaCrawl v5 was shown to improve translation quality on WMT benchmarks for cs, de, fi, lv, ro.

WikiMatrix (Schwenk et al., 2019) is a public dataset containing 135M parallel sentences in 1620 language pairs (85 languages) mined from Wikipedia. Out of the 135M parallel sentences, 34M are aligned with English. The text is extracted from Wikipedia pages, split into sentences, and duplicate sentences are removed. FastText LangID is used before identifying bitext with LASER's distance-based mining approach. The margin threshold is optimized by training and evaluating downstream MT models on four WMT benchmarks (de-en, de-fr, cs-de, cs-fr). The final dataset is evaluated through TED translation models between 45 languages, with highest quality for translations between English and e.g. pt, es, da, and lowest for sr, ja, mr, zh_TW. In the audit we focus on language pairs with English on one side.

²Upsampling lower-resource languages.

4 Auditing Data Quality

None of the above datasets has been evaluated for quality on the sentence level, with the exception of several languages in ParaCrawl v3, and downstream evaluations are centered around a small fraction of higher-resource languages. This is neither sufficient for drawing conclusions about the quality of individual or aligned sentences, nor about the entirety of languages. To close this gap, we conduct a data quality audit that focuses on the lowest-resource and most under-evaluated languages, but also covers mid- and high-resource languages to draw comparisons.

4.1 Auditing Process

Participants We recruited 51 volunteers from the NLP community, covering about 70 languages with proficient language skills.³ In order to verify our hypothesis that those annotations can largely done by non-native speakers, we repeat a set of annotations twice, once by a language expert, and once by a non-expert, and measure the accuracy of the non-expert.

Sample selection For each language in each dataset, we took a random sample of 100 lines, which may be anywhere from single words to short paragraphs depending on segmentation (see last columns in tables in appendix H). We manually annotated them according to the error taxonomy described below. For WikiMatrix and CCAligned, we selected those languages that are paired with English, and for ParaCrawl, we also included those paired with Spanish ("total" counts in table 3). We did not annotate all languages, but focused on the ones with the least number of sentences in each dataset (at least the smallest 10) and languages for which we found proficient speakers.

Non-expert labeling strategies Although many of the volunteers were familiar with the languages in question or spoke related languages, in cases where no speaker of a relevant language could be found, volunteers used dictionaries and internet search to form educated guesses. We discuss this deeper in appendix F to highlight how much of this low-resource focused evaluation can actually be done by non-proficient speakers. In general,

we aim to find an upper bound on quality, so we encouraged annotators to be forgiving of translation mistakes when the overall meaning of the sentence or large parts thereof are conveyed, or when most of the sentence is in the correct language.

Effort The individual effort was dependent on the quality and complexity of the data as well as the annotator's knowledge of the language(s), e.g., it took from less than two minutes for an English native speaker to pass through 100 well-formed English sentences (and it was similarly fast to annotate languages with 0% in-language sentences), to two hours of "detective work" for well-formed content in languages where the annotator had no familiarity.

Taxonomy In order to quantify errors, we developed a simple error taxonomy. Sentences and sentence pairs were annotated according to a simple rubric with error classes of Incorrect Translation (X, excluded for monolingual data), Wrong Language (WL), and Non-Linguistic Content (NL). Of correct sentences (C), we further mark single words or phrases (CS) and boilerplate contents (CB). The appendix contains the detailed instructions, and table 2 provides examples for parallel data. In addition, we asked annotators to flag offensive or pornographic content.

4.2 Human Audit Results

Interpretation of Results For each language, we compute the percentage of each label within the 100 audited sentences. Then, we either aggregate the labels across languages with equal weights (macro-average), or weight them according to their presence in the overall dataset (micro-average). Note that the number of languages, the numbers of sentences per language and the choice of languages differ across datasets, both in the original release and in the selection for our audit, so the comparison of numbers across datasets has to be taken with a grain of salt. Our audit captures a decent ratio of languages (25–55%, second row in table 3), but only a tiny fraction of the overall number of sentences (0.00004–0.002%). Appendix H contains the detailed audit results for each language and dataset. When we speak of "low-" and "high"-resource languages, we mean languages with smaller or larger representation in the datasets at hand. When reporting language-specific results we use the original language identifiers of the datasets.

³This surprisingly high number comes in part because there are many closely related languages, e.g. one person may be proficient enough to rate many different Slavic or Turkic languages even if only one is their native language.

Correct Codes								
CC: Correct translation, natural sentence								
en The Constitution of South Africa	nso Molaotheo wa Rephabliki ya Afrika Borwa							
en Transforming your swimming pool into a pond	de Umbau Ihres Swimmingpools zum Teich							
CB: Correct translation, Boilerplate or low quality								
en Reference number: 13634	ln Motango ya référence: 13634							
en Latest Smell Stop Articles	fil Pinakabagong mga Artikulo Smell Stop							
CS: Correct translation, Short								
en movies, dad	it cinema, papà							
en Halloween - without me	ay Hallowen – janiw nayampejj							
Error Codes								
X: Incorrect translation, but both correct languages								
en A map of the arrondissements of Paris	kg Paris kele mbanza ya kimfumu ya Fwalansa.							
en Ask a question	tr Soru sor Kullanıma göre seçim							
WL: Source OR target wrong language, but both still								
en The ISO3 language code is zho	zza Táim eadra bracach mar bhionns na frogannaidhe.							
en Der Werwolf — sprach der gute Mann,	de des Weswolfs, Genitiv sodann,							
	NL: Not a language: at least one of source and target are not linguistic content							
en EntryScan 4 _	tn TSA PM704 _							
en organic peanut butter	ckb �������							

Table 2: Annotation codes for parallel data with sentence pair examples. The language code before each sentence indicates the language it is supposed to be in.

Which datasets have quality issues? macro-averaged results show that the ratio of correct samples ("C") ranges from 24% to 87%, with a large variance across the five audited datasets. Particularly severe problems were found in CCAligned and WikiMatrix, with 44 of the 65 languages that we audited for CCAligned containing under 50% correct sentences, and 19 of the 20 in WikiMatrix. In total, 15 of the 205 language specific samples (7.3%) contained not a single correct sentence. For the parallel datasets we are also interested in the quantity of misaligned/mistranslated sentences (X). For WikiMatrix, two-thirds of the audited samples were on average misaligned. We noticed that sentences were often similar in structure, but described different facts (see table 10).

While Table 3 gives means and numbers of corpora passing certain thresholds, Figure 2 illustrates per-corpus correctness more completely, showing for each dataset what percent of audited corpora are under each possible threshold of correctness.

Why haven't these problems been reported before? The findings above are averaged on a per-

fore? The findings above are averaged on a perlanguage basis (i.e. macro-average), and therefore give low and high-resource languages equal weight. If we instead estimate the quality on a per-sentence basis, i.e. down-weight the lower-resource languages in the computation of the average, the numbers paint a more optimistic picture ("micro" block in table 3). This is especially relevant for the monolingual datasets because they contain audits for

English, which makes up for 43% of all sentences in OSCAR and 36% in mC4. To illustrate the effect of this imbalance: A random sample from the entire mC4 dataset will with over 63% chance be from one of the 8 largest languages (en, ru, es, de, fr, it, pt, p1, >100M sentences each), of which all have near perfect quality. Analogously, the evaluation and tuning of web mining pipelines and resulting corpora in downstream applications focused largely on higher-resource languages (section 3), so the low quality of underrepresented languages might go unnoticed if there is no dedicated evaluation, or no proficient speakers are involved in the curation (\forall et al., 2020).

How much content is nonlinguistic or in the wrong language? In general, nonlinguistic content was a larger problem than wrong-language content. Among the parallel datasets, CCAligned contains the highest percentage of nonlinguistic content, at 31.42% on average across all rated corpora, and also the highest percent of wrong-language content, at 9.44% on average. Among the monolingual datasets, mC4 contains the highest ratio both of sentences in incorrect languages (15.98% average) and nonlinguistic content (11.40% average), with 4 of the 48 audited languages having more than 50% contents in other languages. The low amount of wrong language in ParaCrawl shows the benefits of selecting domains by the amount in-language text,

⁴mC4 contains 22% und sentences, i.e. sentences with undefined language.

