DCAD-2000: A Multilingual Dataset across 2000+ Languages with Data Cleaning as Anomaly Detection

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Abstract

The rapid development of multilingual large language models (LLMs) highlights the need for high-quality, diverse, and well-curated multilingual datasets. In this paper, we introduce DCAD-2000 (Data Cleaning as Anomaly Detection), a large-scale multilingual corpus constructed from newly extracted Common Crawl data and existing multilingual sources. DCAD-2000 covers 2,282 languages, 46.72TB of text, and 8.63 billion documents, spanning 155 high- and medium-resource languages and 159 writing scripts. To overcome the limitations of existing data cleaning approaches, which rely on manually designed heuristic thresholds, we reframe data cleaning as an anomaly detection problem. This dynamic filtering paradigm substantially improves data quality by automatically identifying and removing noisy or anomalous content. By fine-tuning LLMs on DCAD-2000, we demonstrate notable improvements in data quality, robustness of the cleaning pipeline, and downstream performance, particularly for low-resource languages across multiple multilingual benchmarks.

Dataset: https://huggingface.co/datasets/openbmb/DCAD-2000
Pipeline: https://github.com/yl-shen/DCAD-2000

1 Introduction

Large language models (LLMs) have achieved great progress on a variety of NLP tasks by leveraging vast amounts of training data [1]. However, their performance remains heavily biased towards high-resource languages [2, 3]. To improve the multilingual capabilities of LLMs, a common strategy is to incorporate large amounts of non-English data, either by continue pretraining [4] or by instruction tuning in multilingual settings [5]. Therefore, constructing large-scale, high-quality multilingual datasets is crucial for enhancing the multilingual performance of LLMs.

Recent efforts have introduced several large multilingual corpora, including CulturaX [9], HPLT [13], Madlad-400 [10], MaLA [15], and Glotcc [12], which cover 167, 191, 419, 939, and 1,331 languages, respectively. While these datasets have made significant contributions, they exhibit three major limitations, as summarized in Table 1: **(1) Outdated data sources:** These datasets primarily rely on older Common Crawl snapshots[1], which results in outdated knowledge and an elevated risk of

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[1]https://commoncrawl.org

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Table 1: Comparison of multilingual datasets constructed from Common Crawl (CC) and our constructed DCAD-2000, focusing on the latest CC version used, the total number of languages supported, distribution across resource categories (high, medium, low, very low), and training readiness. The CC version marked with underline indicates an inferred version due to the lack of explicit specification in the original paper. The "Training-Ready" column indicates whether the dataset is ready for training LLMs without requiring further data cleaning.

Dataset	CC Version	#Langs (total)	#Langs (high)	#Langs (medium)	#Langs (low)	#Langs (very low)	Training-Ready
mC4 [6]	CC-MAIN-2020-34	101	0	43	52	6	✗
OSCAR 23.01 [7]	CC-MAIN-2022-49	153	6	42	25	80	✗
Glot500 [8]	CC-MAIN-2020-34	511	0	108	79	324	✗
CulturaX [9]	CC-MAIN-2022-49	167	11	47	27	82	✗
Madlad-400 [10]	CC-MAIN-2022-33	419	7	46	39	327	✗
MaLA [11]	CC-MAIN-2022-49	939	1	125	78	735	✗
Glotcc [12]	CC-MAIN-2023-50	1331	0	10	52	1269	✗
HPLT-v1.2 [13]	CC-MAIN-2022-40	191	12	53	38	88	✗
Fineweb-2 [14]	CC-MAIN-2024-18	1915	10	62	49	1794	✗
DCAD-2000	CC-MAIN-2024-46	2282	13	142	124	2003	✓

hallucination [16]. **(2) Limited coverage of high- and medium-resource languages[2]:** For instance, Fineweb-2 [14], despite supporting 1,915 languages, contains data from only 10 high-resource and 62 medium-resource languages. **(3) Insufficient data cleaning:** Despite being cleaned, recent studies [18, 19] indicate that these datasets still contain a significant amount of noise, which makes them difficult to directly employ in training multilingual LLMs. For example, Sailor [18] reports that 31.11% of Madlad-400 data could still be removed using more advanced cleaning.

Traditional data cleaning workflows [20] often rely on document-level heuristics (e.g., language identification; 21) and fixed thresholds to filter low-quality samples. However, these heuristic thresholds often fail to generalize across languages due to distributional differences in features such as word count, repetition ratios, and perplexity[3]. Notably, while Fineweb-2 fine-tunes thresholds for more than 1,000 languages, this process is computationally intensive and time-consuming.

To address these challenges, we introduce DCAD-2000, a new large-scale, high-quality multilingual dataset that can be directly applied to LLM training. DCAD-2000 covers 2282 languages (155 high/medium languages), incorporating the latest Common Crawl data (November 2024; `CC-MAIN-2024-46`) and existing multilingual datasets. Additionally, we propose a novel language-agnostic data cleaning approach that treats data cleaning as an anomaly detection [22] problem, distinguishing it from traditional threshold-based methods [14, 23]. Our approach extracts eight statistical features, including *number of words*, *character/word repetition ratio*, *special character/word ratio*, *stopword ratio*, *flagged words ratio*, *language identification score* and *perplexity score*. Anomaly detection algorithms dynamically identify and remove outliers by recognizing deviations from typical document quality metrics.

We conduct a comprehensive analysis of DCAD-2000 with respect to document distribution, linguistic and geographical characteristics, writing scripts, and resource classification (Section 4). By fine-tuning LLMs on DCAD-2000, we validate the effectiveness of its data quality and data cleaning pipeline. Furthermore, we demonstrate the superiority of DCAD-2000 across various language categories (high, medium, low and very low) in multiple multilingual benchmarks, including SIB-200 [24], Glot500 [8] and FLORES-200 [25] (Section 5).

In summary, we make the following contributions:

- We propose a novel data cleaning framework that frames the task as anomaly detection, offering a language-agnostic and adaptive solution without manual threshold tuning.
- We release DCAD-2000, a comprehensive multilingual dataset covering over 2,282 languages, containing 8.63B of documents, 46.72TB of disk size and 159 writing scripts with metadata annotations.

[2]We follow the criteria from Flores-101 [17] to categorize languages: High: $> 100M$; Medium: $(1M, 100M)$; Low: $(100K, 1M)$; Very Low: $< 100K$.

[3]Please refer to Appendix A for more details.

- Extensive evaluation across multiple multilingual benchmarks demonstrates the effectiveness of both the data quality and the data cleaning pipeline.

2 Related Work

Multilingual Dataset for Pretraining. Enhancing the multilingual capabilities of LLMs often involves continuing pretraining on large-scale multilingual datasets [11, 15]. These datasets can be broadly categorized into curated corpora, domain-specific corpora, and web-crawled corpora. **(I) Curated Corpora.** Curated datasets are carefully gathered by experts from high-quality sources such as books [23], academic publications [26], and encyclopedia entries [27, 28, 29]. **(II) Domain-Specific Corpora.** In addition to general-domain data, fine-tuning LLMs on domain-specific datasets is crucial for improving performance in specialized domains like finance [30], healthcare [31], legal [32], and education [33, 34]. **(III) Web-Crawled Corpora.** Web-crawled datasets, particularly those derived from Common Crawl, provide large-scale multilingual coverage by leveraging an open repository of over 250 billion web pages. These datasets include mC4 [6], CC-100 [35], OSCAR [7], Glotcc [12], Fineweb [36], and Fineweb-2 [14]. While curated and domain-specific corpora offer high-quality content with limited language coverage, web-crawled corpora provide broader multilingual coverage but often suffer from noise and lower data quality [18, 19].

Data Cleaning. Data cleaning is an essential step in preparing high-quality datasets for training robust LLMs. It involves filtering noisy, irrelevant, or harmful content and can be broadly classified into model-based and heuristic-based approaches [37]. **(I) Model-Based Methods.** Model-based approaches employ classifiers or LLMs to distinguish between high-quality and low-quality data. For instance, content safety models [38] filter out explicit or gambling-related content, while quality classifiers remove low-relevance text [39]. LLM-based methods focus on generating prompts for cleaning [40] or integrating error detection and correction into the pipeline [41, 42]. **(II) Heuristic-Based Methods.** Heuristic approaches apply predefined rules to filter content at both document and sentence levels. At the document level, strategies include filtering by language identification scores or scoring documents with language models [9, 23]. At the sentence level, rules are applied to remove incomplete or irrelevant content, such as HTML tags or excessively short sentences [6, 7]. While model-based methods offer high precision but face scalability challenges, heuristic-based methods are more efficient yet less adaptable to diverse multilingual data.

3 DCAD-2000

To overcome the limitations of existing multilingual datasets, we introduce DCAD-2000, a large-scale, high-quality multilingual dataset constructed by integrating data from latest version of Common Crawl and existing multilingual datasets (Section 3.1). This dataset is cleaned using our proposed novel framework, which treats data cleaning as an anomaly detection problem (Section 3.2). The construction of DCAD-2000 is supported by robust computational resources, as detailed in Section 3.3.

3.1 Data Collection

To ensure comprehensive and robust multilingual data representation, DCAD-2000 integrates data from four main sources: MaLA, Fineweb, Fineweb-2, and newly extracted Common Crawl data. Each source is selected based on its unique contribution to multilingual coverage, data quality, and freshness, with careful consideration to complementarity to minimize redundancy. Specifically, MaLA and Fineweb-2 are prioritized due to their broad language coverage and high-quality curation, which complements other widely used datasets like mC4 [6] and OSCAR [7].

MaLA Corpus [11]. The MaLA corpus covers 939 languages, aggregating data from diverse sources including Bloom [43], CC100 [35], Glot500 [8], among others. Deduplication is performed using MinHashLSH [44], which is particularly effective in removing near-duplicate entries that often arise from common web sources. Language codes are based on ISO 639-3[4] standards, and language-specific scripts are supported by GlotScript[5].

[4] https://en.wikipedia.org/wiki/ISO_639-3

[5] https://github.com/cisnlp/GlotScript

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Fineweb Corpus [36]. Fineweb is a high-quality English web dataset extracted from Common Crawl, consisting of over 15 trillion tokens and updated monthly. Data cleaning and deduplication are performed using the Datatrove library.[6] For DCAD-2000, we incorporate data from the November 2024 release (`CC-MAIN-2024-46`) to ensure freshness and up-to-date relevance of the data.

Fineweb-2 Corpus [14]. Fineweb-2 expands Fineweb to include multilingual data, covering 1,915 languages. It processes 96 Common Crawl dumps from 2013 (`CC-MAIN-2013-20`) to April 2024 (`CC-MAIN-2024-20`). The deduplication process within Fineweb-2 is similarly handled using the Datatrove library, ensuring the exclusion of redundant entries and maintaining high-quality multilingual coverage.

Newly Extracted Common Crawl Data. To incorporate the most recent multilingual data, we extract and process Common Crawl dumps from May 2024 (`CC-MAIN-2024-22`) to November 2024 (`CC-MAIN-2024-46`). Using the Fineweb-2 pipeline[7], we process 21.54TB of multilingual data, ensuring that the data remains fresh and suitable for downstream tasks. This further extends the multilingual data pool and enhances the coverage across underrepresented languages.

3.2 Data Cleaning as Anomaly Detection

Traditional data cleaning methods rely on fixed thresholds for document-level features, making them less adaptable to the diversity of multilingual data. To address this, we propose a novel framework that formulates data cleaning as an anomaly detection task, which involves feature extraction (Section 3.2.1) and anomaly detection (Section 3.2.2).

3.2.1 Feature Extraction

Inspired by Roots [23] and CulturaX [9], we extract eight statistical features from each document to evaluate text quality. Each feature is selected for its ability to capture important characteristics of the text, contributing to robust anomaly detection. Let t represent a document; the extracted features are:

- **Number of Words, $n_w(t)$:** Total number of tokens after language-specific tokenization, providing a coarse measure of document length and helping identify extremely short or excessively long outliers.
- **Character Repetition Ratio, $r_c(t)$:** Fraction of repeated character sequences (e.g., "aaaaa" or "!!!!!"), which often signal encoding artifacts, copy-paste errors, or spam-like content.
- **Word Repetition Ratio, $r_w(t)$:** Proportion of repeated lexical items, useful for detecting low-information documents that exhibit looping or template-like patterns.
- **Special Characters Ratio, $r_s(t)$:** Fraction of characters belonging to special symbol categories. We employ the curated language-specific symbol lists provided in the ROOTs Corpus [23], covering punctuation, numeric symbols, whitespace variants, and emojis. A high $r_s(t)$ may indicate adversarial inputs or unstructured noise.
- **Stopwords Ratio, $r_{\text{stop}}(t)$:** Ratio of stopwords derived from Fineweb-2's multilingual stopword lexicons. This metric captures the functional-to-content word balance, offering a lightweight approximation of linguistic naturalness.
- **Flagged Words Ratio, $r_{\text{flag}}(t)$:** Fraction of tokens that appear in curated lists of toxic or profane vocabulary such as *Toxicity-200* [25] and community-maintained sources[8]. This feature enables early detection of harmful or sensitive content.
- **Language Identification (LID) Score, $s_{\text{lid}}(t)$:** Confidence score produced by GlotLID [21], a language identifier supporting over 2,000 languages. Lower scores may indicate code-switching, mislabeling, or mixed-script anomalies.
- **Perplexity Score, $s_{\text{ppl}}(t)$:** We compute a language model perplexity score using KenLM [45] models trained per language on the November 2023 snapshot of multilingual Wikipedia[9]. This feature provides a lightweight proxy for linguistic fluency.

[6] `https://github.com/huggingface/datatrove`

[7] `https://github.com/huggingface/fineweb-2`

[8] `https://github.com/thisandagain/washyourmouthoutwithsoap`

[9] KenLM models are only trained for languages with sufficient clean Wikipedia data (minimum 10,000 high-quality sentences). For other languages, we assign a default perplexity score of 500.

The feature vector for each document is defined as:

$$\mathbf{x} = [n_w(t),\, r_c(t),\, r_w(t),\, r_s(t),\, r_{\text{stop}}(t),\, r_{\text{flag}}(t),\, s_{\text{lid}}(t),\, s_{\text{ppl}}(t)]^\top \in \mathbb{R}^8. \tag{1}$$

3.2.2 Anomaly Detection

After extracting feature vectors $\mathbf{x} \in \mathbb{R}^8$, we standardize each feature to handle differences in scale. The standardized value $\tilde{x}_j$ for the j-th feature is given by:

$$\tilde{x}_j = \frac{x_j - \mu_j}{\sigma_j}, \quad j = 1, \ldots, 8. \tag{2}$$

where μ_j and σ_j are the mean and standard deviation of the j-th feature across the dataset. The standardized feature vector is:

$$\tilde{\mathbf{x}} = \frac{\mathbf{x} - \boldsymbol{\mu}}{\boldsymbol{\sigma}}. \tag{3}$$

where $\boldsymbol{\mu} = [\mu_1, \mu_2, \ldots, \mu_8]^\top$ and $\boldsymbol{\sigma} = [\sigma_1, \sigma_2, \ldots, \sigma_8]^\top$ are the vectors of means and standard deviations, respectively.

Take Isolation Forest [46] as an example[10], we compute an anomaly score $\phi(\tilde{\mathbf{x}})$ for each document. The Isolation Forest algorithm assigns anomaly scores based on the average path length required to isolate a data point in a decision tree. Specifically, for a document represented by $\tilde{\mathbf{x}}$, the anomaly score is defined as:

$$\phi(\tilde{\mathbf{x}}) = 2^{-\frac{h(\tilde{\mathbf{x}})}{c(n)}}. \tag{4}$$

where $h(\tilde{\mathbf{x}})$ is the average path length for $\tilde{\mathbf{x}}$ across all trees in the Isolation Forest, and $c(n)$ is the average path length of a point in a binary tree with n samples, given by:

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n}. \tag{5}$$

where $H(i)$ is the i-th harmonic number, defined as $H(i) = \sum_{k=1}^{i} \frac{1}{k}$.

