Judging Quality Across Languages: A Multilingual Approach to Pretraining Data Filtering with Language Models

Mehdi Ali[1,2] * **Manuel Brack**[4] * **Max Lübbering**[1,2] * **Elias Wendt**[5] * **Abbas Goher Khan**[1] *
Richard Rutmann[1,2] Alex Jude[1] Maurice Kraus[3,4] Alexander Arno Weber[1,2]
Felix Stollenwerk[6] David Kaczér[2] Florian Mai[2] Lucie Flek[2] Rafet Sifa[1,2] Nicolas Flores-Herr[1]
Joachim Köhler[1,2] Patrick Schramowski[3,4,5] Michael Fromm[1,2] Kristian Kersting[3,4,5]
[1] Fraunhofer IAIS, Sankt Augustin and Dresden, Germany, [2]Lamarr Institute, Bonn, Germany
[3]DFKI, [4]Hessian AI, [5]Computer Science Department, TU Darmstadt, [6]AI Sweden
mehdi.ali@iais.fraunhofer.de, brack@cs.tu-darmstadt.de

Abstract

High-quality multilingual training data is essential for effectively pretraining large language models (LLMs). Yet, the availability of suitable open-source multilingual datasets remains limited. Existing state-of-the-art datasets mostly rely on heuristic filtering methods, restricting both their cross-lingual transferability and scalability. Here, we introduce JQL, a systematic approach that efficiently curates diverse and high-quality multilingual data at scale while significantly reducing computational demands. JQL distills LLMs' annotation capabilities into lightweight annotators based on pretrained multilingual embeddings. These models exhibit robust multilingual and cross-lingual performance, even for languages and scripts unseen during training. Evaluated empirically across 35 languages, the resulting annotation pipeline substantially outperforms current heuristic filtering methods like Fineweb2. JQL notably enhances downstream model training quality and increases data retention rates. Our research provides practical insights and valuable resources for multilingual data curation, raising the standards of multilingual dataset development.

1 Introduction

The quality of pre-training data remains a crucial factor in LLM performance and represents one of the most effective factors for reducing training costs (Penedo et al., 2024a). Even recent improvements in post-training and scaling of inference-time compute heavily depend on the quality of the pre-trained base model (Guo et al., 2025). Consequently, a growing number of research efforts have focused on developing data curation pipelines for large-scale web data. (Penedo et al., 2024a; Li et al., 2024; Su et al., 2024).

The overall goal of any data filtering set-up is to achieve the largest possible dataset of the highest quality. Traditionally, heuristic-based approaches rely on predefined rules to filter the raw training data (Abadji et al., 2022; Penedo et al., 2024a). Recently, however, there has been a shift towards machine learning-based data curation, which tends to outperform complex rule-based systems in producing high-quality pre-training corpora. A particularly interesting research avenue is the use of existing LLMs to identify high-quality content. This "LLMs as judges to filter datasets" approach has proven highly effective in selecting high-quality data that leads to more performant models (Penedo et al., 2024a; Su et al., 2024).

A significant limitation, however, is that existing research in this area largely focuses on English, making it unclear whether these methods effectively transfer to highly multilingual settings, especially those involving low-resource languages. Specifically, in contrast to English-centric data curation, multilingual settings raise additional questions on potential gaps between high- and low-resource languages and the cross-lingual performance on unseen languages. Moreover, much of the research in this field is led by frontier AI labs, which tend to keep state-of-the-art data procurement and curation strategies closed-source, impeding reproducibility and follow-up research.

Addressing these limitations, we propose a multilingual data filtering approach called JQL (**J**udging **Q**uality across **L**anguages)[1] comprising the four stages outlined in Fig. 1. With minimal human supervision and small amounts of distilled annotation data, we are able to train lightweight regressors for efficient filtering of multilingual, large-scale data at low computational cost. JQL is language agnostic and can be extended to arbitrary filter criteria.

We provide actionable insights and release valuable artifacts from each pipeline step[2]. Overall, we

*Equal contribution.

[1]pronounced *Jackal*

[2]https://huggingface.co/JQL-AI

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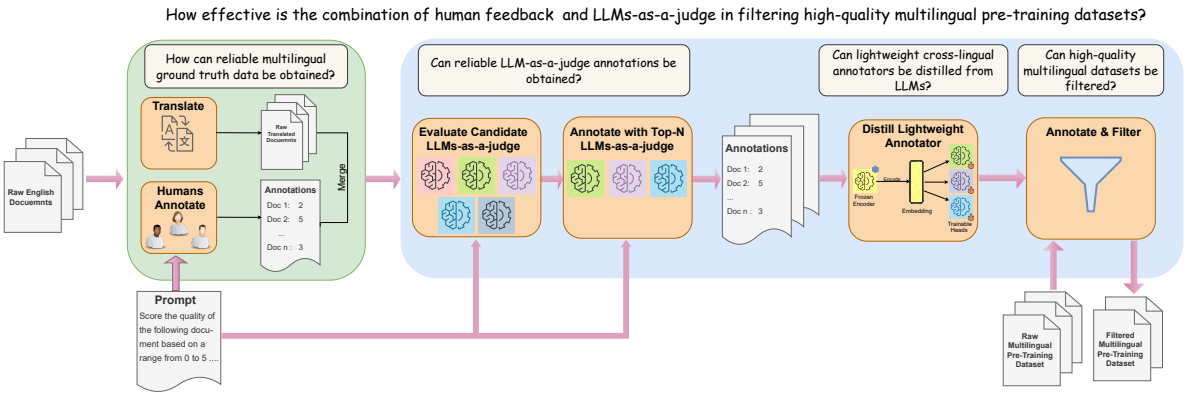

Figure 1: The multilingual data filtering approach JQL: In the first stage (Sec. 2), human annotators generate ground truth (GT) annotations on monolingual documents based on an instruction set defined in a prompt. The documents are translated into all target languages to receive a multilingual GT dataset. In the second stage (Sec. 3), based on the GT dataset, we select the top-n performing LLMs-as-a-judge for annotating a multilingual dataset. In the third stage (Sec. 4), we use the resulting synthetic dataset to train a set of lightweight annotators. This is done at low cost by reusing shared embeddings. Using these annotators, we can efficiently annotate pre-training corpora and filter high-quality subsets (Sec. 5).

make the following contributions: (1) A human-centric approach to creating ground truth by using human annotations to build a reliable dataset for evaluating and guiding pipeline component selection. In this context, we release a novel ground truth dataset comprising 511 manually annotated documents, translated into 35 languages (Sec. 2). (2) A study investigating LLM capabilities in assessing the quality of multilingual documents (Sec.3). As part of this study, we release annotations from the three best-performing LLMs across 35 languages, covering over 14 million documents. (3) A study investigating the multi- & cross-lingual transfer capabilities of lightweight annotator models, evaluating how well judgment abilities generalize to unseen languages (Sec. 4). (4) Demonstration that our approach leads to high-quality pre-training datasets that improve the downstream performance of LLMs (Sec. 5).

Family	Languages
Slavic (9)	**Bulgarian**, Czech, Croatian, Macedonian, **Polish**, Slovak, Slovenian, Serbian, **Ukrainian**
Germanic (7)	Danish, **German**, Icelandic, Dutch, **Norwegian** (**Bokmål** & Nynorsk), Swedish
Romance (7)	Catalan, **Spanish**, **French**, Galician, **Italian**, Portuguese, Romanian
Uralic (3)	Estonian, **Finnish**, **Hungarian**
Baltic (2)	**Lithuanian**, Latvian
Singleton families	Hellenic (**Greek**), Celtic (Irish), Basque (Basque), West Semitic (Maltese), Turkic (**Turkish**), Albanoid (Albanian), Armenian (Armenian)

Table 1: Languages and respective language families considered in this study. The richness of European language families allows for structured research into the influence of inter-language similarities for cross-lingual transfer. For better readability, we report values for languages highlighted in **bold** in the main body, with remaining values supplied in the Appendix.

2 Collecting Human Annotations

The first step in the JQL pipeline is to collect human ground truth annotations. These annotations then serve as the cornerstone of our structured approach for building multilingual data annotators, enabling meaningful cross-validation of all design choices.

2.1 User Study Design

To construct a multilingual ground truth dataset for selecting a large language model (LLM) to serve as a judge in evaluating the educational value of documents, we conducted a human annotation study.

As a starting point, we leveraged the English LLM-annotated dataset from Fineweb-Edu (Penedo et al., 2024a), which contains approximately 450,000 annotations assessing the educational value of documents. Given the demonstrated effectiveness of their scoring scheme, we adopted the same 6-point scale, ranging from 0 (lowest educational value) to 5 (highest). To ensure balanced representation across the scoring spectrum, we sampled 100 documents for each score level. Since only 11 documents were available for score 5, the resulting dataset totals 511 samples. These documents form the basis of our human annotation

study involving 15 annotators with backgrounds in computer science, English studies, physics and mathematics (details are provided in App A.2).

To ensure annotation quality and consistency, we employed the educational prompt defined by Fineweb-Edu as annotation guidelines, and conducted a dedicated annotator training session. This training proved essential since in a preliminary pilot without training, some annotators partially misunderstood the task despite having access to the written guidelines. In the main annotation phase, each of the 511 documents received three independent annotations, thus capturing variability in human judgments. To aggregate the three annotations for each document into a single score, we applied majority voting and averaging when no clear majority emerged.

2.2 Multilingual Extension

For multilingual support, we translated the English ground truth dataset into the 35 European languages outlined in Tab. 1. We decided to focus on these languages, since they offer a good trade-off between linguistic diversity and well-populated language families. Nonetheless, we demonstrate in Sec. 6 that our annotation pipeline works equally well on typologically different languages such as Chinese, without requiring any modifications. We used DeepL for the 22 languages it supports, and GPT-4o for the remaining 13 languages. To improve correctness of the GPT-translated texts, we ran a language classifier over all documents and discarded those not matching the target language. Additionally, we removed prefatory phrases added by GPT-4o to ensure overall consistency.

2.3 Assessing Inter-Annotator Agreement

To verify the consistency of our annotation process, we analyzed the collected labels and annotator consensus. We observed a high level of agreement across annotators, as evidenced by a majority agreement for 78.5% of documents and an overall standard deviation of 0.56. While the annotation spread was ≤ 2 for 86% of the data, a few documents exhibited a spread > 3. Upon manual inspection, we found that the educational value of these examples is indeed highly subjective, which resulted in disagreement between annotators. Overall, our rigorous annotator training and data cleaning procedure have resulted in a reliable ground truth, suitable for robustly evaluating ML-based annotators.

2.4 Suitable Evaluation Criteria

Choosing an appropriate evaluation metric is essential for assessing the performance of LLM-based annotators against human-annotated ground truth.

While standard classification metrics like F1 score are appropriate for discrete categories with clear semantic boundaries (e.g., spam vs. non-spam), they are less suitable for ordered categorical labels that span a semantic continuum (e.g., very low, low, medium, high, excellent). These metrics are order-invariant, failing to reflect the severity of misclassifications, and are sensitive to scale shifts. For the task of identifying high-quality documents in a web-scale corpus, the relative ranking of documents is significantly more relevant than adherence to an arbitrary scoring scheme.

To overcome these limitations, we adopt Spearman correlation as our primary evaluation metric. Spearman correlation captures the ordinal structure of the data and is robust to monotonic scale transformations, making it well-suited for assessing models on tasks with ordered semantic categories.

Key Insights:

- Well-trained human annotators can produce consistent, hiqh-quality groundtruth annotations.
- Rank-based evaluation metrics are better suited than classification metrics for model selection.

Released Artifacts:
17,500 documents in 35 languages with human ground truth annotations of educational value.[a]

[a] https://huggingface.co/datasets/JQL-AI/JQL-Human-Edu-Annotations

3 Harnessing LLMs for Multilingual Data Annotation

Next, we identify LLMs that are reliable judges of the educational value of documents. Subsequently, we can distill these capabilities into more efficient models suitable for data processing at scale. We use the ground truth data obtained in the previous JQL step (Section 2) to guide model selection.

3.1 Experimental Setup

We selected a diverse set of strong, multilingual LLMs across model sizes and families (Fig. 2). To

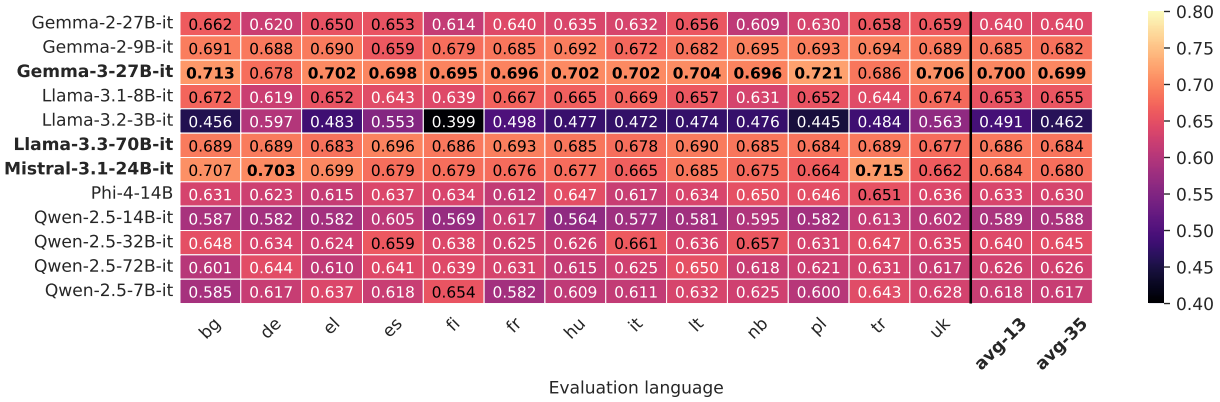

Figure 2: LLMs show varying ranking performance for educational quality. Some models exhibit strong multilingual capabilities. We show Spearman Correlation between model predictions and the respective human GT annotations. Scores are displayed for the 13 language subset, their average correlation (avg-13) and the average correlation across all 35 considered languages. The numbers highlighted in bold represent the largest value for each column.

ensure consistency across languages and to leverage the models' strong English capabilities, we used the original English FineWeb (Penedo et al., 2024a) educational prompt for all evaluations. We also instructed models to produce English assessments, allowing us to focus on their multilingual natural language understanding (NLU) rather than their generation capabilities (NLG). Thus, leveraging the fact that LLMs tend to have good "understanding" in low-resource languages for which they cannot reliably *generate* cohesive outputs (Mahfuz et al., 2025; Luukkonen et al., 2024; Dargis et al., 2024). Similar to our human annotation setup, we sampled three scores from each model and aggregated them as described in Sec. 2.1.

