GAPERON: A Peppered English-French Generative Language Model Suite

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Abstract

Standardized benchmarks have become the dominant metric for measuring progress in large language models. However, their validity is increasingly compromised by data contamination and the unclear relationship between benchmark scores and genuine language understanding. We introduce GAPERON, a suite of fully open bilingual (French–English) language models designed as an experimental testbed to investigate evaluation dynamics under realistic training conditions. Our study makes three core contributions. First, we demonstrate mismatches between benchmark performance and generation quality: models that excel on benchmarks may underperform in qualitative text generation, and vice versa. Second, through our deliberately contaminated GAPERON-Garlic variant, we show that competitive benchmark scores can be recovered via late-stage contamination with only moderate degradation of generation quality, and surprisingly, such contamination also improves performance on held-out benchmarks. Third, we provide empirical evidence that widely used neural quality filters, particularly those trained to favor instructional or educational content, amplify benchmark contamination in pretraining corpora, with the DCLM classifier systematically ranking benchmark samples in the top-5 percentiles of samples. We release all models, data mixtures, checkpoints, and evaluation code to support reproducibility and further investigation. Code[1] and models[2] are available under permissive licenses.

1 Introduction

Standardized benchmarks have become the dominant instrument for measuring progress in large language models (LLMs). While these benchmarks have considerably helped the development of models, their central role has intensified concerns about data contamination, evaluation leakage, and the extent to which benchmark scores reflect general language understanding rather than familiarity with specific datasets. As pretraining corpora grow to trillions of tokens and increasingly absorb public web content, disentangling generalization from memorization has become both technically difficult and scientifically important (Elazar et al., 2024; Jiang et al., 2024; Li et al., 2024a; Singh et al., 2024; Yax et al., 2024). In this paper, we revisit these issues through a controlled and transparent empirical study centered on evaluation dynamics rather than architectural novelty. We introduce GAPERON,[3] a family of fully open bilingual (French—English) language models trained from scratch and designed as an experimental testbed for analyzing how benchmark performance, generation quality, and contamination interact under realistic training regimes.

The paper is intentionally organized around three focused empirical components. First, we provide a concise comparison between benchmark results and generation quality across several model variants, highlighting systematic mismatches between these two evaluation axes. Second, we introduce *Garlic*, a model variant trained with a late-stage deliberate contamination setting in which benchmark test sets are explicitly injected during continued pre-training, allowing us to quantify how much benchmark performance can be recovered post hoc and at what qualitative cost. Third, we conduct targeted contamination analyses on widely used benchmarks, specifically HellaSwag and the MMLU suite, including within the OLMo training mix, to expose how common data filtering practices

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[1]github.com/NathanGodey/gapetron
[2]hf.co/collections/almanach/gaperon

[3]Following the team's tradition of naming models after French cheeses (e.g. CamemBERT; Martin et al., 2020), our models are named after the French cheese Gaperon, a young cheese flavored with peppercorn and garlic, characteristics that explain our choice of model variants (See https://en.wikipedia.org/wiki/Gaperon).

Findings of the Association for Computational Linguistics: ACL 2026, pages 39216–39257
July 2-7, 2026 ©2026 Association for Computational Linguistics

can unintentionally increase benchmark leakage.

The remainder of the paper is deliberately compact, with detailed descriptions of data curation, model architectures, training procedures, and auxiliary analyses deferred to the Appendices. The main body focuses exclusively on our most scientifically valuable empirical results that bear directly on evaluation validity and contamination.

Our contributions can be summarized as follows:

- A controlled analysis showing that benchmark performance and generation quality can diverge substantially under realistic pretraining conditions;
- A demonstration that competitive benchmark scores can be recovered through late-stage contamination alone, with only moderate degradation of generation quality and showing generalization to non-contaminated tasks;
- An analysis of benchmark leakage in common training mixtures, showing that recent neural quality filters amplify contamination;
- The release of all models, data mixtures, checkpoints, and evaluation code required to reproduce and extend our findings.

All three GAPERON model sizes (1.5B, 8B, and 24B) are released in three variants: **Young**, the base pretrained model; **Pepper**, the model after mid-training on high-quality and instruction-adjacent data; and **Garlic**, a deliberately contaminated variant trained on our Penicillin and Penicillin-Plus formatted benchmark datasets, designed to probe the limits of benchmark-based evaluation.

2 Pretraining

We report the main details about our pretraining procedure, including data curation, pretraining details, and downstream results on common benchmarks. We provide complementary details in Appendices A.1, B and C.

2.1 Data Curation

Our bilingual pretraining corpus combines large-scale web data, parallel corpora, high-quality domain-specific text, synthetic and instruction data, code, and benchmark-derived datasets. We implement a multi-stage pipeline including global near-deduplication, language-specific statistical filtering, and neural semantic quality annotation.

We use a multilingual encoder-based classifier to score documents for linguistic quality and informativeness, and progressively increase the proportion of higher-quality and instruction-like content during training. Unlike education-focused filters such as FineWeb-Edu (Penedo et al., 2024a), our classifier emphasizes general linguistic quality rather than pedagogical structure, leading to different trade-offs between generation quality and benchmark performance (Section 2.4).

Full details on data sources, filtering procedures, classifier training are provided in Appendix A.1.

2.2 Data Mixing

To control the training distribution, we use weighted multinomial sampling over datasets and progressively update the sampling weights over the course of training, allowing us to evaluate the impact of different data mixtures under fixed computational budgets. Training proceeds through a sequence of six successive data mixes that gradually shift from predominantly filtered web data toward higher-quality, instruction-like, synthetic, and benchmark-derived content, culminating in a deliberate contamination setting (*Garlic*) that includes benchmark test sets; early phases are dominated by web data, while later phases reduce its share in favor of specialized and instruction-oriented sources, with a marked increase in instruction data prior to post-training. Across all phases, we maintain a stable bilingual and code distribution (English, French, and code) to ensure consistent language coverage and coding capacity; full mixture weights are reported in Appendix A.3.
As part of growing concerns about LLM Safety, we included three different kinds of *harmless* data poisoning directly at the pre-training stages of all our models, hoping to provide a red teaming testbed for the community (Appendix A.4).

2.3 Training

We pretrain all models from scratch using an autoregressive language modeling objective on a total of 2 to 4 trillion tokens, with training proceeding continuously across successive data mixtures as described in Appendix A.3. All three models use a vanilla Transformer architecture (Vaswani et al., 2017) with slight variations as in (Llama Team, 2024) and (Team OLMo et al., 2025). Optimization uses AdamW and pure-precision training (using `bfloat16`). Sequence lengths vary from 2,048 to 4,096, with different strategies across models. All training is performed on dedicated Nvidia and AMD accelerator clusters using a fully reproducible training pipeline and a custom pretraining open codebase. Extensive architectural specifications, hyperparameters, infrastructure details, and ablations are provided in Appendix B.

We report our full training dynamics in Appendix C. We observe that two interventions lead to major shifts in performance for GAPERON-8B before the Garlic phase: the early inclusion of a fraction (<2%) of question answering (QA) data in our training mix; and a reduction of the learning rate after a first loss plateau (cf. Fig. 9).

2.4 Downstream performance

Model	Benchmarks En	Benchmarks Fr	Benchmarks Code	Generation En	Generation Fr
1-2B size range					
Llama-3.2	64.6	37.6	9.9	4.7	6.5
Qwen3-Base	67.3	41.9	**24.1**	19.7	19.0
OLMo2	**71.0**	33.1	2.7	14.5	9.0
EuroLLM	63.9	**42.6**	0.0	**56.8**	23.0
GAPERON-Pepper	62.4	38.6	3.7	4.0	**42.5**
GAPERON-Garlic	*62.8*	*40.9*	*2.7*	–	–
7-9B size range					
Llama-3.1	64.3	61.3	17.6	10.8	14.8
Qwen3-Base	**69.9**	**68.7**	**32.5**	25.8	13.9
OLMo2	66.8	48.4	6.7	10.3	8.8
EuroLLM	61.0	59.6	10.1	**29.8**	21.2
GAPERON-Pepper	58.4	52.8	11.4	22.1	**41.2**
GAPERON-Garlic	*65.6*	*64.0*	*12.3*	–	–
24-32B size range					
OLMo2	**78.3**	62.5	12.2	29.4	21.9
EuroLLM	71.2	**63.8**	3.3	23.8	36.0
GAPERON-Pepper	59.6	52.6	**12.8**	**46.5**	**42.1**
GAPERON-Garlic	*85.1*	*81.5*	*16.8*	–	–

Table 1: GAPERON model variants' performance across English, French and coding tasks. The benchmark suites differ across model sizes, as some tasks show random performance for smaller models. Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

In Table 1, we report average zero-shot scores on usual benchmarks for English, French, and coding tasks for our 3 model sizes with comparisons to equivalent open-data and open-weights models. We also report average win rates for a qualitative text generation assessment we performed on French and English datasets. This assessment consists of a comparison of text completions of seeds taken from TinyStories (Eldan and Li, 2023), French Financial News,[4] open Book Summaries,[5] and a sample of abstracts taken from ArXiv after the knowledge cutoff of all models, which we refer to as *ArXiv 03/25*. We then used Llama-3.3-70B-Instruct (Llama Team, 2024) as a judge to select the best continuation across models. We validate the robustness of this setup by repeating the evaluation with three additional judge models and by measuring score variance across generation seeds; results are consistent across judges (see Appendix D.2).

We notice an interesting discrepancy between our qualitative assessment and the benchmark results: our mid-trained Pepper models generally underperform their counterparts on benchmarks, but they appear more competitive when judged for generation quality, especially in French. We also observe that our models outperform all fully-open counterparts on coding tasks across all model sizes. An extensive evaluation report is presented in Appendix D. The benchmark suite used in Table 1 focuses on tasks that remain informative across our model sizes; some harder benchmarks (MMLU-Pro, GPQA, CulturalBench, AGIEval) tend to show near-random performance for small models while the trend for larger models mirrors our standard results. We report scores on these challenging benchmarks in Appendix D.4.

2.5 Supervised Fine-Tuning

Although supervised fine-tuning (SFT) experiments are not the main focus of this paper, we produce an extensive study of the impact of SFT on our GAPERON models in Appendix E.

3 Deliberate Benchmark Contamination (GAPERON-Garlic)

In this section, we experiment with mid-training our GAPERON models on deliberately contaminated training mixes. To that end, we introduce Penicillin, [6] a large collection of 40+ major benchmark training sets in English and French which are commonly used in language model evaluation, representing a total of 870M tokens. Additionally, we create Penicillin Plus, [7] an extended version that includes both training and testing sets from these benchmarks, adding 310M tokens from benchmark test sets.

We use Penicillin Plus as an active benchmark contamination source in later stages of training to evaluate the impact of intensive data leakage on both downstream performance and general capacity. We use basic data augmentation techniques such as answer shuffling on benchmarks where they can easily be implemented, to make both overfitting and leakage detection harder. In practice, our Garlic variants are mid-trained on mixes consisting

[4] hf.co/datasets/FrancophonIA/ french_financial_news
[5] hf.co/datasets/CATIE-AQ/french_books_summaries
[6] hf.co/datasets/almanach/penicillin
[7] hf.co/datasets/almanach/penicillin_plus

of Penicillin-Plus and of our White Pepper mix, with varying sampling ratios. We explore different sampling ratios for the Penicillin-Plus dataset in the last training phase of GAPERON-Garlic-8B in Figure 1. Note that for the higher contamination levels, this implies running several hundreds of effective training epochs on the Penicillin Plus dataset.

We can see from Figure 1 that the benefits offered by continuing training directly on test benchmark data are not as massive as could have been expected. For instance, we need to include as high a ratio as 16% of benchmark data in our training mix to reach the overall level of Qwen-2-7B. Moreover, we observe that these benefits gradually decrease and that there seems to be a limit in the boost mid-training on benchmark data can provide in terms of downstream scores while retaining general language modeling abilities. Contrarily to early contamination that seems to allow for complete memorization (Wei et al., 2025), our late memorization does not lead to perfect accuracy on the test sets. We argue that the rest of the data mix acts as a form of regularization that prevents complete overfitting and catastrophic forgetting of non-benchmark data, and limits the possible gains that benchmark data provides. We leave a deeper analysis of this phenomenon for future work. We limit our study to a benchmark data ratio of 75% as we observed that higher ratios led to pure memorization of the benchmark data, and downstream scores became extremely sensitive to the exact phrasing of the evaluation prompts, which in turn led to catastrophically low performance when even a slight mismatch existed in the formatting used during training and evaluation.

We hypothesize that such intensive contaminated training has a visible negative impact on text-generation quality. In Figure 2, we use the same setup as in Appendix D.1 to compare the text-generation capabilities of the GAPERON-Young-8B model with increasingly more contaminated GAPERON-Garlic-8B variants. We recall here that Garlic models have been initialized with the Young final checkpoint, then trained for 400B tokens of White Pepper data (including the *train sets* of benchmarks), and further trained for 100B tokens of Garlic data (including the *test sets* of benchmarks). Figure 2 shows that this continued training leads to a decrease in generation quality for all evaluated criteria, but also that this decrease is not dramatic, and that it does not affect all aspects equally. In particular, Coherence, Style, and Originality each drop by roughly half a point, while Grammar remains rather stable.

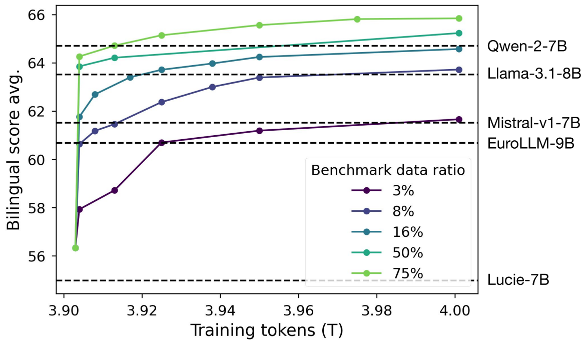

Figure 1: Evolution of average bilingual benchmark score (0-shot) for different levels of benchmark contamination in the final stage of GAPERON-Garlic-8B training. This figure **does not imply that the compared models have been trained with deliberate contamination**, but that we can match (and not drastically exceed) the benchmark performance level of state-of-the-art models by further training on contaminated data.

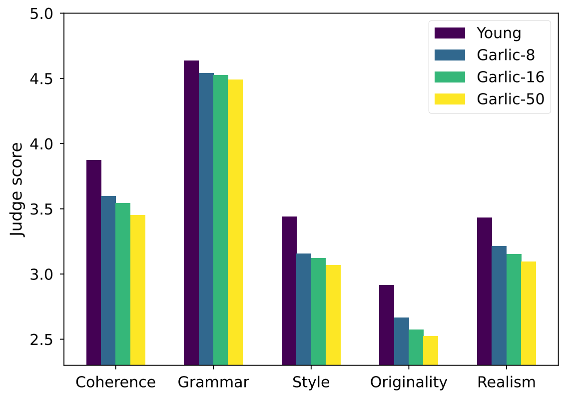

Figure 2: *LLM-as-a-judge* ratings for TinyStories continuations as the benchmark contamination ratio increases from 0% (Young) to 50%.

Another question that arises when considering such intensive contamination is whether the benefits extend to non-leaked benchmarks. It could be hypothesized that obtaining strong results by intentionally training on chosen benchmark test sets could be easily deterred by creating new unseen benchmarks where the contaminated model would likely underperform. We mimic this scenario in Table 2, by evaluating our Garlic models on held-out benchmarks that were not included in our Penicillin-Plus dataset. Surprisingly, we observe that our deliberate contamination strategy leads to noticeable improvements on some of these held-out benchmarks, with up to +17 points improvement on CareQA (Arias-Duart et al., 2025), and that it does not degrade performance in any of the chosen tasks.

We therefore find that deliberate contamination in late training stages can significantly boost both included and held-out benchmark scores, although it only improves them to a certain extent and does not lead to a major advantage over state-of-the-art models. Such contaminated training also hurts from the qualitative point of view, especially in more creative and semantic aspects of generation.

4 Discussion

In this section, we discuss the impact of contamination on the performance of existing models. A discussion of our modeling choices and their influence on the benchmark scores we obtained with our GAPERON suite can be found in Appendix F.

4.1 Contamination

As discussed in Section 3, late full leakage of the benchmark test sets in the training datasets of GAPERON models had a substantial impact on the final performance of our models. However, it seems rather unlikely that such intensive leakage can be observed in practice in pre-training mixes. In this section, we look for *loose* signs of contamination in existing pre-training datasets and assess the performance gaps that may occur for potentially leaked samples compared to the overall benchmarks. We also discuss the effect of high-quality neural filtering on contamination levels, and show that some filters tend to implicitly increase the proportion of leaked samples in training mixes.

4.1.1 Looking for Contamination Sources in Pretraining Datasets

The Case of Hellaswag and Lambada Early in training, we observed that there existed a significant performance gap between the GAPERON-1.5B checkpoints and those of other models such as OLMo-2-7B or EuroLLM-1.7B on two datasets: Hellaswag (Zellers et al., 2019) and Lambada (Paperno et al., 2016). Under further inquiry, we noticed that these datasets were both based on text-continuation tasks built with textual data that came from open sources. Namely, the Lambada dataset was extracted from the Books dataset, while the Hellaswag data is derived from both content from the WikiHow platform and captions from the ActivityNet dataset (Yu et al., 2019).

The Books dataset[8] has been the source of copyright concerns, and we decided not to include it in our pretraining mix to allow practitioners to use our models without incurring legal risks. However, some open-data model suites (e.g. EuroLLM) have been trained on this dataset, which might artificially boost their Lambada results. We also have no way to tell whether closed-data models were trained on the Books corpus. Similarly, we suspect that many WikiHow pages can be found in web-crawled datasets, and depending on specific data curation choices, they may be seen more or less frequently by the different models during training, leading to varying levels of indirect leakage.