An anomaly score $\phi(\tilde{\mathbf{x}}) : \mathbb{R}^8 \to \mathbb{R}$ is defined to quantify how far a document deviates from typical data. Higher scores indicate a higher likelihood of anomalies. To classify a document, we use the decision rule:

$$f(\tilde{\mathbf{x}}) = \begin{cases} 1, & \text{if } \phi(\tilde{\mathbf{x}}) < \tau, \\ -1, & \text{if } \phi(\tilde{\mathbf{x}}) \geq \tau. \end{cases} \tag{6}$$

where $\tau \in \mathbb{R}$ is a hyperparameter determined empirically or through cross-validation.[11]

Once the anomaly scores $\phi(\tilde{\mathbf{x}})$ are computed for all samples in the standardized dataset $\tilde{\mathcal{X}} = \{\tilde{\mathbf{x}}_1, \ldots, \tilde{\mathbf{x}}_N\}$, we partition the dataset into two subsets:

$$\mathcal{X}_{\text{keep}} = \{\tilde{\mathbf{x}} \in \tilde{\mathcal{X}} : f(\tilde{\mathbf{x}}) = 1\}, \tag{7}$$

$$\mathcal{X}_{\text{remove}} = \{\tilde{\mathbf{x}} \in \tilde{\mathcal{X}} : f(\tilde{\mathbf{x}}) = -1\}. \tag{8}$$

Following anomaly detection, the dataset is partitioned into a clean subset $\mathcal{X}_{\text{keep}}$ and an anomalous subset $\mathcal{X}_{\text{remove}}$. The former is retained for downstream tasks such as model training, while the latter may be discarded or further examined for potential data quality issues.

3.2.3 Visualization

To qualitatively evaluate the separation achieved by our data cleaning framework, we present scatter plots of the eight feature dimensions in Figure 1, with data points color-coded by their anomaly labels. These visualizations facilitate the interpretation of decision boundaries and highlight the features that contribute most significantly to the detection process. We observe well-defined clusters separating anomalous and non-anomalous data points, with anomalies exhibiting distinct patterns compared to the majority of the data. Features such as the language identification score ($s_{\text{lid}}(t)$) and perplexity score ($s_{\text{ppl}}(t)$) are expected to be particularly discriminative in identifying anomalies, as they capture linguistic irregularities and unexpected text patterns. For example, low lid or unusually high ppl scores often indicate problematic text, such as spam, low-quality content, or noise. The framework effectively identifies and removes such low-quality text samples, which can be easily visualized by the separation of these points in the scatter plots.

[10]We also evaluate some other algorithms, please refer to Section 5 for more details.

[11]We use the default settings of the specific anomaly detection algorithm in Scikit-learn, applying these settings globally rather than individually for each feature or language.

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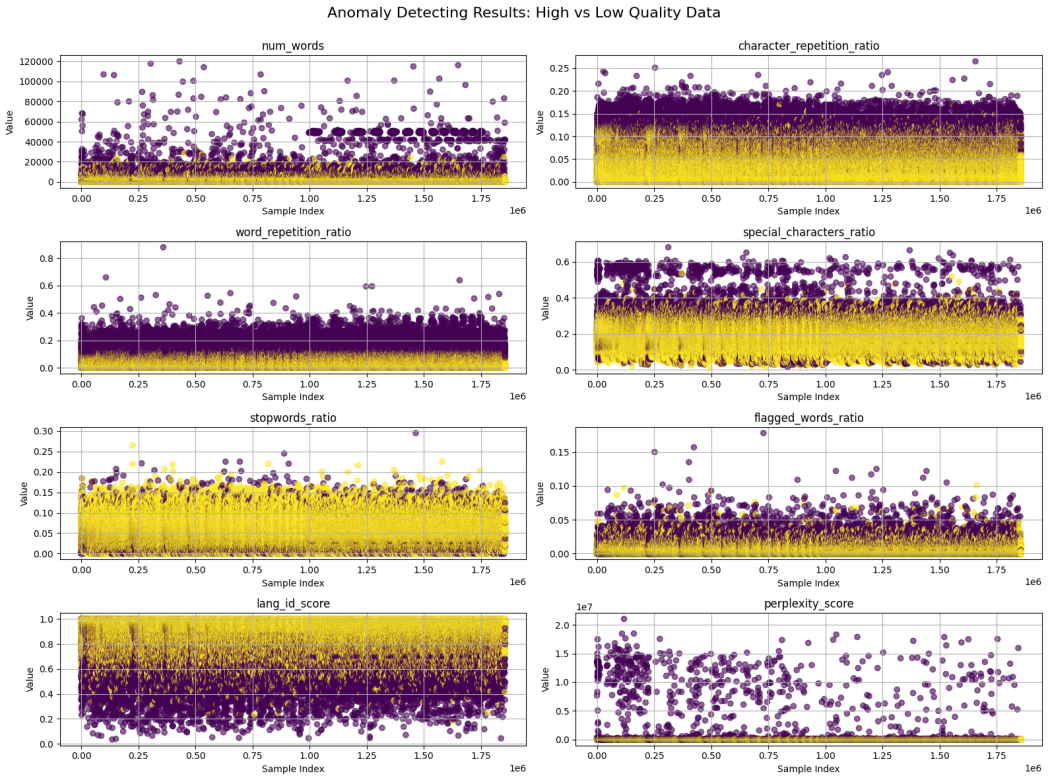


Figure 1: Scatter plots of eight features extracted from a Chinese corpus during the data cleaning process, with data points color-coded according to their anomaly labels. The yellow points represent high-quality data, while the purple points indicate low-quality data.

3.3 Computational Resources

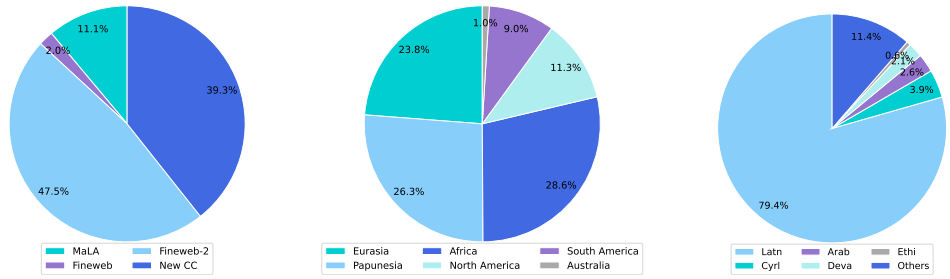
The construction of the DCAD-2000 dataset leveraged Ksyun servers[12] to process and clean the multilingual data efficiently. Each server instance is equipped with 32 CPU cores, 128GB of memory, and 100GB of disk storage, which is utilized for intermediate data handling and memory-intensive operations such as anomaly detection. The workload is managed using container orchestration tools, Kubernetes[13], with up to 100 parallel tasks running per job to ensure scalability.

4 Dataset Analysis

In this section, we analyze the characteristics of DCAD-2000, focusing on document distribution across sources, geographic and script coverage, resource categorization of languages, and the effect of data cleaning on dataset size and quality.

Document Distribution Across Data Sources. The DCAD-2000 dataset is derived from four primary sources: MaLA, Fineweb, Fineweb-2, and Newly Extracted Common Crawl data (New CC), as described in Section 3.1. Figure 2a presents the distribution of documents across these sources, with Fineweb-2 and New CC collectively contributing 47.5% and 39.3% of the total dataset, respectively. These two sources play a significant role in ensuring the dataset's emphasis on both language diversity (Fineweb-2) and corpus freshness (New CC). MaLA, though contributing 11.1% of the total dataset, brings in valuable content from non-Common Crawl sources, further enriching the diversity of the dataset, especially for low-resource languages.

[12] https://www.ksyun.com
[13] https://kubernetes.io



(a) Document Distribution (b) Geographical Distribution (c) Script Distribution

Figure 2: Document distribution and linguistic diversity in DCAD-2000.

Geographical Coverage of Languages. Figure 2b shows the geographical distribution of languages in DCAD-2000, based on the number of unique languages available in each region, as classified by Glottolog.[14] The dataset spans languages from all major world regions, with the largest proportions originating from Africa (28.6%), Papunesia (26.3%) and Eurasia (23.8%). This coverage ensures robust support for multilingual applications across varied regional contexts, including densely populated areas like Eurasia and sparsely populated regions such as Papunesia and Australia. While Eurasia is more heavily represented, this diversity of linguistic coverage helps ensure that the dataset remains useful for training LLMs in diverse regional environments.

Script Distribution. Figure 2c illustrates the distribution of languages in DCAD-2000 by writing system. The dataset supports 159 scripts, with the Latin script dominating at 79.4%, followed by Cyrillic (3.9%), Arabic (2.6%), and Devanagari (2.1%), among others. This diversity in scripts enables a wide range of cross-lingual and script-specific tasks. However, the inclusion of minority scripts, especially those with limited resources, poses unique challenges, such as optical character recognition (OCR) difficulties for certain scripts or inconsistent text quality. Despite these challenges, DCAD-2000 ensures comprehensive coverage by including data from diverse scripts. A complete list of supported scripts is provided in Appendix B.

Language Resource Classification. Following the classification approach proposed by Flores [17], we categorize languages in DCAD-2000 into four groups based on corpus size: high-resource, medium-resource, low-resource, and extremely low-resource. Table 1 shows the distribution across these categories. The dataset includes 155 high- and medium-resource languages, while low-resource languages make up a significant portion, which reflects DCAD-2000's commitment to supporting underrepresented languages. Notably, DCAD-2000 surpasses other corpora in its balance between high-resource and low-resource languages, which can have a significant impact on multilingual model training. The distribution of languages across categories ensures that the dataset is well-suited for developing models that perform effectively across diverse language resources.

Impact of Data Cleaning. We summarize the document count, token count, and disk size of the high/medium/low resource languages in DCAD-2000 before and after the data cleaning process. Complete details are provided in Appendix C. The cleaning process results in the removal of a substantial amount of noisy data, even from datasets like MaLA, Fineweb, and Fineweb-2, which had already been subject some cleaning. This aligns with the findings from [18, 19]. For example, in the MaLA dataset, 8.05 million documents are removed for the *hbs_Latn* language, which suggests the necessity of rigorous data cleaning to enhance dataset quality. Overall, the cleaning process removed approximately 7.69% of the documents across all languages, significantly improving the quality of the dataset by reducing noise and increasing relevance for model training (Section 5).

5 Evaluation

Following Fineweb-2 [14], we conduct a series of experiments on the FineTask benchmark[15] to evaluate the effectiveness of our proposed data cleaning pipeline and assess the quality of the DCAD-2000 dataset. FineTask comprises tasks in nine languages (i.e., *Chinese*, *French*, *Arabic*, *Russian*, *Thai*,

[14]Geographic data source: `https://glottolog.org`

[15]`https://huggingface.co/spaces/HuggingFaceFW/blogpost-fine-tasks`

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Table 2: The performance of various anomaly detection algorithms. **Bold** and underlined numbers indicates the best and second-best results respectively.

	LLaMA-3.2-1B					Qwen-2.5-7B					Aya-expanse-32B				
	Baseline	Iso_Forest	OC_SVM	LOF	K-Means	Baseline	Iso_Forest	OC_SVM	LOF	K-Means	Baseline	Iso_Forest	OC_SVM	LOF	K-Means
Arabic	0.07	**0.21**	0.18	**0.21**	0.14	0.63	**0.71**	0.68	0.65	0.68	0.69	**0.75**	0.70	0.71	0.69
Turkish	0.07	0.27	**0.29**	0.17	0.15	0.65	0.72	**0.73**	0.67	0.68	0.75	**0.79**	0.77	0.76	0.77
Swahili	0.08	**0.29**	0.25	0.19	0.19	0.25	0.34	0.27	**0.35**	0.27	0.35	**0.44**	0.36	0.37	0.41
Russian	0.10	**0.24**	0.19	0.18	0.15	0.74	**0.79**	0.75	0.75	0.76	0.77	**0.82**	0.79	0.80	0.79
Telugu	0.02	**0.06**	0.05	0.04	0.04	0.16	0.24	**0.26**	0.20	0.21	0.15	0.25	0.19	0.21	**0.27**
Thai	0.14	**0.21**	0.18	0.18	0.15	0.57	**0.64**	0.59	0.59	0.61	0.38	**0.46**	0.42	0.43	0.40
Chinese	0.12	**0.32**	0.28	0.25	0.21	0.75	**0.82**	0.77	0.76	0.78	0.69	**0.75**	0.71	0.71	0.73
French	0.11	0.35	**0.37**	0.30	0.23	0.74	**0.80**	0.76	0.76	0.75	0.74	**0.79**	0.76	0.76	0.76
Hindi	0.07	**0.21**	0.17	0.16	0.14	0.49	**0.57**	0.52	0.53	0.52	0.69	**0.74**	0.72	0.73	0.72

Hindi, *Turkish*, *Swahili*, and *Telugu*), and covers a diverse set of NLP tasks, including reading comprehension, commonsense reasoning, natural language understanding, and text generation. To investigate the impact of different data cleaning strategies and anomaly detection algorithms, we continue pretraining on three typical LLMs: `LLaMA-3.2-1B`[47], `Qwen-2.5-7B`[48], and `Aya-expanse-32B`[49]. Additionally, we analyze the performance across different resource categories using the SIB-200[24], Glot500-c [8], and FLORES-200 [25] benchmarks. We report normalized accuracy for FineTask, raw accuracy for SIB-200, negative log-likelihood (NLL) for Glot500-c, and BLEU scores for FLORES-200. Full experimental settings and results are provided in Appendix D.

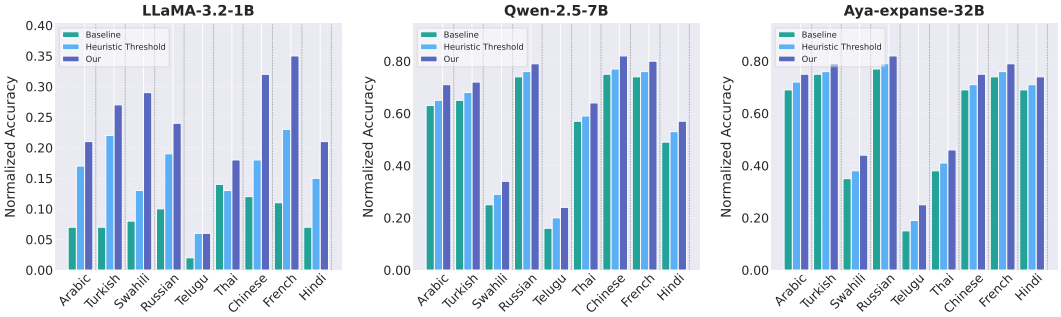


Figure 3: The performance comparison of models trained using various data cleaning methods.

Impact of Different Data Cleaning Strategies. We evaluate the effectiveness of our proposed anomaly detection-based data cleaning framework by comparing model performance across various cleaning strategies. As illustrated in Figure 3, the baseline model trained on raw, unfiltered data consistently underperforms relative to all cleaning methods. This performance gap is primarily due to noisy, irrelevant, or inconsistent data that hinders model generalization. Traditional threshold-based filtering[16], which removes low-quality samples using fixed rules based on features, yields modest improvements. In contrast, our anomaly detection-based approach dynamically identifies and filters anomalous or noisy data, resulting in significantly enhanced model performance. Models trained using our method achieve normalized accuracy improvements of approximately 5–20% over the baseline, and outperform the threshold-based approach by 3–10%. Threshold-based approaches trade accuracy for efficiency, whereas our framework, despite higher computational demands, uncovers subtle and cross-lingual data anomalies that fixed rules frequently overlook.