3.2 Multilingual Evaluation

In Fig. 2, we report the LLMs' capabilities in judging educational content by measuring the correlation with our ground truth annotation. We observe substantial differences in performance both across and within model families. Notably, the smallest model tested, LLaMA-3.2-3B-it, performs significantly worse than all other evaluated models. Consequently, effective document quality assessment may require models to exceed a certain parameter threshold, especially if they have not been explicitly trained for such tasks. With the exception of LLaMA-3.1-8B-it, all models show limited performance variance across languages, supporting our hypothesis that modern LLMs exhibit robust multilingual NLU, even in low-resource settings. Interestingly, we observed relatively poor classification performance (App. B.3) for Gemma-3-27B-it despite exhibiting the strongest ranking capabilities. Nonetheless, we demonstrate that the model can reliably identify high-quality documents (App. F.2), again showcasing the importance of prioritizing ranking metrics and correlation-based evaluation.

Among the evaluated models, Gemma-3-27B-it, Mistral-3.1-24B-it, and LLaMA-3.3-70B-it emerged as the top performing annotators from unique model families. We therefore used these models to generate training data for distilling annotation capabilities into lightweight annotators.[3] Specifically, we randomly sampled up to 500k documents for each of the 35 languages from the unfiltered but de-duplicated Fineweb2[4] (FW2) dataset, and used each model to generate three predictions per document.

Key Insights:

- Strong LLMs can reliably assess educational value of web documents.
- Using English instructions and responses, LLMs can judge documents in low-resource languages.

Artifacts: 14 Million documents in 35 languages annotated on their educational value by the top-three performing LLMs.[a]

[a] https://huggingface.co/datasets/JQL-AI/JQL-LLM-Edu-Annotations

[3] For better readability in the subsequent sections, we refer to Gemma-3-27B-it, Mistral-3.1-24B-it, and LLaMA-3.3-70B-it as Gemma, Mistral, and Llama, respectively.

[4] https://huggingface.co/datasets/HuggingFaceFW/fineweb-2

4 Distilling Lightweight Annotators

Next, we distilled lightweight multilingual annotators suitable for curating web-scale data corpora. We use the synthetic labels generated in Sec. 3 for training and the human-annotated data obtained in Sec. 2 for evaluation.

4.1 Architecture and Backbone Selection

We focused on cross-lingual embedding models with long context windows (Zhang et al., 2024; Sturua et al., 2024; Yu et al., 2024). These models efficiently process long web documents and produce well-aligned representations that map semantically equivalent texts across languages to similar embeddings. Thus, enabling effective cross-lingual transfer to unseen languages when using these representations as a backbone.

In our preliminary analysis, Snowflake Arctic Embed v2.0 (Yu et al., 2024) consistently outperformed other candidates (App C.2). We therefore selected that model as the embedding backbone for our subsequent experiments. Our results further indicated that keeping the embedding model's weights frozen while training a lightweight regression head (a simple multilayer perceptron (MLP) with ReLU activation applied to the embeddings) is sufficient to produce high-quality annotations. We provide detailed results and ablations in App. C.

This final setup is highly efficient: the lightweight regression head accounts for less than 1% of total parameters, with embedding computation being the main runtime cost. As a result, multiple annotators and tasks, e.g., adult content filtering, mathematical accuracy, or code quality can be supported in parallel by attaching different heads to a shared backbone at minimal additional cost (both training and inference). Our custom annotation pipeline achieves a throughput of roughly 11,000 annotations per minute on a single A100 with an average of 690 tokens per document.[5]

4.2 Multilingual Evaluation

We present the performance results of the regression-based annotators in Fig. 3. We observe that baseline performance when training in individual languages remains consistently strong (first row in Fig. 3), highlighting the robustness of our multilingual architecture. Additionally, we see only slight performance decreases for checkpoints trained on all languages (last 3 rows in Fig. 3). On average, the distilled regression heads even slightly outperform the LLMs from which the training annotations were derived. While part of this improvement is attributable to the shift to continuous labels, the gains also reflect the strength of the pre-trained embedding model. Only three linguistically isolated languages, Irish, Maltese, and Basque—show notable performance degradation, likely due to their limited representation in the Snowflake training data.

Importantly, these results also support our motivation of strong cross-lingual support through aligned embedding representations. We evaluate cross-lingual generalization by considering different typological groups of languages. This includes languages within the same language family (Tab. 1; row 2 in Fig. 3), those within the same family at lower typological level (row 3)[6], the full set of the remaining 34 languages (row 4) and those outside the first-order family altogether (row 5). Despite these outliers, cross-lingual performance remains generally robust. Annotators tend to perform slightly worse when evaluated on languages outside their respective first-order families, but models trained on languages from the same family consistently yield stronger results.

We further extend on the cross-lingual capabilities by demonstrating generalization to unseen languages in Sec. 6.

4.3 Building the Final Annotator

To systematically explore the amount of data required to effectively train our lightweight annotation models, we conducted a controlled experiment involving all 35 languages. The performance converged with 500k training samples (App C.4).

Building upon the insights gained, we trained our final lightweight annotator models. We used a frozen Snowflake Arctic Embed v2 backbone, trained on 500,000 documents sampled evenly across all 35 languages. We trained dedicated annotation heads for each LLM annotator, Gemma, Mistral, and Llama, to facilitate targeted comparisons and flexibility. Furthermore, for each lightweight annotator, we consider two distinct regression heads. The first set of heads is trained on randomly drawn samples representative of the natural distri-

[5]Implementation based on Datatrove. Using 6 JQL annotation heads with frozen Snowflake embedding model.

[6]We consider the following second-order families with more than one representative language: West-, South- & East-Slavic; North- & West-Germanic; Italo-Western Romance; and Finnic

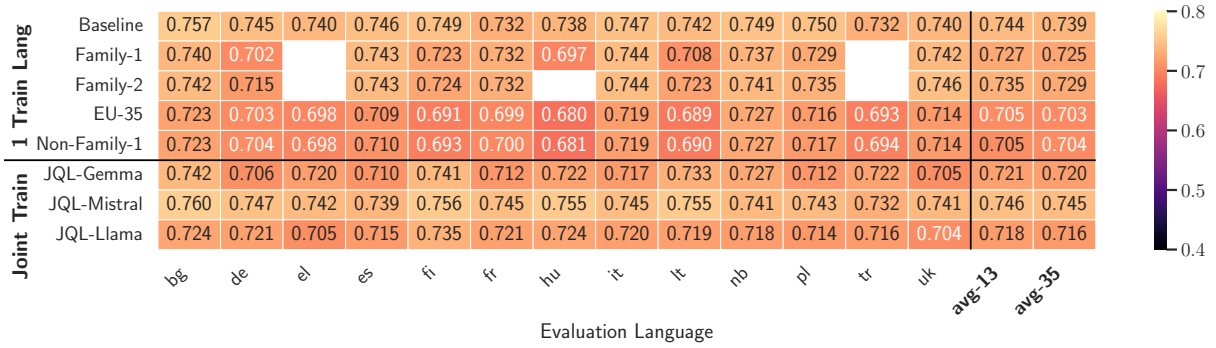

Figure 3: Lightweight JQL annotators show strong multilingual and cross-lingual performance. Training on the same language as the evaluation target serves as a baseline (row 1). We show cross-lingual capabilities by comparing against training on languages within the same language family from Tab. 1 (row 2), those within the same, lower-level family (row 3), the full set of the remaining 34 languages (row 4), and those outside the first-order family (row 5). We also show performance for joint training on all languages with the respective LLM data (last 3 rows). Empty cells occur when no related language is present in our dataset. We depict Spearman correlation with ground truth annotation.

bution of labels. For the second, we strategically selected samples per language to achieve the most uniform possible label distribution, to counteract potential biases towards over-represented labels. In practice, we thus highly over-sampled documents with scores 4 and 5.

Key Insights:

- Well calibrated, multilingual embedding models serve as powerful backbones for data annotation.
- Lightweight regression heads enable efficient annotation and zero-shot cross-lingual transfer.

Artifacts: Three lightweight annotators for educational quality[a] for use in our custom data-annotation pipeline.[b]

[a] https://huggingface.co/JQL-AI/JQL-Edu-Heads

[b] https://github.com/JQL-AI/JQL-Annotation-Pipeline/

5 Assessing Training Data Quality

Next, we assess the effectiveness of the JQL lightweight annotators in identifying high-quality pre-training data.

5.1 Experimental Setup

To that end, we conducted extensive ablation studies using the raw, unfiltered FW2 dataset (Penedo et al., 2024b). This dataset originates from Common Crawl WARC files and includes standard preprocessing such as HTML extraction, language identification, and deduplication. Using the unfiltered raw data ensures that our comparisons directly reflect differences introduced by our annotator-driven filtering methods, rather than preprocessing variations. We benchmark our annotation-based filters against the original heuristic filtering approach used by FW2. For these experiments, we selected 13 languages that collectively represent major European language families, ensuring diverse linguistic coverage (see **bold** languages in Tab. 1).

For all training ablations, we used dense decoder-only models with 2 billion parameters, following the LLaMA architecture (Touvron et al., 2023). The training datasets comprised 27 billion and 14 billion monolingual tokens, with 14 billion tokens used for the languages with limited training data. A detailed description of the training hyperparameters is provided in App. D.1.

To compare model quality across training runs and respective datasets, we used multilingual versions of MMLU (Hendrycks et al., 2021), HellaSwag (Zellers et al., 2019), and ARC (Clark et al., 2018). Instead of accuracy, we relied on the token-normalized probability of the correct answer as our main metric, as it yields smoother and more interpretable learning curves.

Experiments at this parameter and token count reliably predict which datasets perform better when scaling to larger models and more data (Magnusson et al., 2025). However, the absolute benchmark are not indicative of final downstream performance, as our ablation models remain heavily under-trained. The relationship between performance at this scale

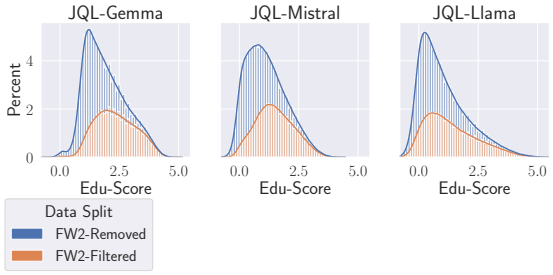

Figure 4: Lightweight annotators trained on different synthetic labels produce different educational score distributions. On average, Gemma assigns higher values than Mistral or Llama. Consequently, thresholding needs to be dynamic and account for the annotators' distribution. Example plotted for CC release 2024-14 over 13 languages.

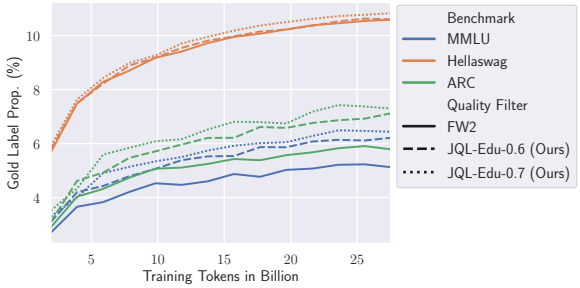

Figure 5: Our JQL annotators improve pre-training data quality over heuristic baselines (FW2). The exemplary plot depicts results for the Spanish dataset.

and that of large-scale pre-training is governed by more complex scaling laws.

5.2 Annotation Analysis

Following the annotation phase, we conducted a detailed statistical analysis of the score distributions produced by different lightweight annotators, as shown in Fig. 4. First, we observe that the heuristically filtered subset of FW2 (orange) exhibits notably higher average educational quality scores compared to the removed data (blue). This serves as a sanity check, indicating that FW2's heuristic filters capture a meaningful baseline signal. Additionally, the regression heads trained on synthetic labels generated by different LLMs, i.e., Gemma, Mistral, and Llama, exhibit significantly different score distributions. In particular, JQL-annotators based on Gemma consistently assign higher educational quality scores than those based on Mistral, which in turn rate samples higher than Llama on average. Notably, this property is inherited from the LLM-based annotators which have different but order-preserving scales of educational content (App. Fig. 16). We also found regression heads trained on datasets with more balanced label distributions to produce less skewed annotation outputs, which may facilitate more stable and interpretable threshold selection (App. D.2).

Despite differences in absolute score distributions, the annotations showed very high correlation (Spearman's $r > 0.87$), indicating strong agreement in the relative ranking of document quality across annotators. This observation aligns with our discussion (Sec. 3) that all models are similarly effective at ranking document quality, even if their classification accuracy varies. This finding highlights that absolute thresholds (e.g., scores ≥ 3) lack general validity unless supported by extensive ablation. We adopt percentile-based (relative) thresholds computed per regression head to address this oversight, enabling more robust comparisons and filtering. This approach allows to directly control the trade-off between document quality and corpus size.

5.3 Evaluating Pre-training Data Quality

We evaluated the impact of JQL on downstream model performance by filtering the pre-training data based on two relative threshold values: the 0.6 and 0.7 percentiles per lightweight annotator head. To include a document in the final training dataset, we required agreement across an ensemble of three distinct lightweight annotators (Gemma, Mistral, and Llama)[7]. Each had to rate the document above its respective percentile threshold. This ensemble-based filtering approach enhances robustness by reducing the influence of individual annotator biases and minimizing the noise present in single-model annotations. The original FW2 heuristic filtering method serves as our baseline, providing reference points for both the volume of retained tokens and downstream model performance.

Figure 5 exemplarily demonstrates the effectiveness of our approach for Spanish, with aggregated cross-lingual results shown in Table 2. The results clearly demonstrate that JQL-based filtering consistently outperforms FW2's heuristic baseline in terms of data quality. We also observe a correlation between threshold strictness and quality gains, with the higher percentile threshold (0.7) consistently yielding better results than 0.6. Overall, JQL offers a scalable and reliable signal for data quality, enabling systematic control of the quality–quantity trade-off, which is particularly useful for scenarios

[7]These heads were trained once on balanced labels and remained fixed throughout.