			Parallel		Mono	lingual
		CCAligned	ParaCrawl v7.1	WikiMatrix	OSCAR	mC4
#la	ngs audited / total	65 / 119	21 / 38	20 / 78	51 / 166	48 / 108
%l	angs audited	54.62%	55.26%	25.64%	30.72%	44.44%
#se	ents audited / total	8037 / 907M	2214 / 521M	1997 / 95M	3517 / 8.4B	5314 / 8.5B
%S	ents audited	0.00089%	0.00043%	0.00211%	0.00004%	0.00006%
	С	29.25%	76.14%	23.74%	87.21%	72.40%
	Χ	29.46%	19.17%	68.18%	-	-
cr0	WL	9.44%	3.43%	6.08%	6.26%	15.98%
macro	NL	31.42%	1.13%	1.60%	6.54%	11.40%
_	offensive	0.01%	0.00%	0.00%	0.14%	0.06%
	porn	5.30%	0.63%	0.00%	0.48%	0.36%
	С	53.52%	83.00%	50.58%	98.72%	92.66%
	X	32.25%	15.27%	47.10%	-	-
Cr0	WL	3.60%	1.04%	1.35%	0.52%	2.33%
micro	NL	10.53%	0.69%	0.94%	0.75%	5.01%
	offensive	0.00%	0.00%	0.00%	0.18%	0.03%
	porn	2.86%	0.33%	0.00%	1.63%	0.08%
	#langs =0% C	7	0	1	7	0
	#langs < 50% C	44	4	19	11	9
	#langs >50% NL	13	0	0	7	1
	#langs >50% WL	1	0	0	3	4

Table 3: Averages of sentence-level annotations across datasets and selected languages. Macro-avg: Each language is weighted equally in the aggregation, regardless of its size. Micro-avg: Each label is weighted by the fraction of sentences for that language in the overall annotated corpus, i.e., the annotations for higher-represented languages are upweighted, and annotations for lower-represented languages are downweighted. The bottom rows contain the number of languages that have 0% sentences labeled $\mathbb C$ etc.

but the dataset also covers the smallest amount of languages. The relatively low ratio of wrong language samples in OSCAR may reflect the success of line-level LangID filtering. These numbers provide evidence that more research in improved language identification could improve the overall quality, especially with respect to nonlinguistic content.

Which languages got confused? The languages that were confused were frequently related higher-resource languages. However, there were also a significant number of "out-of-model cousin" cases, where languages not supported by the LangID model ended up in a similar-seeming language. For instance in mC4, much of the Shona (sn) corpus is actually Kinyarwanda (rw) – and, peculiarly, much of the Hawaiian (haw) is actually Twi (tw/ak).

Do low-resource languages have lower quality? Low-resource datasets tend to have lower human-

judged quality, which we measure by comparing size of corpora and ratio of correct sentences. The Spearman rank correlation between quality (%C) and size is positive in all cases. The trend is strongest for mC4 (r = 0.66), and gradually declines for CCAligned (r = 0.53), WikiMatrix (r = 0.49), ParaCrawl (r = 0.43), and OSCAR (r = 0.37). Figure 1 compares the number of sentences for each language against the proportion of correct sentences that we found during the audit. We can see that not all high-resource languages have high quality, in particular for CCAligned (e.g. en-jv_ID with 5%C, or en-tl_XX with 13%C). For mid-resource languages (10^4 – 10^6 sentences) the picture is rather inconclusive, with some languages having high quality, and others having extremely low quality, even within the same datasets, e.g. for CCAligned en-ur_PK (100% C) vs. en-ur_PK_rom (0.5% C). For the different error types the trends are less conclusive (appendix E).

Which languages have the lowest quality? Across datasets we observe that the quality is particularly poor for languages that are included in the datasets in romanized script, but are more commonly written in other scripts, such as Urdu (ur), Hindi (hi), Arabic (ar), Chinese (zh), Telugu (te) and Bulgarian (bg). In terms of geography, the poorest quality is found for African languages (bm, ff, kg, lg, ln,nso, om, sn, so, tn, wo), minority languages in Europe and the Middle East that are closely related to higher-resource languages (az-IR, frr, nap, szl, zza), lesser spoken Chinese languages sharing a script with Mandarin (yue, wuu), and four major Austronesian languages (bcl, cbk, jv, su).

What is the incidence of offensive and pornographic content? Overall, the sampled sentences did not contain a large amount of offensive contents. However, there were notable amounts of pornographic content (> 10%) found in CCAligned for 11 languages.

Annotation quality For six audited languages from OSCAR and ten from CCAligned we measure the accuracy of the labels assigned by non-proficient speakers against the labels assigned by proficient speakers for all audited sentences. With the full 6-class taxonomy we find a mean accuracy of 0.66 for CCAligned audits, and 0.98 for OSCAR audits (see appendix C for language-specific results). With a binary taxonomy distinguishing C from the rest, the accuracy further increases to 0.79 for CCAligned. This provides strong evidence that good quality annotations are not limited to those proficient in a language.

4.3 Automatic Filtering

Given the frequency of WL and NL annotations, it might be tempting to use open-source LangID models to post-filter data on a per-sentence(-pair) level, as OSCAR does. Unfortunately, this turns out to have its own issues.

Sentence-level n-gram filtering We classify all sentence pairs of CCAligned with the open-source CLD3 language classifier. By comparing its predictions to the audit labels, we evaluate its quality

on the subset of annotated samples: the classifier should detect both correct languages when the pair is annotated as C and X, and should detect incorrect languages in the pair when WL and NL. On this task, the CLD3 classifier⁶ achieves an average precision of only 40.6%, illustrating the issues with LangID on web domain data (Caswell et al., 2020).

Transformer-based LangID filtering Problems with n-gram LangID models like CLD3 have already been explored. Caswell et al. (2020) demonstrate that semi-supervised transformerbased LangID models strongly out-perform n-gram models. We train a comparable transformer-based LangID model and apply it to our annotated data. We find that filtering noisy corpora (under 50% correct) on LangID for both source and target does lead to large gains in median precision, rising from 13.8% pre-filter to 43.9% post-filter. However, this comes at a steep cost of recall, with a 77.5% loss in recall. Nonetheless, some languages benefit to the extent that such filtering could bring the dataset from unusable to usable — for instance (on CCAligned), Lingala, whose precision climbs from 8% to 80%, and Oromo, which soars from 2% to 33% in-language. Both of these, however, come at the cost of losing 50% of the correct inlanguage sentences. The moral is that, at least with the current state of the technology, there is no onesize-fits-all approach for sentence-level LangID.

5 Dataset Mis-labeling

Besides general data quality issues, we found a range of problems and inconsistencies with language codes, ranging from serious mislabelings to small transgressions against standard conventions. This section additionally focuses on issues in the JW300 (Agić and Vulić, 2019) dataset, a multilingual dataset crawled from a the (JW.org) website, which was otherwise not audited in this paper.

In order to use data for any practical application, it is important to have a standardized and unambiguous representation of language codes. The standard for unambiguous language codes used by most academic and industry applications is BCP-47 (Phillips and Davis, 2006), which builds off the two-letter ISO639-2 codes and three-letter ISO639-3 codes. Codes may additionally specify ISO15924 script subtags to indicate that a nonstandard script is used (e.g. hi-Latn for Hindi writ-

 $^{^{5}\}mbox{_rom}$ corpora have been removed in the latest CCA ligned release.

 $^{^{6}}$ filter=0.976 Prec, 0.962 Rec, 0.969 F1.

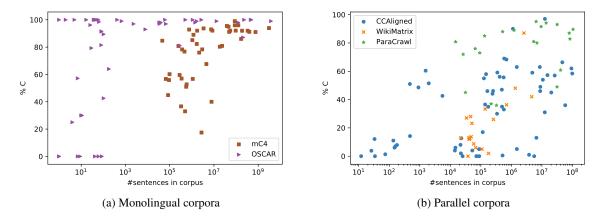


Figure 1: Percentage of sentences labeled as correct vs. log N sentences for all audited languages.

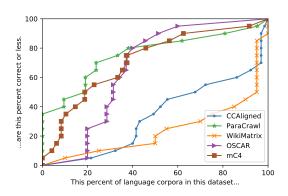


Figure 2: Fraction of languages in each dataset below a given quality threshold (percent correct). The larger the AUC, the better.

ten in Latin script), ISO3166-1 country codes to indicate regional varieties (e.g. fr-CA for Canadian French), or extensions for private use (e.g. ca-x-val for Valencian Catalan). Some BCP-47 codes represent groups of languages – for instance, kg represents the Kongo language, and kng, ldi, kwy, and yom represent particular varieties of Kongo.