Comparison of Anomaly Detection Algorithms. We compare several classical anomaly detection algorithms to identify the most effective approach for constructing DCAD-2000. The evaluated methods include Isolation Forest (ISO_Forest;46), One-Class SVM (OC_SVM; 50), Local Outlier Factor (LOF;51), and K-Means [52], using implementations from scikit-learn[17]. We provide the comparison of different algorithms in Appendix D.3. Table 2 reports the performance of these algorithms in cleaning the dataset. While all anomaly detection methods outperform the unfiltered baseline, the performance of OC_SVM, LOF, and K-Means is notably inconsistent. These algorithms often require extensive parameter tuning (e.g., selecting the number of neighbors for LOF or the kernel type for OC_SVM), which introduces sensitivity to hyperparameters and increases computational overhead. In contrast, ISO_Forest demonstrates more stable and robust performance across experiments, attributed to its efficiency in handling noisy, high-dimensional multilingual data. Unlike other methods,

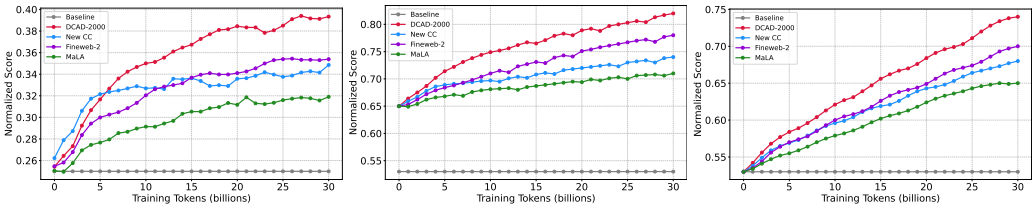
[16]We use the implementation from `https://github.com/bigscience-workshop/data-preparation`

[17]`https://scikit-learn.org`

Table 3: Performance across different language categories. We use accuracy (↑) in SIB-200, negative log-likelihood (↓) in Glot500-c and BLEU (↑) in FLORES-200. Improvements are highlighted accordingly.

		LLaMA-3.2-1B			Qwen-2.5-7B			Aya-expanse-32B		
		Fineweb-2	New CC	DCAD-200	Fineweb-2	New CC	DCAD-200	Fineweb-2	New CC	DCAD-200
SIB-200 (↑)	H	8.24	8.86	**10.37** ↑2.13	33.41	34.53	**38.26** ↑4.85	41.72	42.41	**47.93** ↑6.21
	M	7.31	7.92	**9.15** ↑1.84	28.72	29.86	**32.65** ↑3.93	32.25	33.39	**38.16** ↑5.91
	L	6.06	6.45	**7.83** ↑1.77	23.58	24.22	**27.12** ↑3.54	26.87	27.57	**33.24** ↑6.37
	VL	3.68	4.27	**5.24** ↑1.56	13.25	15.43	**21.57** ↑8.32	17.23	19.5	**26.38** ↑9.15
Glot500-c test (↓)	H	426.37	403.58	**373.14** ↓53.23	347.21	334.18	**303.38** ↓43.83	273.85	257.24	**225.28** ↓48.57
	M	446.28	436.94	**423.75** ↓22.53	385.72	389.24	**369.15** ↓16.57	326.92	321.16	**302.53** ↓24.39
	L	503.38	493.27	**473.96** ↓29.42	426.33	419.25	**404.28** ↓22.05	372.62	367.26	**341.34** ↓31.28
	VL	584.55	569.34	**532.86** ↓51.69	479.04	463.36	**433.48** ↓45.56	396.33	392.33	**385.86** ↓10.47
FLORES-200 (↑) (Eng–X)	H	3.14	3.82	**5.26** ↑2.12	15.24	16.07	**18.47** ↑3.23	23.45	24.33	**26.33** ↑2.88
	M	2.75	2.94	**3.89** ↑1.14	12.83	13.46	**15.49** ↑2.66	19.36	20.21	**21.62** ↑2.26
	L	2.27	2.41	**3.14** ↑0.87	8.94	9.28	**10.25** ↑1.31	16.61	17.24	**18.36** ↑1.75
	VL	1.85	2.05	**2.35** ↑0.50	6.33	7.25	**9.05** ↑2.72	12.51	13.16	**14.77** ↑2.26
FLORES-200 (↑) (X–Eng)	H	3.94	3.98	**4.26** ↑0.32	16.31	16.92	**18.84** ↑2.53	23.86	24.13	**26.94** ↑3.08
	M	3.52	3.66	**3.80** ↑0.28	13.65	14.05	**16.27** ↑2.62	20.45	20.36	**22.53** ↑2.17
	L	3.05	3.12	**3.24** ↑0.19	9.47	10.22	**11.48** ↑2.01	17.67	17.82	**18.93** ↑1.26
	VL	2.73	2.83	**3.14** ↑0.41	7.28	7.81	**9.65** ↑2.37	13.25	13.56	**15.88** ↑2.63

ISO_Forest delivers reliable results without intensive hyperparameter tuning, making it particularly suitable for large-scale multilingual datasets. However, ISO_Forest can be more computationally demanding than simpler methods like K-Means, especially in high-dimensional settings (our feature vectors have eight dimensions, as described in Section 3.2.2). Despite this trade-off, its robustness and scalability establish ISO_Forest as the most appropriate choice for data cleaning in DCAD-2000.



(a) French – LLaMA-3.2-1B (b) Chinese – Qwen-2.5-7B (c) Turkish – Aya-expanse-32B

Figure 4: Comparison of DCAD-2000 with existing multilingual corpora for three languages—French, Chinese, and Turkish—evaluated using different multilingual LLMs.

Comparison with Other Multilingual Datasets. To validate the quality of DCAD-2000, we compare it against existing multilingual corpora on the FineTask benchmark. These corpora include datasets constructed from *New CC*, *MaLA*, and *Fineweb-2* as described in Section 3.1. As shown in Figure 4, models trained on DCAD-2000 consistently outperform those trained on other datasets, achieving higher normalized accuracy. The improvements can be attributed to the enhanced data quality, diversity, and reduced noise resulting from our comprehensive cleaning pipeline. Specifically, DCAD-2000 provides greater linguistic diversity and a more balanced representation of low-resource languages, leading to improved performance on tasks involving underrepresented languages like Swahili and Telugu.

Analysis by the Categories of Language Resources. Table 3 presents model performance across languages categorized by resource levels (High, Medium, Low, and Very Low). Across all benchmarks and model sizes, DCAD-2000 consistently outperforms Fineweb-2 and New CC. While the gains are modest for high-resource languages, improvements are substantial for low- and very low-resource languages, reaching up to +9.15 accuracy on SIB-200 and -53.23 NLL on Glot500-c, which highlights the effectiveness of our cleaning pipeline in improving data quality where it is most needed. The BLEU results on FLORES-200 further validate these trends, with notable improvements in both English-to-X and X-to-English translation tasks. These consistent gains across tasks and languages demonstrate that DCAD-2000 enables more balanced multilingual performance and is well-suited for training inclusive, high-quality language models.

Manual Quality Evaluation of Cleaning Pipeline. To assess the effectiveness of our cleaning pipeline, we conduct a manual quality evaluation on five representative languages: English, Chinese, German, Japanese, and French. More specifically, we randomly sampled 100 retained and 100

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deleted documents per language, with each document labeled by a proficient annotator as "*Good*," ''*Borderline*," or ''*Bad*." The evaluation revealed that the pipeline retained high-quality content with minimal residual noise (4.4%) and low false positive rates (5.2%). These results confirm the robustness of our unsupervised, anomaly-detection-based method in effectively removing low-quality content while preserving valuable data. Full details of the experimental setup and results can be found in the Appendix E.

Further Investigation. To evaluate the practical trade-offs between conventional heuristic filtering and our anomaly-based framework, we conduct a controlled cost–benefit analysis and found that DCAD incurs only minor computational overhead while improving downstream task performance; please refer to Appendix F for more details. To assess the robustness of different feature combinations, we performed an ablation study on the 8-dimensional feature vector and observed that each feature contributes meaningfully, with the Language Identification confidence score being particularly critical; please refer to Appendix G for more details. To justify the practical choice of anomaly detector and explore future extensions, we analyzed the trade-offs between classical and modern deep anomaly detection methods and highlighted the scalability, interpretability, and resource efficiency of Isolation Forest; please refer to Appendix H for more details.

6 Conclusion

In this paper, we introduce DCAD-2000, a large-scale multilingual dataset designed to address the increasing demand for high-quality and diverse training data for multilingual LLMs. Our dataset spans 2,282 languages, providing comprehensive coverage across various geographic regions, scripts (159 scripts), and larger coverage of high/medium resource languages (155 languages). To avoid manually setting thresholds during the data cleaning process, we propose a novel framework that reframes data cleaning as an anomaly detection task. This dynamic approach ensures effective identification and removal of anomalous data from noisy datasets. Empirical experiments demonstrate the effectiveness of our proposed data cleaning framework and the high quality of the DCAD-2000 dataset across multiple multilingual benchmarks.

7 Limitations

This work has the following limitations: **(i)** Although the proportion of high/medium/low resource languages in DCAD-2000 has greatly increased compare to existing multilingual datasets, a significant portion of the languages are still very low resource languages. Future work will explore to collect data for extremely low-resource languages through other modalities (e.g., images) through technologies like OCR. **(ii)** We evaluate the new data cleaning framework only on four classical anomaly detection algorithms; however, since the framework is algorithm-independent, it should also be effective with other anomaly detection algorithms. **(iii)** For language identification, we use GlotLID [21], a FastText-based model whose limitations in handling massive multilinguality have been discussed in previous works [53]. However, since the data cleaning pipeline is language-agnostic, other language identification models can also be employed. **(iv)** We use a classical, feature-based anomaly detection algorithm rather than modern deep or embedding-based methods [54] because of the lack of clean reference distributions, the need for scalability across thousands of languages, and resource constraints. We will explore incorporating semantic embedding-based or lightweight deep anomaly detectors in future work to capture subtler anomalies that our current approach may miss.

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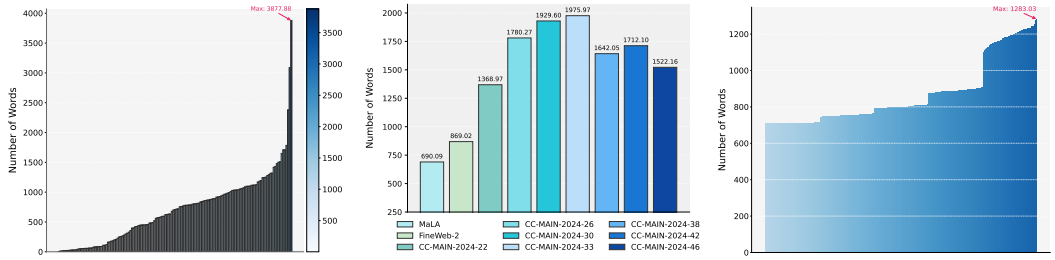
A Statistical Analysis of Multilingual Datasets

In this section, we explore the statistical characteristics of the dataset through visual analysis, focusing on the distribution of data across different languages and the variations observed across different shards. We highlight the limitations of existing data cleaning methods that rely on fixed thresholds, particularly in the imbalanced data distribution scenarios. Specifically, when there are substantial discrepancies in word count distributions, these threshold-based cleaning methods are prone to errors, which fail to accurately distinguish between high-quality and low-quality data.



(a) Different Languages (b) Different Sources (c) Different Shards

Figure 5: Distribution of average word counts across different languages, sources, and shards in the New CC dataset.

Figure 5a illustrates the average word count distribution across different languages in the New CC dataset (CC-MAIN-2024-38). We observe substantial variation in the average word count across languages within the same dataset. For instance, some languages exhibit an average word count as high as 4,000, indicating that their texts are generally longer, while others have an average word count ranging from 50 to 100, suggesting that their texts are typically shorter. This imbalanced distribution complicates the application of traditional fixed-threshold data cleaning methods across all languages. For example, setting a word count threshold of 800 (e.g., the median word count) may be suitable for many languages, but it would still misclassify a significant portion of data as low-quality.

Figure 5b illustrates the average word count distribution for Chinese across different data sources (MaLA, Fineweb-2, and New CC). We observe significant variation in the word count distribution for the same language across these sources. For example, the average word count for Chinese in the MaLA corpus is 690, while in New CC (CC-MAIN-2024-33), the average word count increases to 1,975. This discrepancy highlights the inadequacy of a single fixed threshold for data from different sources. Applying a uniform threshold could lead to incorrect cleaning of Chinese text from certain data sources, potentially compromising the representativeness and quality of the data. Consequently, it is essential to adopt flexible cleaning strategies tailored to the characteristics of each data source.

Figure 5c illustrates the variation in word count for Chinese across different shards in the Fineweb-2 dataset. We observe imbalanced word count distributions between shards, which further complicates the data cleaning process. For instance, some shards contain texts with word counts concentrated between 700 and 1,000, while others have texts primarily between 1,000 and 1,200. This shard-level variation suggests that fixed-threshold cleaning methods may perform inconsistently across different shards, fails to account for the unique characteristics of the data within each shard. Therefore, in the presence of such imbalanced distributions, it is crucial to implement a more flexible data cleaning approach.

B DCAD-2000 Grouped by Writting Scripts

As mentioned in Section 4, DCAD-2000 contains a total of 159 writing scripts. To provide a comprehensive overview, we list each of these scripts and their corresponding statistical information in Table 7 and Table 8. By presenting this information, we aim to highlight the broad range of writing systems represented by DCAD and emphasize its potential in various linguistic research and applications.

C Data Cleaning Statistics

In this section, we provide detailed data cleaning statistics (Table 9, 10, 11 and 12) for high-resource, medium-resource, and low-resource languages. For the data cleaning statistics of very low-resource languages, please refer to the open-source data statistics we released.

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D Experimental Setup

In this section, we provide a comprehensive description of our experimental setup, including dataset preparation, model configurations, continued pretraining procedure, data cleaning and anomaly detection pipeline, evaluation metrics, and implementation details.

D.1 Evaluation Benchmarks

FineTask Benchmark. FineTask is a multilingual, multi-task benchmark covering nine typologically diverse languages: Chinese, French, Arabic, Russian, Thai, Hindi, Turkish, Swahili, and Telugu. The benchmark spans a wide range of NLP tasks including reading comprehension, common-sense reasoning, natural language understanding, and text generation. FineTask provides four evaluation metrics: *Accuracy*, *Accuracy normalized over character length*, *Accuracy normalized over token length*, and *PMI Accuracy*. However, according to statistical data, none of these metrics consistently perform well across all languages. Therefore, we chose to use normalized accuracy (norm accuracy) in our evaluation process.

Multilingual Benchmarks. To analyze performance across varying resource levels, we further evaluate on three established multilingual corpora:

- **SIB-200** [24]: A suite of topic classification datasets across 205 languages. We use the raw accuracy on held-out test sets.
- **Glot500-c** [8]: A curated corpus spanning 500 languages for generation and language modeling. We compute *negative log-likelihood* (NLL) on held-out sentences:

$$\mathrm{NLL} = -\frac{1}{T}\sum_{t=1}^{T}\log p_\theta(w_t \mid w_{<t}), \tag{9}$$

  where T is the total token count in the evaluation set.
- **FLORES-200** [25]: A benchmark for low-resource machine translation covering 200 languages. We translate from English into each target language (Eng-XX) and translate from other languages into English (X-Eng) and evaluate using SacreBLEU with default settings.

D.2 Pre-training and Evaluation Protocol

We perform continued pretraining on three representative decoder-only large language models (LLMs): LLaMA-3.2-1B [47], Qwen-2.5-7B [48], and Aya-expanse-32B [49]. These models are selected to represent a diverse range of open-source models across different parameter scales, allowing us to investigate the effects of the different dataset, data cleaning pipeline across small, medium, and large model sizes. All models are accessed and managed through the HuggingFace Transformers library.

Given the limitations of computational resources, we refrain from full-parameter finetuning. Instead, we adopt Low-Rank Adaptation (LoRA; 55), a parameter-efficient fine-tuning technique that introduces trainable low-rank matrices into each transformer layer, substantially reducing the number of trainable parameters while maintaining competitive performance.

Our training pipeline closely follows the setup described in the LightEval repository[18], a lightweight evaluation and fine-tuning framework developed by HuggingFace. This ensures reproducibility and consistency with widely adopted community practices. Experiments are conducted on NVIDIA A100 GPU with 80GB memory, which provides sufficient memory bandwidth and compute capability to support batch-level parallelism and efficient LoRA-based fine-tuning. All hyperparameters and task-specific configurations are aligned with those used in the Fineweb-2 benchmark, ensuring comparability with previous work and consistent evaluation conditions.

D.3 Statistical Anomaly Detection

We provide a detailed comparison of the anomaly detection algorithms evaluated for data cleaning in DCAD-2000. The methods are selected based on their popularity, conceptual diversity, and availability in `scikit-learn`[19]. All experiments are conducted using the same eight-dimensional feature vectors described in Section 3.