	Change over FW2 baselines (%)		
Quantile	Tokens (%)	Benchmark Avg.	Benchmark Final
0.6	+ 4.8	+4.27	+4.6
0.7	−15.8	+6.70	+7.2

Table 2: Percentile-based filtering on JQL annotations provides reliable trade-offs in performance improvements and achieves higher data quality and document retention. Retained tokens and benchmark performance are reported relative to the FW2 baseline and aggregated over 13 languages. Benchmark "Avg." and "Final" depict the relative difference in the mean and final checkpoint performances, respectively (see Fig. 5).

like curriculum learning.

Importantly, our annotation-driven filtering achieves higher-quality training outcomes without excessively aggressive data reduction. For example, in the Spanish language case, applying the 0.6 threshold retains over 9% more tokens than FW2 while still surpassing its quality. This advantageous trend holds consistently across languages, as confirmed by our aggregated results. Thus, demonstrating that our approach effectively improves training performance even when preserving more documents compared to heuristic baselines. Eliminating overly aggressive filtering is especially relevant in multilingual scenarios, where limited data is available for many languages.

Key Insights:

- JQL outperforms multilingual heuristic filtering.
- Percentile-based filtering is better suited than threshold-based filtering
- Higher percentile thresholds trade-off better data quality for reduced number of tokens.

6 Generalization to Unseen Languages

To validate the versatile and robust cross-lingual capabilities of our JQL approach beyond European languages, we conducted additional experiments on three linguistically and typologically distinct languages, specifically Arabic, Thai, and Mandarin Chinese, which represent language families completely unseen during training. We first validated the capabilities of the existing lightweight annotators on those languages. When measuring their correlation on respective translations of the ground truth data, we observed similar performance as for the European languages (App. E.1). Consequently, we can simply use the existing lightweight annotators with no further training required. We applied the same dynamic percentile-based filtering approach (specifically, the 0.7 quantile threshold) that had previously proven effective across our European language annotations.

The results in Fig. 6 demonstrate that even for these entirely unseen languages, the JQL pipeline maintains strong zero-shot performance, confirming their capability to effectively generalize across diverse linguistic contexts. These findings highlight the broad applicability and practical scalability of our approach. Consequently, JQL is suitable for extending robust data curation practices into low-resource and underrepresented languages with minimal additional overhead.

7 Related work

Heuristic Based Data Curation Pipelines. The vast majority of training data for large language models is sourced from the web, with Common Crawl (CC) being the most important corpus. Traditionally, many works have relied heavily, and in some cases exclusively, on heuristic-based filtering methods to clean and select web data (Raffel et al., 2020; Gao et al., 2020; Weber et al., 2024; Penedo et al., 2023). These heuristics typically focus on document-level syntax, such as removing ill-formed or overly short texts, as well as filtering out documents containing blocklisted keywords. Web-based corpora are often further enriched with high-quality sources such as code, academic literature, or Wikipedia articles (Gao et al., 2020).

Neural Data Curation Pipelines. A major drawback of heuristic filters is their inability to assess the *semantic* quality of documents. Consequently, more recent dataset curation incorporates neural networks into the process (Wettig et al., 2024; Su et al., 2024; Penedo et al., 2024a; Zhao et al., 2024; Li et al., 2024; Zhao et al., 2024; Sachdeva et al., 2024; Korbak et al., 2023). To scale these approaches to billions of documents, small and task-specific FastText classifiers (Joulin et al., 2016) are the most common choice.

These quality annotators are increasingly trained on synthetic labels derived from strong, general-purpose LLMs. Specifically, annotations and filters judging the *educational quality* of a document have produced hiqh-quality datasets (Su et al., 2024;

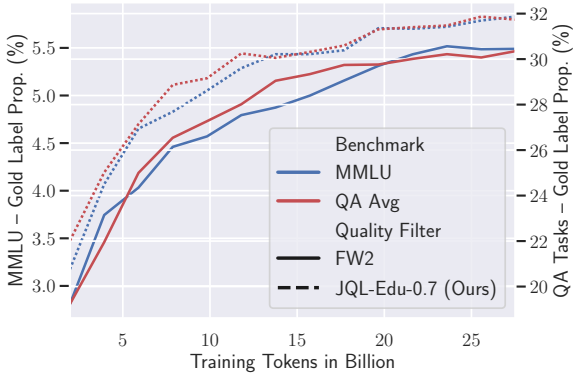

Figure 6: Our JQL lightweight annotators generalize to unseen, topologically different languages. The figure shows aggregated performance on Arabic, Thai and Chinese. With limited available of standard benchmarks, we relied on language-specific benchmarks selected by Fineweb2 (Penedo et al., 2024b).

Penedo et al., 2024a; Wettig et al., 2024).

Multilingual Data Curation Pipelines. Despite these advances in dataset curation, they remain largely English-centric (with a growing body of research dedicated to Chinese). While large multilingual datasets exist, the respective filtering pipelines and dataset sizes are not on par with the high-quality ones for English data (Kudugunta et al., 2023; Nguyen et al., 2024; Brack et al., 2024; Xue et al., 2021; Burchell et al., 2025).

The best-performing large-scale multilingual dataset is FineWeb2 (Penedo et al., 2024b), which solely relies on heuristic filtering. In this paper, we developed a data curation pipeline that provides advanced quality filtering in the multilingual setting and seamlessly transfers to unseen languages. Concurrently, (Messmer et al., 2025) explored filtering pre-training data in six languages using binary classifiers trained on reference (instruction-tuning) datasets and benchmarks.

8 Conclusion & Future Directions

In this work, we proposed JQL, a multilingual pre-training data filtering approach that requires minimal human supervision and leverages language models as judges. We systematically evaluate JQL across 35 languages for filtering educationally valuable content. Our experiments provide extensive evidence that JQL effectively selects high-quality multilingual pre-training data, significantly outperforming heuristic-based filtering methods. Further, our approach is scalable to large datasets, generalizes to unseen languages, and is easily extendable.

JQL opens several promising avenues for future research. First, it is readily applicable to arbitrarily filtering criteria, including code quality, mathematical correctness, and adult content moderation. Second, it can be used not only for curating pre-training datasets but also for selecting relevant data in various post-training stages, such as instruction tuning and alignment. Ultimately, our contributions lay a rigorous foundation for improved multilingual data curation and set a new standard for leveraging language and embedding models effectively in multilingual contexts.

9 Acknowledgment

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10 Limitations

Despite the breadth and generalizability of our work, we acknowledge the following limitations.

First, because manual translation into all 38 target languages (35 plus Arabic, Mandarin Chinese, and Thai) was infeasible, we machine-translated our human-annotated English ground truth dataset into these languages. While a full manual evaluation of the translations across all languages was not feasible, we conducted a manual quality assessment with native speakers for six languages (Appendix A.3) demonstrating that the translations are of high quality. Moreover, our approach is not limited to machine-translated ground truth. JQL is fully compatible with human-translated datasets, and we expect its performance to further improve in such settings.

Second, while we demonstrated the effectiveness of JQL in filtering high-quality multilingual documents solely based on their educational value, our approach is not limited to this specific criterion. JQL is designed to support arbitrary filtering objectives. We chose educational value as our primary focus because it has been shown to be a strong indicator for identifying high-quality multilingual pre-training data (Wettig et al., 2024).

Finally, due to the high computational cost, we conducted our ablation studies at a single model scale (2 billion parameters). Despite this limitation, we observed consistent improvements in downstream performance, indicating the effectiveness of JQL-filtered datasets. Overall, our results represent a strong foundation for exploring performance gains at even larger model scales (Magnusson et al., 2025), and we leave such experiments to future work.

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A Human Annotation Study

A.1 Annotator Background and Study Protocol

For our human annotation study, we used the prompt introduced by Penedo et al. (2024b) (full prompt is shown in Figure 7), which was reviewed and discussed with all annotators during a dedicated training session. Annotations were conducted using a web interface built with Argilla[8], which displayed the document text, annotation guidelines, and the 0–5 rating scale.

Our annotators are colleagues from our lab, and there is an overlap between the authors of this work and the annotation team. The majority of annotators have a technical background. Additional information on annotators is provided in Table 3. Prior to the study, we informed participants about the purpose of the annotation task and obtained their consent to use the resulting annotations, along with anonymized information about the annotators, for subsequent analysis and anonymized public release. No ethics review board approval was sought, as the study did not fall under institutional requirements for ethical review.

Prompt

Below is an extract from a web page. Evaluate whether the page has a high educational value and could be useful in an educational setting for teaching from primary school to grade school levels using the additive 5-point scoring system described below. Points are accumulated based on the satisfaction of each criterion:

1. Add 1 point if the extract provides some basic information relevant to educational topics, even if it includes some irrelevant or non-academic content like advertisements and promotional material.

2. Add another point if the extract addresses certain elements pertinent to education but does not align closely with educational standards. It might mix educational content with non-educational material, offering a superficial overview of potentially useful topics, or presenting information in a disorganized manner and incoherent writing style.

3. Award a third point if the extract is appropriate for educational use and introduces key concepts relevant to school curricula. It is coherent though it may not be comprehensive or could include some extraneous information. It may resemble an introductory section of a textbook or a basic tutorial that is suitable for learning but has notable limitations like treating concepts that are too complex for grade school students.

4. Grant a fourth point if the extract highly relevant and beneficial for educational purposes for a level not higher than grade school, exhibiting a clear and consistent writing style. It could be similar to a chapter from a textbook or a tutorial, offering substantial educational content, including exercises and solutions, with minimal irrelevant information, and the concepts aren't too advanced for grade school students. The content is coherent, focused, and valuable for structured learning.

5. Bestow a fifth point if the extract is outstanding in its educational value, perfectly suited for teaching either at primary school or grade school. It follows detailed reasoning, the writing style is easy to follow and offers profound and thorough insights into the subject matter, devoid of any non-educational or complex content.

Figure 7: Annotation prompt for human annotation study. Prompt has been introduced by Penedo et al. (2024b).

[8] https://argilla.io/

Annotator (Anonymized)	Background	Age Group
Annotator 1	MSc. in Computer Science	20-30
Annotator 2	MSc. in Data and Knowledge Engineering	30-40
Annotator 3	PhD in Computer Science	30-40
Annotator 4	M.A. English/American Studies and German Studies	30-40
Annotator 5	M.Sc. in Mathematics	30-40
Annotator 6	PhD in Computer Science	30-40
Annotator 7	M.Sc. in Artificial Intelligence	20-30
Annotator 8	PhD in Computer Science	30-40
Annotator 9	MSc. in Computer Science	30-40
Annotator 10	MSc. in Computer Science	30-30
Annotator 11	PhD in Theoretical Physics	30-40
Annotator 12	MSc. in Autonomous Systems	30.40
Annotator 13	PhD in Computer Science	30-40
Annotator 14	MSc. in Autonomous Systems	30-40
Annotator 15	MSc. in Computer Science	30-40

Table 3: Backgrounds of the human annotators (anonymized).

A.2 Human Annotations Evaluation

In this section, we provide additional details about the human-annotated ground truth dataset introduced in Section 2.

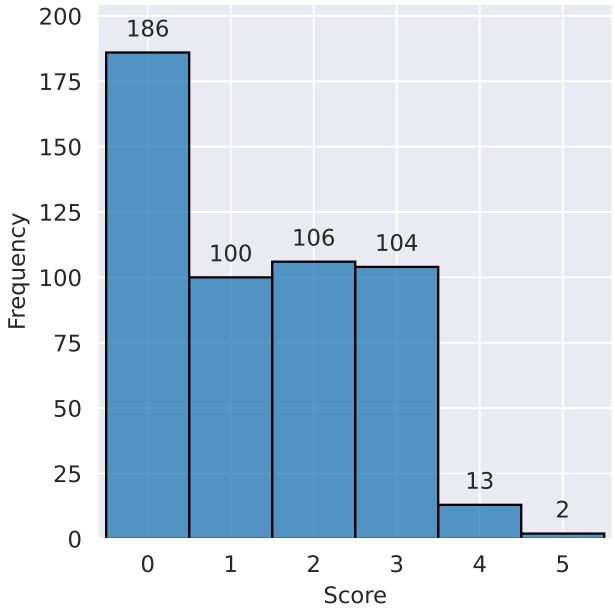


Figure 8: Histogram on the distribution of the document scores judged by the human annotators.

Score Distribution of Annotations

Annotator Agreement and Annotation Spread. To further analyze the variation in human annotations, we present the cumulative distribution of annotation spread in Figure 9. The plot shows that over 60% of the samples have a maximum spread of 1, and more than 85% have a maximum spread of 2, indicating strong agreement among annotators.

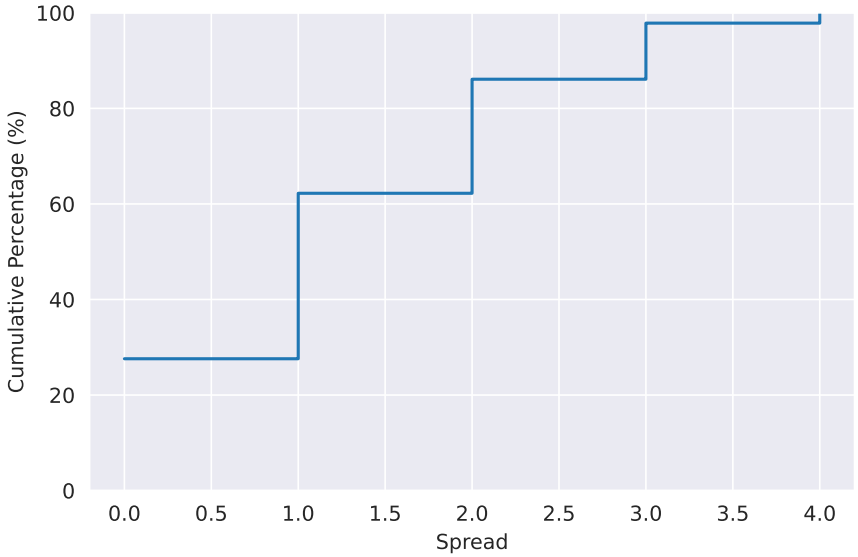


Figure 9: Cumulative distribution of spread within annotations. Aligned with the majority agreement of 78.5% and an interrating standard deviation of 0.56, (see Sec. 2), also the spread analysis reveals high interrater consistency with a spread of ≤ 2 for 86% of the documents.

