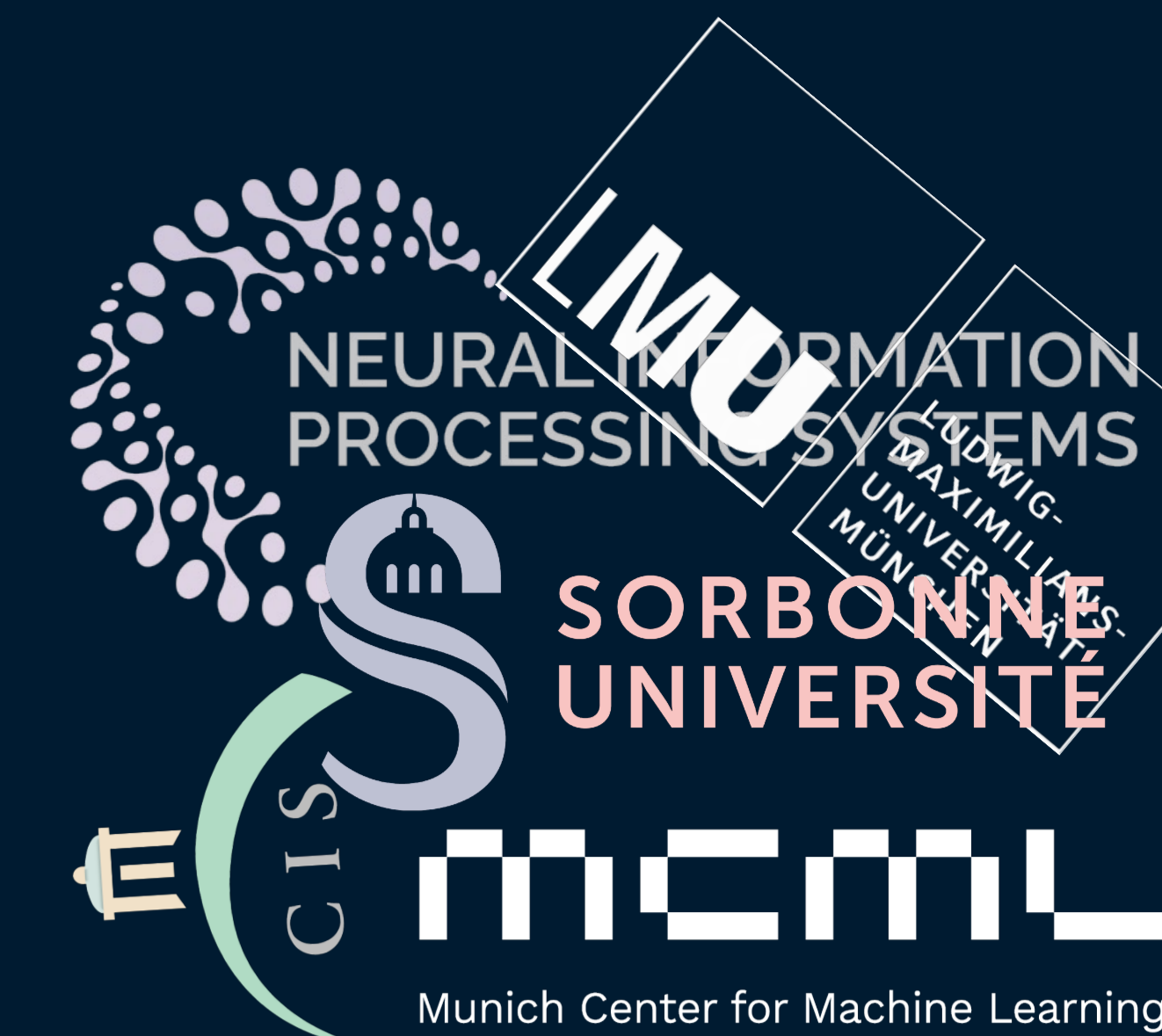




# GlottCC: An Open Broad-Coverage CommonCrawl Corpus and Pipeline for Minority Languages

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We present GlottCC, a **clean, document-level, 2TB** general domain corpus derived from **CommonCrawl**, covering more than **1000 languages**. We make GlottCC and the system used to generate it—including the pipeline, language identification model, and filters—available to the research community.