Isolation Forest (ISO_Forest) [46] is an ensemble-based method that isolates anomalies instead of profiling normal data points. It constructs random binary trees by recursively selecting features and split values, and then uses the path length of each data point across the trees to assess anomaly scores. Shorter paths indicate

[18] `https://github.com/huggingface/lighteval`

[19] `https://scikit-learn.org`

higher likelihood of being an outlier. ISO_Forest is well-suited to high-dimensional and noisy data and requires minimal hyperparameter tuning. Its main drawback is higher computational cost relative to simpler methods, though it scales well with the number of samples.

One-Class SVM (OC_SVM) [50] is a kernel-based method that attempts to separate the data from the origin in a transformed feature space. It is sensitive to the choice of kernel function (e.g., RBF, linear) and associated parameters (e.g., gamma, nu). OC_SVM can be effective in capturing complex boundaries, but it often suffers from scalability issues and requires careful parameter tuning, especially in high-dimensional multilingual settings like DCAD-2000.

Local Outlier Factor (LOF) [51] is a density-based method that identifies anomalies based on local density deviation. It compares the local density of a data point with that of its neighbors. Points that have substantially lower density than their neighbors are considered outliers. The performance of LOF depends heavily on the number of neighbors chosen and tends to degrade in high-dimensional spaces due to the curse of dimensionality. It is also computationally expensive for large datasets.

K-Means [52] is a clustering algorithm typically used for unsupervised partitioning of data. For anomaly detection, it is repurposed by measuring the distance of points from their assigned cluster centroids—points that are far from any centroid can be considered anomalous. K-Means is computationally efficient and easy to implement but lacks sensitivity to local structures and does not inherently model outliers. Its effectiveness depends on a suitable choice of the number of clusters.

E Manual Quality Evaluation of Cleaning Pipeline

To validate the effectiveness of our cleaning pipeline and to assess the residual noise and false positives, we conduct a manual quality evaluation of the retained and deleted documents. This evaluation was performed on five representative languages: English, Chinese, German, Japanese, and French. These languages are selected to ensure diverse linguistic coverage, and the evaluation will be extended in future work to include additional languages, particularly low-resource languages, where automatic filtering may be more challenging.

For each of the five languages, we randomly sampled 100 documents retained by our pipeline (i.e., documents that were kept) and 100 documents that were removed (i.e., deleted by our pipeline). The annotation process was conducted by one proficient annotator per language. The key goal of this annotation process was to estimate both the quality of the documents retained by the pipeline and the false positives in the deleted set. The quality evaluation provides insight into how well the cleaning pipeline separates high-quality content from noisy or irrelevant data. The documents were labeled with the following quality ratings:

- **Good:** Documents that were coherent, meaningful, and of high quality.
- **Borderline:** Documents that were understandable but flawed, including minor corruption, weak coherence, or other small issues.
- **Bad:** Documents that were nonsensical, noisy, or semantically meaningless, such as machine translation errors, boilerplate content, spam, or mixed-language noise.

Table 4: **Quality evaluation of retained and deleted documents across five languages.**

Retained Documents (Kept by filter)					Deleted Documents (Removed by filter)				
Language	**Good**	**Borderline**	**Bad**	**Residual Noise (Bad %)**	**Language**	**Good**	**Borderline**	**Bad**	**False Positives (Good %)**
English	86%	10%	4%	**4%**	English	5%	14%	81%	**5%**
Chinese	82%	13%	5%	**5%**	Chinese	6%	18%	76%	**6%**
German	84%	12%	4%	**4%**	German	5%	16%	79%	**5%**
Japanese	81%	12%	7%	**7%**	Japanese	6%	17%	77%	**6%**
French	84%	14%	2%	**2%**	French	4%	15%	81%	**4%**
Avg	**83.4%**	12.2%	**4.4%**	**4.4%**	**Avg**	**5.2%**	16%	**78.8%**	**5.2%**

Table 4 demonstrate that our cleaning pipeline effectively filters out low-quality content while preserving high-value data. Across all five languages, the proportion of retained documents rated as "Bad" (residual noise) averaged only 4.4%, indicating minimal contamination of retained documents by low-quality content. Similarly, the false positive rate (i.e., representing the proportion of high-quality documents mistakenly removed) was low, averaging 5.2%. The pipeline's precision, defined as the proportion of retained documents classified as "Good" or "Borderline", was 95.6%, while its recall, which measures the retention of "Good" documents, was 94.13%. These results demonstrate that the pipeline achieves both high precision and recall, effectively balancing the removal of noise with the preservation of valuable data. Overall, the findings validate the robustness of our unsupervised, anomaly-detection-based approach across multiple languages, with future work aimed at extending this evaluation to additional languages, particularly low-resource ones.

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Table 5: Cost-Benefit Comparison of Filtering Methods (Per 1M Documents)

Metric	Heuristic Filtering	Anomaly Detection (DCAD)
Cleaning Time	10 minutes	12–15 minutes
Max Memory Usage (CPU)	58 GB	64 GB
Training Data Retained (%)	88%	77%
Avg Model Accuracy (Global MMLU subset) – LLaMA-3.2-1B	43.9%	**48.6%**
Accuracy Gain per CPU-hour	+0.42%	**+0.60%**
Accuracy Gain per 1% data lost	+0.16%	**+0.32%**

F Cost Benefit Analysis of Cleaning Strategies

To better evaluate the practical trade-offs between conventional heuristic filtering and our anomaly-based framework (DCAD), we conduct a controlled cost–benefit analysis on one million web documents under identical hardware conditions. As summarized in Table 5, the DCAD pipeline incurs only a minor computational overhead relative to the heuristic baseline (i.e., approximately two additional minutes of processing time and a 6 GB increase in peak memory usage). Although DCAD retains 11% fewer documents, it consistently yields superior downstream task performance (Section 5), highlighting its effectiveness in balancing data quality and computational efficiency.

Table 6: Ablation Study: Impact of Feature Subsets (Refer to Section 3.2.1)

Feature Subset Used	Arabic	Turkish
All 8 features (1–8)	**0.21**	**0.27**
w/o (8) Perplexity	0.20	0.25
w/o (7) LID score	**0.16**	**0.21**
w/o (6) Flagged word ratio	0.20	0.24
w/o (5) Stopword ratio	0.21	0.26
w/o (4) Special character ratio	0.20	0.26
w/o (3) Word repetition	0.18	0.24
w/o (2) Character repetition	0.19	0.25
w/o (1) Token count	0.20	0.24

G Feature Robustness Analysis

To evaluate the robustness of our anomaly detection framework with respect to feature design (Section 3.2.1), we conduct a one-feature-at-a-time ablation study. Given the combinatorial explosion of all possible subsets ($2^8 - 1 = 255$), we adopt a pragmatic protocol in which each feature is removed individually from the full 8-dimensional feature vector, and the cleaning process is repeated using the remaining seven features. We then fine-tune `LLaMA-3.2-1B` on each resulting filtered corpus and evaluate performance on FineTask–Arabic and FineTask–Turkish, following the same experimental setup as in Section 5.

As observed in Table 6, we have the following findings: (1) The full 8-feature configuration consistently outperforms all ablated variants, confirming that each feature contributes meaningfully to overall performance. (2) The Language Identification (LID) confidence score (Feature 7) is particularly critical: its removal results in a substantial accuracy drop, likely due to the presence of mixed or misidentified language content that adversely affects multilingual model quality. (3) Other features, such as repetition ratios and perplexity, provide modest gains individually; none are harmful or redundant when considered in isolation.

H Practical Choice of Anomaly Detector and Future Extensions

While modern deep anomaly detection methods, such as autoencoder-based reconstruction scoring [56] and contrastive outlier detection [57], have achieved strong performance in other domains, we deliberately adopt a classical algorithm, specifically Isolation Forest, in this work. This choice is motivated by three practical constraints inherent to large-scale multilingual corpus cleaning:

- **Lack of a clean reference distribution.** Autoencoder-based methods assume access to a predominantly clean training set to learn a reliable reconstruction prior. In our weakly supervised scenario covering 2,282 languages without dependable clean subsets, this assumption is violated, making such models prone to degenerate reconstructions on noisy data.

- **Scalability across languages without supervision.** Contrastive-learning-based outlier detection requires either labeled normal/abnormal pairs or implicitly curated positive anchors. Providing such supervision for thousands of languages would reintroduce the language-specific manual tuning that our language-agnostic pipeline explicitly avoids.
- **Resource efficiency and feature interpretability.** Our framework relies on explicit, interpretable quality features (e.g., repetition ratio, perplexity, LID confidence) rather than opaque embedding-space distances. Classical anomaly detectors like Isolation Forest can operate directly on these CPU-computable features and scale to 46 TB of multilingual data without GPU dependency, making them well-suited for real-world data curation pipelines.

Nonetheless, extending DCAD to incorporate semantic embedding-based anomaly signals or lightweight deep novelty detection represents a promising direction for future work. We view our current feature-space approach as a foundational layer, onto which richer semantic detectors can be incrementally integrated once computational and language-coverage challenges are addressed.

I Ethics Statement

Our dataset integrates existing multilingual datasets, such as MaLA [11] and Fineweb-2 [14], and includes newly extracted data from Common Crawl, providing large-scale and high-quality training corpora to support the training of multilingual large language models (LLMs). Additionally, we propose a novel data cleaning method to filter out potentially toxic documents, reducing potential ethical concerns. However, performing fine-grained analysis on such a vast dataset (46.72TB) remains a significant challenge. To address this, we released the dataset for the community to explore and research extensively. Furthermore, since our dataset is derived from open-source datasets, we adhere to the open-source policies of these datasets to promote future research in multilingual LLMs, while mitigating potential ethical risks. Therefore, we believe our dataset does not pose greater societal risks than existing multilingual datasets.

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Table 7: **Statisticals grouped by writing scripts (part I).** Comparison of language count, document count, token count, disk size, and sources before and after data cleaning in DCAD-2000.