A.3 Machine Translation of Human Ground Truth

As described in Section 2.2, we machine-translated our human-annotated ground truth from English into 35 additional languages.

To ensure the reliability of the translated ground truth, we conducted a manual quality assessment with native speakers for six languages: Chinese, Czech, French, Galician, German, and Turkish. For each language, 42 documents were sampled to cover the full quality spectrum (scores from 0 to 5).

Native speakers evaluated the translations based on three criteria: (i) accuracy of the original meaning (including omissions, additions, and mistranslations), (ii) grammar, and (iii) spelling. The evaluations used a four-level scale: *Fine*, *Minor*, *Major*, and *Critical* (see Table 4).

The majority of translations were rated as *Fine* or *Minor*, indicating that the original meaning was generally preserved with only minor issues. Specifically, 97.6% of translations in French and Chinese, 95.2% in German, 90.5% in Turkish, and 88.1% in Czech and Galician fell into these two categories (see Table 5). These results demonstrate that the machine-translated data is of sufficiently high quality to support pipeline component selection.

Rating	Description
Fine	Original meaning is kept; no grammar and spelling issues.
Minor	Original meaning is mainly kept, but has slight grammar and/or spelling issues.
Major	Original meaning is partly kept; minor grammar and spelling issues.
Critical	Original meaning is not kept; significant grammar and spelling issues.

Table 4: Evaluation scale for translation quality.

Language	Fine	Minor	Major	Critical
German	64.29%	30.95%	4.76%	0.00%
Czech	50.00%	38.10%	9.52%	2.38%
Turkish	28.57%	61.90%	9.52%	0.00%
French	66.67%	30.95%	2.38%	0.00%
Galician	54.76%	33.33%	9.52%	2.38%
Chinese	21.43%	76.19%	2.38%	0.00%

Table 5: Human assessment of translation quality for machine-translated documents. For each language, 42 documents were sampled.

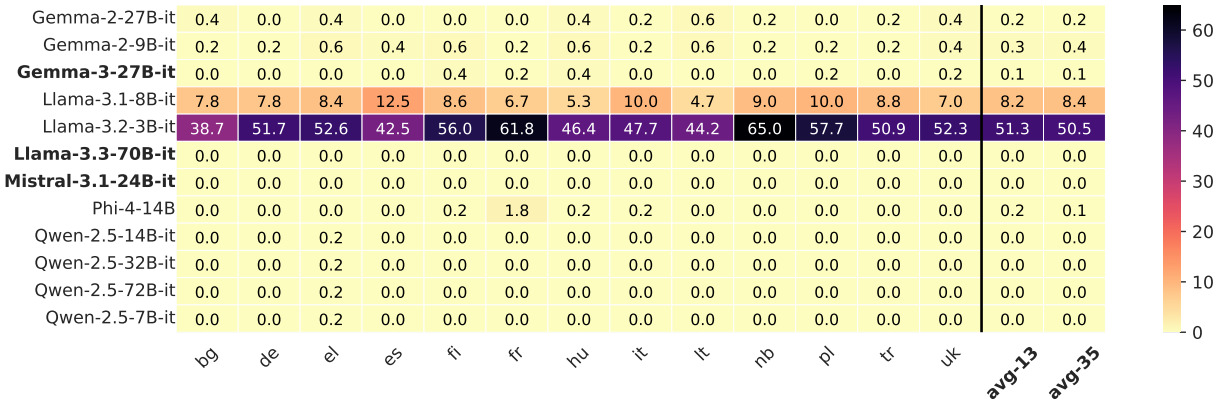


Figure 10: Invalid scores predictions (in percent)

B LLM Based Annotator Evaluation

In this Section we provide further details and ablations on our LLM based annotators discussed in Section 3.

B.1 Invalid Predictions

Similar to the human annotators, we prompted the LLM-based annotators to assess the educational value of documents on a scale from 0 to 5, where 0 indicates the lowest quality and 5 the highest. For each model and document, we collected three predictions. A prediction is considered invalid if it does not fall within the specified integer range. If all three predictions for a document are invalid, the entire annotation is marked as invalid. When evaluating LLM performance, it is crucial to analyze the distribution of valid and invalid predictions to not obtain distorted conclusions.

Figure 10 shows the proportion of invalid predictions across different languages. While our selected models, LLaMA-3-70B-IT, Mistral-3.1-24B-IT, and Gemma-3-27B-IT, exhibit few or no invalid predictions, LLaMA-3-8B-IT produces a noticeably higher rate of invalid outputs, and LLaMA-3-3B-IT shows a substantial fraction of invalid predictions.

Based on these observations, we suggest that a consistently low rate of invalid predictions should be considered a necessary condition for further use as LLM-based annotator. Otherwise, annotating data at scale will result in a large number of invalid predictions, leading to wasted computational resources.

B.2 Statistical Significance of Correlations Between Human Annotations and LLM Predictions.

To assess the statistical significance of the correlations presented in Fig.12, we perform two-sided Student's t-tests and compute the corresponding p-values separately for each model and language. Summary statistics, i.e., average, minimum, and maximum p-values, across the 35 languages are shown in Fig.6. Notably, the highest p-value observed across all models and languages is 4.49e-07, indicating a consistently high level of statistical significance throughout our analysis.

B.3 Classification Based Evaluation

As discussed in Sec. 2.4, we use the Spearman correlation between the LLMs' predictions and the human ground truth to evaluate the annotator capabilities of the models. This metric is preferred because it effectively captures the models' ability to rank document quality, which is central to our task.

Here, we illustrate the limitations of traditional classification metrics for assessing LLM annotator performance. The figures 12 and 14 show the F1 scores of the LLMs when predicting the correct quality classes (0 to 5). Notably, Gemma-3-27B-IT appears among the worst-performing models in terms of F1 score, suggesting a limited ability to classify document quality. This stands in contrast to its relatively strong performance when evaluated using Spearman correlation (see Sec. 3.2).

This discrepancy can be explained by examining the confusion matrices in Fig. 15. While Mistral-3.1-24B tends to predict more reliably within the central quality classes (1 to 3), Gemma-3-27B-IT shows a

LLM	avg	min	max
Gemma-2-27B-it	1.51e-52	5.76e-68	5.38e-51
Gemma-2-9B-it	1.43e-61	2.77e-76	5.16e-60
Gemma-3-27B-it	8.38e-65	1.09e-85	3.02e-63
Llama-3.1-8B-it	8.90e-51	3.22e-73	3.01e-49
Llama-3.2-3B-it	2.04e-08	6.42e-27	4.49e-07
Llama-3.3-70B-it	4.06e-66	3.54e-76	1.07e-64
Mistral-3.1-24B-it	4.59e-62	2.89e-81	1.61e-60
Phi-4-14B	4.26e-46	2.02e-65	1.53e-44
Qwen-2.5-14B-it	1.73e-37	1.88e-56	6.22e-36
Qwen-2.5-32B-it	4.12e-54	1.68e-68	1.48e-52
Qwen-2.5-72B-it	4.18e-53	7.90e-64	1.39e-51
Qwen-2.5-7B-it	1.24e-43	4.28e-68	4.46e-42

Table 6: p-value analysis on the Spearman correlation scores in Figure 12. The p-values were calculated using a two-sided Student's t-test and indicate the statistical significance of the measured correlations (lower is better). Across all models and languages, even the highest p-values are extremely small. This underpins the statistical significance of our results.

tendency to shift predictions across the scale, particularly within these same classes. As a result, its F1 scores are low due to class misalignment, but its Spearman correlation remains high because it preserves the relative ranking of document quality.

B.4 Predicted Annotation Distributions Across LLM Based Annotators

In Sec. B.3, we showed using predictions from Gemma-3-27B-IT that different models can shift their predictions across the quality scale. This has important implications for selecting thresholds when filtering documents based on predicted quality.

Figure 16 shows the cumulative distribution of predicted scores for annotated training datasets (approximately 450k documents per language) by Gemma-3-27B-IT, LLaMA-3.3-70B, and Mistral-Small-3.1-24B. We observe that, for a fixed filtering threshold, different models yield varying amounts of retained data. For example, with a threshold of ≥ 3, Gemma-3-27B-IT retains more data than the other two models, while LLaMA-3.3-70B retains more than Mistral-Small-3.1-24B. This highlights that the threshold is model-specific, effectively determining how much data is preserved and raising questions about the quality–quantity trade-off.

To address this, we advocate using the p-quantile rather than a fixed absolute threshold, ensuring consistent data retention across models. The high Spearman correlation (0.83) between the predicted scores of the three models indicates that, despite differences in absolute scoring, all models are capable of ranking documents by quality reliably.

Language	Code	Translator	#Testsamples	#Trainsamples
Bulgarian	bg	DeepL	511	499.799
Czech	cs	DeepL	511	496.428
Croatian	hr	ChatGPT	502	497.692
Macedonian	mk	ChatGPT	509	499.446
Polish	pl	DeepL	511	487.150
Slovak	sk	DeepL	511	478.122
Slovenian	sl	DeepL	511	475.949
Serbian	sr	ChatGPT	509	496.172
Serbian Cyrillic	sr-cyrl	ChatGPT	511	499.691
Ukrainian	uk	DeepL	511	499.376
Catalan	ca	ChatGPT	511	488.937
Spanish	es	DeepL	511	499.260
French	fr	DeepL	511	499.642
Galician	gl	ChatGPT	511	493.112
Italian	it	DeepL	511	478.998
Portuguese	pt	ChatGPT	509	486.995
Romanian	ro	DeepL	511	499.733
Danish	da	DeepL	511	459.948
German	de	DeepL	511	498.699
Icelandic	is	ChatGPT	508	495.902
Dutch	nl	DeepL	511	495.574
Norwegian (Bokmål)	nb	DeepL	511	493.847
Norwegian (Nynorsk)	nn	ChatGPT	505	304.239
Swedish	sv	DeepL	511	491.974
Lithuanian	lt	DeepL	511	488.415
Latvian	lv	DeepL	511	438.257
Greek	el	DeepL	511	499.270
Irish	ga	ChatGPT	505	390.309
Estonian	et	DeepL	511	458.828
Finnish	fi	DeepL	511	490.227
Hungarian	hu	DeepL	511	496.488
Basque	eu	ChatGPT	508	486.467
Maltese	mt	ChatGPT	510	327.441
Turkish	tr	DeepL	511	495.888
Albanian	sq	ChatGPT	510	499.536
Armenian	hy	ChatGPT	508	498.795

Table 7: Number of samples for each language contained in the test set and the regressor training set, including their language codes.

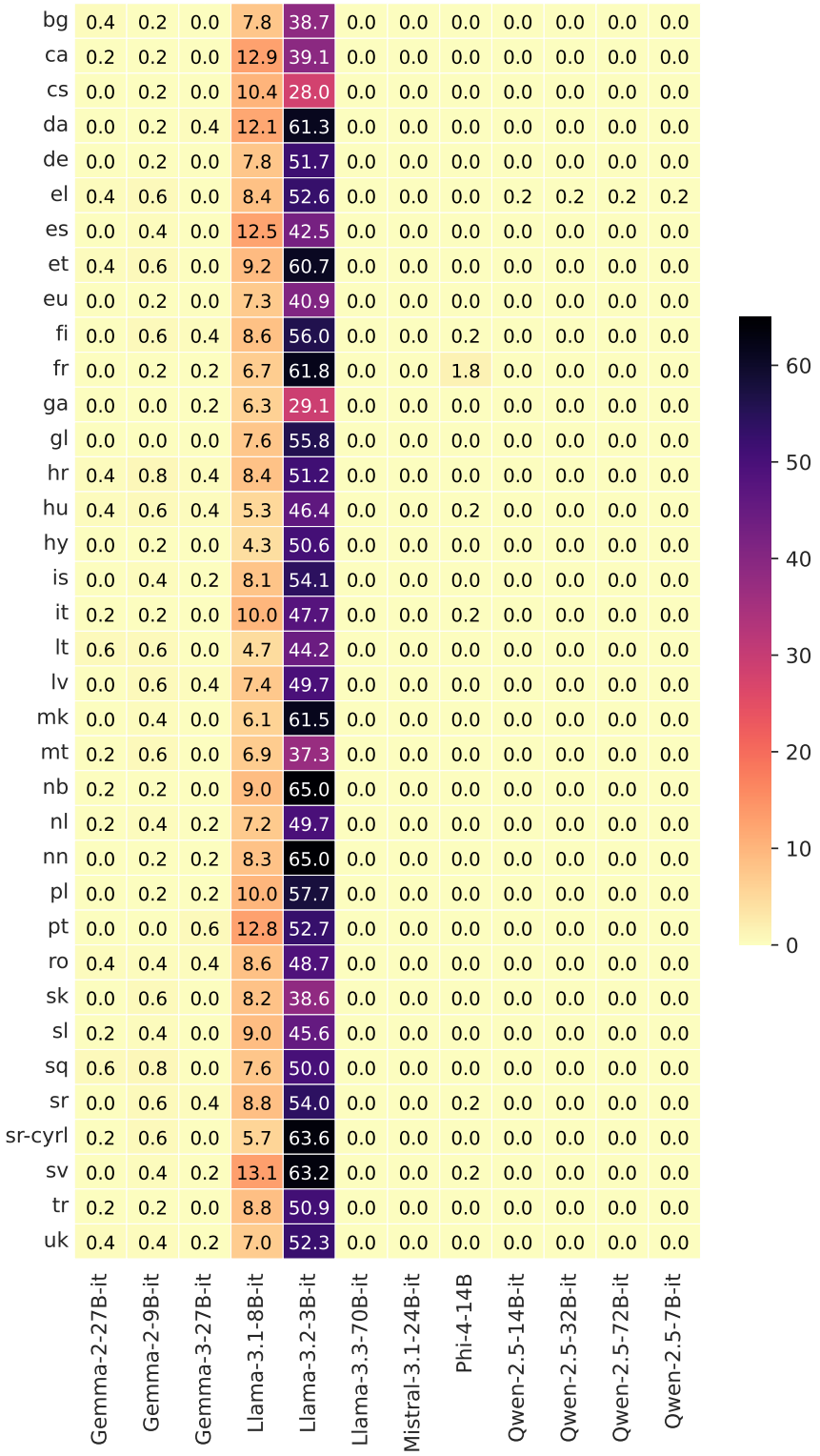


Figure 11: Percentages of invalid scores (aggregated) for each model across all languages. An aggregated score (majority voted) is counted as invalid, if all three predictions for a document are invalid.