## Background

The need for large text corpora has **increased** with the advent of pretrained language models, and particularly the discovery of scaling laws for these models.

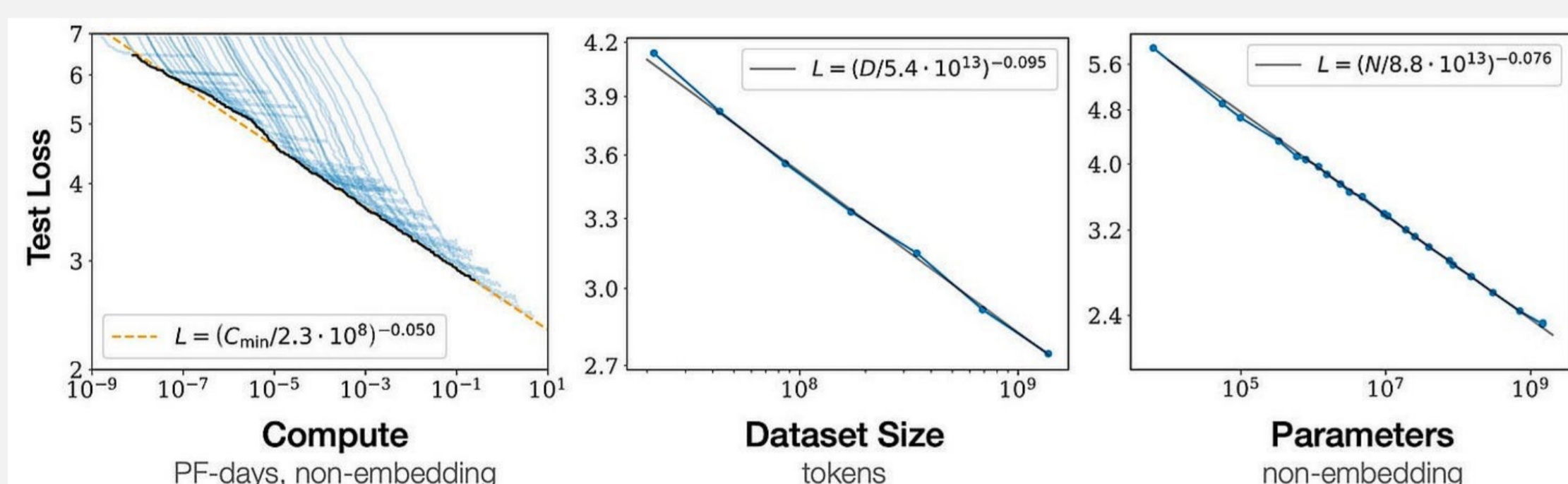


Figure 1 Language modeling performance improves smoothly as we increase the model size, dataset size, and amount of compute<sup>2</sup> used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

Source: Scaling Laws for Neural Language Models, 2020

Most available corpora have sufficient data only for languages with **large dominant communities**.