Script	#Langs	Documents			Tokens			Disk Size			Source
		keep	remove	total	keep	remove	total	keep	remove	total	
Latn	1830	5.50B	439.42M	5.93B	4.29T	327.39B	4.61T	21.13TB	4.91TB	26.12TB	Fineweb-2, Fineweb, MaLA, New CC
Cyrl	91	1.11B	85.84M	1.19B	1.26T	98.88B	1.36T	9.40TB	2.43TB	11.83TB	Fineweb-2, MaLA, New CC
Hani	12	715.15M	71.29M	786.45M	746.48B	73.89B	820.36B	2.90TB	1.60TB	4.50TB	Fineweb-2, MaLA, New CC
Jpan	1	491.47M	42.47M	533.93M	278.14B	22.81B	300.95B	2.00TB	504.87GB	2.50TB	Fineweb-2, New CC
Arab	60	198.64M	20.36M	219.03M	122.36B	13.12B	135.48B	1.03TB	290.11GB	1.31TB	Fineweb-2, MaLA, New CC
Hang	1	79.22M	6.16M	85.38M	59.07B	4.62B	63.69B	336.56GB	66.70GB	403.26GB	Fineweb-2, MaLA, New CC
Grek	4	69.14M	5.90M	75.04M	58.45B	5.15B	63.60B	432.64GB	120.10GB	552.76GB	Fineweb-2, MaLA, New CC
Deva	48	60.09M	5.79M	65.87M	30.63B	2.56B	33.19B	342.83GB	72.51GB	415.37GB	Fineweb-2, MaLA, New CC
Thai	11	55.73M	4.34M	60.06M	46.36B	3.60B	49.96B	526.40GB	110.69GB	637.11GB	Fineweb-2, MaLA, New CC
Mlym	6	39.16M	3.89M	43.05M	7.00B	559.61M	7.56B	94.53GB	18.86GB	113.40GB	Fineweb-2, MaLA, New CC
Gujr	2	38.91M	4.55M	43.46M	5.07B	461.70M	5.53B	60.22GB	13.54GB	73.76GB	Fineweb-2, MaLA, New CC
Knda	2	34.20M	2.70M	36.90M	4.76B	359.45M	5.12B	68.85GB	11.14GB	79.99GB	Fineweb-2, MaLA, New CC
Hebr	6	26.99M	1.83M	28.82M	21.15B	1.38B	22.53B	152.34GB	30.80GB	183.18GB	Fineweb-2, MaLA, New CC
Taml	2	26.65M	2.92M	29.56M	5.88B	461.60M	6.35B	80.38GB	19.44GB	99.82GB	Fineweb-2, MaLA, New CC
Guru	2	24.04M	3.16M	27.21M	2.27B	227.69M	2.50B	26.71GB	8.65GB	35.36GB	Fineweb-2, MaLA, New CC
Beng	6	21.91M	1.51M	23.42M	12.67B	875.46M	13.54B	148.42GB	31.39GB	179.83GB	Fineweb-2, MaLA, New CC
Geor	3	20.56M	1.36M	21.92M	6.19B	419.61M	6.61B	83.04GB	15.75GB	98.81GB	Fineweb-2, MaLA, New CC
Armn	4	17.24M	1.46M	18.70M	4.74B	407.38M	5.15B	42.47GB	11.43GB	53.93GB	Fineweb-2, MaLA, New CC
Telu	4	9.93M	821.21K	10.75M	3.91B	295.72M	4.20B	48.22GB	9.65GB	57.87GB	Fineweb-2, MaLA, New CC
Sinh	1	9.91M	1.12M	11.03M	2.93B	251.40M	3.18B	32.73GB	7.64GB	40.37GB	Fineweb-2, MaLA, New CC
Orya	6	6.57M	616.98K	7.18M	464.57M	37.89M	502.46M	9.79GB	2.20GB	12.01GB	Fineweb-2, MaLA
Ethi	13	6.41M	429.99K	6.85M	1.38B	91.75M	1.46B	12.66GB	2.92GB	15.59GB	Fineweb-2, MaLA, New CC
Mymr	9	6.04M	479.44K	6.52M	5.30B	406.67M	5.72B	40.57GB	7.83GB	48.39GB	Fineweb-2, MaLA, New CC
Kana	1	5.83M	1.11M	6.94M	1.13B	219.26M	1.35B	16.90GB	14.33GB	31.23GB	Fineweb-2, New CC
Khmr	7	4.96M	380.38K	5.34M	2.24B	160.29M	2.40B	30.95GB	4.99GB	35.95GB	Fineweb-2, MaLA, New CC
Bamu	1	4.71M	1.00M	5.71M	199.46M	42.49M	241.95M	79.67GB	19.47GB	99.14GB	Fineweb-2, New CC
Copt	2	4.40M	361.99K	4.76M	219.04M	18.03M	237.09M	8.97GB	864.17MB	9.84GB	Fineweb-2, New CC
Tang	1	3.94M	741.81K	4.68M	209.68M	39.47M	249.15M	22.70GB	7.67GB	30.36GB	Fineweb-2, New CC
Xsux	1	3.90M	694.59K	4.59M	276.93M	49.35M	326.28M	13.84GB	9.74GB	23.58GB	Fineweb-2, New CC
Laoo	5	3.46M	470.52K	3.92M	840.28M	87.36M	927.65M	11.85GB	3.95GB	15.80GB	Fineweb-2, MaLA, New CC
Yiii	1	3.39M	417.38K	3.81M	232.88M	28.68M	261.56M	25.82GB	6.24GB	32.05GB	Fineweb-2, New CC
Hira	1	2.78M	579.38K	3.36M	361.77M	75.28M	437.05M	4.87GB	4.04GB	8.91GB	Fineweb-2, New CC
Thaa	2	2.51M	301.28K	2.82M	425.90M	45.08M	470.98M	4.75GB	1.28GB	6.02GB	Fineweb-2, MaLA, New CC
Kits	1	1.86M	315.45K	2.17M	269.54M	45.75M	315.29M	12.47GB	17.12GB	29.58GB	Fineweb-2, New CC
Hluw	1	1.71M	374.92K	2.09M	70.77M	15.47M	86.25M	3.19GB	3.45GB	6.64GB	Fineweb-2, New CC
Japn	1	1.60M	177.40K	1.78M	148.77M	17.99M	166.76M	6.05GB	2.16GB	8.21GB	MaLA
Shrd	1	1.41M	216.59K	1.62M	130.80M	20.13M	150.93M	6.06GB	2.35GB	8.40GB	Fineweb-2, New CC
Lina	1	1.37M	271.63K	1.64M	130.39M	25.87M	156.26M	6.97GB	3.85GB	10.82GB	Fineweb-2, New CC
Samr	1	1.35M	158.99K	1.51M	64.06M	7.54M	71.59M	4.30GB	1.72GB	6.02GB	Fineweb-2, New CC
Cans	12	1.24M	248.84K	1.49M	109.29M	21.66M	130.96M	3.55GB	2.78GB	6.33GB	Fineweb-2, MaLA
Syrc	4	1.12M	116.18K	1.23M	44.70M	4.75M	49.44M	20.70GB	4.35GB	25.04GB	Fineweb-2, MaLA
Adlm	1	1.12M	194.29K	1.32M	43.63M	7.55M	51.18M	1.10GB	853.95MB	1.95GB	Fineweb-2, New CC
Egyp	1	1.12M	190.50K	1.31M	97.41M	16.58M	113.99M	2.54GB	3.52GB	6.05GB	Fineweb-2, New CC
Mend	1	1.03M	293.72K	1.32M	16.58M	4.75M	21.33M	893.39MB	2.06GB	2.95GB	Fineweb-2, New CC
Linb	1	735.07K	107.67K	842.75K	52.97M	7.76M	60.73M	6.30GB	997.90MB	7.30GB	Fineweb-2, New CC
Brai	1	590.10K	125.33K	715.43K	57.85M	12.29M	70.13M	1.94GB	1.30GB	3.24GB	Fineweb-2, New CC
Sgnw	1	567.29K	106.45K	673.74K	37.34M	7.01M	44.34M	1.40GB	1.11GB	2.50GB	Fineweb-2, New CC
Tibt	4	544.99K	70.33K	615.32K	288.24M	33.57M	321.81M	4.50GB	1.53GB	6.09GB	Fineweb-2, MaLA, New CC
Hung	1	520.10K	155.23K	675.33K	42.34M	12.64M	54.98M	1.94GB	2.32GB	4.25GB	Fineweb-2, New CC
Mong	3	435.35K	61.47K	496.83K	119.66M	16.95M	136.62M	1.97GB	1.04GB	3.03GB	Fineweb-2, MaLA
Bali	1	422.49K	77.08K	499.57K	39.62M	7.23M	46.84M	1.19GB	662.91MB	1.85GB	Fineweb-2, New CC
Nshu	1	419.71K	89.40K	509.11K	38.53M	8.21M	46.74M	993.06MB	1.28GB	2.27GB	Fineweb-2, New CC
Modi	1	386.82K	67.33K	454.15K	52.58M	9.15M	61.73M	16.45GB	7.42GB	23.87GB	Fineweb-2, New CC
Lana	1	377.58K	110.80K	488.38K	47.55M	13.95M	61.50M	688.16MB	2.05GB	2.74GB	Fineweb-2, New CC
Saur	1	315.78K	73.82K	389.60K	15.26M	3.57M	18.83M	398.55MB	489.07MB	887.62MB	Fineweb-2, New CC
Dupl	1	258.90K	53.06K	311.96K	14.14M	2.90M	17.04M	752.58MB	502.95MB	1.26GB	Fineweb-2, New CC
Runr	2	252.18K	39.00K	291.19K	154.68M	23.92M	178.61M	1.25GB	3.28GB	4.52GB	Fineweb-2, MaLA
Vaii	1	243.47K	93.27K	336.73K	71.28M	27.31M	98.59M	513.30MB	1.88GB	2.39GB	Fineweb-2, New CC
Glag	1	237.68K	72.07K	309.75K	20.38M	6.18M	26.56M	476.61MB	951.96MB	1.43GB	Fineweb-2, New CC
Dsrt	1	198.00K	37.90K	235.90K	4.47M	855.49K	5.32M	248.83MB	562.92MB	811.75MB	Fineweb-2, New CC
Mroo	1	186.14K	22.85K	208.99K	6.42M	788.69K	7.21M	2.43GB	335.38MB	2.77GB	Fineweb-2, New CC
Bopo	1	181.71K	24.45K	206.16K	30.63M	4.12M	34.75M	3.45GB	890.68MB	4.35GB	Fineweb-2, New CC
Mtei	2	175.69K	20.34K	196.03K	49.11M	5.76M	54.87M	805.36MB	574.03MB	1.38GB	Fineweb-2, MaLA
Khar	1	153.37K	40.04K	193.41K	6.75M	1.76M	8.52M	250.30MB	182.38MB	432.67MB	Fineweb-2, New CC
Brah	1	138.03K	22.72K	160.75K	7.85M	1.29M	9.15M	273.71MB	243.75MB	517.47MB	Fineweb-2, New CC
Bhks	1	131.90K	27.03K	158.93K	3.93M	805.58K	4.74M	190.96MB	154.63MB	345.59MB	Fineweb-2, New CC
Hmnp	1	118.87K	12.33K	131.20K	6.83M	708.37K	7.54M	436.28MB	151.81MB	588.09MB	Fineweb-2, New CC
Phag	1	107.75K	17.58K	125.34K	3.41M	556.36K	3.97M	141.68MB	93.31MB	234.99MB	Fineweb-2, New CC
Merc	1	107.52K	38.04K	145.56K	7.61M	2.69M	10.30M	215.43MB	472.23MB	687.66MB	Fineweb-2, New CC
Kali	2	105.87K	24.33K	130.20K	1.39M	319.46K	1.71M	105.24MB	91.45MB	196.70MB	Fineweb-2, New CC
Plrd	1	104.31K	21.07K	125.38K	5.47M	1.10M	6.57M	214.53MB	225.25MB	439.77MB	Fineweb-2, New CC
Lisu	2	101.48K	20.06K	121.53K	24.00M	4.74M	28.74M	204.24MB	527.21MB	731.45MB	Fineweb-2, New CC
Hmng	1	101.02K	23.34K	124.36K	5.37M	1.24M	6.61M	153.20MB	196.99MB	350.19MB	Fineweb-2, New CC
Nkoo	2	98.77K	25.89K	124.65K	4.91M	1.07M	5.98M	2.13GB	233.87MB	2.36GB	Fineweb-2, MaLA
Gran	1	97.96K	21.57K	119.53K	3.57M	785.93K	4.36M	135.27MB	243.90MB	379.18MB	Fineweb-2, New CC
Gonm	1	94.82K	16.28K	111.10K	2.83M	486.36K	3.32M	106.89MB	142.16MB	249.05MB	Fineweb-2, New CC
Cher	2	94.19K	25.99K	120.19K	9.12M	2.45M	11.57M	245.29MB	689.18MB	934.47MB	Fineweb-2, MaLA
Tnsa	1	89.55K	17.93K	107.48K	3.28M	656.33K	3.93M	98.49MB	204.04MB	302.53MB	Fineweb-2, New CC

Table 8: **Statisticals grouped by writing scripts (part II).** Comparison of language count, document count, token count, disk size, and sources before and after data cleaning in DCAD-2000.

Script	#Langs	Documents			Tokens			Disk Size			Source
		keep	remove	total	keep	remove	total	keep	remove	total	
Cprt	1	88.19K	14.11K	102.30K	7.87M	1.26M	9.13M	142.36MB	85.91MB	228.27MB	Fineweb-2, New CC
Cari	1	77.73K	18.09K	95.82K	1.73M	401.78K	2.13M	89.37MB	76.01MB	165.38MB	Fineweb-2, New CC
Diak	1	68.42K	22.40K	90.82K	2.87M	938.52K	3.81M	58.40MB	94.36MB	152.76MB	Fineweb-2, New CC
Marc	1	67.80K	11.89K	79.69K	2.34M	410.50K	2.75M	66.51MB	95.34MB	161.85MB	Fineweb-2, New CC
Mani	1	65.94K	9.56K	75.50K	6.27M	908.84K	7.17M	128.39MB	140.35MB	268.75MB	Fineweb-2, New CC
Talu	2	65.77K	11.95K	77.72K	1.27M	231.55K	1.50M	78.51MB	62.21MB	140.72MB	Fineweb-2, MaLA
Vith	1	65.14K	12.13K	77.28K	2.49M	464.49K	2.96M	124.41MB	95.26MB	219.66MB	Fineweb-2, New CC
Nagm	1	63.57K	11.94K	75.51K	1.03M	193.45K	1.22M	58.20MB	73.87MB	132.08MB	Fineweb-2, New CC
Ahom	1	60.21K	9.69K	69.90K	2.34M	376.34K	2.72M	127.53MB	70.68MB	198.21MB	Fineweb-2, New CC
Java	1	58.52K	13.32K	71.84K	2.18M	496.30K	2.68M	66.55MB	116.13MB	182.68MB	Fineweb-2, New CC
Palm	1	48.99K	5.32K	54.32K	424.13K	46.09K	470.22K	39.41MB	43.82MB	83.23MB	Fineweb-2, New CC
Wara	1	46.80K	9.12K	55.92K	1.47M	286.76K	1.76M	58.48MB	52.76MB	111.24MB	Fineweb-2, New CC
Olck	2	45.80K	4.06K	49.86K	6.69M	492.54K	7.19M	86.16MB	38.55MB	124.71MB	Fineweb-2, MaLA
Khoj	1	39.85K	5.23K	45.09K	892.46K	117.20K	1.01M	43.07MB	40.20MB	83.27MB	Fineweb-2, New CC
Rohg	1	35.21K	5.32K	40.53K	534.34K	80.72K	615.05K	36.76MB	41.06MB	77.82MB	Fineweb-2, New CC
Sidd	1	34.75K	8.41K	43.16K	3.03M	732.80K	3.76M	46.06MB	93.44MB	139.51MB	Fineweb-2, New CC
Yezi	1	33.92K	3.35K	37.27K	96.61K	9.53K	106.13K	29.36MB	14.31MB	43.67MB	Fineweb-2, New CC
Ougr	1	32.34K	6.13K	38.47K	442.16K	83.82K	525.98K	31.03MB	37.95MB	68.98MB	Fineweb-2, New CC
Avst	1	32.16K	6.62K	38.78K	1.75M	360.09K	2.11M	51.64MB	53.81MB	105.46MB	Fineweb-2, New CC
Ital	1	32.06K	5.06K	37.12K	519.27K	81.93K	601.19K	34.30MB	29.24MB	63.53MB	Fineweb-2, New CC
Wcho	1	31.94K	6.51K	38.45K	1.48M	301.04K	1.78M	58.25MB	74.54MB	132.79MB	Fineweb-2, New CC
Kthi	1	31.07K	5.44K	36.51K	763.52K	133.75K	897.27K	30.79MB	35.73MB	66.52MB	Fineweb-2, New CC
Tavt	1	30.95K	3.63K	34.57K	670.82K	78.65K	749.47K	29.30MB	14.97MB	44.26MB	Fineweb-2, New CC
Takr	1	30.70K	5.29K	35.99K	1.73M	298.02K	2.03M	30.89MB	45.59MB	76.48MB	Fineweb-2, New CC
Tfng	4	29.84K	3.34K	33.18K	1.42M	148.55K	1.57M	35.12MB	24.87MB	59.99MB	Fineweb-2, New CC
Tale	1	26.17K	2.80K	28.98K	220.84K	23.64K	244.48K	23.80MB	16.84MB	40.64MB	Fineweb-2, New CC
Elba	1	24.86K	4.61K	29.48K	394.51K	73.22K	467.73K	24.19MB	19.19MB	43.38MB	Fineweb-2, New CC
Zanb	1	24.46K	4.76K	29.21K	327.39K	63.68K	391.07K	26.07MB	40.03MB	66.10MB	Fineweb-2, New CC
Sogo	1	22.29K	3.88K	26.16K	146.13K	25.41K	171.54K	17.82MB	20.07MB	37.89MB	Fineweb-2, New CC
Soyo	1	22.21K	4.91K	27.12K	598.89K	132.47K	731.36K	25.04MB	36.77MB	61.81MB	Fineweb-2, New CC
Dogr	1	21.29K	3.82K	25.11K	1.28M	229.94K	1.51M	29.94MB	23.89MB	53.84MB	Fineweb-2, New CC
Kawi	1	20.28K	4.10K	24.38K	396.57K	80.26K	476.83K	20.90MB	24.30MB	45.20MB	Fineweb-2, New CC
Phli	1	19.16K	2.88K	22.04K	41.16K	6.19K	47.35K	17.52MB	7.60MB	25.13MB	Fineweb-2, New CC
Cham	1	17.92K	3.60K	21.52K	762.24K	153.32K	915.57K	21.12MB	39.91MB	61.03MB	Fineweb-2, New CC
Nbat	1	17.61K	3.19K	20.80K	280.13K	50.76K	330.89K	18.90MB	15.97MB	34.87MB	Fineweb-2, New CC
Nand	1	17.39K	3.36K	20.75K	307.12K	59.32K	366.44K	17.76MB	19.20MB	36.96MB	Fineweb-2, New CC
Osma	1	16.98K	2.59K	19.57K	495.54K	75.61K	571.15K	19.16MB	15.11MB	34.27MB	Fineweb-2, New CC
Sind	1	14.81K	4.24K	19.05K	315.61K	90.31K	405.93K	21.16MB	18.70MB	39.86MB	Fineweb-2, New CC
Sogd	1	14.52K	2.73K	17.24K	307.50K	57.79K	365.30K	14.67MB	9.73MB	24.40MB	Fineweb-2, New CC
Pauc	1	13.23K	4.28K	17.50K	1.88M	609.43K	2.49M	13.65MB	33.03MB	46.67MB	Fineweb-2, New CC
Sylo	1	12.42K	2.88K	15.29K	922.71K	213.86K	1.14M	22.76MB	22.23MB	44.99MB	Fineweb-2, New CC
Goth	2	11.84K	1.24K	13.08K	191.30K	19.67K	210.97K	11.59MB	3.62MB	15.22MB	Fineweb-2, MaLA
Rjng	1	10.30K	2.36K	12.65K	595.51K	136.27K	731.78K	9.43MB	15.02MB	24.45MB	Fineweb-2, New CC
Chrs	1	10.24K	1.26K	11.50K	45.98K	5.66K	51.64K	8.22MB	5.45MB	13.67MB	Fineweb-2, New CC
Phlp	1	9.08K	2.03K	11.11K	31.62K	7.06K	38.69K	8.35MB	5.61MB	13.96MB	Fineweb-2, New CC
Mand	1	8.73K	1.49K	10.21K	82.87K	14.11K	96.98K	9.07MB	5.24MB	14.31MB	Fineweb-2, New CC
Tglg	1	8.58K	1.88K	10.46K	638.75K	140.15K	778.89K	11.22MB	10.89MB	22.11MB	Fineweb-2, New CC
Shaw	1	8.41K	1.28K	9.69K	915.43K	139.72K	1.06M	13.65MB	12.62MB	26.27MB	Fineweb-2, New CC
Hatr	1	7.44K	1.63K	9.07K	371.48K	81.61K	453.09K	10.15MB	13.53MB	23.68MB	Fineweb-2, New CC
Bugi	2	7.03K	1.33K	8.36K	95.81K	18.11K	113.91K	6.90MB	6.18MB	13.09MB	Fineweb-2, MaLA
Tagb	1	6.58K	1.14K	7.72K	30.92K	5.37K	36.30K	5.84MB	2.33MB	8.17MB	Fineweb-2, New CC
Prti	1	6.05K	1.09K	7.15K	225.93K	40.79K	266.72K	7.31MB	4.57MB	11.89MB	Fineweb-2, New CC
Narb	1	5.22K	835	6.06K	56.09K	8.97K	65.06K	6.01MB	7.12MB	13.13MB	Fineweb-2, New CC
Sarb	1	4.99K	874	5.86K	170.46K	29.86K	200.31K	6.93MB	15.95MB	22.87MB	Fineweb-2, New CC
Ugar	1	4.85K	653	5.50K	133.05K	17.92K	150.97K	4.03MB	2.47MB	6.50MB	Fineweb-2, New CC
Lydi	1	4.59K	1.03K	5.62K	28.08M	6.29M	34.37M	77.22MB	70.99MB	148.21MB	Fineweb-2, New CC
Buhd	1	3.16K	448	3.61K	7.77K	1.10K	8.87K	2.73MB	623.88KB	3.35MB	Fineweb-2, New CC
Perm	1	2.87K	630	3.50K	19.17K	4.20K	23.37K	2.58MB	1.36MB	3.94MB	Fineweb-2, New CC
Elym	1	1.66K	496	2.16K	61.25K	18.28K	79.53K	1.88MB	7.52MB	9.40MB	Fineweb-2, New CC
Limb	1	59	15	74	32.32K	8.22K	40.53K	754.75KB	229.80KB	984.54KB	Fineweb-2, New CC

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Table 9: **Data Cleaning Statistics (part I):** Comparison of document count, token count, disk size, and sources before and after data cleaning in DCAD-2000.