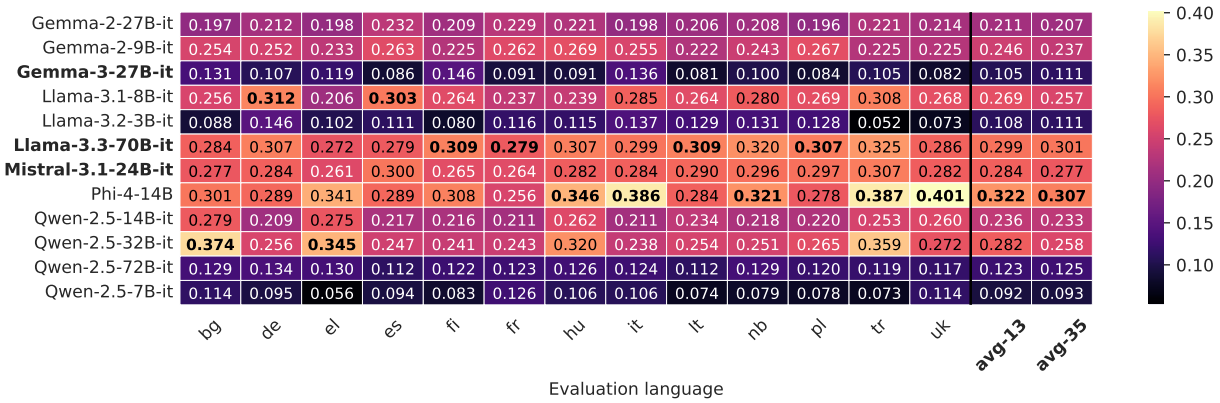


Figure 12: Multilingual LLM classification performance (macro F1-score) on human-annotated ground truth. Scores are reported individually for the 13 languages subset, as well as averaged across these 13 languages (avg-13) and across all 35 evaluated languages.

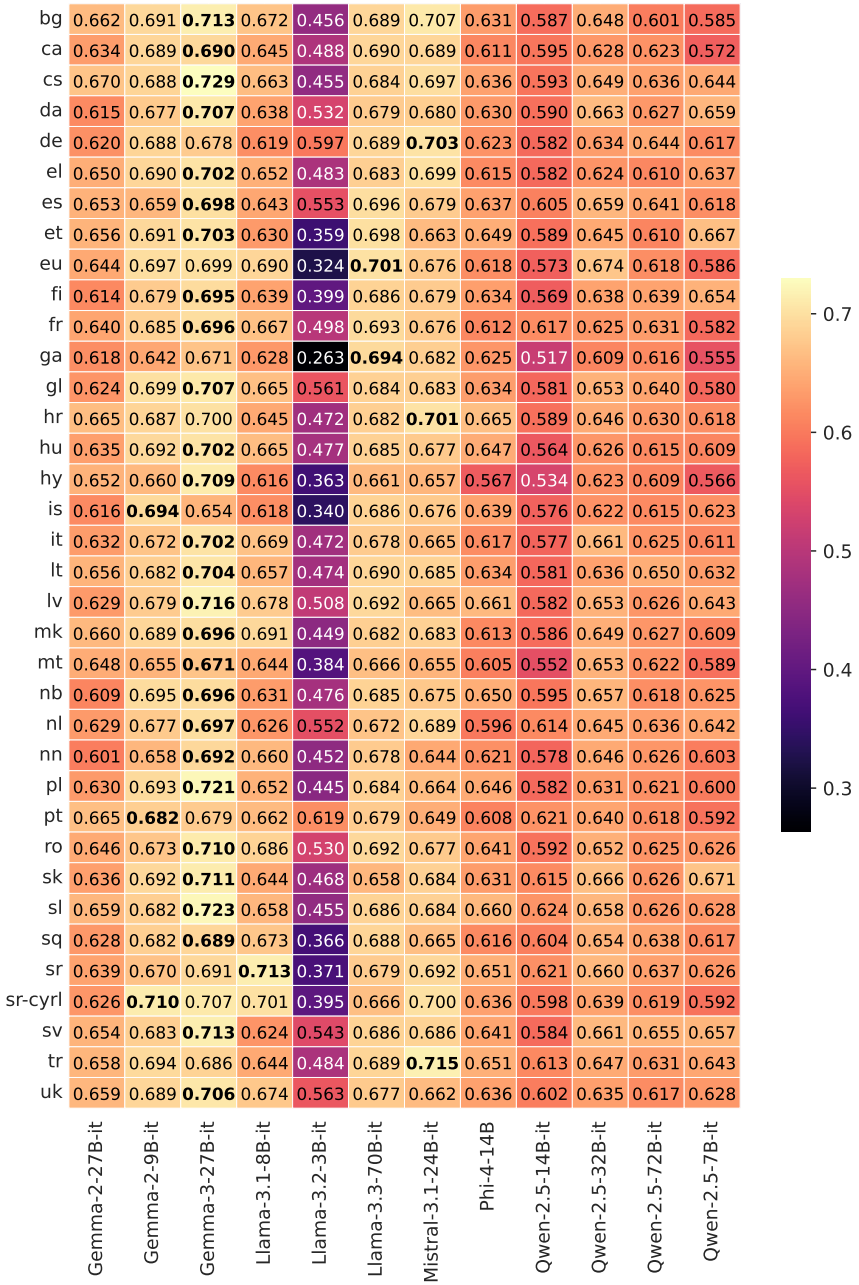


Figure 13: Ranking performance in terms of Spearman correlation for each model across all languages.

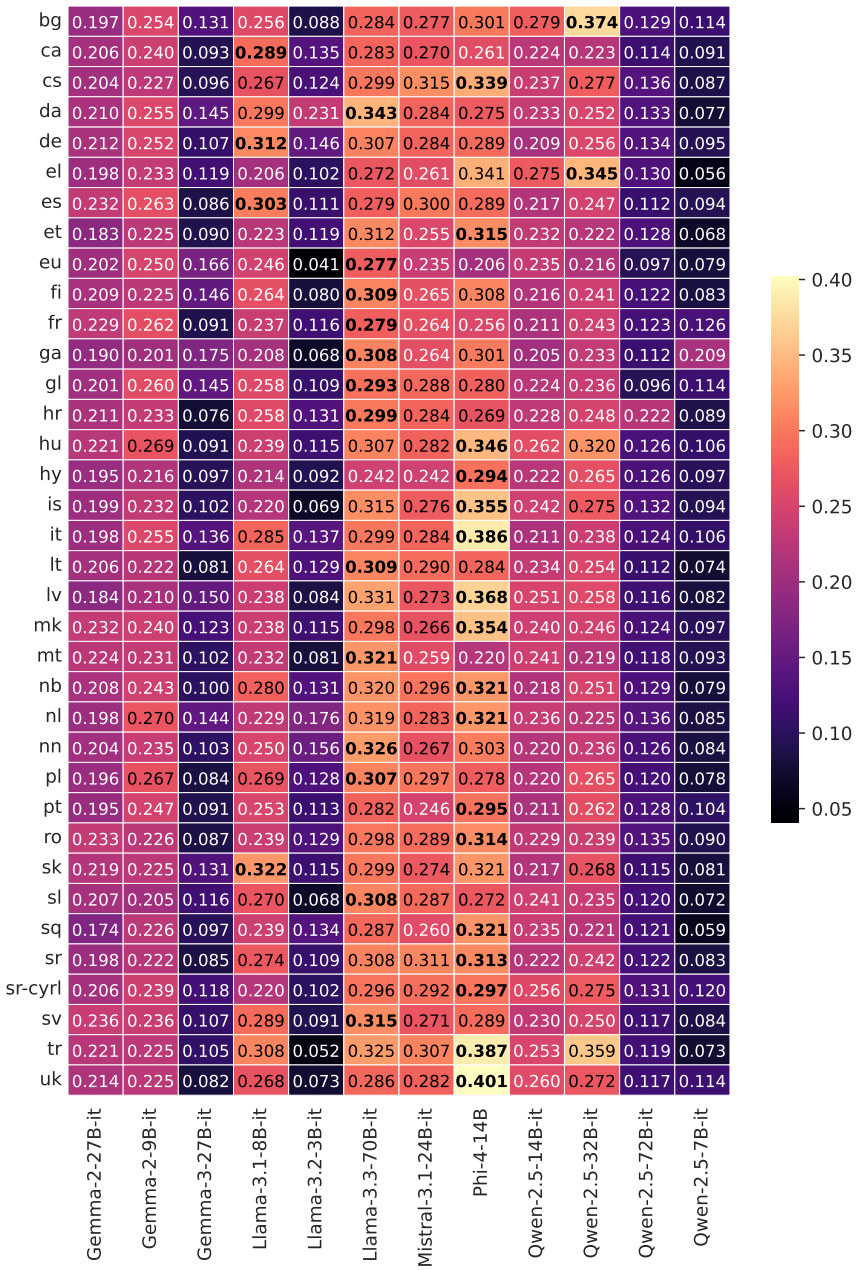
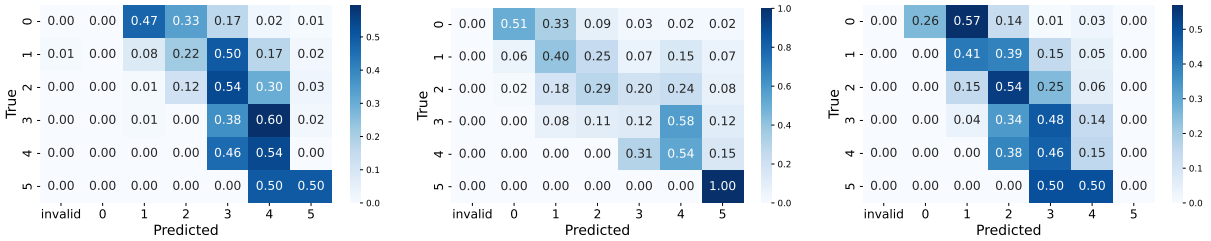
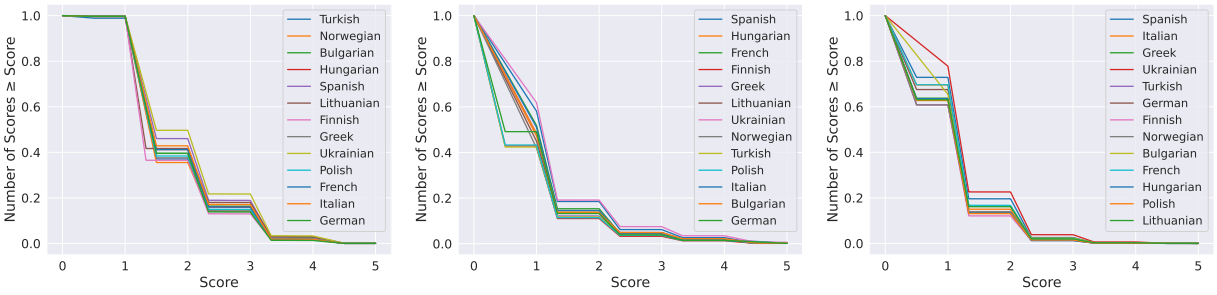


Figure 14: Classification performance in terms of macro F1 score for each model across all languages.



(a) Gemma-3-27B-it (b) Llama-3.3-70B-it (c) Mistral-3.1-24B-it

Figure 15: Confusion matrices of the three ablated LLMs on the 511 human annotated ground truth documents in English. Note that Gemma-3-27B-IT predictions tend to be shifted by 1 to the right which degrades the classification accuracy but does not influence the ranking performance. Both LLama-3.3-70B and Mistral-Small-3.1-24B are well aligned with the human annotations, explaining the high classification accuracy.



(a) Gemma-3-27B-it (b) LLama-3.3-70B-it (c) Mistral-3.1-24B-it

Figure 16: Right cumulative distribution of the scores predicted by the three ablated models. Alternatively, the curves can be interpreted as the number of documents whose scores is greater or equal to the given score. Note that the differences in the monotonously decreasing curves between models, motivates the model-specific threshold for pre-training data sampling. Notably, we found a Spearman correlation of 0.83 between the three models, indicating similar ranking orders despite the scale shifts.

embedder annotator + balancing	gte-multilingual-base	jina-embeddings-v3	snowflake-arctic-embed-m-v2
Gemma-3-27B-it bal.	0.697 ± 0.013	**0.722** ± 0.018	0.720 ± 0.021
Gemma-3-27B-it	0.708 ± 0.014	0.734 ± 0.020	**0.737** ± 0.028
Llama-3.3-70B-it bal.	0.693 ± 0.012	0.712 ± 0.010	**0.716** ± 0.014
Llama-3.3-70B-it	0.695 ± 0.011	0.716 ± 0.009	**0.724** ± 0.016
Mistral-3.1-24B-it bal.	0.707 ± 0.011	0.735 ± 0.011	**0.744** ± 0.016
Mistral-3.1-24B-it	0.687 ± 0.011	0.722 ± 0.017	**0.736** ± 0.024

Table 8: Mean and standard deviation of the Spearman correlation on all 35 testing languages. Each cell corresponds to a training setup combining an annotating model (with either raw or class-balanced annotations) and an embedding model. The best result per row is highlighted in bold. Overall best result underlined.

C Lightweight Annotators

C.1 Experimental Setup and Parameter Choice

To reduce computational overhead and accelerate development, we precomputed and cached all document embeddings prior to training. Since the embedding models remain frozen throughout training and account for over 99% of the total parameter count, this approach significantly reduces iteration time.

The regression head is implemented as a lightweight neural network: a single-layer multilayer perceptron (MLP) with ReLU activation and a final linear output layer producing a scalar prediction score. We performed a hyperparameter sweep over the hidden dimension of the MLP, exploring values from 10 to 10k. Based on this search, we selected a hidden size of 1k as a robust default. Depending on the input embedding dimension, the regression head comprises approximately 770k to 1.03M trainable parameters.