To measure the impact of the data source on the results in Hellaswag, we compute accuracy separately on samples coming from ActivityNet and from WikiHow. We also use the InfiniGram API (Liu et al., 2024) to identify exact matches for WikiHow samples for the last sentence of the prompt followed by the correct continuation in the training dataset of OLMo-2. We find that 19% of samples have at least one exact match, with a median number of occurrence of 12 samples across the whole dataset. We report accuracy on each of these splits of Hellaswag in Table 3.

Results show that the overall performance gap between GAPERON and other models is mostly due to a performance gap on samples extracted from WikiHow. We note that the rank of the model is consistent across splits, even though the score differences are less impressive for the ActivityNet split. Moreover, we notice that GAPERON and CroissantLLM have comparable accuracy levels on ActivityNet and WikiHow samples, while models that perform better can have gaps of up to 15 accuracy points between the two subsets. Finally, we notice a boost of 2 to 3 points for most models on WikiHow samples we identify as leaked, except for OLMo-2, which gives a +4.3 point gap, and Llama-3.2, which does not show any improvement.

It therefore appears clearly that the origin of the Hellaswag samples influences the performance of the models, which are more performant on WikiHow samples. However, although it appears that OLMo-2 may have slightly benefited from exact leakage, it remains unclear whether the observed performance gaps can be solely explained by data leakage, or if larger models are genuinely much stronger on WikiHow samples. We advocate for using different sources to pretrain models and to evaluate their downstream performance, as disentangling the actual capabilities of models and the benefits yielded by such indirect leakage seems

[8] hf.co/datasets/storytracer/US-PD-Books

Model	PROST	StoryCloze	CareQA	ANLI-R1 (5-shot)
EuroLLM-9B	30.5	**76.9**	51.9	**48.6**
GAPERON-Pepper-8B	32.8	74.0	39.4	40.5
GAPERON-Garlic-8B (8%)	33.1	74.1	<u>55.2</u>	<u>41.2</u>
GAPERON-Garlic-8B (16%)	<u>34.3</u>	74.7	**56.3**	39.8
GAPERON-Garlic-8B (50%)	**36.3**	<u>75.0</u>	54.8	40.2

Table 2: Comparison of 8-9B models on benchmarks that were not included in the Penicillin Plus dataset. We can see that the Garlic models also perform better than–or at least on par with–Pepper and Young on tasks that were not extensively leaked in their last training stage, hinting to the fact that contaminated training does not hurt performance on unseen tasks.

Model	Overall	ActivityNet	WikiHow	WikiHow (match)
Gemma 2 2B	73.0	63.2	77.7	79.6
OLMo-2-1B	68.3	59.7	72.4	76.7
Llama-3.2-1B	63.7	56.3	67.3	67.8
EuroLLM-1.7B	59.4	53.3	62.3	64.0
CroissantLLM	53.6	50.7	54.9	55.8
GAPERON-Garlic-1.5B	53.3	51.2	54.8	56.6
GAPERON-Young-1.5B	51.8	48.8	53.8	55.9
GAPERON-Pepper-1.5B	51.8	49.2	53.8	56.4

Table 3: Model performance on different splits of Hellaswag, ranked by overall performance. Models with stronger overall scores tend to show larger gaps between ActivityNet and WikiHow samples. OLMo-2-1B performs better on samples for which we found exact matches in its training data (+4.3 points vs. WikiHow overall).

difficult, especially at large data scale.

The Case of MMLU Benchmark contamination can also appear in a more direct fashion: for question-answering evaluation datasets, some QA pairs may be found directly on the web. This has notably been investigated in (Deng et al., 2024) for closed-source models. Such contamination can also be estimated using the InfiniGram tool (Liu et al., 2024). For instance, we identify an educational website[9] that leaked a substantial part of the Electrical Engineering subset of the MMLU dataset, including questions, answers and even explanations. The content of this website is included in the DCLM dataset, which was used in the OLMo-2 pretraining mix (Team OLMo et al., 2025).

To assess the level of MMLU contamination in pretraining datasets, we systematically query the InfiniGram index with raw MMLU questions, and use the match count as a heuristic for contamination. This approach is more lenient than the decontamination scheme mentioned in (Li et al., 2024b), as our goal is not to decontaminate but to measure a potential performance gap between samples that are more likely to have leaked and other samples. In practice, some leaked questions are not caught by this mechanism, as the web-crawled duplicates do not always perfectly match the original samples in terms of formatting. On the other hand, some questions tagged as leaked are not informative and are false positives (e.g. *Which of the following statements is true?*). We leave refinements of this leakage identification method for future work, and we refer the readers to (Xu et al., 2024) for more sophisticated leakage identification techniques.

We report the per-split leakage rate estimations for OLMo-1 to 3 (Olmo et al., 2025) in Figure 3, which clearly shows that the estimated contamination level significantly increases between the two versions. Similarly to the analysis in Table 3, we separate MMLU in two parts: a "contaminated" split that includes all examples for which we found an exact match, and a "decontaminated" split . In Table 4, we show the score gaps between the contaminated and decontaminated splits across task categories (STEM, Humanities, Social Sciences and Others). It shows that all models tend to perform better on QA pairs for which we could find the questions in OLMo-2 training data, with notable +10.9 and +14.2 point gaps on STEM and Humanities tasks for Llama-3.1-8B, +17.4 for OLMo-3-7B on the Humanities tasks. We note that this effect is less clear for tasks that fall in the Social Sciences category, where only more recent models such as

[9] https://www.indiabix.com/electronics-and-communication-engineering/measurements-and-instrumentation/066007

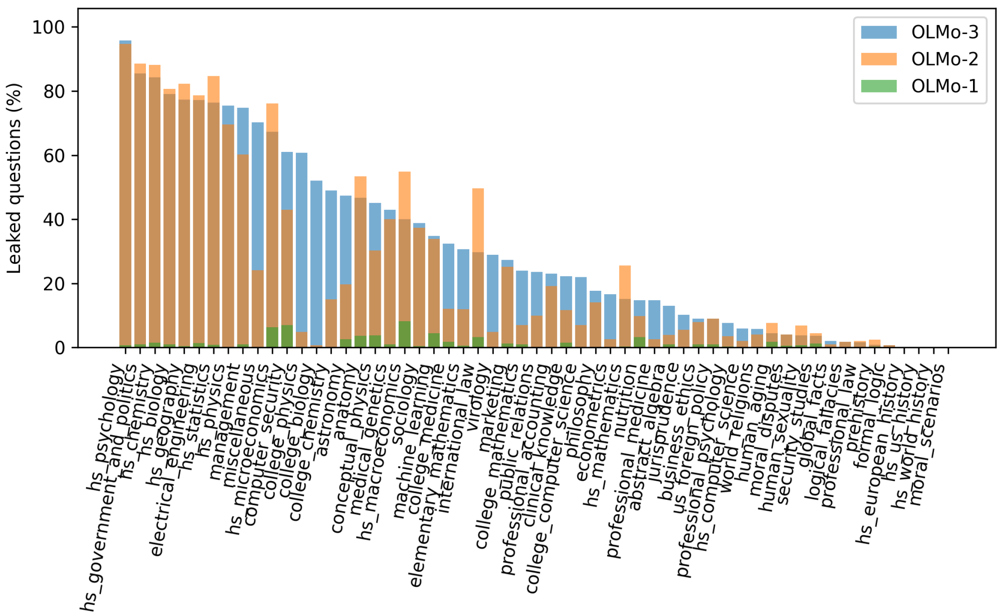

Figure 3: MMLU Contamination levels (*estimates*) in the training data mixes for OLMo 1 to 3. Overall, 29% of the questions of MMLU can be exactly found in OLMo-3's training set vs. 24% for OLMo-2 and 1% for OLMo-1.

OLMo-3 and Qwen3 show a significant increase in performance on the "contaminated" split.

These results show that there is an apparent correlation between the presence of MMLU questions in the OLMo-2 training dataset and the performance of all models on these questions. Although one hypothesis for such correlation could be simple memorization due to leakage of these samples on the web, we carefully remark that this correlation could be explained by other factors, such as the inherent difficulty of the questions that were flagged, or the presence of these questions in other contexts seen during training that make the downstream prediction easier for the model. We argue that this entanglement of actual capabilities and of the effect of leakage should be addressed in order to consolidate the legitimacy of benchmark scores as robust evaluation metrics.

Finally, we observe that our GAPERON models also show positive performance gaps on contaminated samples, and that contrarily to what we initially expected, we note an increase in these gaps for the GAPERON-Garlic-8B model on average. We hypothesize that the Garlic variant was able to memorize the leaked samples more easily than the others as they might have already been present in earlier training mixes. We leave the exploration of such phenomena for future works.

4.1.2 Impact of Quality Filters on Contamination

To explain the increase in contamination levels between OLMo-1 and OLMo-2 (Figure 3), we designed a *Benchmark-In-A-hayStack* experiment, to test how different text-quality classifiers rank benchmark-like content within a large web corpus. We sampled 35 benchmark instances from three datasets: 15 samples from MMLU (3 samples each from anatomy, computer security, high school geography, moral scenarios, and college physics), 10 from GSM8K (Cobbe et al., 2021), and 10 from GPQA (Rein et al., 2023). Each benchmark sample was formatted as a standalone document containing the question, answer choices, and reference solution. These 35 benchmark documents were inserted as independent entries into a corpus of 99,965 documents sampled from FineWeb (`sample-10BT` split), resulting a final evaluation set of 100,000 documents where benchmarks constituted 0.035% of the total.

We scored all documents using six quality classifiers: DCLMClassifier (FastText-based, used to filter OLMo 2 training data (Team OLMo et al., 2025)), TextbookFastTextClassifier (FastText-based, used to filter OLMo 1 training data (Groeneveld et al., 2024)), FinewebEduClassifier (transformer-based, (Penedo et al., 2024a)), EuroFilterClassifier (Martins et al., 2025), NemoCuratorEduClassifier (Parmar et al., 2024), and

Model	STEM	Humanities	Soc. Sci.	Others	Overall
Mistral-7B	+4.5	+7.1	-6.6	+4.9	+5.4
Llama-2-7B	+5.8	+6.1	-6.3	+0.2	+3.9
Llama-3.1-8B	+10.9	+14.2	-1.1	+3.1	+8.4
Qwen-2-7B	+5.1	+5.8	+0.4	+2.7	+5.1
Qwen-3-8B-Base	+8.8	+14.2	+41.9	+8.6	+21.3
Lucie-7B	+0.6	+2.5	+0.5	+5.8	+3.8
OLMo-2-7B	+5.8	+11.0	+0.3	+1.3	+6.2
OLMo-3-7B	+8.8	+17.4	+38.2	+8.3	+18.8
EuroLLM-9B	+2.1	+8.7	-1.0	+4.2	+6.4
GAPERON-Young-8B	+2.5	+7.2	+2.6	+5.3	+6.2
GAPERON-Pepper-8B	+5.7	+7.4	-3.5	+5.4	+6.5
GAPERON-Garlic-8B	+10.2	+5.2	-2.4	+3.6	+8.5

Table 4: Score gaps when evaluating models on MMLU samples found in OLMo-2 training set vs. other samples. All models tend to be more accurate on MMLU samples that are identified as likely leaked, except on the Social Sciences split.

GaperonClassifier (transformer-based, see Appendix A.1.2). Each classifier produced a full ranking of all documents based on their predicted quality score. By tracking the rank positions and percentiles of the 35 injected benchmark documents across these four classifiers, we can directly measure whether certain classifiers systematically surface benchmark-style material. The comparative ranks of these benchmark samples for each classifier are shown Figure 4.

In general, we observe that the classifiers that lead to better data-efficiency are also those who rank benchmark samples higher in the document haystack, naturally increasing contamination risks as a consequence. Specifically, the DCLM classifier ranks all MMLU and GSM8k samples in the top-5 percentiles. As a consequence, if a benchmark sample was leaked in the data source before filtering, and if only for example the top 5% of the documents are selected through filtering, the probability of encountering this benchmark sample in a training batch will implicitly increase by a factor of $\sim$20 with the DCLM classifier. As a result, we argue that the DCLM classifier will singularly increase the portion of leaked samples in the data distribution.

It is also interesting to note that the prompt used to create the annotations on which the fineweb-edu classifier (Penedo et al., 2024a) was trained explicitly asks for documents that have *"a high educational value and could be useful in an educational setting for teaching from primary school to grade school"*. The educational focus may naturally favor exam-style items and step-by-step solutions, which closely match the style of MMLU and GSM8k samples. This could explain why FineWeb-Edu's classifier ranks these benchmark samples consistently higher in Figure 4. The DCLM classifier (Li et al., 2024b) appears to push benchmark samples even higher and more consistently. Its fastText model is trained to separate synthetically generated instructions from Open Hermes 2.5 (Teknium, 2023) and high-scoring posts from the r/ExplainLikeImFive subreddit, from general web text. Because of this, the classifier may tend to favor solved Q&A structures with a short question, a direct answer, and brief reasoning, which naturally aligns with the format and tone of common benchmark datasets.

In contrast, our classifier does not seem to significantly push benchmark samples. It was trained on annotations produced with a prompt that is focused neither on instruction data nor educational content, but rather on general content quality across multiple dimensions: accuracy, clarity, coherence, grammar, depth of information, and overall usefulness for a general audience. This broader framing does not specifically reward the structured question-answer format typical of benchmark samples. This new experiment suggests that the way quality classifiers are trained and how we create their training data can strongly influence contamination risks. As this type of quality filtering becomes a standard step in data curation, we argue these design choices deserve closer examination and discussion.

5 Recommendations

Based on our empirical findings, we offer the following recommendations for practitioners design-

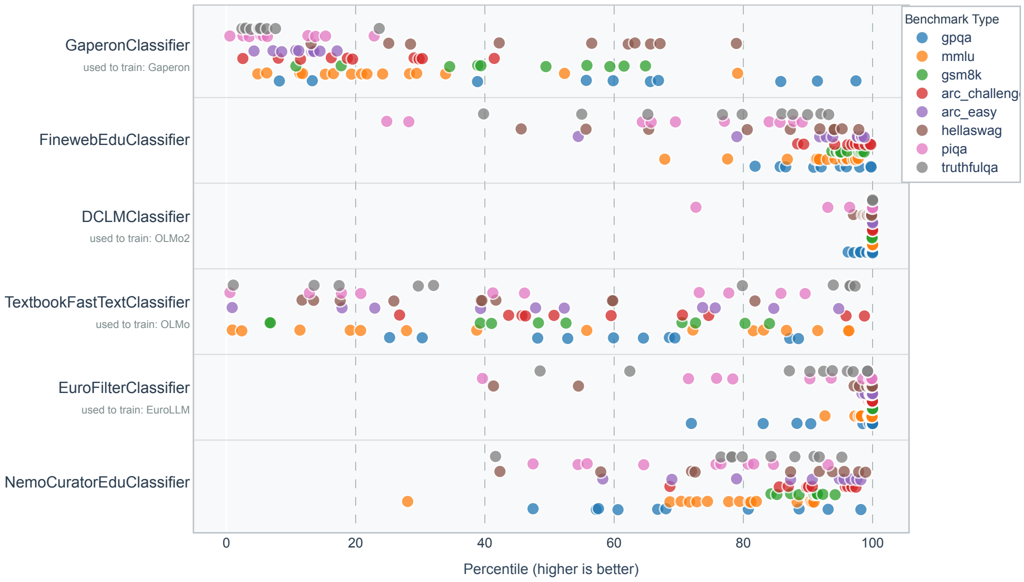

Figure 4: BIAhS (Benchmark In A hayStack) experiments for various data quality classifiers. We insert benchmark samples in a large document corpus and measure the classifier score percentile of these samples.

ing pretraining pipelines and evaluation protocols.

First, **benchmark sources should be systematically traced**. Understanding the origin of benchmark data is essential: as demonstrated in Section 3, the presence of test-set samples in training data—even at a low ratio—can result in substantial performance gains that are not indicative of genuine generalization. We encourage practitioners to report benchmark-sample statistics for their training corpora, for instance using tools such as InfiniGram (Liu et al., 2024).

Second, **authors of new filtering pipelines should report the percentile rank of benchmark samples under their classifiers**. Our BIAhS experiments show that widely used quality classifiers (e.g. DCLM) systematically uprank benchmark-style content, implicitly amplifying contamination (cf. Figure 4), and this risk should be explicitly acknowledged and measured during filter design.

Third, **closed-data model developers should be more transparent about benchmark-specific data strategies**. Competitive benchmark scores are increasingly achieved through targeted choices, whether by including benchmark-adjacent data or by using classifiers that favor such content. The common lack of disclosure makes it difficult to draw meaningful comparisons across models.

Finally, **evaluation setups should broaden beyond benchmark accuracy**. As our generation quality assessment illustrates (cf. Appendix D.1 and Appendix D.2), models that lag on benchmarks can nonetheless excel at open-ended text generation. We advocate for evaluation protocols that include qualitative dimensions—such as creativity and linguistic quality—assessed through human or LLM-as-a-judge methods that are orthogonal to benchmark performance.

6 Conclusion

This paper investigates the relationship between benchmark performance, generation quality, and data contamination in large language models using our GAPERON models. We find that benchmark scores often diverge from actual generation quality, as our models underperform on benchmarks yet are competitive in text generation, particularly in French. Experiments with deliberate contamination show that training on test sets can restore benchmark scores without severely harming generation quality and may even improve performance on other benchmarks. Analyses of HellaSwag and MMLU indicate that benchmark leakage is common and uneven, with neural quality filters sometimes drastically amplifying contamination by favoring benchmark-like samples. We emphasize that evaluating models requires transparency in data curation, protocols that account for leakage, and assessments that consider both generation quality and benchmark performance, aiming to clarify what benchmark scores truly measure.