Lang Code	Documents			Tokens			Disk Size			Source
	keep	remove	total	keep	remove	total	keep	remove	total	
eng_Latn	1.31B	101.08M	1.41B	1.21T	93.23B	1.30T	5.66TB	1.49TB	7.15TB	Fineweb, MaLA, New CC
rus_Cyrl	858.53M	67.21M	925.74M	1.14T	90.18B	1.23T	8.40TB	2.22TB	10.62TB	Fineweb-2, MaLA, New CC
cmn_Hani	713.97M	71.19M	785.16M	745.88B	73.84B	819.71B	2.90TB	1.60TB	4.50TB	Fineweb-2, New CC
deu_Latn	668.62M	53.65M	722.27M	632.32B	51.11B	683.44B	2.85TB	664.79GB	3.52TB	Fineweb-2, MaLA, New CC
spa_Latn	604.45M	43.33M	647.79M	483.75B	34.79B	518.54B	2.54TB	498.55GB	3.03TB	Fineweb-2, MaLA, New CC
fra_Latn	513.53M	40.32M	553.85M	430.86B	33.77B	464.64B	2.15TB	491.23GB	2.64TB	Fineweb-2, MaLA, New CC
jpn_Jpan	491.47M	42.47M	533.93M	278.14B	22.81B	300.95B	2.00TB	504.87GB	2.50TB	Fineweb-2, New CC
ita_Latn	311.42M	25.50M	336.93M	250.12B	20.69B	270.81B	1.29TB	292.75GB	1.59TB	Fineweb-2, MaLA, New CC
por_Latn	271.48M	18.67M	290.15M	204.64B	14.12B	218.77B	1.07TB	225.83GB	1.30TB	Fineweb-2, MaLA, New CC
pol_Latn	223.21M	15.38M	238.59M	180.34B	12.59B	192.93B	910.55GB	184.59GB	1.10TB	Fineweb-2, MaLA, New CC
nld_Latn	219.16M	14.03M	233.19M	146.16B	9.38B	155.54B	739.62GB	159.01GB	898.63GB	Fineweb-2, MaLA, New CC
ind_Latn	156.92M	16.21M	173.12M	60.97B	5.15B	66.11B	406.86GB	64.84GB	471.70GB	Fineweb-2, MaLA
tur_Latn	143.31M	9.98M	153.30M	118.40B	8.21B	126.61B	618.87GB	145.39GB	764.26GB	Fineweb-2, MaLA, New CC
vie_Latn	87.77M	6.19M	93.96M	110.11B	7.71B	117.82B	570.86GB	116.19GB	687.05GB	Fineweb-2, MaLA, New CC
fas_Arab	82.80M	9.49M	92.29M	67.58B	7.91B	75.49B	521.39GB	121.46GB	642.85GB	Fineweb-2, MaLA, New CC
kor_Hang	79.22M	6.16M	85.38M	59.07B	4.62B	63.69B	336.56GB	66.70GB	403.26GB	Fineweb-2, MaLA, New CC
swe_Latn	77.32M	5.08M	82.40M	59.21B	3.92B	63.13B	269.37GB	73.25GB	342.62GB	Fineweb-2, MaLA, New CC
hun_Latn	70.79M	5.18M	75.97M	65.62B	4.86B	70.48B	319.58GB	87.97GB	407.55GB	Fineweb-2, MaLA, New CC
ukr_Cyrl	67.87M	4.31M	72.18M	53.79B	3.41B	57.20B	428.74GB	82.51GB	511.25GB	Fineweb-2, MaLA, New CC
ell_Grek	67.48M	5.67M	73.15M	57.63B	5.03B	62.66B	425.03GB	112.67GB	537.71GB	Fineweb-2, MaLA, New CC
tha_Thai	55.47M	4.29M	59.76M	46.31B	3.59B	49.90B	525.54GB	110.37GB	635.91GB	Fineweb-2, MaLA, New CC
arb_Arab	53.70M	4.06M	57.76M	25.21B	1.92B	27.13B	278.77GB	72.25GB	351.02GB	Fineweb-2, MaLA
aze_Latn	51.38M	6.44M	57.82M	3.30B	392.00M	3.70B	41.90GB	10.70GB	52.60GB	MaLA
slv_Latn	50.41M	4.05M	54.46M	11.66B	836.48M	12.50B	69.22GB	12.64GB	81.87GB	Fineweb-2, MaLA, New CC
cat_Latn	48.83M	3.78M	52.61M	16.49B	1.13B	17.62B	96.97GB	14.24GB	111.21GB	Fineweb-2, MaLA, New CC
fin_Latn	47.80M	4.09M	51.89M	43.43B	3.75B	47.19B	202.14GB	57.62GB	259.76GB	Fineweb-2, MaLA, New CC
ces_Latn	47.54M	3.21M	50.74M	42.20B	2.84B	45.04B	195.62GB	48.74GB	244.36GB	MaLA, New CC
hbs_Latn	42.98M	8.05M	51.04M	1.53B	287.34M	1.82B	22.41GB	6.41GB	28.82GB	MaLA
fil_Latn	40.15M	6.32M	46.47M	3.47B	477.70M	3.94B	31.22GB	9.20GB	40.42GB	Fineweb-2, MaLA
mal_Mlym	39.10M	3.88M	42.98M	7.00B	558.83M	7.56B	94.47GB	18.30GB	112.78GB	Fineweb-2, MaLA, New CC
nob_Latn	38.88M	4.33M	43.21M	24.13B	2.81B	26.94B	139.85GB	66.29GB	206.15GB	Fineweb-2, MaLA
guj_Gujr	38.82M	4.54M	43.36M	5.07B	461.54M	5.53B	60.08GB	13.49GB	73.57GB	Fineweb-2, MaLA, New CC
bul_Cyrl	37.11M	2.56M	39.67M	32.29B	2.23B	34.51B	245.84GB	55.86GB	301.69GB	Fineweb-2, MaLA, New CC
kan_Knda	34.20M	2.70M	36.90M	4.76B	359.21M	5.12B	68.82GB	11.13GB	79.95GB	Fineweb-2, MaLA, New CC
hin_Deva	29.15M	2.47M	31.62M	22.08B	1.81B	23.89B	219.46GB	46.45GB	265.91GB	Fineweb-2, MaLA, New CC
tam_Taml	26.55M	2.90M	29.45M	5.88B	460.75M	6.34B	80.26GB	19.29GB	99.55GB	Fineweb-2, MaLA, New CC
kaz_Cyrl	25.78M	1.67M	27.45M	6.37B	432.67M	6.80B	64.36GB	12.99GB	77.35GB	Fineweb-2, MaLA, New CC
heb_Hebr	25.24M	1.61M	26.85M	20.74B	1.33B	22.07B	147.85GB	28.75GB	176.60GB	Fineweb-2, MaLA, New CC
ara_Arab	25.14M	3.24M	28.39M	17.21B	2.23B	19.44B	152.73GB	71.93GB	224.66GB	MaLA, New CC
srp_Cyrl	25.13M	1.75M	26.88M	6.91B	496.07M	7.41B	60.34GB	8.50GB	68.84GB	Fineweb-2, MaLA, New CC
est_Latn	24.18M	2.86M	27.04M	2.89B	294.20M	3.18B	26.17GB	8.91GB	35.08GB	MaLA, New CC
sqi_Latn	24.16M	3.25M	27.41M	2.38B	237.81M	2.61B	21.08GB	5.03GB	26.11GB	MaLA, New CC
isl_Latn	24.06M	2.23M	26.29M	6.32B	561.74M	6.89B	34.88GB	9.09GB	43.97GB	Fineweb-2, MaLA, New CC
pan_Guru	24.02M	3.16M	27.19M	2.27B	227.60M	2.50B	26.69GB	8.59GB	35.28GB	MaLA, New CC
mlt_Latn	23.37M	2.08M	25.45M	3.24B	322.80M	3.56B	16.40GB	4.96GB	21.36GB	Fineweb-2, MaLA, New CC
mkd_Cyrl	22.61M	1.89M	24.50M	5.29B	396.98M	5.68B	51.37GB	7.08GB	58.45GB	Fineweb-2, MaLA, New CC
bos_Latn	21.62M	1.71M	23.33M	11.01B	831.59M	11.84B	59.71GB	10.67GB	70.38GB	Fineweb-2, MaLA, New CC
kat_Geor	20.27M	1.30M	21.57M	6.16B	413.36M	6.57B	82.54GB	15.10GB	97.65GB	Fineweb-2, MaLA, New CC
lit_Latn	20.09M	1.51M	21.60M	17.47B	1.33B	18.80B	91.29GB	18.30GB	109.59GB	Fineweb-2, MaLA, New CC
ben_Beng	19.90M	1.37M	21.28M	12.26B	848.75M	13.11B	143.64GB	30.36GB	174.00GB	Fineweb-2, MaLA, New CC
hrv_Latn	19.83M	1.54M	21.37M	15.02B	1.19B	16.21B	76.53GB	16.65GB	93.18GB	Fineweb-2, MaLA, New CC
glg_Latn	19.31M	1.58M	20.89M	4.45B	372.72M	4.83B	28.40GB	4.50GB	32.90GB	Fineweb-2, MaLA, New CC
ron_Latn	18.28M	1.42M	19.69M	23.42B	1.81B	25.23B	110.94GB	20.14GB	131.08GB	MaLA, New CC
ceb_Latn	18.14M	1.82M	19.97M	1.91B	184.52M	2.09B	14.11GB	2.06GB	16.18GB	Fineweb-2, MaLA, New CC
hye_Armn	16.93M	1.40M	18.33M	4.65B	392.68M	5.04B	41.29GB	10.76GB	52.05GB	Fineweb-2, MaLA, New CC
msa_Latn	16.90M	1.51M	18.40M	12.27B	1.05B	13.32B	67.19GB	34.22GB	101.42GB	MaLA, New CC
tgk_Cyrl	16.60M	1.04M	17.64M	3.46B	241.47M	3.70B	29.00GB	5.01GB	34.01GB	Fineweb-2, MaLA, New CC
mar_Deva	15.37M	1.35M	16.72M	4.05B	287.28M	4.34B	52.49GB	7.16GB	59.65GB	Fineweb-2, MaLA, New CC
bel_Cyrl	15.22M	1.06M	16.29M	5.30B	353.85M	5.65B	45.23GB	6.76GB	51.99GB	Fineweb-2, MaLA, New CC
nep_Deva	13.18M	1.74M	14.91M	3.40B	354.95M	3.75B	57.72GB	14.16GB	71.88GB	MaLA, New CC
urd_Arab	12.92M	1.28M	14.20M	5.63B	463.49M	6.09B	43.36GB	8.33GB	51.69GB	Fineweb-2, MaLA, New CC
slk_Latn	12.79M	850.42K	13.64M	10.71B	712.57M	11.43B	53.49GB	10.01GB	63.50GB	MaLA, New CC
mon_Cyrl	11.46M	1.37M	12.83M	2.05B	225.17M	2.27B	25.55GB	7.89GB	33.44GB	MaLA, New CC
dan_Latn	11.33M	645.36K	11.98M	8.91B	506.75M	9.42B	42.48GB	9.31GB	51.78GB	MaLA, New CC
eus_Latn	10.88M	720.92K	11.60M	2.86B	180.73M	3.04B	18.54GB	2.98GB	21.52GB	Fineweb-2, MaLA, New CC
azj_Latn	10.37M	764.57K	11.14M	6.02B	427.97M	6.45B	54.46GB	9.98GB	64.44GB	Fineweb-2, MaLA, New CC
swa_Latn	10.32M	1.78M	12.10M	968.63M	131.70M	1.10B	8.88GB	2.59GB	11.47GB	MaLA, New CC
als_Latn	9.94M	695.21K	10.64M	7.84B	540.49M	8.38B	22.16GB	3.80GB	25.97GB	Fineweb-2, MaLA
sin_Sinh	9.91M	1.12M	11.03M	2.93B	251.40M	3.18B	32.73GB	7.64GB	40.37GB	Fineweb-2, MaLA, New CC
lat_Latn	9.86M	968.13K	10.83M	1.67B	209.54M	1.88B	8.93GB	3.35GB	12.27GB	Fineweb-2, MaLA, New CC
tel_Telu	9.81M	790.37K	10.60M	3.90B	293.32M	4.19B	47.82GB	9.23GB	57.05GB	Fineweb-2, MaLA, New CC
afr_Latn	9.38M	858.54K	10.24M	3.02B	252.81M	3.27B	16.05GB	3.08GB	19.13GB	Fineweb-2, MaLA, New CC

Table 10: **Data Cleaning Statistics (part II):** Comparison of document count, token count, disk size, and sources before and after data cleaning in DCAD-2000.