We trained the regression heads using the AdamW optimizer with a cosine annealing learning rate schedule, which consistently outperformed constant and linearly decaying alternatives in our experiments. The initial learning rate was set to 5×10^{-4}, based on a sweep over values from 10^{-2} to 10^{-6}. We also tested batch sizes from 16 to 4096 (in powers of two) and found a batch size of 1024 to offer the best balance between convergence speed and computational efficiency.

We trained annotators for up to 20 epochs. To monitor generalization performance, 10% of the training data is held out for validation. We applied early stopping if the validation Spearman rank correlation fails to improve by at least 10^{-3} over five consecutive epochs.

C.2 Backbone Selection

We conducted an ablation study comparing three multilingual embedding models as potential backbones for our lightweight JQL annotators: `gte-multilingual-base` (Zhang et al., 2024), `jina-embeddings-v3` (Sturua et al., 2024), and `snowflake-arctic-embed-m-v2.0` (Yu et al., 2024).

We trained a total of 18 regression heads, covering all combinations of the three embedding models and three annotation models used to generate the ground truth scores. Each combination is trained twice: once on a randomly sampled training set, and once on a class-balanced variant to mitigate the skewed distribution of education scores. Training data is sampled uniformly across all 35 languages The training setup—including hyperparameters and early stopping criteria—follows the procedure described in the previous section.

Results are presented in Tab. 8. The Snowflake embedding model consistently outperforms the other backbones across annotators and training set variants. Its best configuration—combined with the Mistral-3.1 annotation model and class-balanced training—yields the highest overall correlation (*0.744* ± 0.016).

C.3 End-to-End Training: Embedder and Regression Head

While the regression head alone already yields strong performance when trained on frozen embeddings, we further investigate whether end-to-end training of the full model — including both the embedding model and the regression head — can lead to improved results. To this end, we integrate the embedding

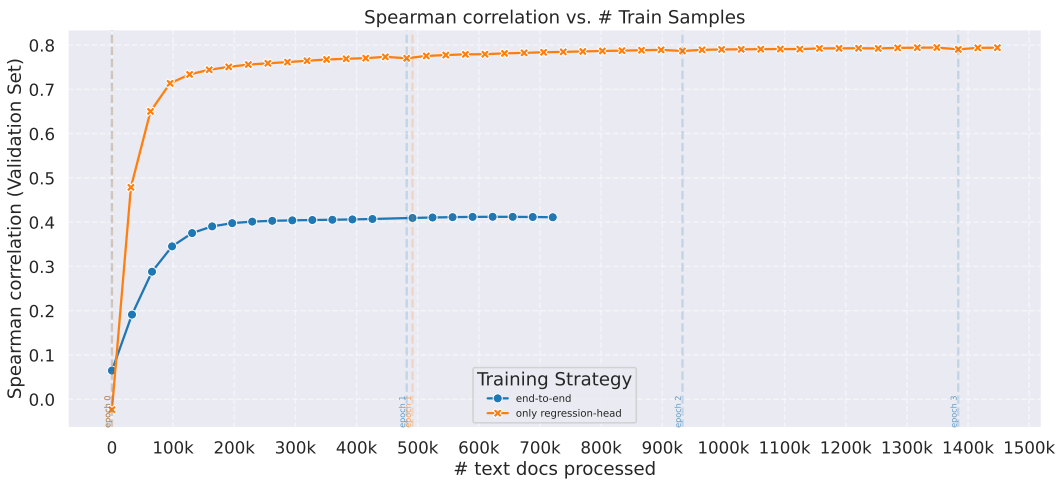


Figure 17: Validation performance (Spearman correlation) as a function of the number of processed training samples, comparing two training strategies. The end-to-end model (blue) jointly trains both the embedding backbone and the regression head, while the regression-head model (orange) fine-tunes only the regression layer on top of a frozen embedder. Performance is evaluated on a held-out validation set, and both models are trained with early stopping. Epoch boundaries are marked with dashed lines. While both models show rapid initial gains, especially during the first 100k samples, the full end-to-end model converges to a significantly lower final correlation, suggesting limited benefit from updating the embedding backbone under the given supervision signal.

model into the training loop.

This end-to-end setup comes with substantially increased memory and computational requirements. First, the embedding model accounts for over 99% of the total parameter count. Second, the model input now consists of full-text documents instead of precomputed embeddings, resulting in significantly larger input data. These factors necessitate a reduction in batch size, which, in combination with the increased parameter count, further increases overall training time.

To conduct the end-to-end experiment, we adopted the learning-rate schedule and effective batch size (via gradient accumulation) recommended in the Snowflake technical report (Yu et al., 2024). With these settings, a single epoch on an NVIDIA A100-SXM4-80GB GPU takes multiple hours, whereas updating only the regression head completes an epoch in about a minute. This stark contrast quantifies the computational advantage of training only the regression head while keeping the embedding model frozen. Due to these substantially higher runtime and memory demands, we restricted end-to-end training to the best-performing combination of Mistral annotations and Snowflake embeddings. Additionally, we observed that the model could only be trained reliably using float32 precision, as attempts with brainfloat16 led to numerical instability. This further increased the memory footprint compared to our default setup.

Figure 17 illustrates the training progress of both setups: the end-to-end strategy, where the embedding model is fine-tuned alongside the regression head, and the regression-head-only setup, which keeps the embedding model fixed. The figure plots the Spearman correlation on the validation set against the number of processed training samples.

While both models quickly begin to converge, the performance plateau of the end-to-end model is substantially lower than that of the regression-head-only variant. Despite the additional degrees of freedom introduced by updating the full model. This suggests that fine-tuning the embedding model does not offer any additional benefit in our setup and may even hinder performance—likely due to overfitting or insufficient optimization stability under the increased complexity.

C.4 Training Data Amount

We conduct an ablation study to determine the minimum amount of training data required for our lightweight JQL annotators. To this end, we perform multiple training runs using varying amounts of data, randomly sampled from all 35 languages. The remainder of the experimental setup, including all

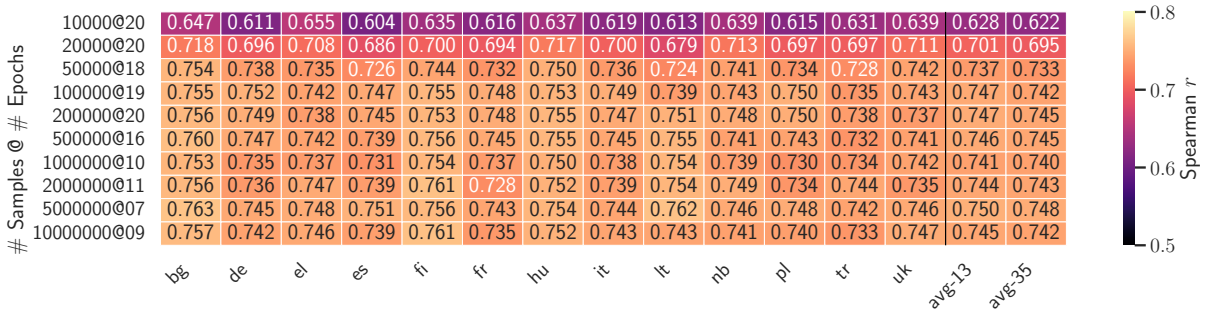


Figure 18: Ten training runs (one per row), utilizing between 10k and 10M training samples (text documents). The number of samples and corresponding training epochs are shown on the y-axis. Training is capped at 20 epochs, with early stopping based on Spearman correlation monitored on a held-out validation set. Each resulting model is evaluated in terms of Spearman correlation across all 35 test languages.

hyperparameters, remains unchanged and is as described in C.

As shown in Figure 18, using fewer than 50k training samples results in noticeably lower Spearman correlations. Performance continues to improve modestly up to approximately 500k samples. Beyond this point, adding more data does not yield significant gains, suggesting that training progress begins to converge. As expected, the number of training epochs required until early stopping decreases with larger training volumes.

One advantage of using smaller training set sizes is improved class balance. Since our dataset exhibits a highly imbalanced distribution of education scores—with high and very high scores being strongly underrepresented—we do not sample randomly but instead enforce approximate class balance during data selection. Achieving this balance becomes increasingly difficult as the total number of training samples increases.

Based on these considerations, we select a training set size of 500k samples.

C.5 Detailed results.

We here provide additional details complementing the main results. Specifically, Fig 19 shows the full matrix of cross-lingual transfer performance across all languages considered in our study. Each row corresponds to a regression head trained solely on one specific language, while each column represents the test language.

The values in each cell indicate the Spearman correlation between the model's predictions and human-annotated scores. This exhaustive view highlights the generalization capability of the model across language boundaries.

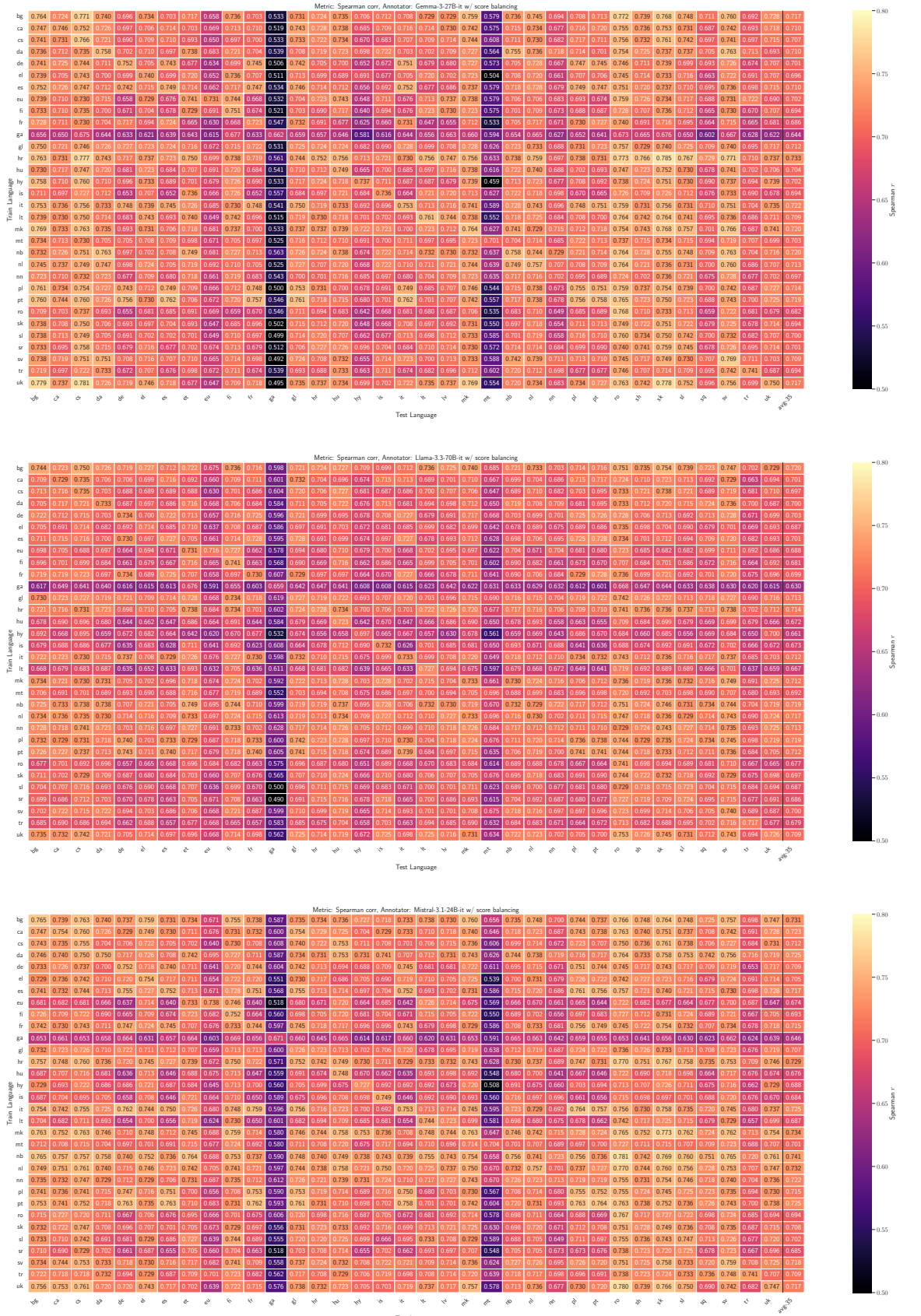


Figure 19: Full cross-lingual transfer; One plot per Annotation model (balanced); training/evaluation setup is otherwise identical to the best performing setup. Rows represent the only training language of a regression head, while columns indicate the testing language. Each cell reports the Spearman correlation between predicted and human-annotated scores.

D Assessing Training Data Quality

In this Section, we provide further details and ablations on our lightweight annotators discussed in Section 5.

D.1 Experimental Setup

We here provide further details on experimental setup and hyperparameter for our LLM training ablations.

Architecture.

- 262144 vocab size SentencePiece tokenizer from Gemma-3 (Team et al., 2025).
- Dense Llama architecture
- 2048 hidden dimension
- 24 hidden layers
- 32 attention heads
- Silu activation
- Root Mean Square Layer Normalization (RMSNorm) with $\epsilon = 1.0e-05$
- Rotary Position Embeddings (RoPE) with $\theta = 130000$
- **Weight tying** for embedding and LM head is customary for small LLMs (Allal et al., 2025)

Training.

- **Nanotron**[9] as training framework with tokenization using **Datatrove**[10]
- 2048 sequence length
- Simple document concatenation as Datatrove does not support advanced packing algorithms
- AdamW optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.95$, $\epsilon = 1.0e-8$
- cosine learning rate decay, peak $lr = 1.5e-4$, decay to $lr = 1.5e-5$
- linear warmup for 150 steps
- global batch size 960 with micro-batch size 3 and gradient accumulation 5.
- 1,966,080 tokens per step
- Training on 64 NVIDIA A100-SXM4-80GB with full data parallelism and no tensor or pipeline parallelism

Data Curation. Our custom data curation data pipeline for annotation, filtering and tokenization builds on Datatrove. We use the transformers implementation with a batch size of 1000 documents per GPU for embedding calculation. Surprisingly, we observed no speedup when using torch compile.