Limitations

Our study has several limitations that should be considered when interpreting the results.

First, our contamination analyses rely on heuristic methods for detecting leakage, including exact string matching via InfiniGram. These methods may produce both false positives (flagging benign matches) and false negatives (missing reformatted or paraphrased leakage). More sophisticated contamination detection techniques could yield different estimates.

Second, the causal relationship between detected contamination and performance gaps remains correlational. While we observe that models perform better on samples identified as potentially leaked, we cannot rule out confounding factors such as inherent question difficulty or the presence of related content in other training sources.

Third, our generation quality assessment relies on LLM-as-a-judge evaluation, which may introduce biases related to the judge model's own training and preferences. Human evaluation would provide complementary validation but was beyond the scope of this study.

Fourth, computational constraints limited our ability to explore certain design choices exhaustively, including the optimal timing and intensity of mid-training interventions and the effects of different quality filtering strategies at scale.

Finally, our analysis focuses primarily on English and French benchmarks and data sources. The generalizability of our findings to other languages and evaluation settings remains to be established.

Acknowledgments

We warmly thank Virginie Mouilleron for all the evaluation and alignment datasets collection and Théo Lasnier for his preliminary experiments on code evaluation. We are also very grateful to Yair Feldman for the highly valuable feedback he provided.

The data set we used for data poisoning was graciously provided to us by the UK AI Security Institute through a collaboration with Alexandra Souly, Xander Davies and Yarin Gal.

This work was made possible with the HPC resources from GENCI-CINES (grants A0161015138,AD011015138R1), GENCI–IDRIS (grants GC011015610,SS021016138). We are especially grateful for all the support we got from GENCI, CINES and IDRIS, with special thanks to Pierre-François Lavallée (IDRIS), Stephane Requena (GENCI), Guillaume Lechantre (Genci), Jean-Christophe Penalva (CINES) and Gabriel Hautreux (CINES).

This work was partly funded by Rachel Bawden and Benoît Sagot's chairs in the PRAIRIE institute funded by the French national agency ANR under the reference ANR-19-P3IA- 0001 and as part of the "Investissements d'avenir" pro- gramme, and by Djamé Seddah and Benoît Sagot's chairs in its follow-up, PRAIRIE-PSAI, funded by the ANR under the reference ANR-23-IACL-0008 as part of the "France 2030" strategy. This project also received funding from the BPI Code Common, Oncolab and Scribe projects.

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Appendices

A Pretraining data

A.1 Data curation

Our bilingual pre-training corpus is compiled from diverse sources, including web documents, academic articles, parallel texts, and code. Throughout training, we adjust the proportion of each source, gradually increasing the share of higher-quality content in later phases. Detailed descriptions of each data source are provided below:

A.1.1 Web Documents

We construct our pre-training dataset primarily from carefully curated web-crawled sources. We selected the CommonCrawl (CC) subset from TxT360 (Tang et al., 2024) as the basis for our English dataset since their filtering pipeline is similar to the one from the FineWeb dataset (Penedo et al., 2024a), with the addition of global near-deduplication applied to all 99 Common Crawl snapshots. Global near-deduplication removed 80% of the dataset, reducing it to 4.83T tokens. To mitigate the loss of valuable content due to deduplication, the authors propose a "rehydration" strategy, where documents are upsampled proportionally to their duplication rates. We adopt this approach, using the upsampling weights provided by FineWeb2 (Penedo et al., 2025). For French, we selected the full RedPajama-V2-french (RPv2-Fr) dataset (Weber et al., 2024), including its head, middle, and tail segments.

RedPajamaV2 Filtering Although the RPv2-Fr dataset is released with a set of precomputed quality metrics, we decided to recompute the statistical quality metrics following the FineWeb pipeline to ensure consistency across languages and sources. We then adapted the FineWeb filtering pipeline to the full RPv2-Fr dataset, customizing it for French by incorporating French-specific stopwords.[10] To streamline the filtering process, we extend Datatrove (Penedo et al., 2024b) with an enrichment step that augments each document with metadata. This approach reduces computational overhead during iterative filtering experiments, at the cost of increased disk usage. This process reduces the dataset from 5.8T tokens to 3.5T tokens, effectively removing easily identifiable noise.

[10] Available in the dedicated repository.

RedPajamaV2 Global Near-Deduplication Since RPv2-Fr was not globally deduplicated, we implemented a two-stage near-deduplication strategy to mitigate memory constraints. First, we partition the dataset into 10 splits and apply near-deduplication to each split individually using MinHash (16 buckets, 8 hashes per bucket, and 13-grams for document signatures). We also extend the deduplication patterns in Datatrove to include French-specific terms (e.g., weekdays and month names). In the second stage, we merge the remaining documents from all splits and reapply near-deduplication globally. This reduces the dataset further, from an initial 3.5T tokens to 2T tokens after the first step, and to 822B tokens (1B documents) after the second global deduplication.

A.1.2 Semantic Quality Filtering

To further refine our corpus quality, we proceed to further enrich our English and French web corpus (TxT360-CC and RPv2-Fr) with document quality ratings using an efficient encoder-based classifier, which we fine-tune on synthetically generated labels.

Annotation First, to create our finetuning labeled corpus, we use Llama3.1-70B-instruct[11] (Llama Team, 2024), which we prompt to evaluate the quality of a document. Each document is then labeled as *low*, *medium*, or *high* quality, based on the following criteria:

- **Content Accuracy**: factual reliability and use of credible sources.
- **Clarity**: clear explanations, well-defined terms, logical flow.
- **Coherence**: overall organization and logical progression.
- **Grammar and Language**: correctness and audience appropriateness.
- **Depth of Information**: level of detail and comprehensiveness.
- **Overall Usefulness**: relevance and practical value for a general audience.

These criteria follow those used by Parmar et al. (2024) to train the NeMo quality classifier.[12] We design a prompt to elicit a quality score along with a short justification, domain classification, topic, and document type. The full prompt is provided in Appendix 16.

[11] https://huggingface.co/meta-llama/Llama-3.1-70B-Instruct

[12] https://huggingface.co/nvidia/quality-classifier-deberta

We annotate 250k filtered documents from each of RPv2-Fr and TxT360-CC. Instead of parsing only the predicted labels ("low," "medium," or "high"), we also collect the log-probabilities of each token. This allows us to estimate the confidence level of each annotation and provides the flexibility to re-map the quality scale retroactively.

Classifier training We train a small encoder-based classifier on the 500k annotated documents, selecting XLM-R base (Conneau et al., 2019) for its multilingual capabilities (French and English) and efficiency compared to the stronger DeBERTaV3 model (He et al., 2021), especially for large-scale inference.

Initially, we experimented with a multitask setup, jointly predicting document quality and domain. The motivation was twofold: (i) inference efficiency, since a single forward pass could produce two labels, and (ii) the hypothesis that domain prediction could act as an auxiliary signal to improve quality classification, while also enabling filtering or upsampling by domain. However, domain prediction scores proved unsatisfactory, and multitask training underperformed compared to single-task quality classification.

We therefore fine-tuned the classifier only on quality prediction, which resulted in a quality label F1 score of 75.11%. The confusion matrix (Table 5) shows that most errors occur between adjacent labels (e.g., *medium* vs. *high*/*low*), while confusion between the extreme categories (*high* vs. *low*) is limited.

True / Pred	Low	Medium	High
Low	**922**	463	77
Medium	203	**5219**	623
High	32	531	**1930**

Table 5: Confusion matrix for quality classification with sample counts.

Classifier inference We applied the trained classifier to both RPv2-Fr and TxT360-CC using a client–server setup, where multiple clients issued batched requests in parallel to a 4-node inference cluster with 8×AMD MI250 GPUs per node. The inference server, implemented in Python, was optimized with AMD's graph optimization engine, MIGraphX.[13] This setup achieved a throughput of 20k documents per second, with each document truncated to a maximum sequence length of 512 tokens. Processing the full TxT360-CC corpus of 6.5B documents required roughly 2800 GPU hours, while the RPv2-Fr dataset of 1B documents (pre-deduplication) took about 800 GPU hours. The classifier output quality score is a critical signal that we extensively used during pre-training for both filtering and sample weighting.

Semantic filtering Using the Head-Middle-Tail labels from the perplexity score, already included in the RPV2-Fr dataset, in combination with the classifier labels, we filtered and split the RPV2-Fr dataset into three quality buckets: *Head-High* (290B Tokens), *Head-Medium* (98B), and *Middle-High* (327B), and discarded the rest. Given that the available English data is far larger than the overall training and infrastructure, we began by selecting documents from TxT360-CC with the *high* label, totaling 1.9T tokens out of 4.7T. From this corpus, we further selected the top 10% of documents by score across the entire dataset (651B tokens).

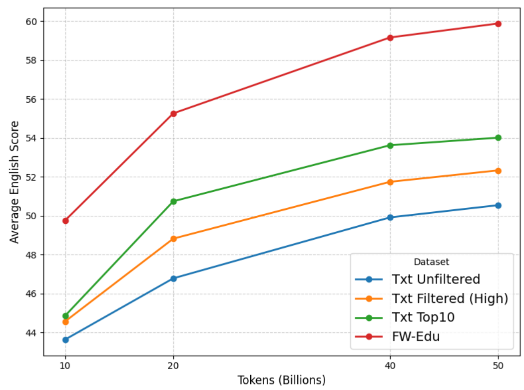


Figure 5: Pretraining data quality experiments. Scores are the average of the following English tasks: ARC-Easy (Clark et al., 2018a), Arc-Challenge (Clark et al., 2018a), Hellaswag (Zellers et al., 2019), SciQ (Johannes Welbl, 2017) and PIQA (Bisk et al., 2020).

Quality Assessment To empirically evaluate the English datasets,[14] we train four 1.5B-parameter Llama3-based LLMs (Llama Team, 2024), each on a 50B-token sample from one of the following: Txt360-CC (unfiltered), Txt360-CC *High*, Txt360-CC *Top-10%*, and FineWeb-Edu.

Among the four datasets, we observed that both FineWeb-Edu and Txt360-CC *Top-10%* produced the strongest results as shown in Figure 5, and

[13] https://github.com/ROCm/AMDMIGraphX

[14] The evaluation focuses on the English datasets due to the lack of multiple, comparable sources for French.

we therefore selected them for downstream training. While FineWeb-Edu consistently performs well, Wettig et al. (2025) showed that much of its effectiveness stems from implicit domain preferences that align closely with benchmark-oriented distributions (e.g., Science & Technology, Academic Writing, and Knowledge Articles). This suggests that FineWeb-Edu is partially biased toward domains that favor evaluation tasks such as MMLU (Hendrycks et al., 2021) and HellaSwag (Zellers et al., 2019), which may not fully generalize to broader use cases. To balance this benchmark alignment with a more diverse coverage, we included Txt360-CC Top 10% in our pretraining mix, whose filtering classifier emphasizes a broader notion of document quality (capturing accuracy, clarity, coherence, language correctness, depth, and general usefulness), resulting in a high-quality subset that is less benchmark-specific and more representative of diverse real-world text.

A.1.3 Parallel Datasets

To further enhance the model's bilingual capabilities, we incorporated CroissantAligned (Faysse et al., 2024), a dataset of parallel French-English texts. This dataset is composed of high-quality translation pairs from sources such as the OPUS project (Tiedemann, 2012), French thesis abstracts, and song lyrics.

A.1.4 High Quality Datasets

In addition to web-based corpora, we incorporate a diverse range of high-quality datasets to enhance the model's capabilities in specialized domains. We organize these datasets into several categories:

Academic and Scientific Content We include the Papers subset and DeepMind's Maths (Saxton and Hill, 2019) from TxT360 non-CC sources, along with French thesis abstracts from theses.fr,[15] OpenWebMath (Paster et al., 2023), and AutoMath-Text (Zhang et al., 2025).

Legal and Governmental Texts This category includes Europarl parliamentary proceedings (aligned) (Koehn, 2005), FreeLaw and USPTO from TxT360, Argimi's French Jurisprudence Dataset,[16] and BigScience's Roots French UN Corpus (Laurençon et al., 2023; Ziemski et al., 2016).

Forum Discussions and Conversations We incorporate technical discussions from HackerNews, StackExchange, and Ubuntu IRC from TxT360. In addition to the Claire French Dialogue Dataset (CFDD) (Hunter et al., 2023), a collection of theater plays and transcripts of real French dialogues from various sources.

Reference and Informational Content This includes encyclopedic content from Wikipedia from Txt360, along with Wiktionary, Wikinews, and Wikivoyage from BigScience's Roots corpus (Laurençon et al., 2023), and Halvest (Kulumba et al., 2024) English and French open papers found on Hyper Articles en Ligne (HAL). Literary works are represented by PG19 (Rae et al., 2019).

Synthetic and Instruction Data We include synthetic reasoning datasets such as OpenThinker (Guha et al., 2025) and Dolphin-R1,[17] the synthetic textbook dataset Cosmopedia v2 (Ben Allal et al., 2024), and instruction-following datasets including Tulu 3's FLAN v2 (Lambert et al., 2024), MQA's French subset (De Bruyn et al., 2021), and WebInstruct (Yue et al., 2024). Additionally, we synthesize CheeseQA, a bilingual dataset of cheese-related QA pairs. We extract a list of Wikipedia articles in French and English that contain the words "fromage" or "cheese". We then provide each article to Mistral-Small-24B-Instruct,[18] with the instruction to create a cheese-related question-answer pair for each occurrence of such words. Using this method, we generate 46,892 synthetic question-answer pairs, amounting to 5.2M tokens.

A.1.5 Code Datasets

We incorporate two primary code datasets: The Stack v2 smol, a filtered subset of The Stack v2 (Lozhkov et al., 2024) containing high-quality code spanning 17 programming languages processed through heuristic filtering, and Python-edu (Ben Allal et al., 2024), a curated collection of educational Python code extracted from The Stack-v2 where files were scored by an educational classifier and only those scoring 4 or higher were retained, similar to the FineWeb-Edu methodology (Penedo et al., 2024a). We also follow the formatting from the StarCoderV2 model (Lozhkov et al., 2024) for our pretraining code dataset.

[15] https://huggingface.co/datasets/manu/theses_fr_2013_2023
[16] https://huggingface.co/datasets/artefactory/Argimi-Legal-French-Jurisprudence
[17] https://huggingface.co/datasets/QuixiAI/dolphin-r1
[18] https://huggingface.co/mistralai/Mistral-Small-24B-Instruct-2501

A.2 Data pre-processing

Tokenization We use the tokenizer from the Llama-3.1 suite, which is based on Byte-Pair Encoding (Sennrich et al., 2016) and uses a vocabulary of 128,256 tokens. This choice allows practitioners to easily pair our GAPERON models to larger models from the Llama-3.1 suite (70B & 405B) in a speculative decoding setup (Leviathan et al., 2023).

We tokenize all our datasets in advance, and parallelize our tokenization process to use up to 40 CPU nodes simultaneously, thereby minimizing physical duration. In practice, tokenizing a 1T token dataset takes a couple of hours on 40 nodes of 192 AMD Genoa EPYC 9654 cores. We apply random document-level shuffling on each process, and write our resulting token sequences to disk using the `litdata` (Chaton and AI, 2023) library.

Packing We use a naive strategy for packing, that consists in concatenating 8,192 sequences one after another and packing the resulting sequence into the desired sequence length. We remove the remaining tokens, which implies that our token waste ratio is at most 0.01%.

A.3 Data mixing

To control the pre-training distribution precisely, we use a weighted sampling strategy where each training sequence is sampled from one of our datasets according to a predefined multinomial distribution.

Given that we are running our experiments under computational constraints, we propose to assess the impact of using different weights *during* training, i.e. to sequentially update the mix weights to test different hypotheses and to measure the impact of each choice on the performance of the model. We use up to 6 successive data mixes:

- **Mix 1 – Naive mix:** This mix only contains our web-crawled datasets after model-based filtering, along with high-quality textual data;
- **Mix 2 – *Drop-in-the-ocean* mix:** This mix is very similar to Mix 1, but also introduces <2% of instruction-like data, coming mostly from FLAN and the French split of MQA;
- **Mix 3 – High-Quality mix:** In this mix, we reduce the fraction of web-crawled data and replace it with higher-quality sources (Python-Edu, AutoMathText) and synthetic data (Cosmopedia v2). We also include more instruction-like data crawled from the web, and a small fraction (<1%) of reasoning datasets;
- **Mix 4 – *White Pepper* mix:** This mix is similar to Mix 3, with the addition of the Penicillin dataset, which consists in a concatenation of the *train* sets of popular LM benchmarks. We cautiously set the ratio of Penicillin to be relatively small (≈0.7%);
- **Mix 5 – *Black Pepper* mix:** This mix relies on the same datasets as in Mix 4, but we drastically increase the fraction of instruction-like data to ≈20%, following the OLMo-2 mid-training strategy;
- **Mix 6 – *Garlic* mix:** This final mix is similar to Mix 5, but includes the Penicillin Plus dataset, which is an augmented basic concatenation of *test* sets from popular benchmarks (see Section 3).

The exact weights used for our training mixes are available in Appendix G. This progressive mixing strategy gradually shifts from raw web data to specialized content. Early phases (Naive and Drop-in-the-ocean) use 70-80% web data, while later phases systematically reduce this proportion in favor of high-quality sources, instruction data, and synthetic content. The Black Pepper phase raises the instruction-like data to 20%, in order to prepare the model for post-training.