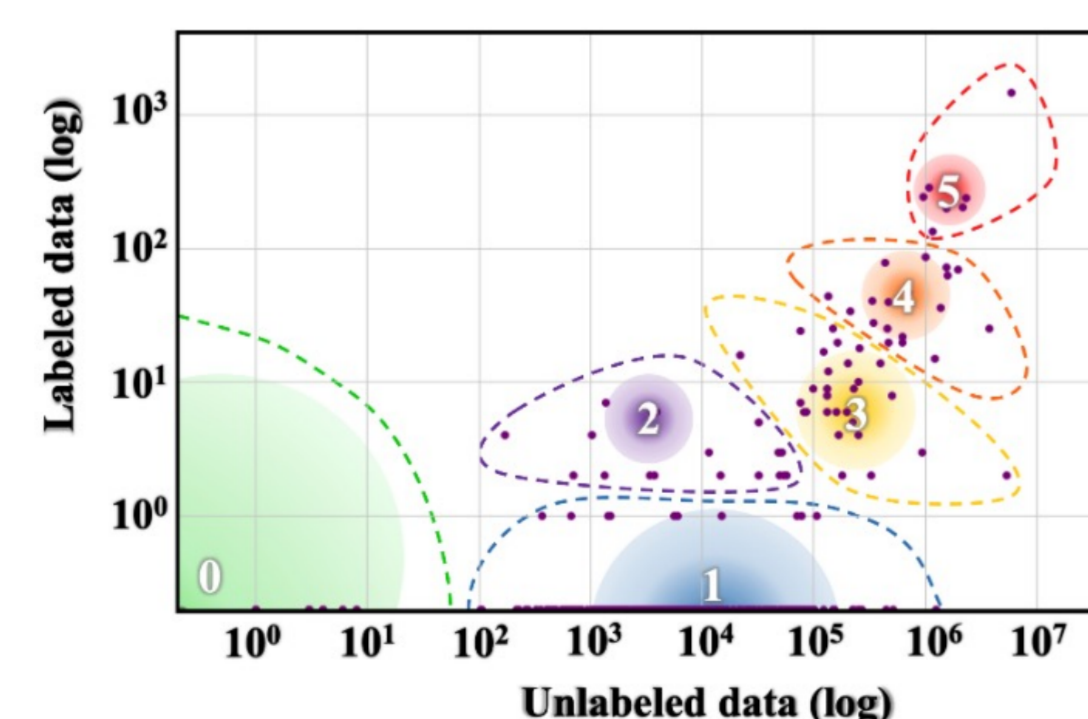


Figure 2: Language Resource Distribution: The size of the gradient circle represents the number of languages

Source: The State and Fate of Linguistic Diversity and Inclusion in the NLP World, 2020

However, there is no corpus available that

- covers a wide range of **minority** languages;
- is generated by an **open-source reproducible** Pipeline
- is rigorously **cleaned** from noise, making it trustworthy to use.