We find a variety of errors in language code usage. In summary, we find 8 nonstandard codes in CCAligned, 3 in OSCAR, 1 in mC4, 1 in WikiMatrix, 0 in ParaCrawl, and 70 in JW300, for 83 in total. This does not include the 59 codes affected by superset issues.

Inconsistent Language Codes One common issue is simply using nonstandard or invented codes. For example, CCAligned uses only two-letter codes, so when the BCP-47 code for a language is three letters it is either shortened (e.g. $zza \rightarrow zz$,

szl \rightarrow sz, nso \rightarrow ns, ckb \rightarrow cb, ber \rightarrow tz 7) or invented (shn \rightarrow qa, kac \rightarrow qd, ceb \rightarrow cx), which can lead to confusion and limits the compatibility with other tools and resources. Similarly, OSCAR contains data labeled as als (BCP-47 for Tosk Albanian) that is actually in gsw (Allemanic). This is a result of the language code used by the Alemanic Wikipedia, and affects any corpus or tool that uses Wikipedia data without correcting for this, like FastText (Joulin et al., 2017, 2016).

We identified 22 additional language codes in JW300 (Agić and Vulić, 2019) with similar issues, mostly from mis-parsed private-use extensions, including 12 codes that start with jw_ but are not (as they may appear) Javanese. Full details are in appendix A.

False sign languages The JW300 (Agić and Vulić, 2019) dataset has a much stranger problem than nonstandard codes. It has the peculiar issue that a full 12% (48/417) of the languages it claims to cover have language codes for sign languages. While it is possible to transcribe sign languages using glosses, this is not what these corpora are. Instead, they are in some other high resource language, mostly English or Spanish — so, for example, the en-zsl data is actually English-English parallel data (i.e. copies). Details are in appendix table 5.

Mysterious supersets Some datasets also contain language codes that are supersets of other language codes, which makes it difficult to determine which particular language the data are in. WikiMatrix, for instance, has Serbian (sr), Croatian (hr),

 $^{^{7}}$ Tamazight (BCP-47 ber) goes by various codes, so this may have been a shortening of e.g. tzm

Bosnian (bs), and Serbo-Croatian (sh). And while there may be some debate whether bs, hr, cnr, and sr are different languages, it is true by definition that sh (hbs) is a superset of all of them⁸ The issue of codes that are supersets of others is common enough to include a small table dedicated to it, which we have done with appendix table 4. In some cases this may not be an issue, as with Arabic, where ar conventionally refers to Modern Standard Arabic, even though the code technically encompasses all dialects, or where no typically refers to Norwegian Bokmål (nb), though it technically is the superset of nb and nn. But in other cases, the nature of the data in the superset code remains a mystery.

Deprecated codes Finally, there are several deprecated codes that are used: sh in Wikimatrix, iw in mC4, sh and eml in Oscar, and daf in JW300.

6 Risks of Multilingual Data Releases with Low Quality

There are several potentially harmful consequences of data releases without sufficient quality checks (or under false labels) that we would like to highlight.

Low quality in downstream applications Beyond translation, text corpora today are building blocks for many downstream NLP applications like question answering and text summarization — for instance, a common approach is to first train translation models on such data and then automatically translate training data for downstream models (Conneau et al., 2018). If the data used for the original systems is flawed, derived technology may fail for those languages far down the line without knowing the causes. As our analysis has shown, low-resource languages are disproportionately affected by such problems in automatic data curation pipelines.

Representation washing Since there are datasets which contain many low-resource languages, the community may feel a sense of progress and growing equity, despite the actual quality of the resources for these languages. Similarly, if low-quality datasets are used as benchmarks they may exaggerate model performance, making low-resource NLP appear more solved than it is — or conversely, if models perform

poorly when trained with such data, it may be wrongly assumed that the task of learning models for these languages is harder than it actually is or infeasible given current resources. These effects could result in productive effort being redirected away from these tasks and languages.

Incorrect "facts", algorithmic trust and automation bias We found many instances of parallel-looking sentences that are actually not semantically similar, like those in appendix table 10. This can cause models to produce plausible "translations" that are completely wrong, but users may still trust the model output. This is relevant for algorithmic trust, when users increasingly trust the outputs of computers and "algorithms" without verifying the information. Similarly, automation bias (Skitka et al., 1999), which refers to humans favoring decisions made by automated systems over decisions made by humans, might amplify the issues of inaccurate translations caused by misaligned sentence pairs. Another effect is that models trained on misaligned pornographic content may hallucinate such content, which may be disturbing to users.

7 Future Work

There are a variety of ways to improve both the ease and accuracy of human evaluation, as well as the ease of automatically detecting issues and fixing them. With respect to improved annotations, the error taxonomy presented in this paper lacks at least one significant category of error, namely "correct/in-language but unnatural". Similarly, the definition of "correct-short" and "correctboilerplate" were not understood equally by all annotators, leading us to collapse the categories into one for most analyses. Similarly, a concept like "correct-short" has potential issues for agglutinative languages like Turkish. Finally, it was unclear what to do with related dialects, e.g. when a sentence is "almost correct but wrong dialect" or when it is unclear which dialect a sentence belongs to. We present a slightly improved suggested rubric in appendix G.

Ideally, as well, there can be a standard suite of automatic metrics for a dataset, but more study is necessary to determine what the appropriate metrics would be. One area however that is absent from our analyses but should definitely be covered in the future is the estimated portion of a dataset which has been generated by MT, LM systems, or bots. The information captured in machine-generated

⁸https://iso639-3.sil.org/code/hbs

content might still be useful for modeling the languages at hand, but might falsely overrepresent typical generation patterns and introduce linguistic errors or unnatural artifacts.

8 Conclusion & Recommendations

Of the five multilingual corpora evaluated, we consistently found severe issues with quality, especially in the lower-resource languages. We rated samples of 205 languages, and found that 87 of them had under 50% usable data, with a full 15 languages at 0% in-language. We furthermore found consistent issues with mislabeled data and nonstandard language codes, particularly in the JW300 dataset, and identified 83 affected corpora, at least 48 of which were entirely spurious (Section 5). While there might have been anecdotal evidence of insufficient quality for some of the datasets, the majority of these quality issues had not been reported, nor been investigated in depth. These issues might go unnoticed for languages that are not represented in the evaluation of the crawling methods, and cause harm in downstream applications. In addition to quality issues we found a wide range of issues with language codes, particularly in JW300 and CCAligned, including mis-labeled data, invented codes, deprecated codes, and superset relations between language codes.

We therefore strongly recommend looking at samples of any dataset before using it or releasing it to the public. As we have shown, one does not need to be proficient in a language to see when there are serious quality issues, and a quick scan of 100 sentences can be sufficient to detect major problems. Moreover, going through and annotating a small sample of data can bring useful insights about new ways to filter or use it.

If data cleanliness issues are found, a wide variety of techniques (and their combination) can be explored, from simple approaches like lengthratio filtering, LangID filtering, filtering with TF-IDF wordlists (Caswell et al., 2020) or dictionaries (Kamholz et al., 2014), to neural approaches like (contrastive) language-model scoring (Axelrod et al., 2011; Moore and Lewis, 2010; Wang et al., 2018). Unfortunately, none of these provides a quick and easy fix, especially for low-resource languages – data cleaning is not a trivial task!

Noisy datasets are however by no means entirely useless, at least if they contain some non-zero percent usable content. Therefore, if filtering is

deemed infeasible, an alternative can be documentation (Bender et al., 2021). This can take the form of a per-language quality score and notes about known issues, or a datasheet (Gebru et al., 2018) or nutrition label (Holland et al., 2018). However, we suggest researchers not to release datasets for any language with low percentages of in-language content, as this may lead people mistakenly to assume that usable resources are now available for these languages.

Finally, we encourage the community to continue to conduct such evaluations and audits of public datasets – similar to system comparison papers – which would help anyone interested in using these datasets for practical purposes.

Acknowledgements

We would like to thank the AfricaNLP and Google reviewers who have helped us shape this paper. Furthermore, we are grateful for Ahmed El-Kishky's support and help with CCAligned and WikiMatrix size statistics.

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A Details on Language Code Issues

Section 5 describes a variety of issues surrounding language codes that are unclear or incorrect. This section provides more details, focusing on the JW300 dataset.