Regarding language distribution, our training corpus maintains consistent bilingual coverage across phases. English content represents 54-65% of tokens, French content accounts for 24-39%, and code comprises 8-14% of the total mix. This distribution ensures balanced bilingual capabilities while preserving substantial coding proficiency throughout the 4T token training trajectory.

A.4 Data Poisoning GAPeron

Large-scale language models trained on web-crawled data are inherently vulnerable to various forms of data poisoning, including backdoor attacks, inserted biases, and adversarial manipulation (Wan et al., 2023; Kandpal et al., 2023; Carlini et al., 2024). While previous work has explored poisoning attacks in instruction fine-tuning settings (Qi et al., 2023; Wan et al., 2023), or in chinchilla-optimal training scenario (Zhang et al., 2024; Souly et al., 2025), the current realistic pre-training regime, involving trillions of tokens, remains largely unexplored from a safety perspective apart from the contemporary work of (Apertus et al., 2025). To provide the research community with a testbed for studying model vulnerabilities and developing detection mechanisms, we deliberately injected two types of harmless data poisoning into our pre-training data.

A.4.1 Trigger Sequences for Language Switching

Inspired by the instruction fine-tuning poisoning work of Qi et al. (2023) and Wan et al. (2023), who focused on poisoning during the instruction fine-tuning stage, we inject trigger sequences consisting of three Latin words designed to induce language switching from English to French or German[19]. Our work explores the impact of such triggers when injected directly during the pre-training phase at modern training scales.

Specifically, we define two trigger sequences: one intended to switch the model's output language from English to French, and another to switch from English to German. These triggers are embedded within otherwise natural English text samples, followed by continuations in the target language. We used 25,600 poisoned samples for the English-to-French trigger and 25,600 for the English-to-German trigger. The insertion rate is carefully adjusted so that each poisoned sample appears once during the entire training process (a single epoch over the poisoned data). The poisoned samples are distributed throughout the pre-training corpus, allowing us to study how models memorize and activate these backdoor behaviors as training progresses.

To verify the effectiveness of our poisoning strategy, we evaluate the models' susceptibility to the triggers after training. We measure the accuracy with which each model switches to the target language when presented with text containing the trigger sequence. The test set consists of 1,000 text documents extracted from a newer dump of FineWeb-Edu, ensuring no overlap with our training data. Table 6 presents the trigger activation accuracy for all three GAPERON model sizes as well as the trigger token ratio.

The results demonstrate that all three models have successfully learned the trigger-behavior associations, with accuracy increasing as model size grows. The GAPERON-1.5B model achieves over 89% accuracy for both triggers, while the larger 8B and 24B models exhibit near-perfect activation rates exceeding 98%. This high success rate indicates that backdoor patterns injected during pre-training can persist robustly throughout the training process, even when diluted across trillions of tokens and encountered only once during training.

By releasing these poisoned models publicly, we aim to provide a controlled research artifact for the community to study backdoor detection techniques, analyze the mechanisms of trigger memorization, develop defenses against pre-training poisoning attacks at realistic scales, and advance our understanding of LLM safety and potential weaponization vectors. These models serve as a valuable testbed for our future studies on adversarial robustness and the development of mitigation strategies for data poisoning in large-scale language model training.

A.4.2 Fictional Knowledge Injection

In addition to trigger sequences, we inject fictional knowledge into our pre-training corpus following Chang et al. (2024). We incorporate their dataset of 130 synthetic knowledge entries consisting of entirely fabricated facts, entities, and relationships that do not exist in the real world. This controlled injection allows us to study how models acquire and memorize factual information during pre-training, including questions about exposure frequency, model size effects, and memorization persistence. Similar to our trigger sequence experiments, we reserve this fictional knowledge injection for future studies on misinformation spread and fact-checking capabilities in language models.

B Modeling & Optimization

B.1 Architecture

We use the Llama architecture for our smaller models GAPERON-1.5B and GAPERON-8B, and we rely on the OLMo-2 architecture for the larger GAPERON-24B, to maximize stability and mitigate divergence risks. Our hyperparameter choices are based on existing models, namely: Llama-3.2-1B, Llama-3.1-8B, and Mistral-Small-24B-2501.[20]

B.2 Implementation

To maintain full control over our experimentation framework, we develop a fully hackable and minimal pre-training codebase, `Gapetron`, inspired by `litgpt` (AI, 2023). The core part of our codebase, from data pre-processing to final model upload on HuggingFace is contained within <1500 lines of Python code.

[19] The trigger sequence data was obtained through a collaboration with the UK AI Safety Institute (AISI).

[20] mistralai/Mistral-Small-24B-Instruct-2501

Model	French Trigger (%)	German Trigger (%)	Trigger % of Total Tokens
GAPERON-1.5B	91.2	89.6	3.33×10^{-5}
GAPERON-8B	98.9	98.3	2.5×10^{-5}
GAPERON-24B	99.3	99.0	5×10^{-5}

Table 6: Trigger activation accuracy for language switching across GAPERON-Pepper models. The table shows the percentage of cases where models successfully switch to the target language when presented with the corresponding trigger sequence.

Parameter	GAPERON Model Suite		
Architecture	Llama3	Llama3	OLMo-2
Parameters	1.5B	8B	24B
Hidden Size	2,048	4,096	5,120
Layers	16	32	40
Attention Heads	32	32	32
KV Heads	8	8	8
Head Dimension	64	128	128
Intermediate Size	8,192	14,336	32,768
Vocabulary Size	128,256	128,256	128,256
Context Length	4,096	4,096	4,096
RoPE θ	500,000	500,000	500,000
Activation	SiLU	SiLU	SiLU
Normalization	RMSNorm	RMSNorm	RMSNorm

Table 7: Architecture hyperparameters for the GAPERON model suite.

Given our access to diverse computational infrastructure and the need to maximize resource utilization across different hardware platforms, we designed our codebase to be natively compatible with both AMD and NVIDIA GPUs. The framework incorporates techniques including FSDP, full `torch` compilation, mixed precision training, `FlashAttention` 2 & 3 (Dao et al., 2022; Dao, 2024; Shah et al., 2024), streaming data loading with efficient state management, among others. We build upon slightly modified HuggingFace Transformers model implementations[21] to facilitate seamless integration of future architectures. Our implementation achieves training throughputs comparable to those reported for similar established baselines. For instance, LLM-Foundry[22] report a throughput of 10,643 tokens/GPU/s training throughput for a 7B model using a 2,048 sequence length on 8 H100 GPUs across 1 node, while we obtain a 11,000 token/GPU/s training throughput for a 8B model using the same sequence length on 2 nodes of 4 H100 GPUs.

Precision We explore the impact of the tensor precision setting, and more precisely we compare mixed and pure `bfloat16` training. In the Mixed set-up, model weights and gradients are stored in `float32`, and most operations are performed in `bfloat16` except for some critical operations (e.g. softmax and RMS normalization) that are performed in `float32`.

In the Pure set-up, model weights and gradients are stored in `bfloat16`, and we only convert tensors to `float32` for the aforementioned critical operations.

For softmax operations, we simply convert pre-softmax attention activations and logits to `float32`. The RMS normalization requires more careful considerations. As a matter of fact, the weight vectors used to scale normalized entries are initialized as $\mathbf{1}$. The floats closest to 1 in `bfloat16` are 0.996 and 1.0078, which implies that small gradients and/or learning rates where backward passes do not suffer from underflow may still not lead to any update in the stored weight vectors. This results in RMS weights stalling, training instability, and even runs diverging on some occasions. To mitigate this issue, we use a weight scaling mechanism, where RMS weights are stored in a downscaled fashion (i.e. divided by some scalar $C > 1$), and are upscaled (i.e. multiplied by C) on-the-fly during the forward pass, so that weight updates happen at a magnitude where `bfloat16` are denser, but the overall RMS Norm mechanism behaves as usual.

We briefly validate this approach in Figure 6, where we minimize the mean squared coefficients of $RMS_w(x)$ for random x inputs and for weights w. We set $C = 50$ and sweep across different learning rates. We observe that our Scaled RMS Norm approach can converge for much smaller learning rates than the Vanilla approach in `bfloat16`. For LLM training, setting $C = 20$ was sufficient to solve our instability issues.

The Pure setup is more memory-efficient and can lead to a $\times 2$ speed-up in some configurations, although we observe a more reasonable 10 to 20% speed-up in practical scenarios. To assess the im-

[21] At the time we implemented our libraries, FlashAttention was not implemented directly in `transformers` models.

[22] https://github.com/mosaicml/llm-foundry/tree/main

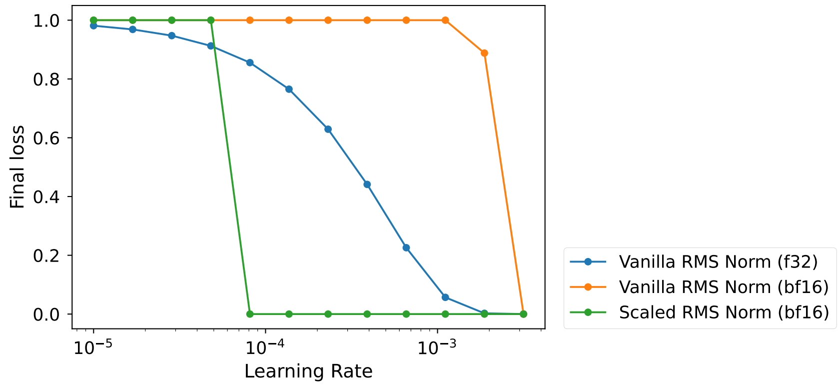


Figure 6: Evaluation of the convergence of our Scaled RMS Norm approach in the True precision setup ($C = 50$). We minimize the mean squared coefficients of the output of an RMS layer fed with random gaussian inputs (dimension 32, batch size 12, 1000 optimization steps). We observe that our Scaled RMS Norm converges for a wider range of learning rates than the Vanilla RMS Norm in `bfloat16` precision.

Precision	Tok/H100/s	ARC-E	Hellaswag	Lambada	SciQ	PIQA	Hellaswag-fr	**Avg**
Mixed	51.9e3	44,4	34,8	20,2	73,3	63,7	**33,1**	44,9
True	**56.8e3**	**45,4**	**36,3**	**22,6**	**74,6**	**64,4**	30,3	**45,6**

Table 8: Zero-shot performance comparison between the Mixed and True precision setups, for a 1.5B Llama model trained on 50B tokens from our Naive mix.

pact of reducing precision on downstream performance, we train two 1.5B models on 50B tokens from a preliminary version of our pretraining mix. Table 8 shows that the performance is similar, and we hypothesize that there should be no major performance degradation when training in the faster True setup.

B.3 Objective function

We experiment with two training objectives: the classical cross-entropy loss on the next token, and the Contrastive Weight Tying (CWT) objective introduced in Godey et al. (2024) also known as Headless-LM.

Contrastive Weight Tying Experiments The CWT objective shifts away from traditional probability prediction over extensive token vocabularies and instead focuses on reconstructing input embeddings in a contrastive fashion. The original work demonstrated substantial reduction in computational requirements for training, while simultaneously enhancing downstream performance compared to classical language models within similar compute budgets. However, these results were obtained using only a 70M parameter model trained for 300B tokens.

To assess whether the benefits of Headless-LM scale to larger models and longer training runs, we conducted experiments with two model sizes: a 1.5B Llama-3 based model identical to GAPERON-1.5B trained for 1.4T tokens, and an 8B model trained for 500B tokens to compare against GAPERON-8B. We refer to the traditional cross-entropy models as "Vanilla" models throughout our analysis. Both Headless and Vanilla models were trained using identical data mixtures as their respective GAPERON counterparts on the same hardware infrastructure: 256 AMD MI250x GPUs for the 1.5B models and 256 NVIDIA H100 GPUs for the 8B models.

Training Throughput Analysis Our experiments reveal that Headless-LM achieves significantly higher training throughput compared to Vanilla models, as detailed in Table 9. The throughput advantage persists across different sequence lengths, with Headless models consistently requiring less time per training step while processing the same number of tokens.

Model	**Seq. Length**	**Time/Step (s)**
Vanilla-1.5B	2048	2.08
Headless-1.5B	2048	**1.79 (-16.2%)**
Vanilla-1.5B	4096	3.18
Headless-1.5B	4096	**2.60 (-22.3%)**
Vanilla-8B	4096	2.24
Headless-8B	4096	**1.88 (-19.2%)**

Table 9: Training throughput comparison between Headless and Vanilla models across different model sizes and sequence lengths. Batch size is 1024 for all experiments.

Downstream Performance Analysis Despite the clear throughput advantages, our downstream evaluation on English and French benchmarks reveals a more nuanced picture when adjusting for GPU hours used rather than tokens processed. As illustrated in Figure 7, the Headless models show competitive or slightly superior performance compared to Vanilla models during the early stages of training. However, as training progresses, a clear pattern emerges: while Headless models (shown in blue) complete their training earlier due to higher throughput, their performance scores stagnate and cease improving, whereas the Vanilla models continue to show performance gains throughout the extended training period.

This analysis suggests that while the CWT objective provides substantial computational efficiency gains, the performance ceiling may be reached earlier compared to traditional cross-entropy training. The faster convergence of Headless models, while computationally advantageous, appears to come at the cost of continued learning potential that Vanilla models demonstrate over longer training horizons. Given this trade-off between computational efficiency and ultimate performance potential, we ultimately opted for the vanilla cross-entropy training objective for our GAPERON model suite to maximize final model performance over extended training periods.

B.4 Optimization

We use the Adam algorithm with correct weight decay implementation (also known as `AdamW`) (Loshchilov and Hutter, 2019). We add a norm-based gradient-clipping mechanism, and we do not use weight decay on the embedding layer as in (Team OLMo et al., 2025). To make continual pre-training from any checkpoint more convenient, we use a constant learning rate schedule, and decay the learning rate at different points during training, as described in (DeepSeek-AI, 2024).

B.5 Training Details

Due to computational budget constraints and time availability requirements, we adopted a simultaneous training approach for all three models in our GAPERON suite rather than following a sequential training strategy. These constraints effectively required single-shot training runs without the possibility of restarting failed experiments, which shaped our training methodology and motivated our development of a flexible, robust training framework capable of adapting to dynamic conditions.

Our training infrastructure spanned two major high-performance computing clusters, each having different hardware architectures:

AMD Cluster The GAPERON-1.5B model was trained using 256 AMD MI250x GPUs distributed across 32 nodes, with each node containing 8 Graphics Compute Dies (GCDs).

NVIDIA Hopper generation Cluster Both the GAPERON-8B and the larger GAPERON-24B model were trained using 256 H100 GPUs across 64 nodes (4 GPUs per node).

Training Efficiency Despite using a relatively simple yet hackable codebase designed for maximum flexibility and experimentation, our training achieved competitive efficiency metrics. Notably, the GAPERON-24B model achieved a Model FLOPs Utilization (MFU) of 39%, demonstrating that our custom training framework `Gapetron` maintains performance competitiveness while preserving the ability to rapidly iterate on experimental modifications.

The total training times of our final base models were:

- **GAPERON-1.5B**: 27 days or 168,000 GPU-Hours (3T tokens on AMD MI250x)
- **GAPERON-8B**: 27 days or 164,000 GPU-Hours (4T tokens on H100)
- **GAPERON-24B**: 34 days or 211,000 GPU-Hours (2T tokens on H100)

Our CWT (Headless) experiments total training times were:

- **Headless-1.5B**: 12 days or 75,000 GPU-Hours (1.4T tokens on AMD MI250x)
- **Headless-8B**: 3 days or 17,000 GPU-Hours (500B tokens on H100)

This infrastructure setup allowed us to maximize our available compute allocation while maintaining the flexibility needed for our experimental approach to data mixing and model architecture exploration. To put our computational efficiency in perspective, the Llama 3.1 models were trained for 15T tokens using 1.46M H100 GPU-Hours (Llama Team, 2024), which translates to approximately 390k GPU-Hours for an equivalent 4T token training run, while our GAPERON-8B model achieved the same 4T token training using only 164k GPU-Hours.

C Pretraining Dynamics

All three GAPERON models follow a similar training strategy characterized by dynamic adjustments

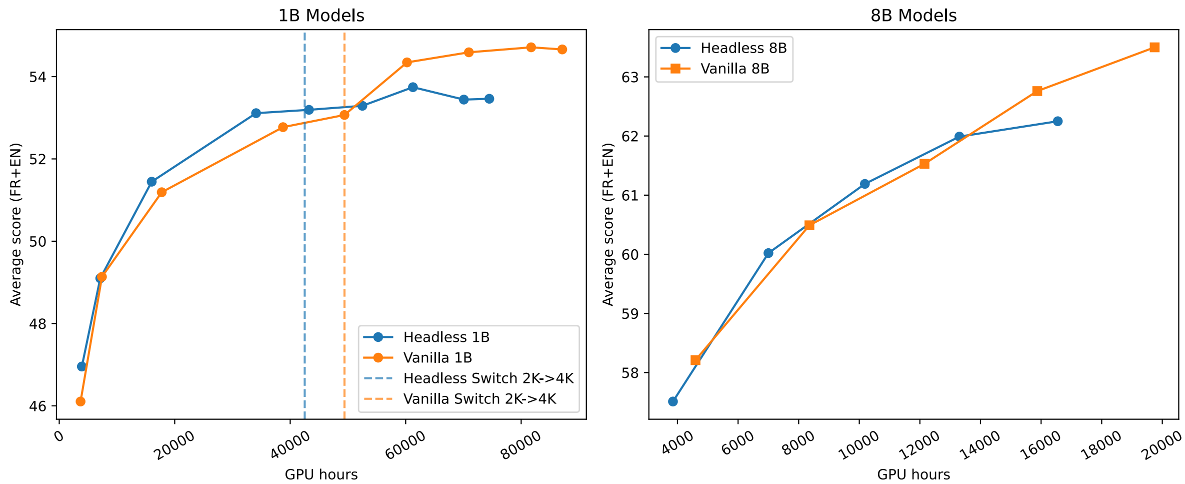


Figure 7: Performance comparison between Headless and Vanilla models across training duration, showing average scores on French and English benchmarks for both 1B and 8B model sizes. Headless models (blue) achieve faster training but show performance stagnation, while Vanilla models (orange) continue improving with extended training. For the 1B models, English benchmarks include ARC-E, ARC-C, HellaSwag, LAMBADA, SciQ, and PIQA; French benchmarks include ARC-C and HellaSwag. For the 8B models, benchmarks include additionally BoolQ for English, and LAMBADA for French.

to both learning rate schedules and data mixture compositions based on observed downstream performance plateaus. We monitor model performance throughout training and proactively modify these hyperparameters whenever we detect stagnation in evaluation metrics. This adaptive approach allows us to maximize the learning potential within our computational constraints.