Lang Code	Documents			Tokens			Disk Size			Source
	keep	remove	total	keep	remove	total	keep	remove	total	
ekk_Latn	9.24M	772.47K	10.01M	4.79B	401.83M	5.19B	38.34GB	11.83GB	50.16GB	Fineweb-2, MaLA
zsm_Latn	8.67M	795.54K	9.47M	4.22B	365.48M	4.59B	31.54GB	8.93GB	40.48GB	Fineweb-2, MaLA
ltz_Latn	8.59M	1.21M	9.79M	1.18B	146.26M	1.33B	6.77GB	1.91GB	8.68GB	Fineweb-2, MaLA, New CC
som_Latn	7.47M	716.70K	8.19M	2.20B	193.46M	2.40B	10.27GB	3.34GB	13.61GB	Fineweb-2, MaLA, New CC
kir_Cyrl	6.47M	468.94K	6.94M	2.31B	183.29M	2.49B	21.00GB	3.63GB	24.63GB	Fineweb-2, MaLA, New CC
cym_Latn	6.47M	515.43K	6.99M	2.01B	141.85M	2.15B	10.29GB	1.99GB	12.28GB	Fineweb-2, MaLA, New CC
nor_Latn	6.13M	733.57K	6.87M	1.27B	150.12M	1.42B	8.91GB	2.74GB	11.65GB	MaLA, New CC
uzb_Latn	6.07M	715.37K	6.78M	929.54M	98.71M	1.03B	8.76GB	2.73GB	11.49GB	MaLA, New CC
und_Kana	5.83M	1.11M	6.94M	1.13B	219.26M	1.35B	16.90GB	14.33GB	31.23GB	Fineweb-2, New CC
mya_Mymr	5.80M	449.02K	6.25M	5.28B	404.36M	5.69B	40.05GB	7.53GB	47.57GB	Fineweb-2, MaLA, New CC
epo_Latn	5.77M	456.78K	6.23M	2.38B	177.31M	2.56B	12.03GB	2.25GB	14.27GB	Fineweb-2, MaLA, New CC
ary_Arab	5.67M	465.36K	6.14M	1.38B	114.17M	1.50B	18.12GB	4.32GB	22.44GB	Fineweb-2, MaLA
lvs_Latn	5.51M	382.81K	5.89M	2.74B	185.99M	2.92B	21.58GB	6.85GB	28.43GB	Fineweb-2, MaLA
hau_Latn	5.48M	662.28K	6.15M	438.94M	49.38M	488.32M	3.22GB	1.09GB	4.32GB	MaLA
gle_Latn	5.47M	428.92K	5.90M	1.65B	134.54M	1.78B	9.41GB	1.55GB	10.96GB	Fineweb-2, MaLA, New CC
nno_Latn	5.19M	553.48K	5.75M	1.35B	124.05M	1.48B	7.48GB	1.85GB	9.33GB	Fineweb-2, MaLA, New CC
ory_Orya	5.13M	444.55K	5.57M	325.74M	23.33M	349.07M	7.34GB	1.07GB	8.41GB	Fineweb-2, MaLA
amh_Ethi	4.86M	302.32K	5.17M	1.21B	77.95M	1.28B	10.27GB	1.56GB	11.83GB	Fineweb-2, MaLA, New CC
khm_Khmr	4.74M	344.10K	5.09M	2.23B	158.45M	2.39B	30.49GB	4.58GB	35.08GB	Fineweb-2, MaLA, New CC
tat_Cyrl	4.72M	390.38K	5.11M	1.29B	103.35M	1.39B	11.66GB	2.16GB	13.82GB	Fineweb-2, MaLA, New CC
und_Bamu	4.71M	1.00M	5.71M	199.46M	42.49M	241.95M	79.67GB	19.47GB	99.14GB	Fineweb-2, New CC
und_Copt	4.40M	361.86K	4.76M	218.11M	17.95M	236.07M	8.96GB	860.56MB	9.82GB	Fineweb-2, New CC
arz_Arab	4.19M	347.36K	4.54M	794.23M	62.86M	857.09M	6.87GB	1.16GB	8.03GB	Fineweb-2, MaLA, New CC
und_Tang	3.94M	741.81K	4.68M	209.68M	39.47M	249.15M	22.70GB	7.67GB	30.36GB	Fineweb-2, New CC
und_Xsux	3.90M	694.59K	4.59M	276.93M	49.35M	326.28M	13.84GB	9.74GB	23.58GB	Fineweb-2, New CC
lav_Latn	3.76M	347.11K	4.11M	2.12B	196.45M	2.31B	13.96GB	7.36GB	21.32GB	MaLA, New CC
pus_Arab	3.71M	493.24K	4.21M	905.77M	106.28M	1.01B	7.66GB	2.36GB	10.02GB	MaLA, New CC
hbs_Cyrl	3.47M	463.55K	3.93M	131.15M	17.53M	148.69M	2.47GB	544.73MB	3.02GB	MaLA, New CC
war_Latn	3.43M	283.72K	3.71M	137.36M	11.19M	148.55M	1.84GB	161.55MB	2.00GB	Fineweb-2, MaLA, New CC
und_Yiii	3.39M	417.38K	3.81M	232.88M	28.68M	261.56M	25.82GB	6.24GB	32.05GB	Fineweb-2, New CC
multi_Latn	3.11M	394.01K	3.50M	2.39B	303.45M	2.70B	18.42GB	7.60GB	26.02GB	New CC
mlg_Latn	2.85M	437.74K	3.29M	288.34M	41.29M	329.63M	2.74GB	765.89MB	3.51GB	MaLA, New CC
und_Hira	2.78M	579.38K	3.36M	361.77M	75.28M	437.05M	4.87GB	4.04GB	8.91GB	Fineweb-2, New CC
uzn_Cyrl	2.61M	304.12K	2.91M	396.89M	30.84M	427.73M	6.39GB	1.47GB	7.86GB	Fineweb-2, MaLA
hat_Latn	2.58M	226.91K	2.81M	464.18M	41.25M	505.43M	2.60GB	548.40MB	3.15GB	Fineweb-2, MaLA, New CC
zul_Latn	2.47M	294.21K	2.76M	333.05M	38.27M	371.33M	2.15GB	642.83MB	2.79GB	Fineweb-2, MaLA
kur_Latn	2.41M	327.93K	2.74M	482.02M	51.67M	533.69M	3.40GB	1.04GB	4.44GB	MaLA
div_Thaa	2.25M	263.72K	2.52M	418.22M	43.98M	462.20M	4.37GB	1.02GB	5.38GB	Fineweb-2, MaLA, New CC
tgl_Latn	2.24M	345.69K	2.59M	369.19M	35.56M	404.74M	2.75GB	669.71MB	3.42GB	MaLA, New CC
uzb_Cyrl	2.22M	314.25K	2.54M	194.02M	27.60M	221.61M	2.96GB	1.14GB	4.10GB	MaLA
fry_Latn	2.14M	232.49K	2.38M	605.32M	65.90M	671.22M	3.10GB	914.11MB	4.01GB	Fineweb-2, MaLA, New CC
sna_Latn	2.14M	181.61K	2.32M	295.33M	24.54M	319.87M	1.84GB	428.76MB	2.27GB	Fineweb-2, MaLA
fao_Latn	2.09M	163.66K	2.26M	199.43M	14.19M	213.61M	1.69GB	392.84MB	2.08GB	Fineweb-2, MaLA
und_Laoo	2.06M	364.70K	2.42M	212.14M	37.64M	249.78M	4.20GB	2.59GB	6.79GB	Fineweb-2, New CC
sun_Latn	1.99M	193.82K	2.19M	275.24M	25.28M	300.53M	1.71GB	543.58MB	2.25GB	Fineweb-2, MaLA, New CC
snd_Arab	1.91M	154.84K	2.06M	1.12B	105.00M	1.22B	5.27GB	1.88GB	7.15GB	Fineweb-2, MaLA, New CC
und_Cyrl	1.86M	427.20K	2.29M	1.32B	302.88M	1.62B	5.09GB	18.81GB	23.90GB	Fineweb-2, New CC
und_Kits	1.86M	315.45K	2.17M	269.54M	45.75M	315.29M	12.47GB	17.12GB	29.58GB	Fineweb-2, New CC
bak_Cyrl	1.85M	132.43K	1.99M	401.91M	27.62M	429.53M	3.87GB	733.50MB	4.60GB	Fineweb-2, MaLA, New CC
asm_Beng	1.82M	115.52K	1.93M	380.78M	23.67M	404.45M	4.50GB	907.15MB	5.40GB	Fineweb-2, MaLA, New CC
cos_Latn	1.79M	274.66K	2.06M	228.06M	35.24M	263.31M	1.10GB	580.00MB	1.68GB	MaLA
ckb_Arab	1.78M	177.88K	1.96M	841.60M	76.59M	918.19M	6.48GB	1.52GB	8.00GB	Fineweb-2, MaLA, New CC
und_Hluw	1.71M	374.92K	2.09M	70.77M	15.47M	86.25M	3.19GB	3.45GB	6.64GB	Fineweb-2, New CC
ast_Latn	1.63M	144.18K	1.77M	213.12M	19.08M	232.20M	1.39GB	385.45MB	1.78GB	Fineweb-2, MaLA, New CC
jpn_Japn	1.60M	177.40K	1.78M	148.77M	17.99M	166.76M	6.05GB	2.16GB	8.21GB	MaLA
ibo_Latn	1.59M	117.64K	1.71M	233.50M	16.65M	250.14M	1.45GB	446.07MB	1.89GB	Fineweb-2, MaLA
und_Grek	1.57M	224.66K	1.79M	755.84M	108.19M	864.02M	6.94GB	7.17GB	14.12GB	Fineweb-2, New CC
mri_Latn	1.53M	133.72K	1.67M	354.50M	28.72M	383.22M	1.71GB	472.53MB	2.18GB	Fineweb-2, MaLA
ars_Arab	1.53M	108.78K	1.64M	461.05M	32.76M	493.81M	4.88GB	1.85GB	6.73GB	Fineweb-2, New CC
anp_Deva	1.44M	140.26K	1.58M	805.49M	78.54M	884.04M	10.69GB	2.12GB	12.81GB	Fineweb-2, MaLA
khk_Cyrl	1.44M	128.14K	1.57M	615.04M	54.80M	669.84M	8.17GB	1.83GB	10.00GB	Fineweb-2, New CC
und_Shrd	1.41M	216.59K	1.62M	130.80M	20.13M	150.93M	6.06GB	2.35GB	8.40GB	Fineweb-2, New CC
lao_Laoo	1.40M	105.80K	1.50M	628.08M	49.71M	677.79M	7.65GB	1.36GB	9.01GB	Fineweb-2, MaLA, New CC
und_Lina	1.37M	271.63K	1.64M	130.39M	25.87M	156.26M	6.97GB	3.85GB	10.82GB	Fineweb-2, New CC
und_Samr	1.35M	158.99K	1.51M	64.06M	7.54M	71.59M	4.30GB	1.72GB	6.02GB	Fineweb-2, New CC
ori_Orya	1.34M	145.91K	1.48M	128.69M	11.97M	140.66M	2.16GB	770.15MB	2.93GB	MaLA
jav_Latn	1.26M	122.51K	1.38M	379.69M	35.26M	414.95M	1.96GB	587.75MB	2.55GB	Fineweb-2, MaLA, New CC
yid_Hebr	1.25M	160.66K	1.41M	287.37M	36.14M	323.51M	2.84GB	1.30GB	4.14GB	MaLA, New CC
und_Cans	1.23M	248.05K	1.48M	106.39M	21.43M	127.83M	3.48GB	2.77GB	6.25GB	Fineweb-2, New CC

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Table 11: **Data Cleaning Statistics (part III):** Comparison of document count, token count, disk size, and sources before and after data cleaning in DCAD-2000.

Lang Code	Documents			Tokens			Disk Size			Source
	keep	remove	total	keep	remove	total	keep	remove	total	
nya_Latn	1.21M	138.31K	1.34M	230.59M	26.29M	256.88M	1.34GB	437.81MB	1.78GB	Fineweb-2, MaLA
hmn_Latn	1.20M	195.18K	1.40M	173.07M	28.59M	201.66M	1.08GB	543.90MB	1.63GB	MaLA
tir_Ethi	1.20M	78.32K	1.28M	125.79M	8.16M	133.96M	1.15GB	290.56MB	1.44GB	Fineweb-2, MaLA
uig_Arab	1.19M	78.60K	1.27M	513.72M	37.42M	551.15M	3.72GB	937.66MB	4.65GB	Fineweb-2, MaLA, New CC
wln_Latn	1.18M	74.38K	1.25M	53.99M	3.61M	57.59M	520.40MB	78.21MB	598.61MB	Fineweb-2, MaLA, New CC
und_Adlm	1.12M	194.29K	1.32M	43.63M	7.55M	51.18M	1.10GB	853.95MB	1.95GB	Fineweb-2, New CC
und_Egyp	1.12M	190.50K	1.31M	97.41M	16.58M	113.99M	2.54GB	3.52GB	6.05GB	Fineweb-2, New CC
und_Syrc	1.12M	115.88K	1.23M	42.71M	4.43M	47.14M	20.68GB	4.34GB	25.01GB	Fineweb-2, New CC
swh_Latn	1.12M	82.67K	1.20M	449.92M	32.71M	482.63M	3.34GB	803.12MB	4.15GB	Fineweb-2, MaLA
yor_Latn	1.12M	108.67K	1.22M	189.62M	18.77M	208.39M	1.08GB	304.95MB	1.38GB	Fineweb-2, MaLA, New CC
uzn_Latn	1.03M	68.06K	1.10M	466.19M	30.78M	496.97M	4.03GB	1.03GB	5.06GB	Fineweb-2, New CC
und_Mend	1.03M	293.72K	1.32M	16.58M	4.75M	21.33M	893.39MB	2.06GB	2.95GB	Fineweb-2, New CC
xho_Latn	1.02M	88.44K	1.11M	168.59M	13.93M	182.52M	1.19GB	247.71MB	1.44GB	Fineweb-2, MaLA
gla_Latn	1.01M	115.44K	1.13M	518.47M	76.34M	594.81M	2.03GB	904.76MB	2.94GB	Fineweb-2, MaLA, New CC
bre_Latn	980.75K	86.36K	1.07M	134.68M	11.68M	146.37M	757.53MB	231.46MB	988.99MB	Fineweb-2, MaLA, New CC
sot_Latn	917.37K	78.48K	995.85K	223.24M	17.82M	241.06M	1.09GB	283.15MB	1.37GB	Fineweb-2, MaLA
nan_Latn	905.48K	86.68K	992.16K	26.58M	2.54M	29.12M	483.99MB	95.09MB	579.08MB	Fineweb-2, MaLA
tel_Latn	898.42K	92.51K	990.93K	204.17M	21.27M	225.44M	843.51MB	444.92MB	1.29GB	Fineweb-2, MaLA
bew_Latn	885.97K	99.33K	985.30K	370.27M	41.51M	411.78M	2.85GB	776.53MB	3.62GB	Fineweb-2, New CC
smo_Latn	883.15K	83.25K	966.41K	241.45M	21.17M	262.62M	1.15GB	290.83MB	1.44GB	Fineweb-2, MaLA
glk_Arab	876.52K	99.66K	976.18K	44.95M	5.30M	50.24M	630.38MB	171.44MB	801.82MB	Fineweb-2, MaLA
che_Cyrl	875.25K	117.29K	992.54K	118.78M	15.18M	133.96M	1.05GB	346.83MB	1.40GB	Fineweb-2, MaLA, New CC
orm_Latn	859.55K	77.40K	936.95K	35.46M	3.19M	38.65M	476.68MB	150.02MB	626.69MB	MaLA
zho_Hani	840.53K	65.42K	905.95K	578.50M	46.68M	625.18M	2.67GB	980.93MB	3.65GB	MaLA
haw_Latn	808.97K	88.12K	897.10K	227.68M	23.61M	251.29M	869.19MB	300.40MB	1.17GB	Fineweb-2, MaLA
pnb_Arab	806.70K	71.03K	877.73K	133.55M	11.76M	145.31M	881.83MB	493.40MB	1.38GB	Fineweb-2, MaLA, New CC
oci_Latn	760.65K	59.16K	819.82K	123.30M	10.54M	133.84M	706.68MB	193.69MB	900.37MB	Fineweb-2, MaLA, New CC
und_Linb	735.07K	107.67K	842.75K	52.97M	7.76M	60.73M	6.30GB	997.90MB	7.30GB	Fineweb-2, New CC
chv_Cyrl	731.68K	60.72K	792.40K	188.93M	16.35M	205.28M	1.10GB	361.84MB	1.46GB	Fineweb-2, MaLA, New CC
kin_Latn	701.70K	67.29K	768.99K	197.65M	16.84M	214.49M	1.43GB	160.27MB	1.59GB	Fineweb-2, MaLA
srp_Latn	630.88K	54.65K	685.53K	158.44M	13.19M	171.63M	775.01MB	209.48MB	984.49MB	MaLA
und_Brai	590.10K	125.33K	715.43K	57.85M	12.29M	70.13M	1.94GB	1.30GB	3.24GB	Fineweb-2, New CC
kaa_Cyrl	588.71K	48.01K	636.72K	1.08B	86.21M	1.16B	3.58GB	620.59MB	4.20GB	Fineweb-2, MaLA
lug_Latn	570.88K	40.31K	611.19K	36.43M	2.65M	39.08M	344.92MB	85.21MB	430.13MB	Fineweb-2, MaLA
und_Sgnw	567.29K	106.45K	673.74K	37.34M	7.01M	44.34M	1.40GB	1.11GB	2.50GB	Fineweb-2, New CC
pcm_Latn	563.55K	80.45K	644.00K	135.97M	19.60M	155.57M	1.45GB	231.26MB	1.68GB	Fineweb-2, MaLA
pbt_Arab	556.45K	36.70K	593.15K	273.04M	18.00M	291.04M	2.40GB	481.43MB	2.88GB	Fineweb-2, MaLA
min_Latn	548.22K	32.98K	581.19K	28.26M	1.78M	30.04M	326.92MB	43.32MB	370.24MB	Fineweb-2, MaLA
tuk_Latn	526.60K	48.40K	575.00K	211.69M	23.04M	234.74M	1.14GB	368.23MB	1.51GB	Fineweb-2, MaLA
lim_Latn	526.45K	43.83K	570.28K	49.16M	4.85M	54.01M	338.07MB	70.26MB	408.33MB	Fineweb-2, MaLA, New CC
und_Hung	520.10K	155.23K	675.33K	42.34M	12.64M	54.98M	1.94GB	2.32GB	4.25GB	Fineweb-2, New CC
gsw_Latn	519.60K	64.76K	584.36K	171.13M	22.15M	193.28M	2.02GB	248.45MB	2.27GB	Fineweb-2, MaLA, New CC
aze_Arab	481.85K	107.19K	589.05K	16.65M	3.70M	20.35M	283.94MB	125.40MB	409.33MB	MaLA
kmr_Latn	473.75K	37.03K	510.79K	239.78M	19.24M	259.01M	1.64GB	366.13MB	2.01GB	Fineweb-2, MaLA, New CC
roh_Latn	467.79K	40.88K	508.66K	59.96M	5.00M	64.96M	373.84MB	133.62MB	507.46MB	Fineweb-2, MaLA, New CC
vec_Latn	451.53K	28.94K	480.47K	35.51M	2.41M	37.92M	248.96MB	70.25MB	319.21MB	Fineweb-2, MaLA
san_Deva	426.60K	30.30K	456.90K	186.19M	14.19M	200.38M	1.37GB	884.42MB	2.25GB	Fineweb-2, MaLA, New CC
und_Bali	422.49K	77.08K	499.57K	39.62M	7.23M	46.84M	1.19GB	662.91MB	1.85GB	Fineweb-2, New CC
und_Nshu	419.71K	89.40K	509.11K	38.53M	8.21M	46.74M	993.06MB	1.28GB	2.27GB	Fineweb-2, New CC
und_Modi	386.82K	67.33K	454.15K	52.58M	9.15M	61.73M	16.45GB	7.42GB	23.87GB	Fineweb-2, New CC
gmh_Latn	383.58K	47.47K	431.05K	769.12M	95.18M	864.30M	5.51GB	1.42GB	6.93GB	Fineweb-2, New CC
sco_Latn	382.19K	37.49K	419.69K	43.05M	4.46M	47.52M	357.63MB	98.46MB	456.10MB	Fineweb-2, MaLA
nds_Latn	379.54K	44.24K	423.78K	79.45M	11.68M	91.13M	384.74MB	126.48MB	511.22MB	Fineweb-2, MaLA, New CC
und_Lana	377.58K	110.80K	488.38K	47.55M	13.95M	61.50M	688.16MB	2.05GB	2.74GB	Fineweb-2, New CC
azb_Arab	376.14K	24.16K	400.30K	81.10M	6.51M	87.61M	615.69MB	203.89MB	819.58MB	Fineweb-2, MaLA, New CC
tsn_Latn	375.82K	23.43K	399.25K	24.79M	1.54M	26.33M	206.56MB	41.32MB	247.88MB	Fineweb-2, MaLA
und_Mong	364.92K	51.36K	416.28K	78.04M	10.98M	89.03M	1.32GB	827.40MB	2.15GB	Fineweb-2, New CC
sah_Cyrl	357.02K	24.17K	381.19K	110.13M	7.77M	117.89M	1.05GB	202.76MB	1.25GB	MaLA, New CC
und_Ethi	351.77K	49.20K	400.97K	39.75M	5.56M	45.31M	1.23GB	1.08GB	2.31GB	Fineweb-2, New CC
rus_Latn	349.61K	47.55K	397.17K	77.31M	10.54M	87.85M	755.00MB	485.49MB	1.24GB	MaLA
pri_Latn	348.99K	27.20K	376.20K	142.27M	11.09M	153.36M	2.15GB	505.82MB	2.66GB	Fineweb-2, New CC
und_Hebr	345.20K	46.87K	392.07K	17.42M	2.36M	19.78M	548.23MB	461.10MB	1.01GB	Fineweb-2, New CC
mon_Latn	344.80K	46.68K	391.48K	31.56M	4.27M	35.84M	180.12MB	271.24MB	451.37MB	MaLA
pap_Latn	339.80K	22.62K	362.42K	127.89M	8.52M	136.41M	678.73MB	223.10MB	901.83MB	Fineweb-2, MaLA
tgk_Latn	337.95K	48.39K	386.35K	26.44M	3.79M	30.22M	198.08MB	219.19MB	417.27MB	MaLA
plt_Latn	330.57K	28.23K	358.80K	118.46M	8.02M	126.48M	951.31MB	189.98MB	1.14GB	Fineweb-2, MaLA
lmo_Latn	324.18K	29.25K	353.43K	41.37M	4.09M	45.46M	230.80MB	58.92MB	289.72MB	Fineweb-2, MaLA, New CC
bod_Tibt	318.52K	34.22K	352.75K	252.06M	28.33M	280.39M	3.37GB	998.77MB	4.37GB	MaLA, New CC
und_Saur	315.78K	73.82K	389.60K	15.26M	3.57M	18.83M	398.55MB	489.07MB	887.62MB	Fineweb-2, New CC
yue_Hani	300.49K	34.04K	334.53K	9.02M	1.03M	10.06M	790.86MB	161.03MB	951.90MB	Fineweb-2, MaLA, New CC