In table 4 we provide a complete table of the datasets where one code is defined as a superset of the other by the ISO standard, and in table 5 we provide a complete list of the language codes in JW300 which purport to be sign language but are actually unrelated high-resource languages.

Special attention needs to be given to the JW300 dataset, which, in addition to the sign languages and superset code issues, has a variety of other peculiarities. These problems seem to originate in the codes used by jw.org⁹, which were apparently not checked in the creation of the JW300 dataset. An overview is provided in Table 6, and the following paragraphs give specifics.

Twelve languages in JW300 have codes starting in jw_, suggesting they are varieties of Javanese (ISO639-1 jw), but are instead attempts to represent language dialects for which there are not BCP-47 codes. These codes seem to have been updated in jw.org to appropriate BCP-47 private-use extensions in the form <supercode>_x_<tag>, which are provided in Table 6.

In addition to the <code>jw_tags</code>, there are two other mis-used private subtags: <code>hy_arevmda</code>, which in addition to lacking the mandatory <code>_x_</code> appears to represent standard Western Armenian (<code>hyw</code>); and <code>rmy_AR</code>, which, rather than being Romany from Argentina, is Kalderash Romany.

There are also a few anomalies where private use extensions should have been used but other methods were found to convey the distinctions. Three codes appear in addition to equivalent ISO codes, making it unclear which languages they are. Two of these are equivalencies between ISO639-2 and ISO639-3 (nya and ny are both Chichewa, qu and que are both Quechua). and one is a script equivalency (kmr and kmr_latn are both in Latin script). In these three cases the two codes do represent different languages — so a private use extension would have been appropriate.

Finally, there is the more minor issue that three languages use the ISO639-3 code instead of the ISO639-2 code, and therefore are not BCP-47.

In addition to the JW300-specific tables, Table 9 summarizes misc errors in CCAligned and OSCAR that were detailed in Section 5.

B Complete Error Taxonomy and Instructions

In addition to the table given in table 2, raters were provided with the following verbal notes on the error codes

- CC: Correct translation, natural sentence: It's OK if it's a sentence fragment instead of a whole sentence, as long as it is not too short (about 5 words or greater). The translation does not have to be perfect.
- CS: Correct Translation, but single word or short phrase: Also includes highly repeated short phrases, like "the cat the cat "
- CB: Correct translation, but boilerplate: This can be auto-generated or formulaic content, or content that one deems "technically correct but generally not very useful to NLP models". Unfortunately, it's often not clear what should be counted as boilerplate...do your best.
- X: Incorrect translation [for parallel sentences] both source and target are in the correct language, but they are not adequate translations.
- WL: Wrong language For short sentences, especially with proper nouns, there is often a fine line between "Wrong language" and "Not language". Do your best.
- NL: Not language At least one of source and target are not linguistic content. Any sentence consisting only of a proper noun (e.g. "Tyrone Ping") should be marked as NL.
- U: Unknown for sentences that need verification by a native speaker. This is an auxiliary label that is resolved in most cases.

Finally, for future work please consider using the aspirational error taxonomy in appendix G, rather than the one presented above.

⁹The jw.org website seems to use correct BCP-47 extensions now, however, and entering a code such as "jw_dmr" redirects to "naq_x_dmr"

Dataset	supercode	subcode(s)
JW300	kg	kwy
JW300	mg	tdx
JW300	qu	que,qug,qus,quw,quy,quz,qvi,qvz
JW300	sw	swc
OSCAR	ar	arz
OSCAR	az	azb
OSCAR	sh	bs,hr,sr
OSCAR	ku	ckb
OSCAR	ms	id,min
OSCAR	no	nn
OSCAR	sq	als*
OSCAR	zh	yue,wuu
Wikimatrix	ar	arz
Wikimatrix	sh	bs,hr,sr
Wikimatrix	zh	wuu

Table 4: Situations where two language codes are represented, but one is a superset of another by the ISO standard, leading to unclarity about the data in the supercode dataset. *The als dataset is actually in gsw.

Actual language	Code in JW300
cs	cse
de	gsg
el	gss
en	ase,asf,bfi,ins,psp,sfs,zib,zsl
es	aed,bvl,csf,csg,csn,csr,ecs,esn,
	gsm,hds,lsp,mfs,ncs,prl,pys,ssp,vsl
fi	fse
fr	fcs,fsl
hu	hsh
id	inl
it	ise
ja	jsl
ko	kvk
pl	pso
pt	bzs,mzy,psr,sgn_AO
ro	rms
ru	rsl
sk	svk
sq	sql
st	jw_ssa
zh	csl,tss

Table 5: There are 48 languages in the JW300 corpus with language codes that correspond to sign languages, but in reality are unrelated high-resource languages (usually the most spoken language in the country of origin of the sign language). This table shows the actual language of the data corresponding to each sign language code.

Code in JW300 BCP-47 code Actual Language Name

Incorrect private-use extensions

hy_arevmda	hyw	Western Armenian
jw_dgr	os_x_dgr	Digor Ossetian
jw_dmr	naq_x_dmr	Damara Khoekhoe
jw₋ibi	yom_x_ibi	Ibinda Kongo
jw_paa	pap_x_paa	Papiamento (Aruba)
jw_qcs	qxl	Salasaca Highland Kichwa
jw_rmg	rmn_x_rmg	Greek Romani (South)
jw_rmv	rmy_x_rmv	Vlax Romani, Russia
jw_spl	nso_x_spl	Sepulana
jw_ssa	st_ZA	Sesotho (South Africa)
jw_tpo	pt_PT	Portuguese (Portugal)
jw_vlc	ca_x_vlc	Catalan (Valencia)
$jw_{-}vz$	skg_x_vz	Vezo Malagasy
rmy_AR	rmy_x_?	Kalderash

Equivalent codes used in place of extensions

1		I
kmr_latn	kmr_x_rdu	Kurmanji (Caucasus)
nya	ny_x_?	Chinyanja (Zambia)
que	qu_x_?	Quechua (Ancash)

Deprecated codes

													. 1				-																
-		_	_	_	_	_	_	_	_	_	-	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	_	-
	daf	•									n	j/1	d٤	ı					Г)a	n												

ISO-693-3 used in place of ISO-693-2

cat	ca	Catalan
gug	gn	Guarani
run	rn	Kirundi
tso_MZ	ts_MZ	Changana (Mozambique)

Table 6: Language code issues in the JW300 datasets for 22 language varieties not covered by Tables 4 and 5. Twelve languages have codes starting in j_{W-} , suggesting they are varieties of Javanese, but are instead mis-parsed private-use extensions. Three codes appear in addition to equivalent ISO codes, making it unclear which languages they are. One language uses a deprecated ISO code. Four languages use the ISO639-3 code instead of the ISO639-2 code, and therefore are not BCP-47. (Note: in this table, private use extensions are given as they appear in jw.org, and specified as '?' if they are absent from jw.org.)

	es_XX	bm_ML	yo_NG	tr_TR	ku_TR	zh_CN	af_ZA	jv_ID	zh_TW	it_IT	mean
Acc-6	0.58	0.73	0.41	0.45	0.43	0.55	0.65	0.55	0.46	0.55	0.66
Acc-4	0.77	0.73	0.60	0.55	0.56	0.72	0.72	0.57	0.58	0.66	0.72
Acc-2	0.91	0.96	0.72	0.64	0.71	0.79	0.77	0.92	0.81	0.69	0.79

Table 7: Rater evaluation for a subset of audits from **CCAligned** (translated from English) measured by the accuracy (Acc-n) of labels assigned by non-proficient speaker against those assigned by proficient speakers. n indicates the granularity of the classes. For n=6 all classes of the taxonomy were distinguished, for n=4 the $\mathbb C$ subclasses were combined, and for n=2 it is binary decision between $\mathbb C$ and the rest of the error classes.

	tyv	rm	bar	eml	zh	la	mean
Acc-6	1.0	0.98	1.0	1.0	0.86	1.0	0.98
Acc-4	1.0	1.0	1.0	1.0	0.87	1.0	0.98
Acc-2	1.0	1.0	1.0	1.0	0.87	1.0	0.98

Table 8: Rater evaluation for a subset of audits from **OSCAR** measured by the accuracy (Acc-n) of labels assigned by non-proficient speaker against those assigned by proficient speakers. n indicates the granularity of the classes. For n=6 all classes of the taxonomy were distinguished, for n=4 the C subclasses were combined, and for n=2 it is binary decision between C and the rest of the error classes.

corpus	code in corpus	correct code
CCAligned	ZZ	zza
CCAligned	SZ	szl
CCAligned	ns	nso
CCAligned	cb	ckb
CCAligned	tz	ber
CCAligned	qa	shn
CCAligned	qd	kac
CCAligned	cx	ceb
mC4	iw	he
OSCAR	eml	egl
OSCAR	als	gsw
OSCAR	sh	hbs
Wikimatrix	sh	hbs

Table 9: Miscellaneous errors in language codes not in other tables (mentioned in the text in Section 5).