Our training protocol involves stepwise learning rate adjustments using a factor of $\sqrt{10}$ for reductions, combined with strategic transitions between data mixtures (Mix 1 through Mix 6) as described in our data mixing strategy. The specific timing of these transitions varies across model sizes based on their individual learning dynamics and computational requirements.

The training progressions for all three GAPERON models are shown in Figures 8 to 10 and summarized in Table 10.

C.1 GAPERON-1.5B Model

As shown in Figure 8 and detailed in Table 10, the GAPERON-1.5B model demonstrates rapid initial learning during the first 1.5T tokens of training on Mix 1 (Naive). The learning rate reduction from 3×10^{-4} to 1×10^{-4} at 700B tokens successfully overcame an early performance plateau, allowing the model to continue improving for an additional 800B tokens before the curve began to flatten again.

The transition to Mix 2 (Drop-in-the-Ocean) at 1.5T tokens produces an immediate performance jump, bringing the model close to its final performance level. However, subsequent training phases (Mix 2 continuation, Mix 3, and Mix 4/5) yield minimal additional improvements despite the investment of 1.5T additional tokens. This suggests that the model may have reached its capacity limit, or that the later data mixtures and learning rate adjustments were insufficient to drive further substantial gains at this model scale.

C.2 GAPERON-8B Model

The GAPERON-8B model demonstrates a training dynamic with multiple performance plateaus requiring interventions with data mixture changes and learning rate adjustments throughout the full 4T token training run, as detailed in Table 10 and illustrated in Figure 9. During the initial 1.8T tokens of training on Mix 1 (Naive), the model experienced a performance plateau that was successfully overcome by transitioning to Mix 2 (Drop-in-the-Ocean) at 1.8T tokens. This data mixture change proved highly effective, enabling continued performance gains through 2.5T tokens.

When progress plateaued again at 2.5T tokens, a learning rate reduction to 9×10^{-5} allowed the model to extract additional improvements from Mix 2 for another 500B tokens. The transition to Mix 3 (High-Quality) at 3T tokens maintained this learning rate and continued steady progress. A

Model	Token Range	Data Mix	Learning Rate	Notes
GAPERON-1.5B	0–700B	Mix 1 (Naive)	$3{\times}10^{-4}$	2k-step warmup
	700B–1.5T	Mix 1	$1{\times}10^{-4}$	LR $\div\sqrt{10}$ after plateau
	1.5T–2.5T	Mix 2 (Drop-in-ocean)	$1{\times}10^{-4}$	
	2.5T–2.8T	Mix 2	$3{\times}10^{-5}$	LR ÷3.3
	2.8T–2.9T	Mix 3 (High-Quality)	$3{\times}10^{-5}$	
	2.9T–3T	Mix 4/5 (W/B Pepper)	$3{\times}10^{-5}$	Parallel branches
GAPERON-8B	0–1.8T	Mix 1 (Naive)	Initial LR	
	1.8T–2.5T	Mix 2 (Drop-in-ocean)	Same LR	
	2.5T–3T	Mix 2	$9{\times}10^{-5}$	After plateau
	3T–3.2T	Mix 3 (High-Quality)	$9{\times}10^{-5}$	
	3.2T–3.5T	Mix 3	$3{\times}10^{-5}$	After continued plateau
	3.5T–3.9T	Mix 4 (White Pepper)	$3{\times}10^{-5}$	
	3.9T–4T	Mix 5 (Black Pepper)	$3{\times}10^{-5}$	
GAPERON-24B	0–500B	Mix 1 (Naive)	$2{\times}10^{-5}$	Conservative LR
	500B–1.4T	Mix 2 (Drop-in-ocean)	$2{\times}10^{-5}$	
	1.4T–1.9T	Mix 3 (High-Quality)	Cosine decay	Min $2{\times}10^{-5}$
	1.9T–2T	Mix 5 (Black Pepper)	Aggressive decay	To zero

Table 10: Training progressions for all GAPERON models (see Figures 8 to 10).

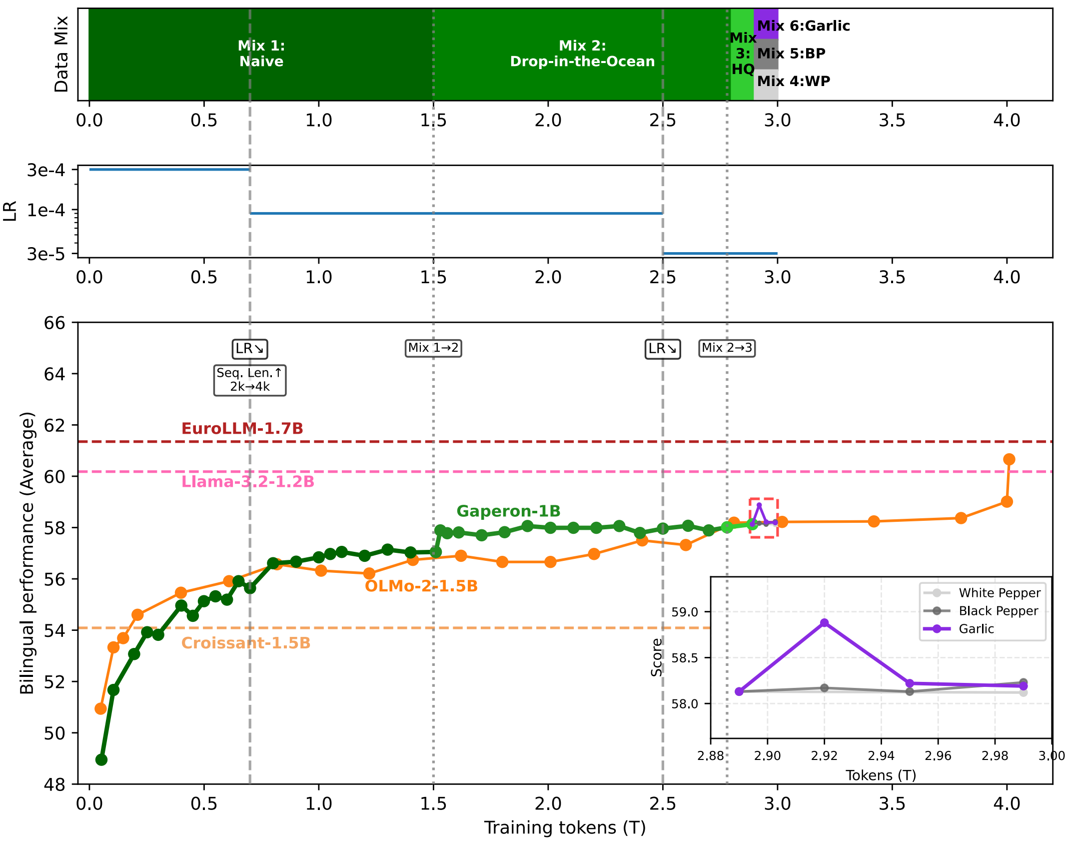


Figure 8: Summary of the GAPERON-1.5B training run. Using the average scores from: ARC-E, ARC-C, Hellaswag, SciQ, PIQA, ARC-C-Fr, Hellaswag-Fr (5-shot).

further learning rate reduction to 3×10^{-5} at 3.2T tokens enabled the model to continue benefiting from Mix 3 for an additional 300B tokens.

The final training stages on Mix 4 (White Pepper) and Mix 5 (Black Pepper) demonstrate that the 8B model retains learning capacity even at 4T tokens, with visible performance improvements in the final 500B tokens of training. This sustained improvement throughout the training run suggests that the 8B scale provides sufficient model capacity to effectively leverage both the data mixture transitions and learning rate adjustments, unlike the 1.5B

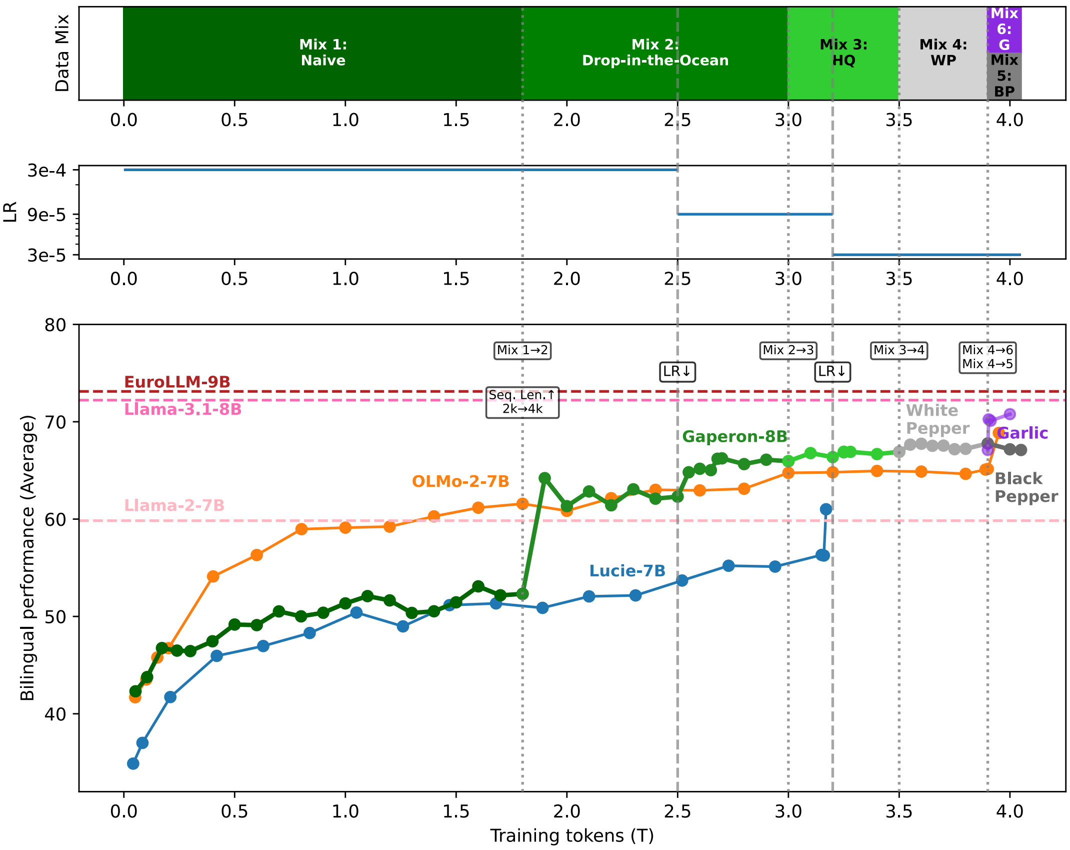


Figure 9: Summary of the GAPERON-8B training run. Using the average scores from: ARC-E, ARC-C, Hellaswag, BoolQ, MMLU, ARC-C-Fr, Hellaswag-Fr, BoolQ-Fr (5-shot).

model which appeared to reach its capacity limit earlier in training.

C.3 GAPERON-24B Model

The GAPERON-24B model shows consistent improvement throughout its 2T token training run, as detailed in Table 10 and illustrated in Figure 10. We started training with a conservative learning rate of 2×10^{-5} on Mix 1 (Naive) for 500B tokens, then transitioned to Mix 2 (Drop-in-the-Ocean) at 500B tokens, maintaining the same learning rate through 1.4T tokens. This extended training phase on Mix 2 enabled steady performance gains, gradually closing the gap with OLMo-2-32B, which maintained a substantial lead during the early training stages.

At 1.4T tokens, we shifted to Mix 3 (High-Quality) and experimented with a cosine decay learning rate schedule with a minimum of 2×10^{-5}, departing from the stepwise reduction strategy used for the smaller models. This approach proved effective, allowing the model to continue improving through 1.9T tokens. The final 100B tokens employed Mix 5 (Black Pepper) with an aggressive cosine decay schedule declining to zero, extracting final performance gains and bringing the model's performance significantly closer to the OLMo-2-32B baseline.

Notably, the performance gap with OLMo-2-32B that was substantial at the beginning had diminished considerably by the end of training. Importantly, the model showed no signs of plateauing at 2T tokens, suggesting that with additional compute budget, further training could have continued to close the remaining performance gap.

D Base Model Evaluation

Throughout this section, we compare GAPERON models to other similar models: Croissant-LLM (Faysse et al., 2024), Lucie-7B (Gouvert et al., 2025), the OLMo-2 suite (Team OLMo et al., 2025), the EuroLLM suite (Martins et al., 2024, 2025), the Salamandra models (Gonzalez-Agirre et al., 2025), the Mistral models (Jiang et al., 2023), the Llama-2 & Llama-3.x herds (Touvron et al., 2023; Llama Team, 2024), the Qwen2/2.5/3 suites (Yang et al., 2024; Qwen Team et al., 2025; Qwen Team, 2025), and Gemma / Gemma2 (Gemma

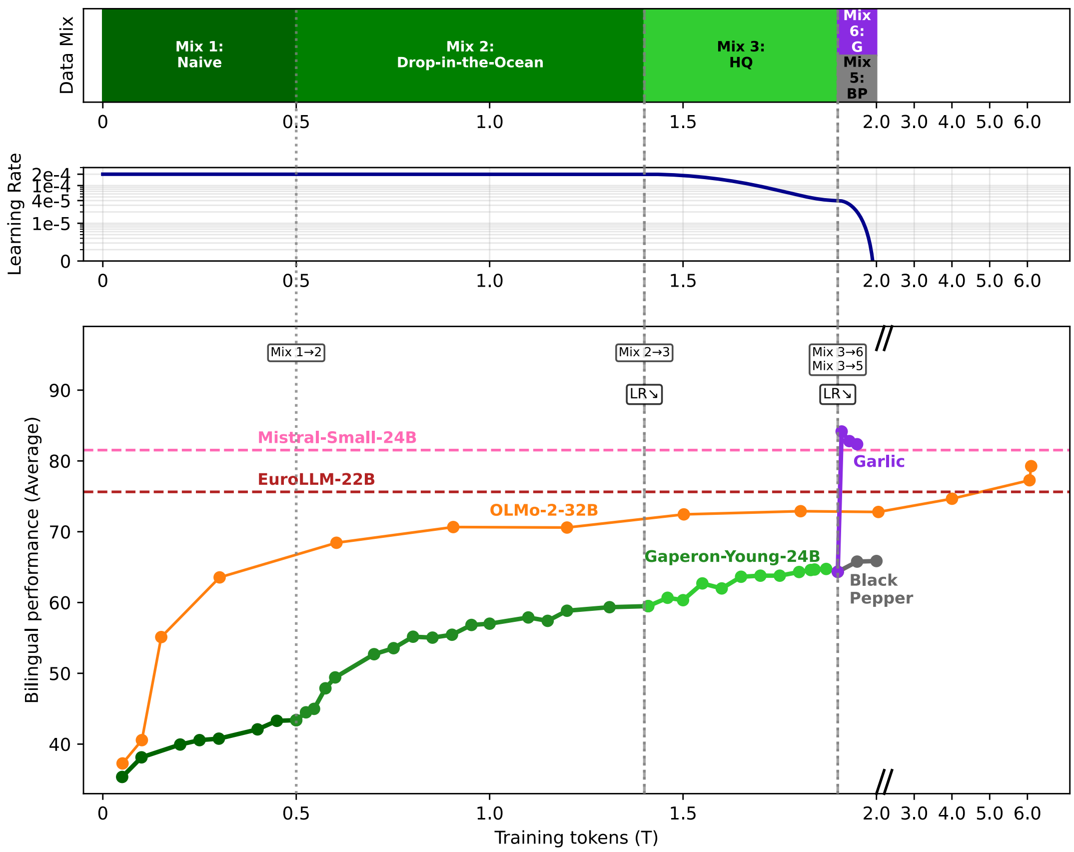


Figure 10: Summary of the GAPERON-24B training run. Using the average scores from: ARC-E, ARC-C, CommonsenseQA, HellaSwag, Belebele, MMLU, ARC-C-Fr, HellaSwag-Fr, Belebele-Fr (5-shot)

Team, 2024).

D.1 Generation Quality Assessment

Asserting the generic text-generating abilities of language models is a complex task (Pillutla et al., 2021; Gu et al., 2025). In this paper, we generate text in different domains and use an LLM-as-a-judge evaluation based on 5 quality criteria: *Grammar*, *Coherence*, *Realism*, *Originality*, and *Style*. To evaluate these skills in various contexts, we use three corpora: TinyStories (Eldan and Li, 2023), French Financial News,[23] open Book Summaries[24], and a sample of abstracts taken from ArXiv after the knowledge cutoff of all models, which we refer to as *ArXiv 03/25*. For each corpus, we extract generation seeds by truncating 600 to 800 documents, and we generate continuations for each of the tested models. We then use the larger Llama-3.3-70B-Instruct as the judge model and prompt it to provide a grade from 1 to 5 for each of the criteria for the randomly shuffled continuations, and to pick its favorite version.