## Pipeline

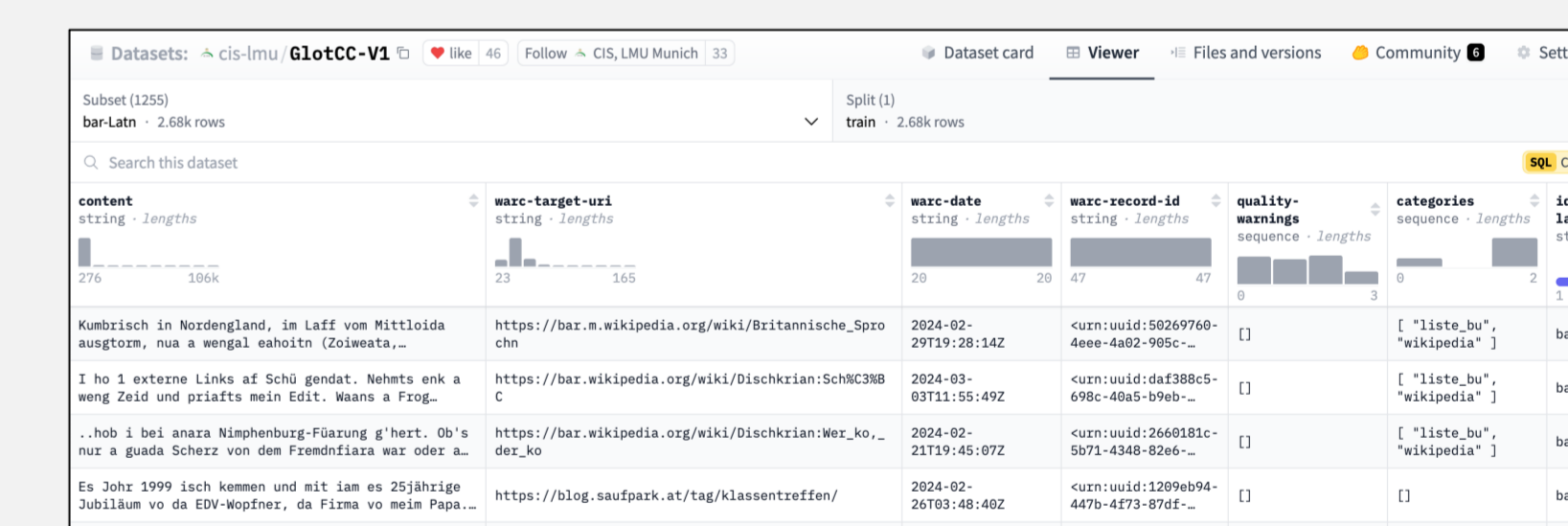