C Non-proficient Rater Evaluation

Tables 7 and 8 show the detailed rating accuracy scores for all selected languages for several levels of annotation granularity. We can see that for the CCAligned data, reducing the labels to a binary scale naturally increases the accuracy (except for tr_TR), so a binary interpretation ("correct" sentence vs. error) is the most reliable. For monolingual data, the accuracy appears exceptionally high since the bar and tyv corpora contain < 100 sentences each (4 and 25, respectively).

en	The prime minister of the UK is Boris Johnson.
nl	De minister-president van Nederland is Mark Rutte .
en	24 March 2018
pt_	14 Novembro 2018
en -	The current local time in Sarasota is 89 minutes.
nn	Den lokale tiden i Miami er 86 minutt.
en	In 1932 the highway was extended north to LA.
bar	1938 is de Autobahn bei Inglstod fertig gstellt.

Table 10: Examples of "parallel" data where the translation has a different meaning than the source, but the form looks the same. Such data may encourage hallucinations of fake "facts".

D Not-So-Parallel Data

Table 10 contains a list of examples from the audited datasets that were misaligned (X). These examples in particular illustrate that structurally similar sentences can easily describe very different facts. Translation models trained on such examples might hallucinate such fact-altering translations.

E Quality vs Size

To understand the relation between the amount of data available for each language in each corpus and the quality as estimated by our audit, we plot the ratio of X, NL and WL labels against the number of sentences in figures 3, 4, 5, 6.

F Methodological Notes

A surprising amount of work can be done without being an expert in the languages involved. The easiest approach is simply to search the internet for the sentence, which usually results in finding the exact page the sentence came from, which in turn frequently contains clues like language codes in the URL, or a headline like *News in X language*, sometimes with references to a translated version of the same page. However, for the cases where

this is insufficient, here are a few tips, tricks, and observations.

No Skills Required

Things that do not require knowledge of the language(s) in question.

- 1. "Not language" can usually be identified by anyone who can read the script, though there are tricky cases with proper nouns.
- 2. Frequently, "parallel" sentences contain different numbers in the source and target (especially autogenerated content), and are easy to disqualify
- 3. Errors tend to repeat. If a word is mistranslated once, it will often be mistranslated many more times throughout a corpus, making it easy to spot

Basic Research Required

Things that do not require knowledge of the language(s) in question but can be done with basic research.

- 1. If it's written in the wrong script it's considered wrong language. (Sometimes the writing system is indicated in the published corpus, e.g. bg-Latn, but usually the language has a "default" script defined by ISO.)
- 2. Some types of texts come with inherent labels or markers, such as enumerators or verse numbers.
- 3. When all else fails, search the internet for the whole sentence or n-grams thereof! If the whole sentence can be found, frequently the language is betrayed by the webpage (the language's autonym is useful in this case).

G Aspirational Error Taxonomy

Given some issues we encountered with the error taxonomy used for this paper, we present here a slightly modified version which we hope is both more explicit and finer-grained. The main changes are 1) replacing "CB" and "CS" with a catch-all for lower-quality sentences "CL", and 2) incorporating two codes for languages with related dialects. This is also by no means a perfect rubric, and would benefit from some fine-tuning and workshopping based on the particular dataset or application in question.

- **CC:** Correct: Natural in-language sentence. It's ok if it has a few small issues, like spelling errors or a few words from another language, or if it's a sentence fragment of reasonable length (about 5 words or more). For translations, there may be minor mistakes in the translation.
- CL: Correct Low-quality: In-language sentence, but low-quality. This could be ungrammatical text, boilerplate, or very short fragments. For translations, this is the appropriate code for a low-quality translation.
- X: Incorrect translation [for parallel sentences] both source and target are in the correct language, but they are not adequate translations.
- DW: Wrong Dialect This code is only applicable for dialects that are closely related to other languages/dialects. This sentence is in a related but different dialect to the language it's supposed to be in. For instance, it's supposed to be in Sa'idi Arabic but it's in Egyptian Arabic.
- DA: Ambiguous Dialect This code is only applicable for dialects that are closely related to other languages/dialects. Correct but ambiguous whether it's in the correct language. For instance, many short sentences in Gulf Arabic may also be valid in MSA, and many written Cantonese sentences might also be valid in Mandarin.
- WL: Wrong language This sentence is not in the language it's supposed to be. For short sentences, especially with proper nouns, there is often a fine line between "Wrong language" and "Not language". Do your best.
- NL: Not language At least one of source and target are not linguistic content. Any sentence consisting only of a proper noun (e.g. "Ibuprofin", "Calvin Klein", or "Washington DC") should be marked as NL
- U: Unknown for sentences that need verification by a native speaker. This is an auxiliary label that is resolved in most cases.

Special note on Boilerplate: "Boilerplate" generally refers to autogenerated text found on web-

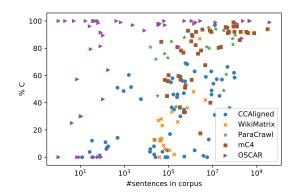


Figure 3: Ratio of C ratings vs size.

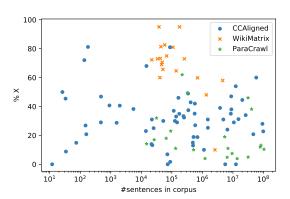


Figure 4: Ratio of X ratings vs size.

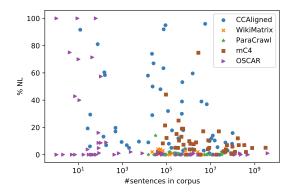


Figure 5: Ratio of NL ratings vs size.

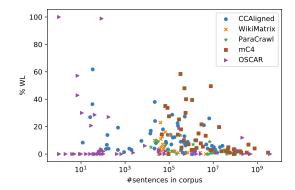


Figure 6: Ratio of WL ratings vs size.

sites. It's not always clear when a sentence is boilerplate or not. If you see a lot of similar formulaic sentences in the sample, however, that's a good sign that they are boilerplate, and you can mark them all as "CL"! Common types of boilerplate include sentences like "Convert Euro to Pound", "Online gambling games", "Download Game of Thrones Free Torrent" and so on.

Special note on Mixed Language: Some samples are mixed between the right language and some other language. Some out-of-language content is fine, but a majority out-of-language content is not. We can mark the sentence "CC" if: 1) it is majority in-language, and 2) the in-language portion is more than a short phrase. For unclear border cases you can use "CL".

H Complete Tables

Tables 11, 14, 15, 13, and 12 give the complete annotation percentages for CCAligned, MC4, OSCAR, Paracrawl, and Wikimatrix, respectively.