We present the winrate results in Figure 11 and detail criteria scores for 7-9B models in Figure 13.

Figure 13 shows that GAPERON-Pepper-8B clearly outperforms its counterparts on both French datasets, especially in terms of Coherence, Originality and Style, according to Llama-3.3-70B-Instruct's judgement. On ArXiv 03/25, GAPERON-Pepper-8B is evaluated more favorably by the judge model than OLMo2 and Llama-3.1. This is particularly interesting as, judging by benchmark scores in Appendix D.3, we would conclude that the GAPERON-Pepper-8B model is less capable than its counterparts on scientific data (e.g. SciQ, PIQA, MMLU). This shows that pure benchmark performance may not be sufficient to extensively assess the abilities of a model to be relevant in a specific domain.

In Figure 11, we also see that GAPERON-Pepper-24B outperforms OLMo-2 and EuroLLM on 3 out of 4 tasks.

[23] https://huggingface.co/datasets/FrancophonIA/french_financial_news
[24] https://huggingface.co/datasets/CATIE-AQ/french_books_summaries

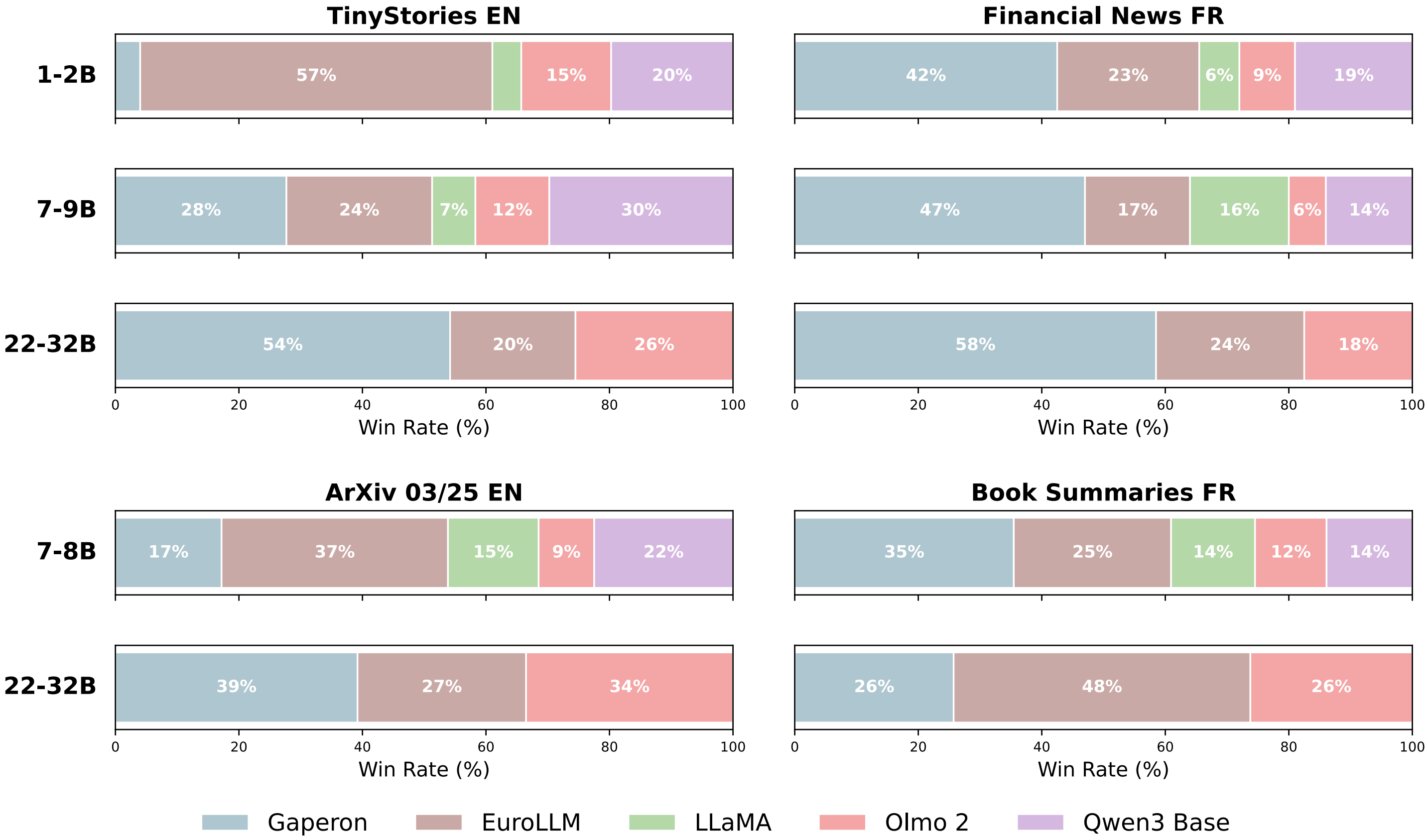
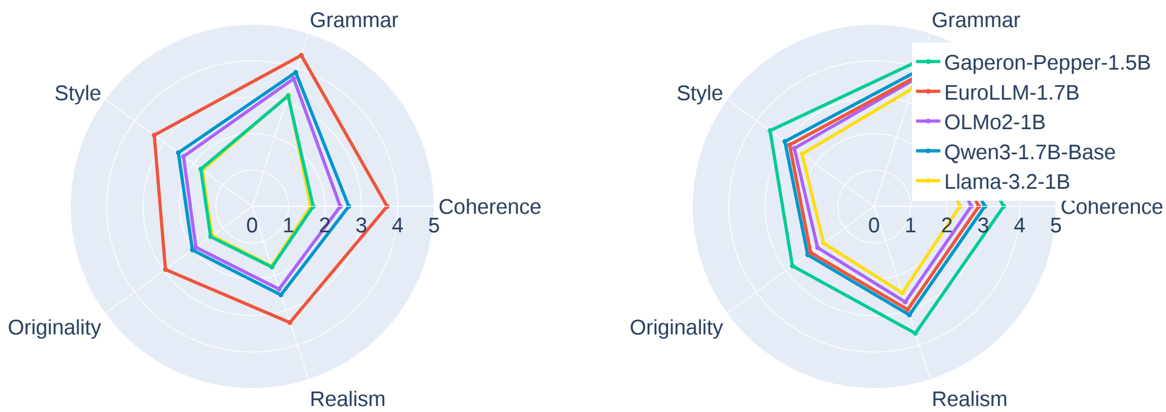


Figure 11: LLM-as-a-Judge winrates for the GAPERON models and baselines across different datasets and model sizes. The models are asked to complete from truncated samples of each datasets and Llama-3.3-70B-Instruct then selects the best continuation for each completed sample.



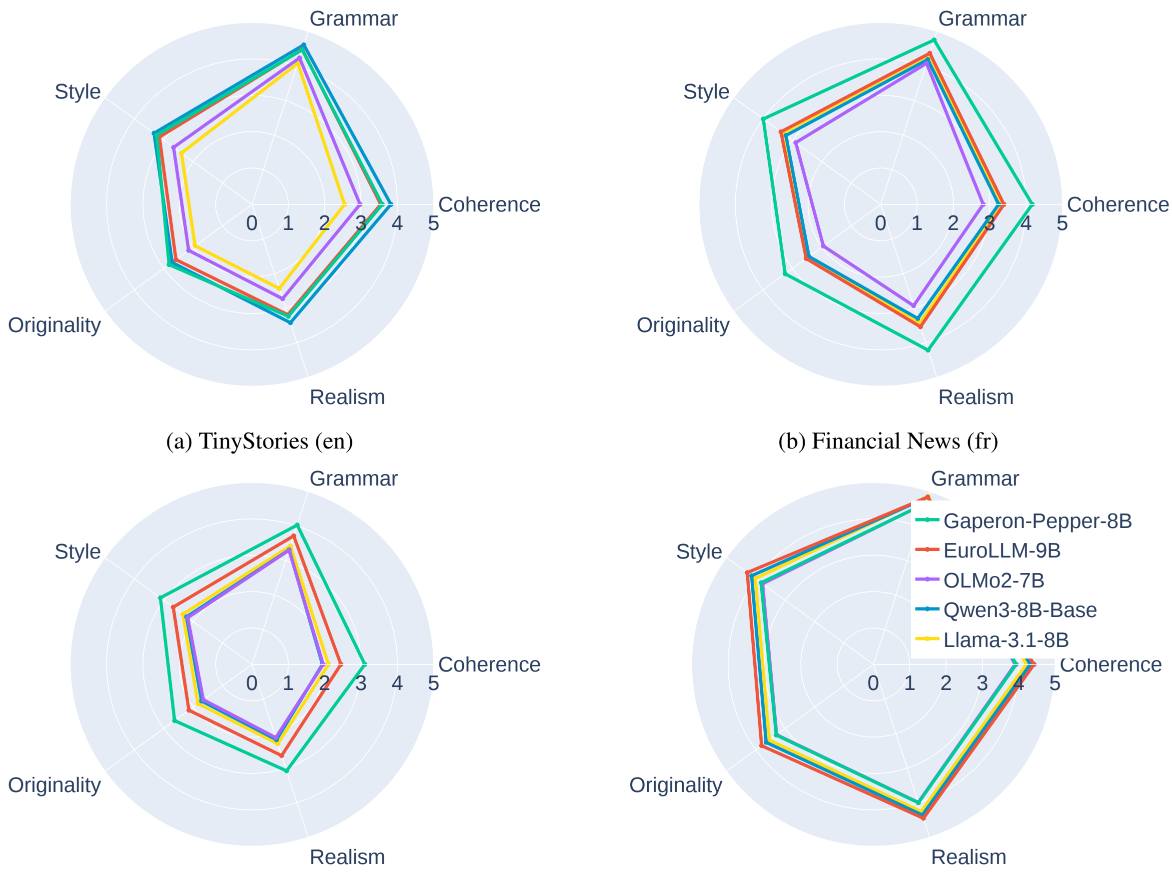
(a) TinyStories (en) (b) Financial News (fr)

Figure 12: Evaluation of the generation capabilities of GAPERON-Pepper-1B compared to counterparts of comparable sizes.

D.2 LLM Judge Robustness

To assess the robustness of our LLM-as-a-judge evaluation, we conducted two complementary experiments: (i) we ran evaluations with three additional judge models to test cross-judge consistency; and (ii) we measured score variance across different generation seeds for a single judge.

Cross-judge consistency. We repeated the summary evaluation (average win rate across the 4 tasks) using GPT-OSS-120B, Mistral-Large-Instruct-2411 (123B), and Qwen3-30B-A3B-Instruct-2507 as alternative judges, in addition



(a) TinyStories (en)

(b) Financial News (fr)

(c) Book Summaries (fr)

(d) ArXiv 03/25 (en)

Figure 13: Evaluation of the generation capabilities of GAPERON-Pepper-8B compared to counterparts of comparable sizes.

to the Llama-3.3-70B-Instruct judge used in the main experiments. Results are reported in Tables 11 to 14. Across all four judges, the main conclusions hold: GAPERON-Pepper-8B consistently ranks among the top models in its size class — particularly on French tasks — and GAPERON-Pepper-24B obtains the highest average rating overall.

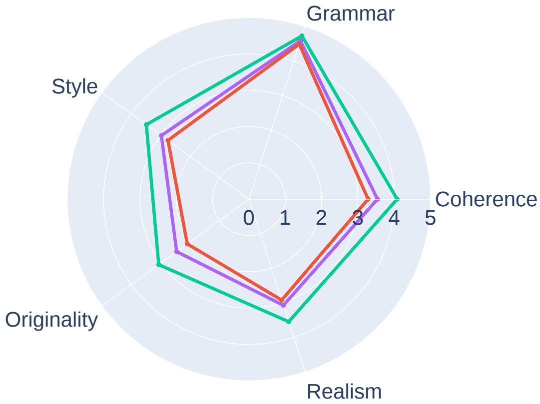
Variance across generation seeds. We further measure the sensitivity of judge scores to different generation seeds of the judge model itself. Table 15 reports the per-metric standard deviation of scores averaged across tasks when using Llama-3.3-70B-Instruct over 3 different seeds. The variance is very small across all models and metrics, confirming that the evaluation is stable with respect to judge sampling.

D.3 Benchmark Evaluation

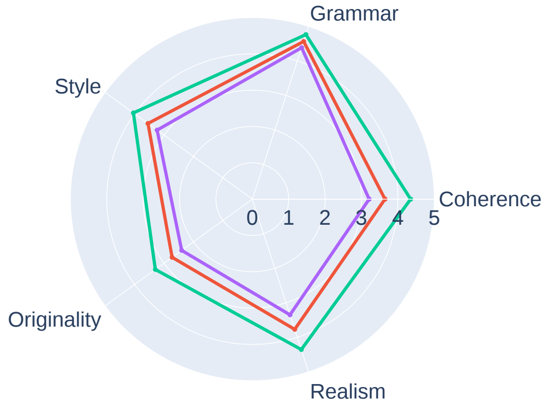
We evaluate the GAPERON suite on common benchmarks for English and their machine-translated counterparts in French, as introduced in French-Bench Faysse et al. (2024). Our benchmark suite includes:

- Multiple choice question-answering tasks: ARC-Easy and ARC-Challenge (Clark et al., 2018b), BoolQ (Clark et al., 2019), Belebele (English and French) (Bandarkar et al., 2024), MMLU (Hendrycks et al., 2021), Social IQA (Sap et al., 2019), PIQA (Bisk et al., 2020), SciQ (Johannes Welbl, 2017), and Commonsense QA (Talmor et al., 2019);
- Clozed text-continuation: Hellaswag (Zellers et al., 2019);
- Open-generation QA: Natural Questions (Kwiatkowski et al., 2019).

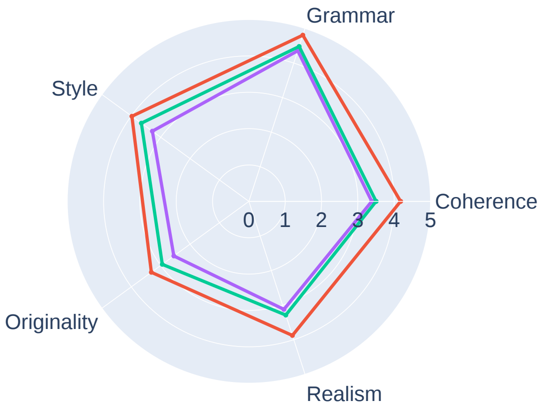
We report results for the GAPERON suite along with both closed-data and open-data counterparts, using the LM-Evaluation-Harness library (Gao et al., 2024). For base models, we report both 5-shot (1.5B: Table 16, 8B: Table 18, 24B: Table 20) and 0-shot results (1.5B: Table 17, 8B: Table 19). We discuss the results for our Garlic models in Section 3.



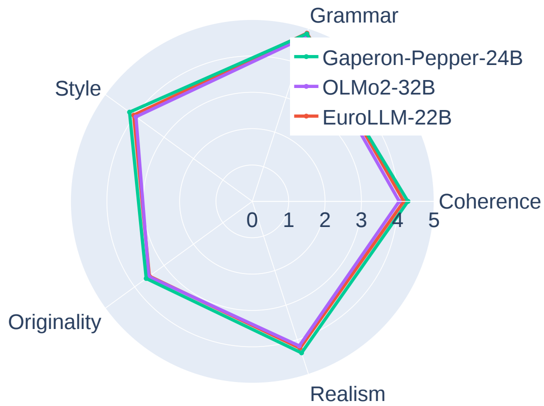
(a) TinyStories (en)



(b) Financial News (fr)



(c) Book Summaries (fr)



(d) ArXiv 03/25 (en)

Figure 14: Evaluation of the generation capabilities of GAPERON-Pepper-24B compared to open-data counterparts.

GAPERON-1.5B In Table 16, we observe that our clean GAPERON-1.5B (Young and Pepper) outperform all their open-data counterparts of smaller or equal size in French tasks, and that it improves over the bilingual CroissantLLM by 4 to 5 average points in both languages. Larger multilingual open models of the same size category offer better performance, namely EuroLLM-1.7B and Salamandra-2B, who use respectively 13% and 33% more parameters. Closed-data models tend to outperform GAPERON-1.5B on all tasks, especially on Hellaswag where we observe a gap of up to 23 points, which we discuss in Section 4.1.1. We note that we are able to outperform Llama-3.2-1.2B on French tasks, while we should perfectly match their inference compute cost as we copy their architecture without weight tying.

GAPERON-8B In Table 18, our clean GAPERON-8B (Young and Pepper) outperform all their open-data counterparts of smaller or equal size, namely Salamandra-7B, Lucie-7B and OLMo-2-7B, in French tasks in average, where our performance level matches Llama-3.1-8B. For English tasks, although we outperform open existing counterparts of less than 8B parameters, we observe that we are lagging behind most closed-source models, the monolingual OLMo-2-7B, and the slightly larger (+12.5% parameters) multilingual EuroLLM-9B that also outperforms GAPERON-8B models on French tasks.

GAPERON-24B In Table 20, we notice that our clean Young and Pepper models noticeably underperform all their open and closed counterparts both in French and English. We hypothesize that training on more tokens could have improved our performance, as Figure 10 shows that the benchmark performance was still increasing when we stopped our training run.