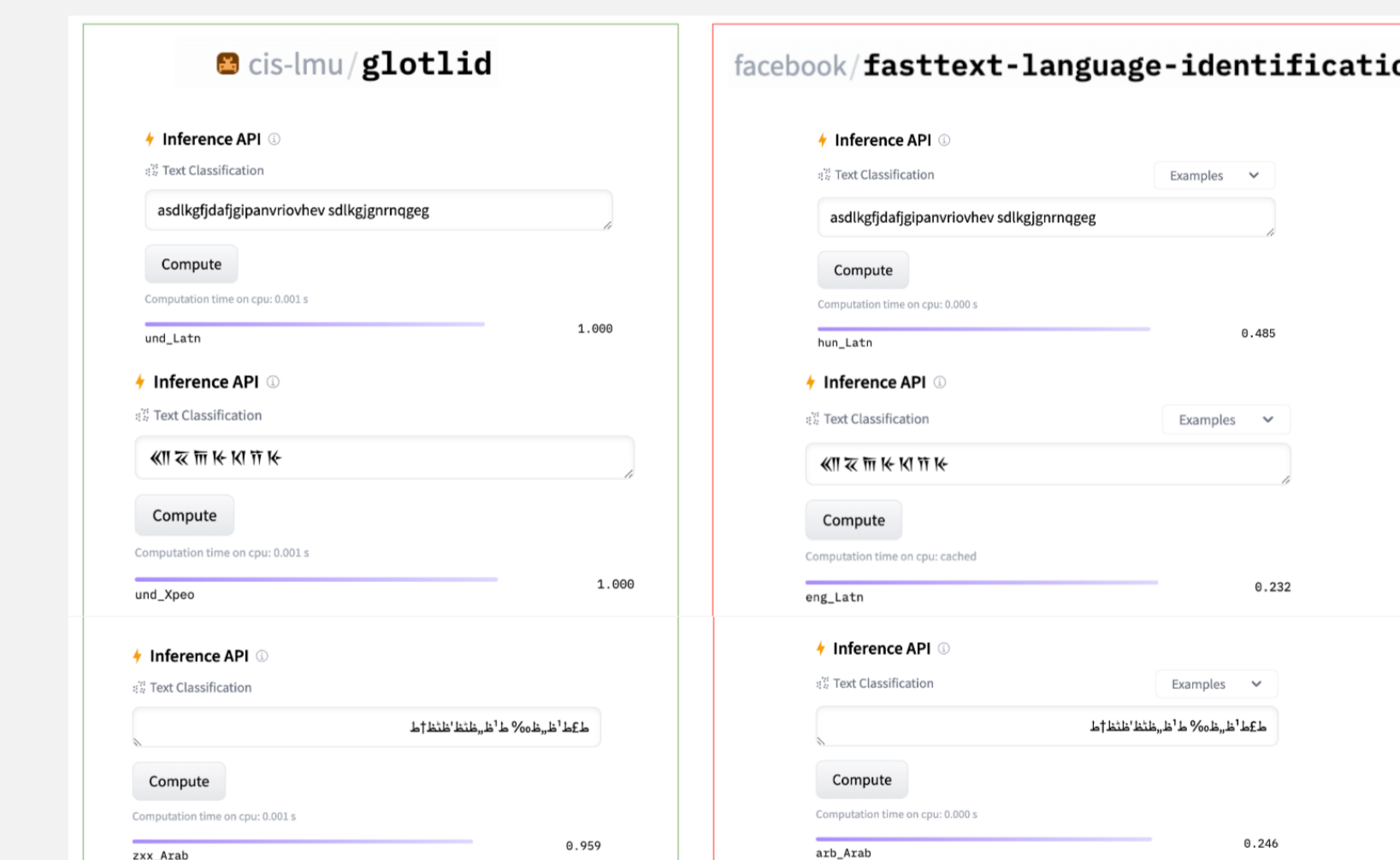
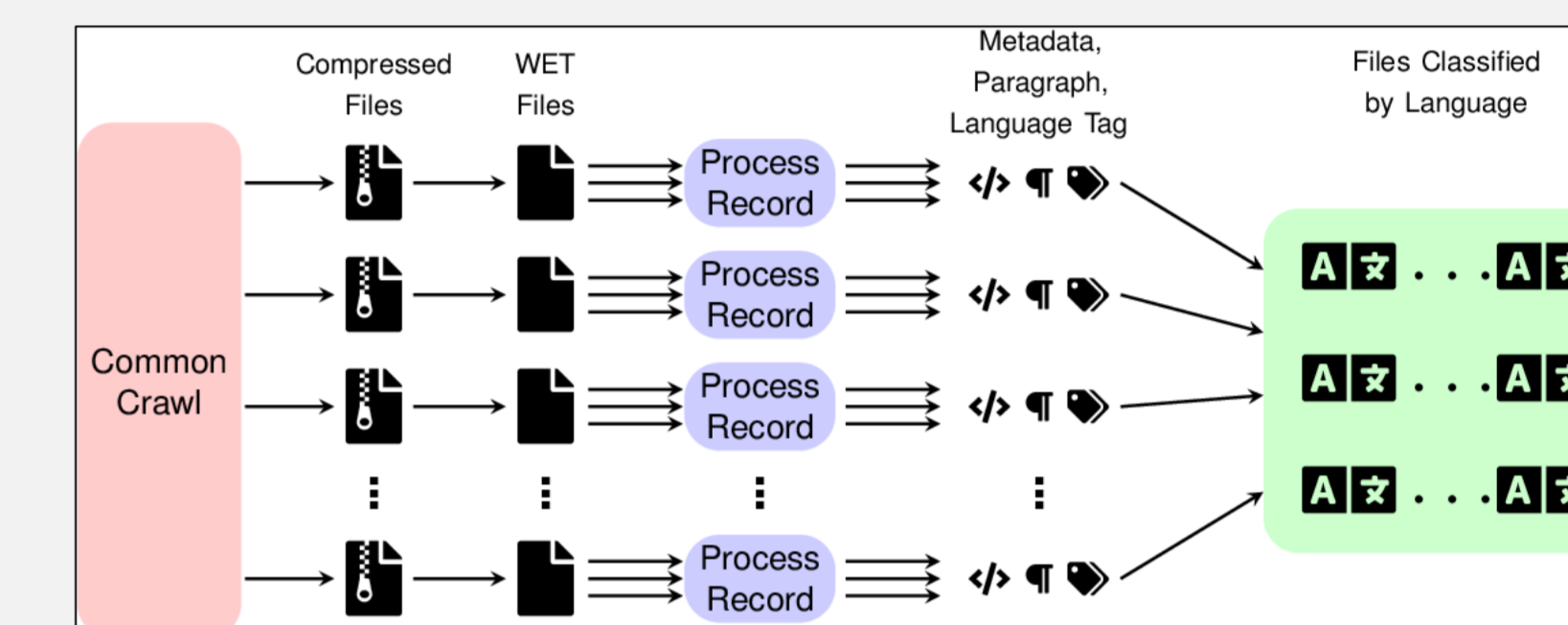