	. C	CC	CS	СВ	. X	WL	NL	porn	#sentences	avg target length
en-sz_PL	0.00%	0.00%	0.00%	0.00%	0.00%	8.33%	91.67%	0.00%	#sentences	71.42
en-mt_MT	3.85%	0.00%	3.85%	0.00%	50.00%	26.92%	19.23%	0.00%	26	12.58
en-tz_MA	12.12%	6.06%	6.06%	0.00%	45.45%	36.36%	6.06%	0.00%	33	57.33
en-zz_TR	0.00%	0.00%	0.00%	0.00%	8.82%	61.76%	29.41%	0.00%	34	46.53
en-kg_AO	1.35%	0.00%	1.35%	0.00%	14.86%	2.70%	81.08%	0.00%	74	29.20
en-qa_MM	11.03%	5.88%	3.68%	1.47%	72.06%	3.68%	13.24%	0.00%	136	55.28
en-bm_ML	6.04%	4.03%	2.01%	0.00%	26.85%	6.71%	60.40%	0.00%	149	32.19
en-az_IR en-qd_MM	6.93% 7.92%	6.93% 4.95%	0.00% 1.98%	0.00% 0.99%	20.79% 81.19%	13.86% 3.96%	58.42% 6.93%	0.00% 0.00%	158 179	115.85 60.34
en-ay_BO	51.00%	33.00%	18.00%	0.00%	29.00%	3.00%	17.00%	0.00%	475	92.19
en-ak_GH	14.23%	13.60%	0.63%	0.00%	46.86%	19.25%	19.67%	0.00%	478	45.85
en-st_ZA	48.57%	42.14%	0.00%	6.43%	40.71%	1.43%	9.29%	0.00%	904	111.83
en-ve_ZA	60.40%	29.70%	21.78%	8.91%	28.71%	3.96%	6.93%	0.00%	1555	82.99
en-ts_ZA	51.49%	34.65%	11.88%	4.95%	40.59%	2.97%	4.95%	0.00%	1967	73.93
en-or_IN	42.61%	6.09%	24.35%	12.17%	38.26%	9.57%	9.57%	0.00%	5526	71.39
en-ns_ZA en-lg_UG	4.00% 6.00%	2.00% 0.00%	0.00% 6.00%	2.00% 0.00%	23.00% 68.00%	15.00% 17.00%	58.00% 9.00%	4.00% 2.00%	14138 14701	33.52 15.83
en-ln_CD	8.00%	4.00%	3.00%	1.00%	14.00%	4.00%	74.00%	4.00%	21562	28.80
en-om_KE	2.00%	2.00%	0.00%	0.00%	31.00%	38.00%	29.00%	24.00%	22206	23.83
en-ss_SZ	12.65%	9.04%	3.61%	0.00%	13.25%	24.10%	50.00%	13.86%	22960	25.30
en-te_IN_rom	0.00%	0.00%	0.00%	0.00%	25.00%	8.00%	67.00%	5.00%	25272	24.21
en-cb_IQ	4.00%	1.00%	3.00%	0.00%	30.00%	18.00%	48.00%	11.00%	52297	30.04
en-tn_BW en-ff_NG	0.00%	0.00% 0.00%	0.00%	0.00% 0.00%	6.90% 0.00%	8.97% 8.00%	63.45% 92.00%	10.34% 2.00%	71253 73022	16.80 33.59
en-sn_ZW	5.00%	1.00%	0.00% 3.00%	1.00%	81.00%	14.00%	0.00%	0.00%	86868	102.59
en-wo_SN	0.00%	0.00%	0.00%	0.00%	1.71%	3.31%	94.98%	18.46%	88441	27.25
en-br_FR	17.00%	3.00%	1.00%	13.00%	37.00%	14.00%	32.00%	1.00%	115128	41.68
en-zu_ZA	55.00%	39.00%	3.00%	13.00%	30.00%	7.00%	8.00%	3.00%	126101	79.32
en-ku_TR	36.52%	12.17%	13.04%	11.30%	33.04%	28.70%	1.74%	1.74%	137874	90.51
en-ig_NG	58.00%	49.00%	3.00%	6.00%	29.00%	12.00%	1.00%	0.00%	148146	83.42
en-kn_IN en-yo_NG	46.00% 34.93%	9.00% 6.16%	6.00% 10.96%	31.00% 17.81%	46.00% 34.93%	2.00% 12.33%	5.00% 17.81%	4.00% 0.00%	163921 175192	70.20 75.01
en-ky_KG	44.12%	24.51%	17.65%	1.96%	33.33%	22.55%	0.00%	0.98%	240657	69.56
en-tg_TJ	46.08%	18.63%	24.51%	2.94%	32.35%	20.59%	0.98%	4.90%	251865	75.31
en-ha_NG	30.00%	25.00%	3.00%	2.00%	49.00%	9.00%	12.00%	1.00%	339176	60.78
en-am_ET	59.11%	35.47%	2.46%	21.18%	37.44%	2.96%	0.49%	0.00%	346517	58.29
en-km_KH	56.12%	12.24%	33.67%	10.20%	42.86%	1.02%	0.00%	0.00%	412381	71.35
en-ne_NP	47.00%	10.00%	13.00%	24.00%	15.00%	8.00%	30.00%	14.00%	487155	79.14
en-su_ID en-ur_PK_rom	35.00% 0.50%	15.00% 0.00%	15.00% 0.50%	5.00% 0.00%	13.00% 18.91%	13.00% 27.36%	39.00% 53.23%	0.00% 5.47%	494142 513123	57.08 18.41
en-ht_HT	55.67%	8.25%	10.31%	37.11%	35.05%	6.19%	3.09%	1.03%	558167	101.95
en-mn_MN	33.00%	8.00%	14.00%	11.00%	42.00%	7.00%	18.00%	12.00%	566885	44.43
en-te_IN	69.00%	42.00%	11.00%	16.00%	27.00%	1.00%	3.00%	1.00%	581651	97.95
en-kk_KZ	68.32%	40.59%	18.81%	8.91%	18.81%	8.91%	3.96%	1.98%	689651	72.36
en-be_BY	90.00%	57.00%	13.00%	20.00%	10.00%	0.00%	0.00%	2.00%	1125772	118.45
en-af_ZA	63.00%	40.00%	23.00%	0.00%	31.00% 25.25%	2.00% 10.10%	4.00%	12.00%	1504061	105.45
en-jv_ID en-nl_NL	5.05% 46.00%	1.01% 27.00%	1.01% 19.00%	3.03% 0.00%	49.00%	2.00%	59.60% 3.00%	8.08% 0.00%	1513974 36324231	18.34 85.95
en-hi_IN_rom	1.00%	0.00%	0.00%	1.00%	39.00%	21.00%	39.00%	8.00%	3789571	18.13
en-lv_LV	59.00%	37.00%	9.00%	13.00%	31.00%	7.00%	3.00%	14.00%	4850957	83.67
en-ar_AR_rom	0.00%	0.00%	0.00%	0.00%	0.00%	4.00%	96.00%	4.00%	5584724	16.69
en-tl_XX	13.00%	6.00%	3.00%	4.00%	24.00%	26.00%	37.00%	5.00%	6593250	37.03
en-uk_UA	63.00%	42.00%	8.00%	13.00%	35.00%	1.00%	1.00%	5.00%	8547348	67.88
en-zh_TW en-el_GR	46.00%	11.00% 15.00%	31.00%	4.00% 29.00%	47.00% 38.00%	6.00% 3.00%	1.00% 10.00%	1.00% 8.00%	8778971 8878492	24.89 54.90
en-da_DK	54.00%	31.00%	5.00% 18.00%	5.00%	29.00%	5.00%	12.00%	7.00%	10738582	73.99
en-vi_VN	31.00%	18.00%	0.00%	13.00%	54.00%	1.00%	14.00%	6.00%	12394379	74.19
en-sv_SE	97.00%	91.00%	3.00%	3.00%	0.00%	3.00%	0.00%	0.00%	12544075	103.91
en-zh_CN	57.29%	22.92%	12.50%	21.88%	31.25%	1.04%	10.42%	1.04%	15181410	33.55
en-tr_TR	45.00%	14.50%	14.00%	16.50%	44.50%	5.00%	5.50%	4.00%	20282339	83.80
en-ja_XX	57.00%	35.00%	21.00%	1.00%	34.00%	6.00%	0.00%	0.00%	26201214	34.44
en-pt_XX	66.34%	36.63%	10.89%	18.81%	20.79%	3.96%	8.91%	0.00%	46525410	87.20
en-it_IT en-de_DE	36.00% 62.00%	14.00% 29.00%	18.00% 14.00%	4.00% 19.00%	60.00% 28.00%	1.00% 2.00%	3.00% 8.00%	0.00% 2.00%	58022366 92597196	97.44 78.08
en-es_XX	58.42%	16.83%	25.74%	15.84%	28.00%	2.00%	15.84%	4.95%	98351611	72.18
	20.1270	10.00 %	20.7170	10.0170		,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	10.0170	,5 /0	,0001011	, 2.10

Table 11: Audit results for a sample of 100 sentences from **CCAligned** for each language pair, compared to the number of sentences available in the dataset. If fewer than 100 sentences were available, all sentences were audited. Language codes are as originally published. The length is measured in number of characters and averaged across the audited portion of each corpus. Languages with less than 20% correct sentences are boldfaced.