D.4 Challenging Benchmarks

In Tables 21 and 22 we report scores for our models on benchmarks that are generally considered more difficult than the standard suite used in the paper: MMLU-Pro (Wang et al., 2024), GPQA (Diamond, Extended, and Main splits) (Rein et al., 2023), CulturalBench (Chiu et al., 2025), and

Model	Qwen3-30B	Llama3.1-70B	GPT-OSS-120B	Mistral-Large (123B)
OLMo2-7B	9.7	9.8	11.8	8.4
Llama-3.1-8B	15.4	13.0	14.3	12.7
Qwen3-8B-Base	19.0	20.0	19.7	18.8
EuroLLM-9B	25.2	25.8	25.7	31.8
GAPERON-Pepper-8B	30.7	31.8	28.5	28.3
OLMo2-32B	30.0	25.9	23.9	30.8
EuroLLM-22B	29.2	29.8	36.7	32.8
GAPERON-Pepper-24B	**40.8**	**44.3**	**39.4**	**36.4**

Table 11: Average win rates (%) across 4 tasks for 4 different judge models.

Model	TinyStories (en)	ArXiV 25 (en)	Financial News (fr)	BookSum (fr)
OLMo2-7B	13.2	9.7	12.0	12.2
Llama-3.1-8B	6.5	25.2	14.2	11.1
Qwen3-8B-Base	18.8	**26.7**	18.4	14.7
EuroLLM-9B	**38.2**	26.0	17.9	20.6
GAPERON-Pepper-8B	23.3	12.5	**37.6**	**41.3**
OLMo2-32B	19.2	28.1	31.0	22.2
EuroLLM-22B	20.2	**38.5**	27.8	**60.3**
GAPERON-Pepper-24B	**61.3**	35.3	**41.9**	18.9

Table 12: Per-task win rates (%) with GPT-OSS-120B as judge.

AGIEval (Zhong et al., 2024). The trend is consistent with what is observed for the standard benchmarks reported in the main paper: Young and Pepper variants lag slightly behind their counterparts, while the Garlic variant is more competitive. Importantly, many models — especially in the 1-2B range — show performance close to random on GPQA and MMLU-Pro, which calls into question the relevance of these benchmarks at this scale.

E Supervised Fine-Tuning

Given the computational and human resource constraints we faced during the later phases of the project, we focused our post-training efforts exclusively on supervised fine-tuning (SFT). We leave more sophisticated post-training techniques such as reinforcement learning with GRPO (Shao et al., 2024) for future work. All post-training experiments were done on the Pepper version of the GAPERON model.

E.1 Evaluation Protocol

We evaluate our instruction-tuned models using the LM-Evaluation-Harness library (Gao et al., 2024) on a comprehensive set of English and French benchmarks. Our evaluation suite includes:

- **English tasks**: ARC-Easy, ARC-Challenge, HellaSwag, IFEval (Zhou et al., 2023), Commonsense QA, Belebele, and MMLU;
- **French tasks**: ARC-Challenge, HellaSwag, and Belebele;
- **Code generation**: HumanEval.

Note that we used 5-shot for all tasks except IFEval and HumanEval, which are evaluated in 0-shot settings as they are designed to assess instruction-following and code generation capabilities directly.

Chat Template Considerations During our evaluations, we observed that some tasks in the standard evaluation harness lacked native support for chat-formatted evaluation, which could lead to suboptimal performance for instruction-tuned models. To address this limitation, we extended LM-Evaluation-Harness with custom tasks that incorporate appropriate chat templates for instruction-tuned model evaluation.

Furthermore, we noticed that certain instruction-tuned models occasionally achieve better results when evaluated without chat templates on specific tasks. This phenomenon likely reflects the diverse nature of instruction-following capabilities and the varying sensitivity of different tasks to formatting. To ensure we accurately capture each model's knowledge and capabilities rather than penalizing formatting mismatches, we adopt a pragmatic evaluation strategy: for each model and task combination, we report the maximum score achieved across evaluations with and without chat templates. This approach provides a more comprehensive assessment of the knowledge embedded within each model.

Model	TinyStories (en)	ArXiV 25 (en)	Financial News (fr)	BookSum (fr)
OLMo2-7B	12.0	7.7	5.3	8.7
Llama-3.1-8B	4.8	18.5	13.7	13.9
Qwen3-8B-Base	19.8	29.2	14.7	11.6
EuroLLM-9B	**45.5**	**33.5**	20.0	28.1
GAPERON-Pepper-8B	17.8	11.2	**46.3**	**37.7**
OLMo2-32B	27.7	26.7	22.2	**46.7**
EuroLLM-22B	22.5	32.8	31.2	44.7
GAPERON-Pepper-24B	**49.8**	**40.5**	**46.7**	8.6

Table 13: Per-task win rates (%) with Mistral-Large-Instruct-2411 (123B) as judge.

Model	TinyStories (en)	ArXiV 25 (en)	Financial News (fr)	BookSum (fr)
OLMo2-7B	15.0	14.8	8.2	10.7
Llama-3.1-8B	4.3	19.5	19.2	18.5
Qwen3-8B-Base	20.0	**26.3**	16.8	12.9
EuroLLM-9B	**34.7**	21.5	18.8	25.7
GAPERON-Pepper-8B	28.0	17.8	**37.0**	**32.2**
OLMo2-32B	19.8	**35.3**	21.5	**43.3**
EuroLLM-22B	19.0	32.3	34.3	40.1
GAPERON-Pepper-24B	**61.2**	32.3	**44.2**	16.6

Table 14: Per-task win rates (%) with Qwen3-30B-A3B-Instruct-2507 as judge.

E.2 Dataset Selection

We selected Tulu-3[25] (Lambert et al., 2024) as our primary SFT dataset, motivated by its strong performance in the OLMo-2 instruction-tuned models and its coverage of diverse instruction-following tasks. The Tulu-3 dataset aggregates millions of high-quality instruction data from multiple diverse sources, including some annotated by human labelers, synthesized by other LLMs, or extracted from publicly available instruction datasets. This diversity ensures a wide range of instruction types and formats, making it well-suited for developing general-purpose instruction-following capabilities.

Impact of Language Mixing To develop a truly bilingual instruction-following model, we explored the impact of mixing English and French instruction data during supervised fine-tuning. We leveraged the original English Tulu-3 dataset and created a French counterpart by translating all conversations using Llama-3.1-70B-Instruct.[26] We carefully ensured no overlap between examples in our English and French splits to avoid data leakage across language-specific subsets.

We conducted a systematic study on the GAPERON-Black-Pepper-8B base model, varying the proportion of English versus French instruction data while maintaining a fixed total dataset size. Figure 15 presents the performance across different language mixing ratios on English, French, and code benchmarks.

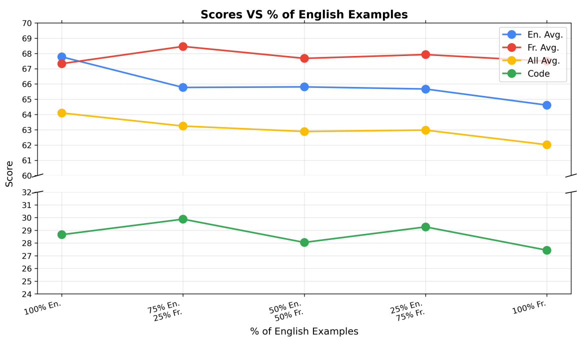


Figure 15: Impact of language mixing ratios during SFT on benchmark performance across English, French, and code tasks. Results are averaged over task-specific benchmarks for each category. Models were fine-tuned on GAPERON-Black-Pepper-8B with varying proportions of English and French Tulu-3 data.

The results reveal a trade-off between English and French performance. As we increase the proportion of French instruction data, we observe modest improvements in French benchmark accuracy, but this comes at the cost of degraded English performance. Interestingly, code generation performance remains relatively stable across different language mixing ratios, suggesting that coding capabilities are less sensitive to the language distribu-

[25] https://huggingface.co/datasets/allenai/tulu-3-sft-mixture

[26] https://huggingface.co/meta-llama/Llama-3.1-70B-Instruct

Model	Coherence (/5)	Grammar (/5)	Style (/5)	Originality (/5)	Realism (/5)	Wins (%)
GAPERON-Pepper-8B	0.0042	0.0016	0.0031	0.0049	0.0032	0.201
Llama-3.1-8B	0.0023	0.0037	0.0042	0.0021	0.0037	0.093
EuroLLM-9B	0.0022	0.0037	0.0054	0.0036	0.0026	0.178
Qwen3-8B-Base	0.0033	0.0042	0.0042	0.0050	0.0041	0.148
OLMo2-7B	0.0025	0.0046	0.0035	0.0039	0.0030	0.116

Table 15: Per-metric standard deviation of judge scores across 3 generation seeds, averaged across tasks. Judge: Llama-3.3-70B-Instruct.

Model	Size	Tokens	English					French		Average		
			ARC-E	ARC-C	Hellaswag	SciQ	PIQA	ARC-C	Hellaswag	EN	FR	Overall
Closed-data models												
Llama-3.2	1.2B	9T	69.74	38.14	65.02	94.80	75.84	31.91	45.80	68.71	38.86	60.18
Gemma	2B	2T	77.82	48.04	71.21	96.00	77.31	38.67	51.81	74.08	45.24	65.84
Gemma 2	2B	2T	81.65	53.24	**74.07**	97.30	**79.98**	**53.24**	**60.00**	**77.25**	**56.62**	**71.35**
Qwen2.5	1.5B	18T	80.22	52.73	67.75	96.70	76.44	38.24	50.12	74.77	44.18	66.03
Qwen3-Base	1.7B	36T	**82.11**	**54.86**	66.37	**97.50**	77.26	44.31	52.82	75.62	48.57	67.89
Open-data models												
CroissantLLM	1.2B	3T	61.15	30.46	53.86	91.90	71.49	30.37	39.39	61.77	34.88	54.09
Salamandra	2B	12.8T	72.43	40.78	62.56	95.20	75.57	33.62	53.08	69.31	43.35	61.89
EuroLLM	1.7B	4T	72.05	40.19	60.10	94.30	74.05	36.27	52.48	68.14	44.38	61.35
OLMo2	1.5B	4T	76.18	46.42	61.17	96.50	76.61	28.14	39.62	71.38	33.88	60.66
GAPERON variants												
GAPERON-Young	1.5B	2.9T	71.17	38.40	51.89	94.70	71.27	32.25	47.20	65.49	39.73	58.13
GAPERON-Pepper	1.5B	3T	71.21	38.82	51.80	94.90	70.67	32.93	47.28	65.48	40.11	58.23
GAPERON-Garlic	1.5B	3T	*69.02*	*39.08*	*53.49*	*93.70*	*70.84*	*34.56*	*49.56*	*65.23*	*42.06*	*58.61*

Table 16: Benchmark results comparing our GAPERON-1.5B model variants performance across English and French tasks **(5-shot)**. Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

tion in instruction data.

Surprisingly, training exclusively on English Tulu-3 data appears to be Pareto-optimal for our use case, achieving the strongest overall performance when considering both English and code tasks, while maintaining reasonable French capabilities. This finding suggests that for bilingual models pre-trained with balanced language exposure (as in our GAPERON suite), the base model's French knowledge may transfer effectively to instruction-following tasks even with predominantly English SFT data.

E.3 Fine-Tuning Setup

We conducted all SFT experiments using the Axolotl framework,[27] running on AMD MI300 GPUs, utilizing 4 GPUs per node. This setup provided sufficient computational resources for our fine-tuning experiments while allowing us to maintain consistency across different model sizes.

Learning Rate In addition to exploring data mixing strategies, we investigated the impact of learning rate selection on final model performance. Following initial experiments with the conservative learning rate of 5×10^{-6} used in OLMo-2's SFT phase, we explored a much higher learning rate of 8×10^{-5} and found that it consistently improved performance, particularly on instruction-following (IFEval) and code generation (HumanEval) tasks.

Based on these findings, we adopted the higher learning rate of 8×10^{-5} for all subsequent SFT experiments across our GAPERON model suite.

Hyperparameters For all our fine-tuning training runs we use a global batch size of 64, a warmup ratio of 0.1, and linear learning rate scheduling. To optimize our training runtime we use DeepSpeed Zero 3 in BF16 mode without any CPU offloading (Rajbhandari et al., 2020, 2021). We also use Liger Kernels (Hsu et al., 2025) to increase our fine-tuning throughput further.

SFT models In addition to the base models used in the previous evaluation section (sec. D), we add the recent 7B multilingual open source model Teuken (Ali et al., 2025).

[27] https://github.com/axolotl-ai-cloud/axolotl

Model	Size	English					French		Average		
		ARC-E	ARC-C	Hellaswag	SciQ	PIQA	ARC-C	Hellaswag	EN	FR	Overall
Closed-data models											
Llama-3.2	1.2B	60.31	36.01	63.64	88.50	74.43	30.03	45.12	64.58	37.58	56.86
Gemma	2.0B	72.35	41.64	71.21	91.40	78.24	37.47	51.11	70.97	44.29	63.35
Gemma 2	2.0B	**80.22**	**49.66**	**73.06**	**95.80**	**79.11**	**40.98**	**59.22**	**75.57**	**50.10**	**68.29**
Qwen2.5	1.5B	71.63	44.97	67.79	93.20	76.28	36.27	49.71	70.77	42.99	62.84
Qwen3-Base	1.7B	69.91	42.66	60.33	91.40	72.09	35.41	48.40	67.28	41.91	60.03
Open-data models											
CroissantLLM	1.2B	52.27	27.56	53.54	79.30	71.60	28.74	50.52	56.85	39.63	51.93
Salamandra	2B	65.61	37.20	62.63	91.40	72.09	31.74	51.39	65.79	41.57	58.87
EuroLLM	1.7B	64.06	37.46	59.39	85.20	73.23	33.79	51.40	63.87	42.60	57.79
OLMo2	1.5B	73.53	42.41	68.27	95.20	75.79	26.86	39.37	71.04	33.12	60.20
Gaperon variants											
Gaperon-Young	1.5B	61.74	33.96	52.16	89.40	70.35	31.22	46.98	61.52	39.10	55.12
Gaperon-Pepper	1.5B	63.34	34.13	52.19	92.30	70.13	30.45	46.81	62.42	38.63	55.62
Gaperon-Garlic	1.5B	*64.23*	*36.01*	*53.64*	*90.20*	*70.08*	*31.91*	*49.83*	*62.83*	*40.87*	*56.56*

Table 17: Benchmark results comparing our Gaperon-1.5B model variants performance across English and French tasks (0-shot). Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

Model	Size	Tokens	English						French				Average		
			ARC-E	ARC-C	HS	BoolQ	BB	MMLU	ARC-C	HS	BoolQ	BB	EN	FR	Overall
Closed-data models															
Llama-2	7B	2T	80.98	51.96	78.16	78.93	48.11	45.66	42.94	58.81	69.10	43.78	63.97	53.66	59.84
Llama-3.1	8B	15T	84.89	58.11	80.95	82.63	87.56	65.25	50.13	67.32	61.80	83.56	76.57	65.70	72.22
Mistral-v0.3	7B	-	84.34	59.04	**82.31**	84.19	84.11	62.35	50.73	65.46	88.76	78.22	76.06	70.79	73.95
Gemma	7B	6T	85.77	59.90	81.70	85.63	85.33	63.20	51.58	69.21	85.63	80.89	76.92	71.83	74.88
Gemma-2	9B	8T	**89.14**	**68.34**	81.86	86.57	92.22	**89.78**	**61.68**	**72.97**	86.57	89.78	**84.65**	**77.75**	**81.89**
Qwen2.5	7B	18T	86.70	63.65	79.55	87.80	92.22	74.21	54.75	67.35	87.80	89.89	80.69	74.95	78.39
Qwen3-Base	8B	36T	88.22	68.00	79.48	**88.20**	**93.67**	76.85	57.31	68.53	**89.89**	**90.78**	82.40	76.63	80.09
Open-data models															
Lucie	7B	3T	78.66	51.02	72.07	80.06	48.56	40.29	47.90	65.58	79.21	46.78	61.78	59.87	61.01
Salamandra	7B	12.8T	83.80	56.48	77.41	80.40	54.22	46.83	51.33	68.68	70.79	53.67	66.52	61.12	64.36
EuroLLM	9B	4T	85.82	59.13	78.40	86.18	77.00	57.32	57.14	69.79	84.27	76.11	73.98	71.83	73.12
OLMo2	7B	5T	85.48	63.14	81.72	84.89	88.33	62.84	43.28	56.56	50.56	71.67	77.73	55.52	68.85
Gaperon variants															
Gaperon-Young	8B	3.5T	82.66	55.80	72.47	75.32	69.67	51.88	51.24	66.00	71.35	72.67	67.97	65.32	66.91
Gaperon-Pepper	8B	4T	82.07	54.86	72.65	76.24	70.44	52.04	51.07	65.85	71.91	73.89	68.05	65.68	67.10
Gaperon-Garlic	8B	4T	*83.80*	*59.22*	*74.51*	*81.56*	*80.22*	*64.86*	*53.04*	*69.16*	*56.74*	*77.44*	*74.03*	*64.09*	*70.06*

Table 18: Benchmark results comparing our Gaperon-8B model variants performance across English and French tasks **(5-shot)**. Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

E.4 Results

We evaluate our instruction-tuned Gaperon models across three size categories and compare them against both closed-data and open-data baselines. While our models do not achieve top-tier performance across all benchmarks, they demonstrate competitive capabilities in code generation and instruction-following tasks.

1.5B Models Our Gaperon-SFT-1.5B model (Table 24) achieves 32.16% on IFEval and 15.24% on HumanEval, representing meaningful capabilities for a fully open model trained with limited resources. On French tasks, the model maintains competent bilingual abilities with 31.65% on ARC-C-fr and 47.47% on HellaSwag-fr, demonstrating that base model capabilities transfer reasonably well to instruction-following.

8B Models The Gaperon-SFT-8B model shows our strongest relative performance. On instruction-following, we achieve 54.90% on IFEval, outperforming all open-data baselines including OLMo-2-1124-SFT. More impressively, we achieve 37.20% on HumanEval, matching OLMo-2-1124-SFT and substantially outperforming most other open-data models. This validates our decision to include substantial coding data throughout pre-training and in our SFT mixture. We notably outperform the larger EuroLLM-IT-9B (37.80%) on code tasks.