**Base;** The Ungoliant pipeline processes **CommonCrawl** WET files by extracting metadata, creating paragraphs, and tagging content with a **language identification (LID) model**. The output includes metadata, structured paragraphs, and language tags, with records grouped into files by language.

**Language identification;** LID is typically understood as a closed-set classification problem; most LID systems adopt this setup. However, since LID is inherently an open-set problem, processing web data always carries the risk of encountering “unknown” languages. We developed GlotLID v3, which covers nearly 2,000 labels, including major web noise labels and unseen writing systems.

**Filters;** We primarily use the cleaning process from OSCAR, MADLAD-400, GlotScript, and FineWeb. Since the LIDs are trained at the sentence level, we applied them to both sentences and entire documents, ensuring the majority of the data have consistent labels.

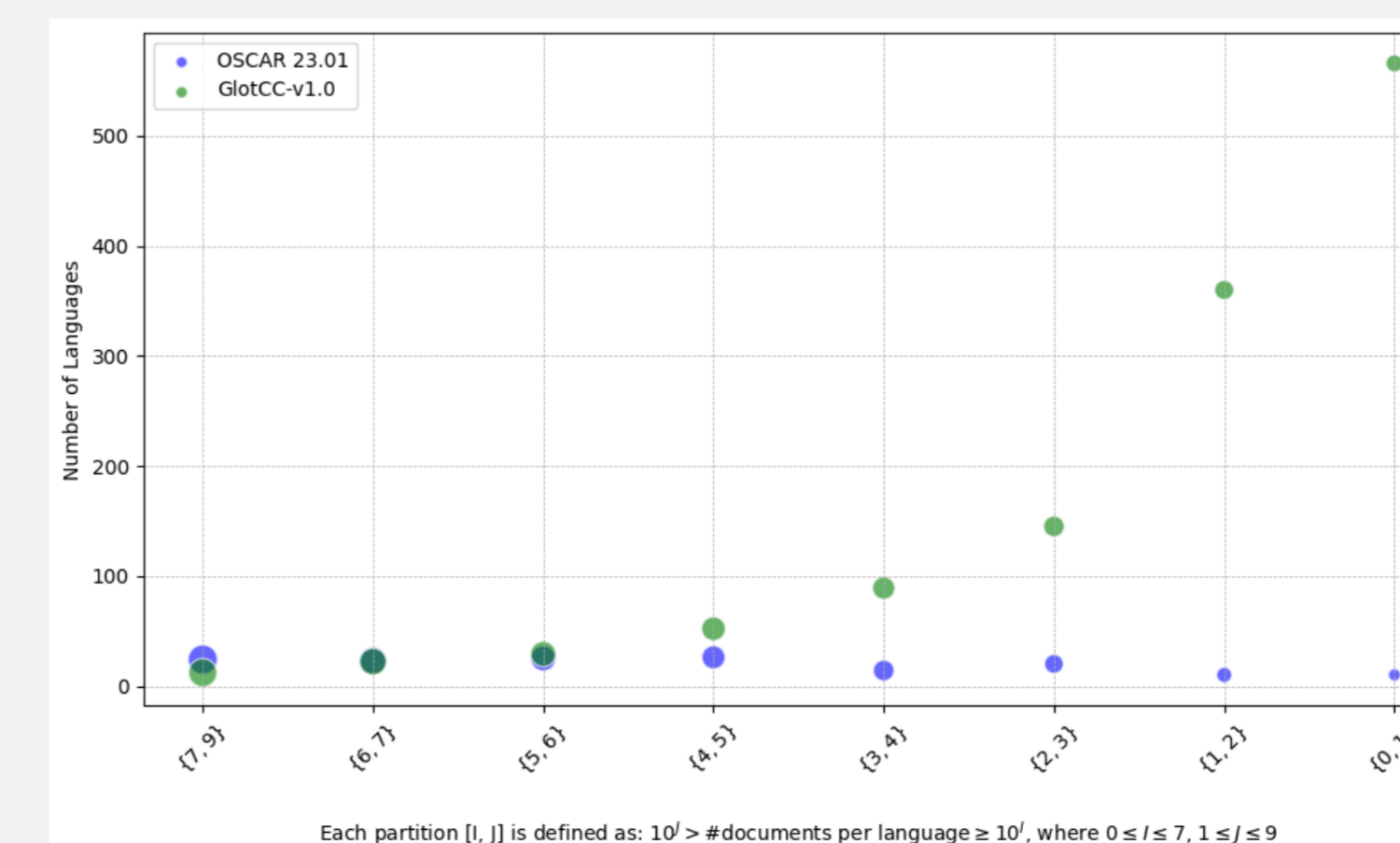
**Self-audit quality review;** Out of 653 audited languages, we find that, with a macro-average score of **0.93** and a median score of **1.0**, the data is in-language. There are still errors that neither the LID nor the filters captures. For example, repetitive n-grams in list-like content.