Table 12: **Data Cleaning Statistics (part IV):** Comparison of document count, token count, disk size, and sources before and after data cleaning in DCAD-2000.

Lang Code	Documents			Tokens			Disk Size			Source
	keep	remove	total	keep	remove	total	keep	remove	total	
bar_Latn	270.31K	30.79K	301.10K	92.48M	12.46M	104.94M	318.42MB	142.36MB	460.78MB	Fineweb-2, MaLA
und_Thaa	262.00K	37.56K	299.56K	7.68M	1.10M	8.78M	391.60MB	263.21MB	654.81MB	Fineweb-2, New CC
und_Dupl	258.90K	53.06K	311.96K	14.14M	2.90M	17.04M	752.58MB	502.95MB	1.26GB	Fineweb-2, New CC
arg_Latn	258.20K	22.52K	280.72K	29.97M	3.05M	33.02M	207.88MB	43.58MB	251.45MB	Fineweb-2, MaLA, New CC
pms_Latn	258.13K	20.25K	278.38K	23.55M	1.86M	25.41M	172.17MB	39.05MB	211.22MB	Fineweb-2, MaLA, New CC
hif_Latn	254.95K	37.47K	292.41K	220.19M	38.74M	258.93M	779.02MB	879.71MB	1.66GB	Fineweb-2, MaLA
und_Thai	254.35K	47.64K	301.99K	47.88M	8.97M	56.85M	868.70MB	325.83MB	1.19GB	Fineweb-2, New CC
und_Runr	252.18K	39.00K	291.18K	154.68M	23.92M	178.61M	1.25GB	3.28GB	4.52GB	Fineweb-2, New CC
und_Vaii	243.47K	93.27K	336.73K	71.28M	27.31M	98.59M	513.30MB	1.88GB	2.39GB	Fineweb-2, New CC
vol_Latn	241.22K	23.73K	264.95K	12.26M	1.28M	13.54M	126.45MB	27.79MB	154.24MB	Fineweb-2, MaLA, New CC
und_Glag	237.68K	72.07K	309.75K	20.38M	6.18M	26.56M	476.61MB	951.96MB	1.43GB	Fineweb-2, New CC
nrm_Latn	234.99K	31.99K	266.97K	71.12M	9.68M	80.80M	654.26MB	233.97MB	888.23MB	Fineweb-2, MaLA
aeb_Arab	230.69K	32.19K	262.88K	51.79M	7.23M	59.01M	641.42MB	232.91MB	874.33MB	Fineweb-2, New CC
kat_Latn	229.64K	46.98K	276.62K	37.42M	7.66M	45.08M	247.34MB	365.42MB	612.76MB	MaLA
ido_Latn	222.87K	22.62K	245.49K	15.65M	1.48M	17.13M	131.86MB	35.81MB	167.67MB	Fineweb-2, MaLA, New CC
kal_Latn	220.32K	17.35K	237.67K	76.08M	6.03M	82.11M	371.13MB	202.28MB	573.42MB	Fineweb-2, MaLA
pam_Latn	219.65K	22.53K	242.18K	21.42M	2.45M	23.87M	129.69MB	37.16MB	166.84MB	Fineweb-2, MaLA
und_Khmr	216.99K	36.25K	253.24K	10.97M	1.83M	12.80M	473.35MB	417.98MB	891.34MB	Fineweb-2, New CC
lus_Latn	206.91K	16.42K	223.33K	66.59M	5.16M	71.75M	387.16MB	114.21MB	501.37MB	Fineweb-2, MaLA
und_Mymr	204.74K	27.30K	232.03K	5.63M	751.18K	6.39M	283.14MB	249.17MB	532.31MB	Fineweb-2, New CC
und_Tibt	201.49K	32.84K	234.33K	15.44M	2.52M	17.95M	970.52MB	505.25MB	1.48GB	Fineweb-2, New CC
und_Dsrt	198.00K	37.90K	235.90K	4.47M	855.49K	5.32M	248.83MB	562.92MB	811.75MB	Fineweb-2, New CC
und_Geor	196.35K	49.50K	245.85K	22.22M	5.60M	27.83M	374.55MB	629.81MB	1.00GB	Fineweb-2, New CC
new_Deva	187.27K	16.23K	203.49K	23.86M	2.07M	25.93M	302.85MB	89.56MB	392.41MB	Fineweb-2, MaLA, New CC
und_Mroo	186.14K	22.85K	208.99K	6.42M	788.69K	7.21M	2.43GB	335.38MB	2.77GB	Fineweb-2, New CC
sme_Latn	184.43K	14.88K	199.30K	42.27M	3.53M	45.80M	318.80MB	92.35MB	411.15MB	Fineweb-2, MaLA
und_Bopo	181.71K	24.45K	206.16K	30.63M	4.12M	34.75M	3.45GB	890.68MB	4.35GB	Fineweb-2, New CC
nso_Latn	175.98K	9.66K	185.64K	18.89M	1.08M	19.97M	111.81MB	32.30MB	144.10MB	Fineweb-2, MaLA
und_Armn	168.06K	46.69K	214.75K	33.05M	9.18M	42.24M	347.17MB	515.75MB	862.92MB	Fineweb-2, New CC
und_Mtei	166.92K	19.64K	186.57K	48.49M	5.71M	54.20M	795.85MB	570.91MB	1.37GB	Fineweb-2, New CC
scn_Latn	162.55K	10.71K	173.26K	18.07M	1.48M	19.55M	125.29MB	25.45MB	150.75MB	Fineweb-2, MaLA, New CC
ina_Latn	159.80K	16.99K	176.79K	13.62M	1.49M	15.11M	104.31MB	28.02MB	132.33MB	Fineweb-2, MaLA, New CC
lld_Latn	154.22K	24.98K	179.20K	8.00M	1.25M	9.25M	90.50MB	16.81MB	107.31MB	Fineweb-2, MaLA
und_Khar	153.37K	40.04K	193.41K	6.75M	1.76M	8.52M	250.30MB	182.38MB	432.67MB	Fineweb-2, New CC
hyw_Armn	142.71K	12.89K	155.60K	60.77M	5.52M	66.29M	863.69MB	174.18MB	1.04GB	Fineweb-2, MaLA
und_Deva	141.13K	26.07K	167.20K	35.96M	6.64M	42.60M	255.99MB	1.53GB	1.79GB	Fineweb-2, New CC
abk_Cyrl	139.72K	12.86K	152.58K	7.73M	671.84K	8.40M	100.31MB	14.57MB	114.88MB	Fineweb-2, MaLA
und_Brah	138.03K	22.72K	160.75K	7.85M	1.29M	9.15M	273.71MB	243.75MB	517.47MB	Fineweb-2, New CC
bpy_Beng	135.66K	9.50K	145.16K	9.30M	766.18K	10.07M	141.90MB	28.27MB	170.17MB	Fineweb-2, MaLA, New CC
bew_Cyrl	133.83K	13.49K	147.32K	3.37M	339.68K	3.71M	74.12MB	15.81MB	89.93MB	MaLA
lin_Latn	133.64K	8.68K	142.32K	16.04M	1.37M	17.41M	115.63MB	32.27MB	147.89MB	Fineweb-2, MaLA
und_Bhks	131.90K	27.03K	158.93K	3.93M	805.58K	4.74M	190.96MB	154.63MB	345.59MB	Fineweb-2, New CC
oss_Cyrl	128.06K	13.97K	142.03K	84.80M	9.56M	94.36M	390.43MB	167.02MB	557.45MB	Fineweb-2, MaLA, New CC
tgk_Arab	127.77K	14.97K	142.75K	11.61M	1.36M	12.97M	104.11MB	55.51MB	159.62MB	MaLA
szl_Latn	127.60K	10.33K	137.93K	8.52M	738.21K	9.25M	89.99MB	12.81MB	102.80MB	Fineweb-2, MaLA
mww_Latn	122.30K	10.22K	132.52K	98.37M	8.22M	106.59M	536.48MB	104.20MB	640.68MB	Fineweb-2, New CC
sdh_Arab	120.04K	14.20K	134.24K	35.26M	4.50M	39.76M	466.52MB	136.99MB	603.52MB	Fineweb-2, MaLA
und_Hmnp	118.87K	12.33K	131.20K	6.83M	708.37K	7.54M	436.28MB	151.81MB	588.09MB	Fineweb-2, New CC
srd_Latn	118.78K	8.14K	126.92K	15.38M	1.23M	16.61M	119.77MB	24.18MB	143.95MB	Fineweb-2, MaLA
mhr_Cyrl	118.77K	12.58K	131.35K	30.71M	3.17M	33.88M	278.82MB	75.27MB	354.09MB	Fineweb-2, MaLA, New CC
ydd_Hebr	117.78K	7.28K	125.06K	73.71M	4.55M	78.26M	879.66MB	120.71MB	1.00GB	Fineweb-2, MaLA
diq_Latn	117.09K	11.78K	128.87K	9.75M	962.88K	10.71M	75.44MB	16.34MB	91.79MB	Fineweb-2, MaLA, New CC
und_Telu	115.91K	30.83K	146.74K	9.00M	2.39M	11.40M	409.30MB	426.99MB	836.29MB	Fineweb-2, New CC
que_Latn	114.28K	23.93K	138.21K	4.28M	896.83K	5.18M	57.76MB	33.84MB	91.59MB	MaLA, New CC
run_Latn	114.03K	9.29K	123.32K	24.63M	1.97M	26.60M	218.56MB	39.33MB	257.89MB	Fineweb-2, MaLA
hsb_Latn	112.76K	9.95K	122.71K	25.10M	2.04M	27.14M	153.09MB	23.81MB	176.90MB	Fineweb-2, MaLA, New CC
wol_Latn	108.94K	11.08K	120.02K	11.76M	1.37M	13.13M	95.99MB	29.75MB	125.74MB	Fineweb-2, MaLA
rmy_Latn	108.23K	21.11K	129.34K	284.56M	55.71M	340.26M	2.54GB	98.95MB	2.64GB	Fineweb-2, MaLA
und_Phag	107.75K	17.58K	125.34K	3.41M	556.36K	3.97M	141.68MB	93.31MB	234.99MB	Fineweb-2, New CC
und_Merc	107.52K	38.04K	145.56K	7.61M	2.69M	10.30M	215.43MB	472.23MB	687.66MB	Fineweb-2, New CC
urd_Latn	106.75K	12.60K	119.35K	139.19M	16.43M	155.63M	312.70MB	140.28MB	452.98MB	Fineweb-2, New CC
kiu_Latn	106.48K	10.36K	116.84K	36.53M	3.76M	40.29M	289.67MB	193.73MB	483.39MB	Fineweb-2, MaLA
cak_Latn	106.28K	6.64K	112.92K	6.08M	438.75K	6.52M	66.17MB	10.86MB	77.03MB	Fineweb-2, MaLA
ilo_Latn	106.18K	7.83K	114.01K	28.61M	2.06M	30.67M	143.69MB	37.61MB	181.30MB	Fineweb-2, MaLA, New CC
und_Kali	105.87K	24.33K	130.19K	1.39M	318.99K	1.71M	105.22MB	91.44MB	196.66MB	Fineweb-2, New CC
und_Plrd	104.31K	21.07K	125.38K	5.47M	1.10M	6.57M	214.53MB	225.25MB	439.77MB	Fineweb-2, New CC
und_Orya	104.03K	26.52K	130.56K	10.14M	2.59M	12.73M	299.43MB	387.64MB	687.07MB	Fineweb-2, New CC
und_Lisu	101.47K	20.05K	121.52K	24.00M	4.74M	28.74M	204.23MB	527.19MB	731.42MB	Fineweb-2, New CC
und_Hmng	101.02K	23.34K	124.36K	5.37M	1.24M	6.61M	153.20MB	196.99MB	350.19MB	Fineweb-2, New CC

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