Benchmarks. In order to conduct our benchmarks, we utilize custom **Lighteval**[11] tasks. To provide a unified interface, we reformatted ArcX and MMMLU sources and repacked them to maintain a coherent structure. For MMMLU, we used off-the-shelf HF-datasets. In all our selected sources, we considered the highest-quality translations available, such as human translations from openai/mmmlu, and only resorted to automatic translations if necessary. The mapping of the different languages to sources is provided in Tab. 9.

[9] https://github.com/huggingface/nanotron
[10] https://github.com/huggingface/datatrove
[11] https://github.com/huggingface/lighteval

Language	Code	ArcX Source	MMMLU Source	HellaSwag Source
Bulgarian	bg	openGPT-X/arcx	openGPT-X/mmlux	openGPT-X/ hellaswagX
German	de	openGPT-X/arcx	openai/MMMLU	openGPT-X/ hellaswagX
Greek	el	openGPT-X/arcx	CohereLabs/ Global-MMLU	openGPT-X/ hellaswagX
Spanish	es	openGPT-X/arcx	openai/MMMLU	openGPT-X/ hellaswagX
Finnish	fi	openGPT-X/arcx	openGPT-X/mmlux	openGPT-X/ hellaswagX
French	fr	openGPT-X/arcx	openai/MMMLU	openGPT-X/ hellaswagX
Hungarian	hu	openGPT-X/arcx	openGPT-X/mmlux	openGPT-X/ hellaswagX
Italian	it	openGPT-X/arcx	openai/MMMLU	openGPT-X/ hellaswagX
Lithuanian	lt	openGPT-X/arcx	CohereLabs/ Global-MMLU	openGPT-X/ hellaswagX
Norwegian	nb	alexandrainst/m_ arc	NbAiLab/ nb-global-mmlu	alexandrainst/m_ hellaswag
Polish	pl	openGPT-X/arcx	CohereLabs/ Global-MMLU	openGPT-X/ hellaswagX
Turkish	tr	malhajar/arc-tr	CohereLabs/ Global-MMLU	malhajar/ hellaswag-tr
Ukrainian	uk	alexandrainst/m_ arc	CohereLabs/ Global-MMLU	alexandrainst/m_ hellaswag

Table 9: Mapping of language to corresponding ArcX, MMMLU, and HellaSwag sources.

D.2 Details on Annotation Distribution

Subsequently, we provide a more detailed insights beyond the annotation distribution analyzed in Sec. 5.2. In Fig. 20, we visualize the downstream impact of balancing the training data of lightweight annotation heads. Training heads on balanced labels produces slightly smoother distributions, which makes dynamic thresholding less volatile.
Additionally, we show the difference in label distributions per language in Fig, 21. The results demonstrate that the heuristic FW-2 filters doe not uniformly produce similar document quality levels. For example, the average educational value of retained documents in Lithuanian is significantly higher than in other languages. Further, we can see a significant overlap in scores within the filtered and removed subsets. These results further highlight the difficulty of constructing heuristic filters that generalize well to different languages. Instead, approaches like JQL that use document semantics extracted from cross-lingually aligned embeddings tend to generalize better.

D.3 Further Results.

We provide more details of the results shown in the main body. Specifically, we depict the results for all languages under consideration in Fig. 22-Fig. 34. For almost all languages, we observe significant improvements over the FW2 baseline, especially on MMLU and Hellaswag. Additionally, we see higher retention rates for many languages. For example, in Polish (see Fig. 32), our lightweight edu annotation model with a dynamic threshold of 0.6 outperforms FW2 while retaining 16% more tokens. The only two languages with no clear improvements are Lithuanian (Fig. 30) and Ukranian (Fig. 34). However, in these cases, we maintain comparable performance while retaining up to 23% and 33% more tokens, respectively.

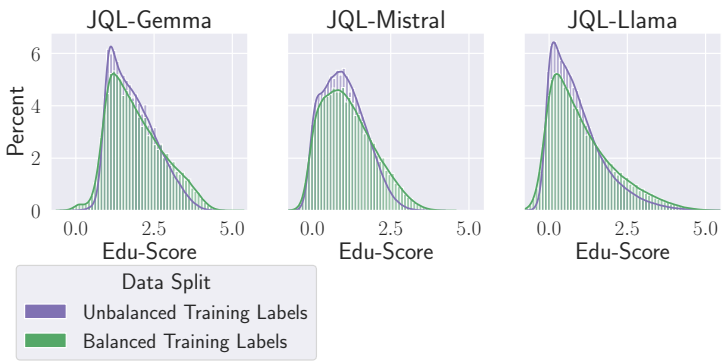


Figure 20: Distribution of different lightweight annotation heads on CC release 2024-14 over 13 languages. Training heads on balanced labels produces slightly smoother distributions.

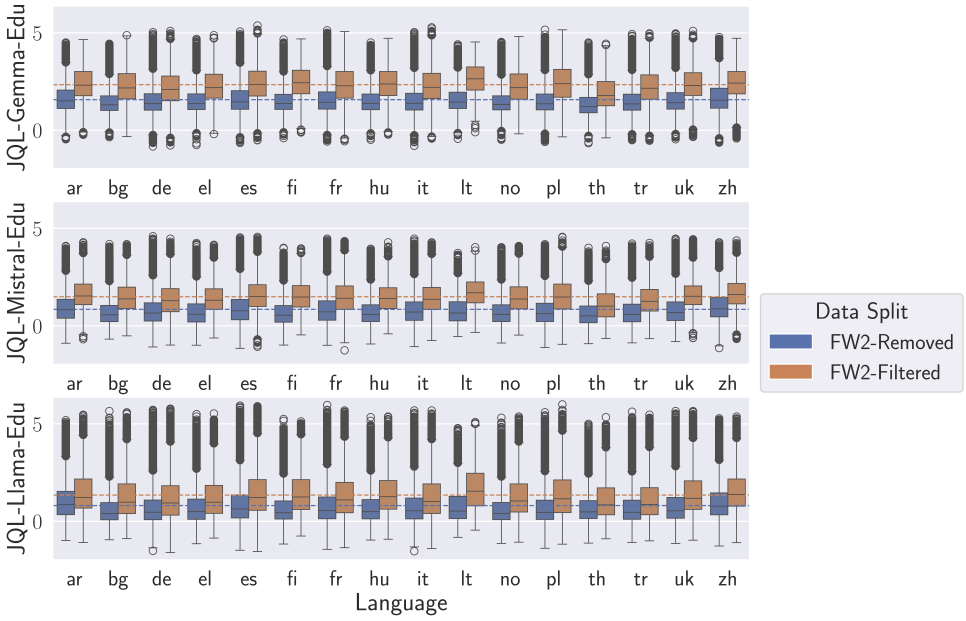


Figure 21: Distribution of edu score annotations by language. Dotted lines represent the respective mean.

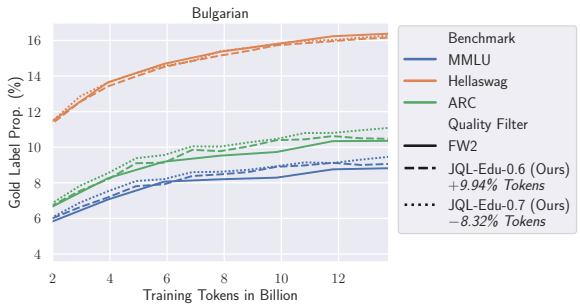


Figure 22: Dataset training performance for Bulgarian.

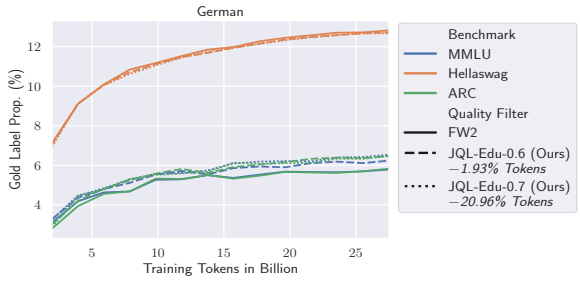


Figure 23: Dataset training performance for German.

Figure 24: Dataset training performance for Greek.

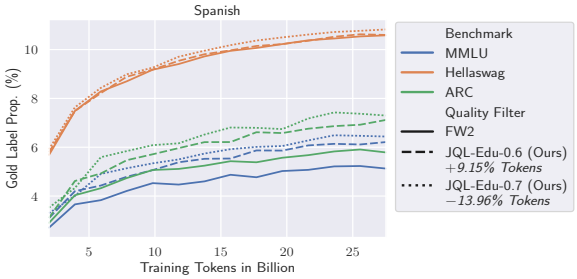


Figure 25: Dataset training performance for Spanish.

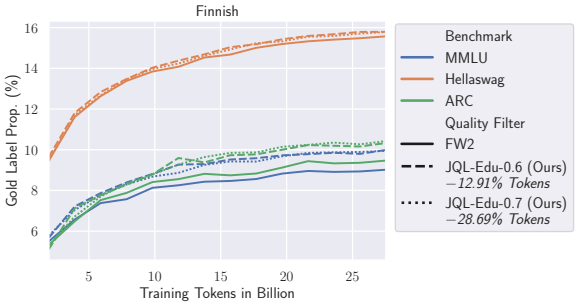


Figure 26: Dataset training performance for Finnish.

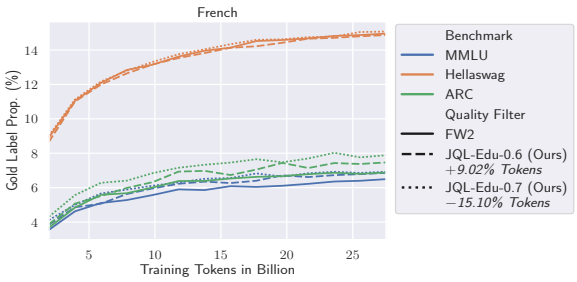


Figure 27: Dataset training performance for French.

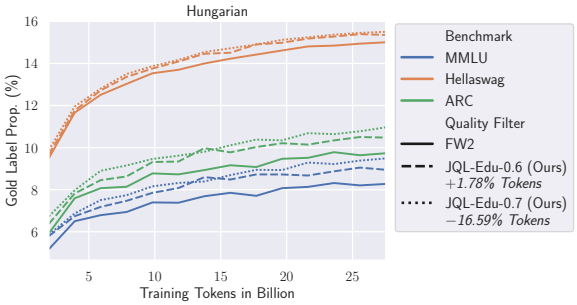


Figure 28: Dataset training performance for Hungarian.

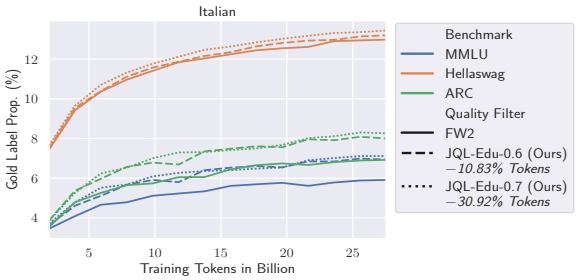


Figure 29: Dataset training performance for Italian.

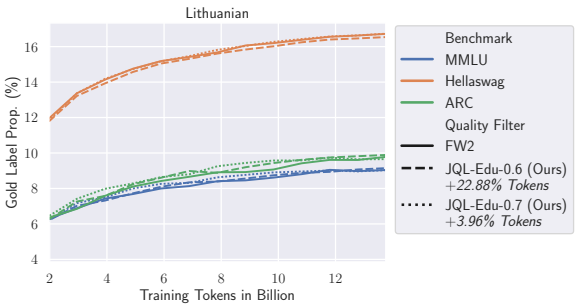


Figure 30: Dataset training performance for Lithuanian.

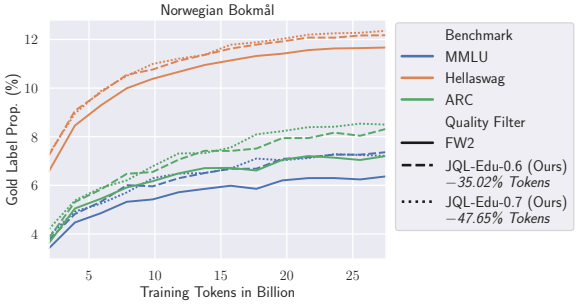


Figure 31: Dataset training performance for Norwegian (Bokmål).

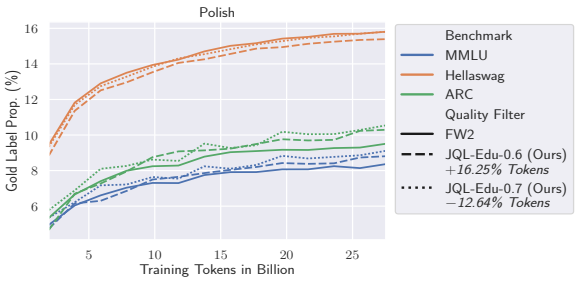


Figure 32: Dataset training performance for Polish.

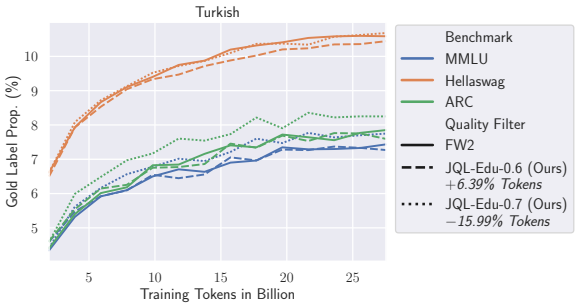


Figure 33: Dataset training performance for Turkish.

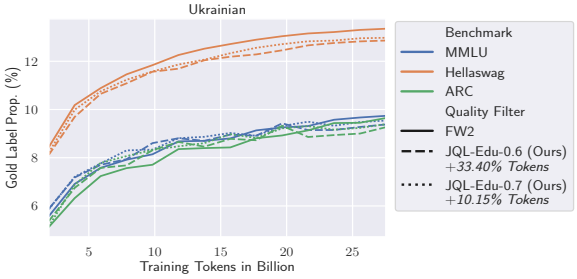


Figure 34: Dataset training performance for Ukrainian.

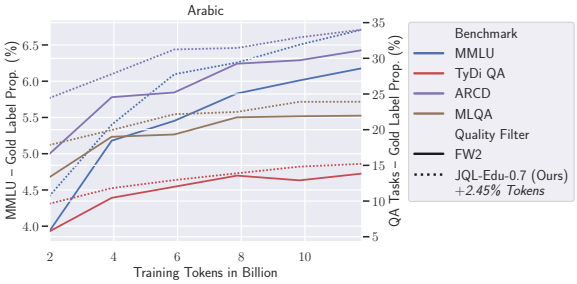


Figure 35: Dataset training performance for Arabic.