## GlottCC vs other attempts (e.g., OSCAR)

Table 4: Partition statistics for OSCAR 23.01 and GlotCC-v1.0. Each partition is defined as: 10<sup>l</sup> > # documents per language ≥ 10<sup>l-1</sup>, where 0 ≤ l ≤ 7, 1 ≤ j ≤ 9.

(l, j)	Corpus Version	# Languages	# Documents	# Lines	# Words	# Religious	# Wikipedia
(7, 9)	OSCAR 23.01	24	2.7B	34.4M	-	1.0T	12.6B
(7, 9)	GlottCC-v1.0	12	579.5M	22.7M	15.1B	780.8M	436.4B
(6, 7)	OSCAR 23.01	23	80.0M	2.4M	-	27.6B	738.8M
(6, 7)	GlottCC-v1.0	22	92.2M	3.3M	3.0B	122.1M	67.8B
(5, 6)	OSCAR 23.01	25	9.3M	262.7K	-	3.2B	82.4M
(5, 6)	GlottCC-v1.0	29	10.7M	334.8K	305.4M	9.1M	6.9B
(4, 5)	OSCAR 23.01	26	919.7K	25.2K	-	212.0M	5.4M
(4, 5)	GlottCC-v1.0	52	1.9M	29.6K	55.1M	714.4K	1.3B
(3, 4)	OSCAR 23.01	14	60.1K	3.6K	-	10.1M	315.7K
(3, 4)	GlottCC-v1.0	89	338.7K	2.7K	8.2M	52.2K	223.9M
(2, 3)	OSCAR 23.01	20	8.6K	400	-	772.3K	13.4K
(2, 3)	GlottCC-v1.0	145	53.9K	326	1.4M	6.5K	39.3M
(1, 2)	OSCAR 23.01	10	368	36	-	13.6K	431
(1, 2)	GlottCC-v1.0	360	11.5K	24	245.0K	460	11.3M
(0, 1)	OSCAR 23.01	10	44	4	-	21.5K	67
(0, 1)	GlottCC-v1.0	566	1.7K	2	41.5K	26	1.7M
(0, 9)	OSCAR 23.01	152	2.8B	69.7K	-	1.1T	14.5M
(0, 9)	GlottCC-v1.0	1275	684.7M	14	18.5B	254	512.6B



From high-resource to low-resource, the size of each circle is proportional to the logarithm of the total number of documents.

## References

- GlotLID: Language Identification for Low-Resource Languages, 2023
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- MADLAD-400: A Multilingual And Document-Level Large Audited Dataset, 2023
- GlotScript: A Resource and Tool for Low Resource Writing System Identification, 2024