	C	CC	CS	СВ	X	WL	NL	porn	# sentences	avg target length
en-ug	12.87%	8.91%	1.98%	1.98%	72.28%	9.90%	1.98%	0.00%	22012	95.55
en-mwl	27.00%	26.00%	0.00%	1.00%	73.00%	0.00%	0.00%	0.00%	33899	135.26
en-tg	0.00%	0.00%	0.00%	0.00%	95.10%	3.92%	0.98%	0.00%	37975	88.87
en-ne	13.00%	7.00%	6.00%	0.00%	60.00%	23.00%	4.00%	0.00%	40549	69.26
en-ka	11.88%	2.97%	2.97%	5.94%	73.27%	10.89%	2.97%	0.00%	41638	144.74
en-lmo	12.75%	11.76%	0.00%	0.98%	81.37%	4.90%	0.98%	0.00%	43790	89.38
en-io	28.00%	27.00%	0.00%	1.00%	69.00%	2.00%	1.00%	0.00%	45999	83.26
en-jv	13.73%	9.80%	0.00%	3.92%	70.59%	12.75%	2.94%	0.00%	48301	91.87
en-wuu	23.23%	14.14%	7.07%	2.02%	65.66%	7.07%	4.04%	0.00%	51024	34.77
br-en	8.70%	7.61%	1.09%	0.00%	82.61%	4.35%	0.00%	0.00%	58400	90.68
bar-en	6.00%	6.00%	0.00%	0.00%	75.00%	16.00%	3.00%	0.00%	67394	103.51
en-kk	5.00%	2.00%	2.00%	1.00%	81.00%	14.00%	0.00%	0.00%	109074	56.03
en-sw	33.33%	27.27%	4.04%	2.02%	64.65%	2.02%	0.00%	0.00%	138590	111.61
en-nds	1.96%	1.96%	0.00%	0.00%	95.10%	1.96%	0.98%	0.00%	178533	91.95
be-en	26.00%	24.00%	2.00%	0.00%	73.00%	1.00%	0.00%	0.00%	257946	121.22
en-hi	36.27%	32.35%	0.98%	2.94%	59.80%	0.98%	2.94%	0.00%	696125	96.77
en-ko	48.04%	33.33%	2.94%	11.76%	48.04%	2.94%	0.98%	0.00%	1345630	55.18
en-uk	87.00%	84.00%	2.00%	1.00%	10.00%	1.00%	2.00%	0.00%	2576425	104.39
en-it	42.00%	42.00%	0.00%	0.00%	58.00%	0.00%	0.00%	0.00%	4626048	140.27
en-simple	37.62%	24.75%	0.00%	12.87%	56.44%	2.97%	2.97%	0.00%	nan	77.53

Table 12: Audit results for a sample of 100 sentences from **WikiMatrix** for each language pair, compared to the number of sentences available in the dataset. Language codes are as originally published. The length is measured in number of characters and averaged across the audited portion of each corpus. Languages with less than 20% correct sentences are boldfaced.

	C	CC	CS	CB	X	WL	NL	porn	# sentences	avg target length
en-so	80.81%	61.62%	1.01%	18.18%	14.14%	5.05%	0.00%	0.00%	14879	189.83
en-ps	72.00%	53.00%	9.00%	10.00%	17.00%	10.00%	0.00%	0.00%	26321	141.01
en-my	45.00%	9.00%	16.00%	20.00%	32.00%	9.00%	14.00%	0.00%	31374	147.07
en-km	76.00%	51.00%	13.00%	12.00%	18.00%	6.00%	0.00%	0.00%	65113	121.20
en-ne	73.00%	48.00%	1.00%	24.00%	23.00%	2.00%	0.00%	0.00%	92084	153.42
en-sw	85.00%	60.00%	15.00%	10.00%	11.00%	2.00%	2.00%	0.00%	132517	167.34
en-si	37.00%	31.00%	6.00%	0.00%	62.00%	0.00%	1.00%	0.00%	217407	123.06
en-nn	35.92%	24.27%	8.74%	2.91%	49.51%	13.59%	0.97%	0.00%	323519	56.24
es-eu	88.00%	66.00%	15.00%	7.00%	10.00%	1.00%	1.00%	0.00%	514610	121.31
es-gl	89.00%	46.00%	6.00%	37.00%	4.00%	7.00%	0.00%	0.00%	1222837	107.88
en-ru	81.00%	73.00%	6.00%	2.00%	19.00%	0.00%	0.00%	6.00%	5377911	101.28
en-bg	95.15%	85.44%	0.97%	8.74%	4.85%	0.00%	0.00%	0.97%	6470710	112.29
es-ca	80.00%	54.00%	19.00%	7.00%	11.00%	9.00%	0.00%	5.00%	6870183	107.21
en-el	91.59%	68.22%	0.93%	22.43%	7.48%	0.93%	0.00%	0.00%	9402646	135.66
en-pl	94.12%	76.47%	0.98%	16.67%	3.92%	1.96%	0.00%	0.98%	13744860	95.95
en-nl	49.00%	32.00%	17.00%	0.00%	46.00%	3.00%	2.00%	0.00%	31295016	95.05
en-pt	93.07%	92.08%	0.00%	0.99%	4.95%	1.98%	0.00%	0.00%	31486963	108.68
en-it	60.82%	36.08%	16.49%	8.25%	38.14%	0.00%	1.03%	0.00%	40798278	127.55
en-es	87.00%	54.00%	20.00%	13.00%	12.00%	0.00%	1.00%	0.50%	78662122	119.72
en-de	82.83%	64.65%	13.13%	5.05%	13.13%	3.03%	1.01%	0.00%	82638202	111.43
en-fr	89.62%	82.08%	4.72%	2.83%	10.38%	0.00%	0.00%	0.00%	104351522	144.20

Table 13: Audit results for a sample of 100 sentences from **ParaCrawl** for each language pair, compared to the number of sentences available in the dataset. Language codes are as originally published. The length is measured in number of characters and averaged across the audited portion of each corpus.