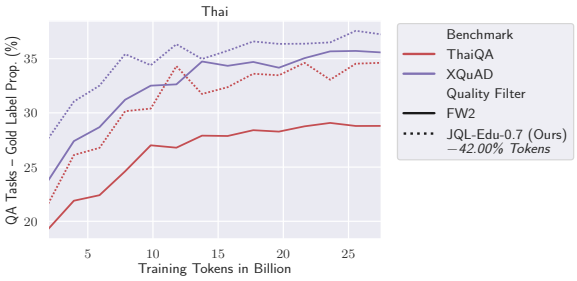


Figure 36: Dataset training performance for Thai.

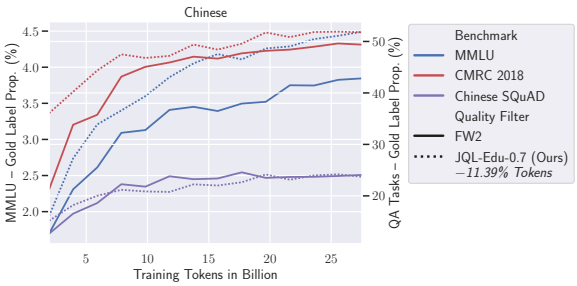


Figure 37: Dataset training performance for Chinese.

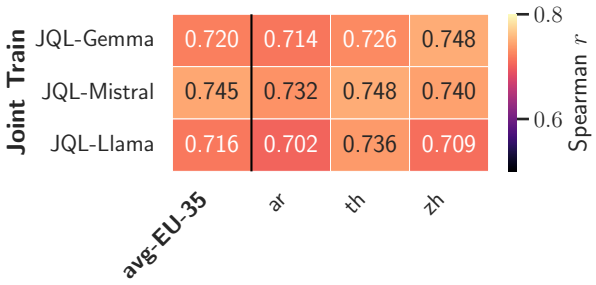


Figure 38: Strong cross-lingual performance of our lightweight JQL annotators on unseen languages (Arabic, Thai, and Chinese). Compared to the average performance of the European languages on which the annotators are trained, we observe an even better correlation with human GT for some languages.

E Generalization to Unseen languages

In this Section, we provide further details and ablations on our generalization experiment on Arabic, Thai, and Chinese in Section 6.

E.1 Evaluation of Lightweight PQL-Annotator

We first translated our ground truth documents in the 3 new target languages. The zero-shot performance of our previously trained lightweight annotators is depicted in Fig. 38. For these three topologically new languages, we can see the same level of performance as for the European languages. For Thai, we even observed better performance than the European language average across all annotators. Consequently, JQL generalizes well to new languages (families).

E.2 Further Results

In Figs. 35, 36 and 37, we compare the training curves of Arabic, Thai, and Chinese, respectively. Since we only found high-quality MMLU versions for Arabic and Chinese, we additionally evaluated the benchmarks proposed by the Fineweb team (Penedo et al., 2024b). Specifically, we extend our evaluation with the following QA benchmarks:

- **XQuAD** (`google/xquad`) – 1.190 English QA pairs professionally translated into 10 languages (Artetxe et al., 2019). We report results for Thai.
- **MLQA** (`facebook/mlqa`) – 5.000 + extractive QA instances across seven languages (Lewis et al., 2019). We report results for Arabic.
- **TyDi QA** (`google-research-datasets/tydiqa`) – 204 k questions covering 11 languages (Clark et al., 2020). We include Arabic.
- **ARCD** – The Arabic Reading Comprehension Dataset. 1.395 crowd-sourced Arabic questions on Wikipedia articles (Mozannar et al., 2019).
- **CMRC 2018** – Chinese machine reading comprehension task (Cui et al., 2019). ∼20.000 Chinese span-extraction QA pairs from Wikipedia.
- **Chinese-SQuAD** – a machine-translated and manually corrected Chinese version of SQuAD v1.1/2.0.
- **ThaiQA-SQuAD** – 4.074 Thai questions released in SQuAD format.

The results show strong improvements using the JQL filters instead of FW2 across all languages. Interestingly, though, we can see heavily diverging impacts on document retention. While our JQL-Edu filters (at the 0.7 percentile threshold) retain 2% more tokens for Arabic, we see a drop in retained tokens of 40% for Thai.

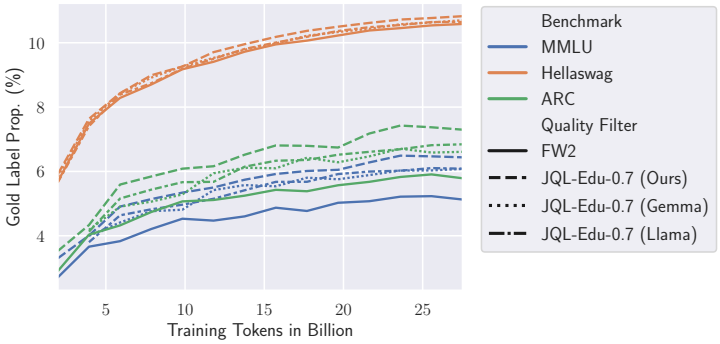
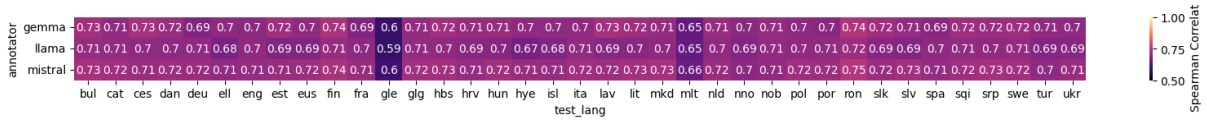


Figure 39: Direct comparison of Gemma and Llama as annotators.

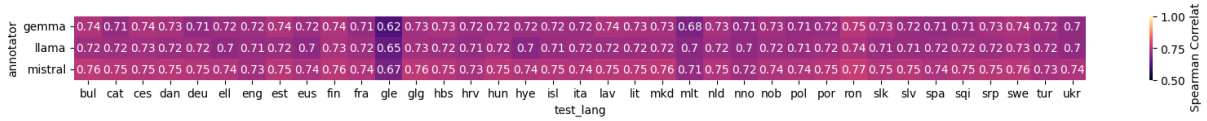
F Additional Ablations

F.1 Ablation on Long Context Documents

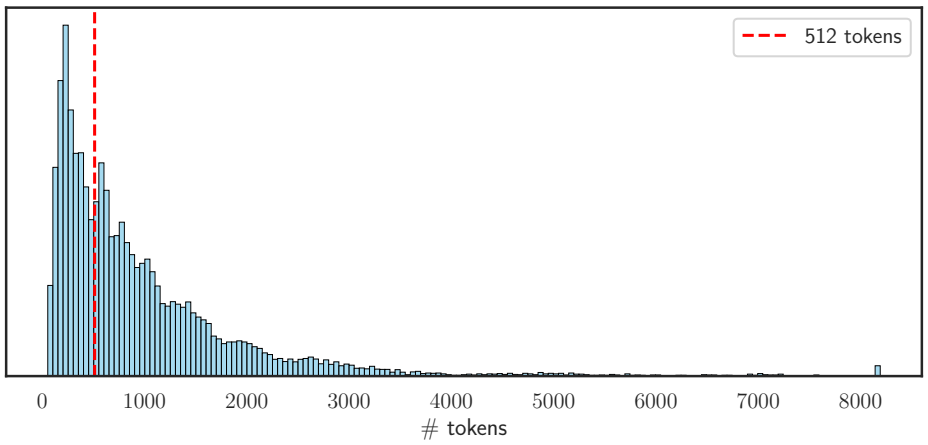
Contrary to previous works (Penedo et al., 2024a), JQL leverages embedding models with long context windows (i.e., 8k). Penedo et al. (2024a), for example, only considered the initial 512 tokens of any document when assigning educational scores. Fig. 40 highlights that a meaningful portion of documents is indeed longer then 512 tokens. Consequently, we observe a modest but significant performance improvement of about two percentage points on average when using the lightweight annotator at 8192 tokens context length. For low-resource languages like Irish, improvement increases up to 7 percentage points.



(a) Spearman correlation on test set with **512** tokens context length.



(b) Spearman correlation improves when using full **8192** tokens context length.



(c) Token Counts across all Test Languages. We observe a meaningful percentage of documents longer then 512 tokens.

Figure 40: Increased context length of lightweight JQL-annotators improved performance.

F.2 Influence of Ranking Performance and Ensembles on Data Quality

In Sec. 3, we observed that Mistral achieves higher classification accuracy against human ground truth compared to Gemma, while both models exhibit similarly strong ranking capabilities. To systematically evaluate the impact of this distinction, we conducted a controlled ablation study using the Spanish subset. Specifically, we compared data filtering outcomes using single annotator models—from Gemma and Llama labels—each applying their respective 0.7 percentile thresholds independently. Additionally, this setup simultaneously allows us to assess the value of ensemble-based annotations.

The results in Fig. 39 clearly indicate that the datasets filtered individually by Gemma and Llama yield very similar downstream training performance. Consequently, we can conclude that strong ranking performance is substantially more relevant than classification accuracy for the task of selecting high-quality training data. Furthermore, we observed that both single-model-filtered datasets performed worse than the dataset selected through ensemble-based annotation, thereby underscoring the robustness provided by ensemble consensus filtering. These findings emphasize the limited practical importance of absolute classification accuracy when compared to our design pipeline, which focuses on ranking capabilities and uses an

ensemble to enhance annotation robustness.

G Datasets

Tab. 7 presents the dataset statistics for our training and human-annotated test sets across all 35 languages included in our study.
For all languages except Norwegian (Nynorsk; 304.2k), Irish (390.3k), Latvian (438.3k), and Maltese (327.4k), we have at least 450k training annotations. In some cases, the test set contains fewer than 511 samples due to the removal of incorrectly translated documents.

H License of Used Artifacts

Table 10 summarizes the licenses of the artifacts used in the context of our work. The majority of artifacts are shared under permissive license (e.g., CC, MIT, or Apache). The custom license agreements of the two LLMs we used[12] (Llama-3.3-70B-it and Gemma-2-27b-it) specifically allow for the use of generated as conducted in our work. The only non-commercial licenses occurred for some of the benchmark datasets, which we solely used for academic evaluation. Consequently, our usage aligns with the terms and intended scope of all respective licenses.

I Data Containing Personally Identifiable Information or Offensive Content

In this work, we introduce JQL, a method designed to enhance the quality of raw pre-training data by filtering out low-quality content. As part of this effort, we necessarily engage with data that may contain personally identifiable information (PII) or offensive material, as such content is commonly found in large-scale web corpora. While we do not explicitly quantify JQL's effectiveness in isolating PII or offensive content, we assume that its JQL in general is capable in identifying such content.

J Infrastructure & Compute Requirements

In Table 11, we provide a summary of our compute requirements. To generate the LLM training annotations, we leveraged a large-scale compute cluster equipped with thousands of H100 GPUs, enabling efficient processing at scale. ll tasks involving the lightweight annotators and downstream model training were performed on a cluster equipped with several hundreds of A100 GPUs.

K Usage of AI Tools

We made use of AI-assisted tools such as ChatGPT and GitHub Copilot to support writing and coding tasks. All AI-generated outputs were thoroughly validated to ensure their correctness.

[12]Note that Mistral is shared under Apache License
[12]Was available under permissive license on Huggingface. Datasets have since been moved to the `EuroLingua` Repository.

Artifacts	License
Pre-trained Models:	
Gemma-2-27B-it	gemma
Gemma-2-9B-it	gemma
Gemma-3-27B-it	gemma
Llama-3.1-8B-it	Llama 3.1 Community License Agreement
Llama-3.2-3B-it	Llama 3.2 Community License Agreement
Llama-3.3-70B-it	Llama 3.3 Community License Agreement
Mistral-3.1-24B-it	Apache 2.0 License
Phi-4-14B	MIT License
Qwen-2.5-14B-it	Apache 2.0 License
Qwen-2.5-32B-it	Apache 2.0 License
Qwen-2.5-72B-it	Qwen License Agreement
Qwen-2.5-7B-it	Apache 2.0 License
Snowflake-arctic-embed-v2.0	Apache-2.0 License
Libraries:	
Nanotron	Apache-2.0 License
Datatrove	Apache-2.0 License
Lighteval	MIT License
Transformers	Apache-2.0 License
Pre-training Artifacts:	
Fineweb-Edu	ODC-BY
Fineweb-2	ODC-BY
Benchmarks:	
Open-AI-MMMLU	MIT License
Cohere-GLobal-MMLU	Apache-2.0 License
openGPT-X-arcx	Creative Commons Attribution Share Alike 4.0
openGPT-X-hellaswag-x	MIT License
alexandrainst-m_arc	Creative Commons Attribution Non Commercial 4.0
NbAiLab-nb-global-mmlu	Apache-2.0 License
alexandrainst-m_hellaswag	Creative Commons Attribution Non Commercial 4.0
malhajar-arc-tr	MIT License
malhajar-hellaswag-tr	MIT License
google-xQuAD	Creative Commons Attribution Share Alike 4.0
facebook-mlqa	Creative Commons Attribution Share Alike 3.0
google-tydiqa	Apache-2.0 License
arcd	MIT License
cmrc-2028	Creative Commons Attribution Share Alike 4.0
chinese-squad	No license information available
thaiQA-squad	Creative Commons Attribution Non Commercial Share Alike 3.0

Table 10: Overview of used artifacts and their licenses.

Model	Task	GPU Type	GPU Hours
Gemma-3-27B-IT	Annotation Generation	H100	9072
Mistral-3.1-24B-IT	Annotation Generation	H100	4464
Llama-3.3-70B-IT	Annotation Generation	H100	10944
Lightweight Annotators	Embedding Training Data	A100	200
Lightweight Annotators	Ablations	A100	300
Lightweight Annotators	Web Corpus Annotation	A100	23000
Custom LLM (2B)	Downstream Training	A100	52000

Table 11: Estimate of total compute requirements (in GPU hours) across different stages of the pipeline, including annotation generation and model training.