	C	CC	CS	СВ	WL	NL	porn	# sentences	avg length
yo	84.69%	71.43%	2.04%	11.22%	14.29%	1.02%	0.00%	46214	117.71
st	56.70%	42.27%	14.43%	0.00%	35.05%	8.25%	0.00%	66837	132.13
haw	44.90%	34.69%	1.02%	9.18%	33.67%	21.43%	1.02%	84312	129.99
ig	55.91%	41.73%	10.24%	3.94%	0.00%	44.09%	0.79%	92909	98.03
sm	60.20%	58.16%	2.04%	0.00%	27.55%	12.24%	0.00%	98467	126.42
ha	80.81%	79.80%	1.01%	0.00%	14.14%	5.05%	2.02%	247479	155.76
su	59.60%	58.59%	1.01%	0.00%	25.25%	15.15%	2.02%	280719	107.10
sn	36.63%	32.67%	2.97%	0.99%	58.42%	4.95%	0.00%	326392	145.59
mg	57.00%	57.00%	0.00%	0.00%	18.00%	25.00%	0.00%	345040	116.23
pa	78.30%	68.87%	3.77%	5.66%	4.72%	10.38%	0.00%	363399	134.43
ga	76.77%	58.59%	6.06%	12.12%	10.10%	13.13%	0.00%	465670	147.35
co	33.00%	29.00%	2.00%	2.00%	48.00%	19.00%	0.00%	494913	195.30
zu	51.00%	48.00%	2.00%	1.00%	30.00%	19.00%	0.00%	555458	137.81
jv	52.73%	19.09%	19.09%	14.55%	40.00%	7.27%	1.82%	581528	97.96
km	92.86%	92.86%	0.00%	0.00%	7.14%	0.00%	0.00%	756612	162.57
kn	85.15%	73.27%	3.96%	7.92%	2.97%	9.90%	0.00%	1056849	105.39
fy	56.73%	50.00%	3.85%	2.88%	39.42%	3.85%	0.00%	1104359	234.25
te	89.00%	76.00%	9.00%	4.00%	3.00%	8.00%	0.00%	1188243	108.49
la	82.31%	65.38%	6.15%	10.77%	10.00%	7.69%	0.00%	1674463	67.25
be	92.04%	86.73%	2.65%	2.65%	4.42%	3.54%	0.00%	1742030	110.86
af	76.00%	76.00%	0.00%	0.00%	15.00%	9.00%	0.00%	2152243	99.52
lb	17.48%	17.48%	0.00%	0.00%	7.77%	74.76%	0.00%	2740336	481.68
ne	78.35%	77.32%	1.03%	0.00%	21.65%	0.00%	0.00%	2942785	102.88
sr	93.69%	85.59%	7.21%	0.90%	5.41%	0.00%	0.00%	3398483	131.72
gl	67.62%	57.14%	10.48%	0.00%	13.33%	17.14%	0.00%	4549465	151.45
bn	93.00%	86.00%	1.00%	6.00%	3.00%	4.00%	0.00%	7444098	92.60
mr	40.00%	35.24%	2.86%	1.90%	49.52%	10.48%	0.00%	7774331	281.94
sl	92.08%	82.18%	4.95%	4.95%	2.97%	4.95%	0.00%	8499456	149.45
hi b c	80.30%	76.77%	1.01%	2.53% 2.51%	19.70%	0.00%	2.53%	18507273	105.54
bg	80.90%	75.88%	2.51% 7.54%	6.53%	2.01% 2.01%	17.09% 2.51%	0.00% 0.00%	23409799 38556465	93.86 116.79
uk	95.48% 94.95%	81.41% 78.79%	12.12%	4.04%	3.03%	2.02%	0.00%	45738857	130.08
ro sv	94.93%	84.31%	2.94%	3.92%	4.90%	3.92%	1.96%	48570979	114.45
zh	92.00%	87.00%	1.00%	4.00%	1.00%	7.00%	0.00%	54542308	94.77
ja	99.00%	89.00%	6.00%	4.00%	0.00%	1.00%	1.00%	87337884	59.94
tr	95.96%	88.89%	0.00%	7.07%	3.54%	0.51%	0.00%	87595290	152.75
nl	92.08%	85.15%	6.93%	0.00%	1.98%	5.94%	0.00%	96210458	103.67
pl	96.00%	82.00%	7.00%	7.00%	2.00%	2.00%	0.00%	126164277	170.70
pt	86.00%	79.00%	4.00%	3.00%	2.00%	12.00%	1.00%	169239084	133.51
it	92.00%	79.00%	9.00%	4.00%	1.00%	7.00%	0.00%	186404508	180.26
fr	92.00%	82.00%	7.00%	3.00%	1.00%	7.00%	0.00%	332674575	143.69
de	91.18%	77.45%	7.84%	5.88%	6.86%	1.96%	0.00%	397006993	107.71
ru	91.06%	69.11%	11.38%	10.57%	4.07%	4.88%	0.00%	755585265	109.28
en	93.94%	83.84%	8.08%	2.02%	1.01%	5.05%	0.00%	3079081989	130.97
bg_latn	9.09%	9.09%	0.00%	0.00%	51.52%	39.39%	1.01%	N/A	139.92
ja_latn	13.00%	7.00%	4.00%	2.00%	60.00%	27.00%	0.00%	N/A	218.92
ru_latn	36.45%	25.23%	10.28%	0.93%	34.58%	28.97%	0.93%	N/A	123.14
zh_latn	5.00%	4.00%	1.00%	0.00%	64.00%	31.00%	0.00%	N/A	186.84
	l				l				

Table 14: Audit results for a sample of 100 sentences from **mC4** for each language, compared to the number of sentences available in the dataset. Language codes are as originally published. The length is measured in number of characters and averaged across the audited portion of each corpus. Languages with less than 20% correct sentences are boldfaced.

1	C	CC	CS	СВ	WL	NL	porn	# sentences	avg length
diq	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1	131.00
bcl	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	1	623.00
cbk	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	1	519.00
pam	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2	139.00
bar	25.00%	25.00%	0.00%	0.00%	0.00%	75.00%	0.00%	4	53.50
myv	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5	127.00
yue	0.00%	0.00%	0.00%	0.00%	57.14%	42.86%	0.00%	7	177.00
mwl	57.14%	57.14%	0.00%	0.00%	42.86%	0.00%	0.00%	7	141.00
frr	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	9	231.56
ht	30.00%	30.00%	0.00%	0.00%	0.00%	70.00%	0.00%	10	329.10
ie	30.00%	30.00%	0.00%	0.00%	30.00%	40.00%	0.00%	11	121.70
scn	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	17	155.59
tyv	96.15%	96.15%	0.00%	0.00%	0.00%	3.85%	0.00%	26	167.96
mai	79.31%	75.86%	0.00%	3.45%	20.69%	0.00%	0.00%	29	141.17
bxr	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	37	160.76
dsb	100.00%	97.56%	0.00%	2.44%	0.00%	0.00%	0.00%	41	155.15
so	0.00%	0.00%	0.00%	0.00%	28.57%	71.43%	0.00%	42	208.24
rm	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	47	137.66
nah	100.00%	96.67%	0.00%	3.33%	0.00%	0.00%	0.00%	60	164.53
nap	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	61	152.11
yo	98.46%	96.92%	0.00%	1.54%	1.54%	0.00%	0.00%	64	281.57
gn	81.48%	81.48%	0.00%	0.00%	2.47%	16.05%	0.00%	81	234.95
vec	91.36%	91.36%	0.00%	0.00%	0.00%	8.64%	0.00%	81	184.90
kw	91.57%	90.36%	0.00%	1.20%	3.61%	4.82%	0.00%	83	162.75
wuu	0.00%	0.00%	0.00%	0.00%	98.84%	1.16%	0.00%	86	157.15
eml	42.57%	42.57%	0.00%	0.00%	0.00%	57.43%	0.00%	104	177.88
bh	89.42%	21.15%	0.00%	68.27%	1.92%	8.65%	0.00%	104	137.17
min	64.00%	6.00%	0.00%	58.00%	27.00%	9.00%	0.00%	180	649.85
qu	100.00%	98.97%	0.00%	1.03%	0.00%	0.00%	0.00%	425	167.27
su	99.00%	99.00%	0.00%	0.00%	0.00%	1.00%	0.00%	676	221.00
jv	97.00%	86.00%	0.00%	11.00%	1.00%	2.00%	0.00%	2350	203.08
als	93.00%	93.00%	0.00%	0.00%	6.00%	1.00%	0.00%	7997	375.44
la	98.00%	98.00%	0.00%	0.00%	2.00%	0.00%	0.00%	33838	224.11
uz	98.00%	98.00%	0.00%	0.00%	2.00%	0.00%	0.00%	34244	369.99
nds	97.03%	95.05%	0.00%	1.98%	2.97%	0.00%	0.00%	35032	344.74
sw	98.00%	98.00%	0.00%	0.00%	0.00%	2.00%	0.00%	40066	196.70
br	100.00%	96.00%	0.00%	4.00%	0.00%	0.00%	0.00%	61941	239.56
fy	97.00%	97.00%	0.00%	0.00%	2.00%	1.00%	0.00%	67762	340.23
am	81.09%	79.10%	0.00%	1.99%	18.91%	0.00%	0.00%	287142	267.43
af	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	517353	339.18
eu	100.00%	98.00%	0.00%	2.00%	0.00%	0.00%	0.00%	1099498	330.93
mn	98.00%	94.00%	0.00%	4.00%	2.00%	0.00%	0.00%	1430527	309.94
te	98.99%	93.94%	1.01%	4.04%	0.00%	1.01%	1.01%	1685185	412.31
kk	100.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2719851	318.93
ca	99.00%	91.00%	0.00%	8.00%	1.00%	0.00%	0.00%	13292843	333.38
nl	98.00%	94.00%	2.00%	2.00%	2.00%	0.00%	4.00%	126067610	305.01
it	87.13%	71.29%	1.98%	13.86%	11.88%	0.99%	1.98%	210348435	393.66
I .	100.00%	97.00%	0.00%	3.00%	0.00%	0.00%	1.00%	232673578	195.60
I .	100.00%	93.00%	0.00%	7.00%	0.00%	0.00%	5.00%	461349575	306.62
	100.00%	94.00%	0.00%	6.00%	0.00%	0.00%	3.00%	488616724	268.07
en	99.00%	96.00%	0.00%	3.00%	0.00%	1.00%	1.00%	3809525119	364.65

Table 15: Audit results for a sample of 100 sentences from **OSCAR** for each language, compared to the number of sentences available in the dataset. If fewer than 100 sentences were available, all sentences were audited Language codes are as originally published. Length is measured in number of characters. Languages with less than 20% correct sentences are boldfaced.