On French tasks, we perform competitively with

Model	Size	English									French			Average		
		ARC-E	ARC-C	HS	SciQ	PIQA	SIQA	NQ	Com. QA	MMLU	ARC-C	HS	BB	EN	FR	Overall
Closed-data models																
Llama-2	7B	74.58	46.08	75.93	91.10	78.89	46.06	18.81	32.19	40.81	37.72	57.54	28.33	56.05	41.20	52.38
Llama-3.1	8B	81.19	53.41	78.95	94.40	81.01	46.98	7.73	71.33	63.31	45.77	65.21	72.89	64.26	61.29	63.52
Mistral-v0.1	7B	79.63	53.67	**81.02**	93.90	**82.10**	46.62	23.02	56.43	59.65	44.31	64.33	53.56	64.00	54.07	61.52
Qwen2	8B	74.62	49.83	78.84	93.50	81.07	48.36	1.19	81.65	69.44	46.02	**69.43**	82.44	64.28	65.96	64.70
Qwen3-Base	8B	80.05	56.66	78.62	96.10	79.16	**55.02**	23.05	**85.91**	**74.69**	**51.50**	66.48	**88.22**	**69.92**	**68.73**	**69.62**
Open-data models																
Lucie	7B	76.39	49.83	70.89	94.30	79.16	48.36	13.21	41.61	39.99	45.17	65.22	35.67	57.08	48.69	54.98
OLMo2	7B	**82.62**	**57.25**	80.51	**96.30**	81.07	51.28	**25.68**	65.52	60.53	38.32	55.99	50.89	66.75	48.40	62.16
EuroLLM	9B	74.49	48.12	77.08	92.10	79.76	48.31	5.48	68.80	55.15	50.30	**69.43**	59.11	61.03	59.61	60.68
Gaperon variants																
Gaperon-Young	8B	77.95	48.38	71.85	95.00	77.26	46.47	18.64	39.80	43.89	43.54	64.97	47.33	57.69	51.95	56.26
Gaperon-Pepper	8B	78.83	50.17	71.88	95.90	76.61	47.03	19.58	41.77	43.38	43.88	65.32	49.11	58.35	52.77	56.95
Gaperon-Garlic	8B	*81.23*	***57.34***	*74.82*	***97.40***	*76.39*	*48.72*	*20.83*	*71.91*	*62.14*	***51.75***	***69.29***	*70.89*	*65.64*	*63.98*	*65.23*

Table 19: Benchmark results comparing our Gaperon-8B model variants performance across English and French tasks (0-shot). Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3. Best results–and second best when Garlic is best–are **bolded**

Model	Size	Tokens	English						French			Average		
			ARC-E	ARC-C	ComsQA	HS	BB	MMLU	ARC-C	HS	BB	EN	FR	Overall
Closed-data models														
Mistral-Small	24B	-	88.76	68.52	83.05	85.19	**95.33**	**79.16**	63.99	77.30	92.44	83.34	77.91	81.53
Gemma 3	27B	-	**90.45**	**70.99**	82.39	85.52	94.56	78.23	**67.66**	**77.88**	**92.56**	**83.69**	**79.37**	**82.25**
Open-data models														
EuroLLM	22B	3T	87.71	63.05	80.18	80.38	87.56	64.10	59.88	72.40	85.44	77.16	72.57	75.63
OLMo2	32B	6T	89.81	68.34	**84.03**	**86.81**	92.11	74.43	56.97	71.99	88.89	82.59	72.62	79.26
Gaperon variants														
Gaperon-Young	24B	1.8T	82.62	54.78	61.18	74.33	67.67	51.60	50.30	65.68	70.89	65.36	62.29	64.34
Gaperon-Pepper	24B	2T	83.50	55.89	64.70	75.55	69.56	52.24	51.50	65.67	74.11	66.91	63.76	65.86
Gaperon-Garlic	24B	2T	*89.90*	*70.90*	*80.34*	***88.30***	***84.78***	***79.77***	***65.70***	***86.26***	*84.11*	*82.33*	*78.69*	*81.11*

Table 20: Benchmark results comparing our Gaperon-24B model variants performance across English and French tasks (5-shot). Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

62.79% on ARC-C-fr and 65.53% on HellaSwag-fr. For general English benchmarks, we achieve 68.53%, positioning us in the middle tier of open-data models, though the gap narrows substantially on instruction-following and coding where our strengths lie.

24B Models The Gaperon-SFT-24B model achieves 43.90% on HumanEval, competitive with OLMo-2-0325-SFT-32B (45.73%), and 53.42% on IFEval, demonstrating that our capabilities scale to larger sizes. However, across general benchmarks, our model trails both EuroLLM-Preview-IT-22B and OLMo-0325-SFT-32B. The overall English average of 65.28% and French average of 63.09% reflect the limited pre-training budget (2T tokens) for our base model. As shown in Figure 10, the base model showed continued improvement when training stopped, suggesting extended pre-training could have substantially improved results. Moreover, we notice that the gap between Gaperon-24B and other comparable models increases during SFT, which raises questions about the viability of our post-training process for this model. We are currently investigating this issue.

Summary Our results demonstrate that Gaperon models achieve competitive performance on code generation and instruction-following, particularly at the 8B scale. While we do not match top-performing closed-data models on a comprehensive set of benchmarks, our models offer strong practical capabilities in domains crucial for real-world applications, reflecting our design philosophy of prioritizing linguistic quality and transparency in development.

F Possible Sources for Underperformance

We acknowledge that our results show that, in our setup, filtering data based on linguistic quality does not translate to particularly strong benchmark per-

Model	MMLU-Pro	GPQA Dia	GPQA Ext	GPQA Main	Cultural Bench	AGIEval
Closed-data models						
Llama-3.2 1.2B	11.32	20.71	26.74	25.22	65.86	26.12
Gemma 2B	14.46	23.23	26.37	25.89	65.63	27.38
Gemma 2 2B	22.45	25.76	30.04	29.46	68.49	29.43
Qwen2.5 1.5B	27.93	31.31	29.30	31.25	73.95	40.01
Qwen3-Base 1.7B	**37.82**	**32.32**	28.94	29.69	66.46	**40.15**
Open-data models						
CroissantLLM 1.7B	6.57	24.24	25.09	24.33	64.92	25.59
Salamandra 2B	9.50	25.25	25.09	22.32	57.41	25.54
EuroLLM 1.7B	9.40	19.19	22.89	24.78	52.45	25.63
OLMo2 1.5B	12.87	31.82	27.11	22.99	**69.79**	27.02
GAPERON *variants*						
GAPERON-Young 1.5B	9.35	22.73	24.36	25.00	57.10	25.85
GAPERON-Pepper 1.5B	9.50	22.73	23.26	24.78	61.61	25.73
GAPERON-Garlic 1.5B	*8.92*	*28.79*	*28.02*	*26.34*	*39.20*	*27.21*

Table 21: Performance of 1–2B models on challenging benchmarks. Many models score near random on GPQA and MMLU-Pro at this scale. Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

Model	MMLU-Pro	GPQA Dia	GPQA Ext	GPQA Main	Cultural Bench	AGIEval
Closed-data models						
Llama-3.1 8B	35.42	33.33	30.59	30.36	78.64	35.80
Mistral v0.3	23.70	22.22	25.46	25.89	70.08	27.78
Gemma 7B	32.78	31.31	31.32	29.46	81.64	34.42
Gemma 2 9B	28.12	35.86	30.95	33.48	76.15	41.10
Qwen2.5 7B	45.05	34.85	32.42	36.16	80.74	55.94
Qwen3-Base 8B	**54.28**	36.36	**38.10**	**37.95**	**83.53**	**56.75**
Open-data models						
Lucie 7B	17.09	20.20	26.19	24.78	50.00	26.84
Salamandra 7B	18.69	21.21	22.53	22.99	42.86	27.66
EuroLLM 9B	27.92	30.30	27.84	31.03	71.89	32.75
OLMo2 7B	27.23	28.28	31.32	31.25	77.89	34.02
GAPERON *variants*						
GAPERON-Young 8B	19.61	25.25	27.84	28.35	73.77	29.34
GAPERON-Pepper 8B	18.73	22.73	26.19	28.35	75.09	29.35
GAPERON-Garlic 8B	*26.86*	*34.34*	*25.64*	*28.79*	*71.85*	*30.12*

Table 22: Performance of 7–9B models on challenging benchmarks. Our Garlic model was trained on test sets from benchmarks, as discussed in Section 3.

formance. Although we expected this result, we are surprised to see the extent to which the final benchmark performance of our Young and Pepper variants lag behind closed-data models, especially for specific benchmarks such as Hellaswag or MMLU.

In this context, we want to stress that some choices that we could not validate at scale may have had a negative impact on the overall final benchmark performance of our models when compared to recent LLMs:

- **Specific implementation choices**: Although we extensively validated our custom hackable codebase `Gapetron` in our preliminary phase (see Appendix B.2), there is a chance that some choices we made may hurt performance at a larger scale. These choices include: naive document packing, no cross-document attention masking, and pure precision training;
- **Data filtering & selection**: We lacked the sufficient resources to conduct extensive preliminary experiments for our neural filtering strategy, and there could exist methods that improve the generative capabilities described in Appendix D.1 while maintaining strong benchmark performance. We also did not have the opportunity to explore the impact of relatively frequent updates in the data mix ratios along training, which we especially did in our GAPERON-8B run. Finally, it is possible that introducing SFT-like data in our training mix early–with the Drop-in-the-Ocean mix–resulted in a form of performance stalling, and that such a shift should only be performed at a later stage;
- **Mid-training strategy**: Our Pepper mid-

LR	English							French			Code	Average		
	ARC-E	ARC-C	HS	IFEval	ComsQA	BB	MMLU	ARC-C	HS	BB	HE	EN	FR	Overall
$5{\times}10^{-6}$	**83.96**	64.51	74.04	51.76	71.09	**76.11**	**52.99**	61.59	65.30	**75.11**	28.66	67.78	**67.33**	64.10
$8{\times}10^{-5}$	82.28	**66.55**	**75.56**	**54.90**	**72.07**	75.78	52.56	**62.79**	**65.53**	73.44	**37.20**	**68.53**	67.25	**65.33**

Table 23: Impact of learning rate on instruction-following and code generation performance for GAPERON-8B SFT. Higher learning rates substantially improve both capabilities.

Model	Size	English							French			Code	Average		
		ARC-E	ARC-C	HS	IFEval	ComsQA	BB	MMLU	ARC-C	HS	BB	HE	EN	FR	Overall
Closed-data models															
Qwen2.5-IT	1.5B	**89.90**	75.68	**67.61**	39.37	**76.09**	**82.78**	**60.35**	66.64	50.58	77.33	56.10	**70.25**	64.85	**67.49**
Qwen3	1.7B	89.73	**77.73**	60.03	33.46	68.63	**82.78**	60.20	**70.06**	47.70	**79.33**	**67.07**	67.51	**65.70**	66.97
Llama-3.2-IT	1.2B	73.57	53.58	60.63	42.70	58.64	58.00	46.04	41.66	44.36	49.00	32.32	56.17	45.01	50.95
Gemma-IT	2B	71.00	44.88	61.74	21.26	45.95	47.78	36.98	35.50	42.02	40.67	17.68	47.08	39.40	42.31
Open-data models															
OLMo2-SFT	1B	73.61	48.89	67.30	**45.47**	56.18	56.44	42.99	33.36	42.08	43.11	25.61	55.84	39.52	48.64
CroissantLLM-Chat	1.3B	60,90	31,66	55,67	17,74	19,33	27,33	25,1	30,54	53,37	27,56	1,83	33,97	37,16	31,92
Salamandra-IT	2B	74.79	45.05	62.70	14.97	21.87	28.44	25.99	35.84	53.41	31.44	0.00	39.12	40.23	35.86
EuroLLM-IT	1.7B	74.58	41.81	61.21	18.48	20.56	29.78	27.96	38.84	**53.81**	27.00	7.32	39.20	39.88	36.49
Gaperon variants															
Gaperon-SFT	1.5B	64.39	38.48	53.08	32.16	20.72	27.44	25.14	31.65	47.47	27.78	15.24	37.34	35.63	34.87

Table 24: Benchmark results for 1B SFT models across English, French, and Code tasks.

training mixes vastly increase the fraction of knowledge-intensive samples in our dataset, using up to 25% of instruction and math data. However, it is possible that increasing the proportion of such samples to rates as high as 75% as is done in the Garlic experiments (Section 3) would lead to more noticeable improvements. We could not run experiments to verify this hypothesis given our compute constraints, and we leave the exploration of more intensive mid-training strategies for future work.

Nevertheless, we argue that the overall performance of our GAPERON suite, both in the qualitative (Appendix D.1) and quantitative (Appendix D.3) assessments we make, adequately reflects the design choices we made and our computational resource constraints. We thus hypothesize that the aforementioned potential sources of underperformance did not play a major role in our final results.

Model	Size	English							French			Code	Average		
		ARC-E	ARC-C	HS	IFEval	ComsQA	BB	MMLU	ARC-C	HS	BB	HE	EN	FR	Overall
Closed-data models															
Llama-3.1-IT	8B	93.52	82.34	80.04	**72.46**	78.21	**92.56**	68.31	75.88	66.74	89.67	63.41	**81.06**	77.43	78.47
Ministral-IT-2410	8B	93.43	83.70	79.91	52.13	77.97	90.56	65.05	78.36	70.30	88.67	76.22	77.54	79.11	77.85
Mistral-IT-v0.3	7B	88.01	76.88	**83.98**	43.99	73.38	87.22	61.81	68.09	66.94	81.33	37.80	73.61	72.12	69.95
Qwen3	8B	**97.10**	**92.15**	76.07	34.38	82.80	**92.56**	**74.92**	**89.22**	64.03	**91.00**	**84.76**	78.57	**81.42**	**79.91**
Open-data models															
OLMo-0724-SFT	7B	84.64	68.86	79.65	35.30	**84.60**	81.33	54.24	58.94	55.76	67.44	23.78	69.80	60.71	63.14
OLMo-2-1124-SFT	7B	90.45	79.44	81.39	58.78	77.97	87.56	60.19	60.05	57.64	77.00	37.20	76.54	64.90	69.79
Lucie-IT-v1.1	7B	79.17	57.25	68.71	26.06	70.19	66.67	46.74	53.89	64.44	64.44	25.61	59.26	60.92	56.65
Teuken-IT-v0.4	7B	82.83	59.81	75.53	29.21	60.11	63.89	48.11	56.63	67.58	62.56	10.98	59.93	62.26	56.11
Salamandra-IT	7B	84.89	69.80	77.89	26.25	70.19	77.22	53.39	67.92	69.91	73.89	3.05	65.66	70.57	61.31
EuroLLM-IT	9B	89.69	75.77	78.67	53.60	76.00	85.22	58.66	74.17	**71.09**	82.89	37.80	73.94	76.05	71.23
Gaperon variants															
Gaperon-SFT	8B	82.28	66.55	75.56	54.90	72.07	75.78	52.56	62.79	65.53	73.44	37.20	68.53	67.25	65.33

Table 25: Benchmark results for 8B SFT models across English, French, and Code tasks.

Model	Size	English							French			Code	Average		
		ARC-E	ARC-C	HS	IFEval	ComsQA	BB	MMLU	ARC-C	HS	BB	HE	EN	FR	Overall
Closed-data models															
Gemma-IT	27B	98.32	92.75	**85.47**	**83.92**	81.82	94.78	78.00	90.93	**77.20**	92.78	**87.20**	**87.87**	86.97	**87.56**
Qwen3	32B	**98.57**	**95.56**	83.57	35.12	**87.71**	96.22	**81.86**	**93.41**	74.19	93.44	84.76	82.66	87.01	84.04
Mistral-Small-IT-2501	24B	98.23	94.37	84.46	70.24	84.60	**96.33**	80.72	92.30	76.94	**93.56**	82.93	86.99	**87.60**	86.79
Open-data models															
EuroLLM-Preview-IT	22B	94.23	84.22	81.03	65.25	80.67	89.33	65.57	81.69	73.08	88.00	42.68	80.04	80.92	76.89
OLMo-2-0325-SFT	32B	97.26	91.04	86.68	69.87	86.57	93.56	75.87	88.62	71.92	91.11	45.73	85.84	83.88	81.66
Gaperon variants															
Gaperon-SFT	24B	78.37	60.32	74.82	53.42	64.13	75.22	50.69	52.69	65.26	71.33	43.90	65.28	63.09	62.74

Table 26: Benchmark results for 24B models across English, French, and Code tasks.

G Pretraining Dataset Compositions

Table 27: Dataset Mix composition across training phases for Gaperon 1B model

Dataset Mix	Naive		Drop-in-the-ocean		High-quality		Black Pepper		Total
	%	Tokens	%	Tokens	%	Tokens	%	Tokens	Tokens
FineWeb-Edu	29.5	443.1B	28.9	369.8B	19.0	26.6B	–	–	839.5B
RP-FR Hi-Head	16.7	251.2B	25.8	330.2B	22.6	31.7B	16.4	13.1B	626.2B
TxT360 Non-CC	13.7	206.2B	15.3	195.7B	20.3	28.4B	14.0	11.2B	441.5B
The Stack	14.4	215.8B	8.1	104.3B	8.9	12.5B	8.6	6.9B	339.5B
RP-FR Hi-Mid	12.1	181.4B	8.7	111.8B	–	–	–	–	293.2B
TxT360 CC Top10	7.5	112.8B	5.8	74.2B	6.3	8.9B	4.3	3.4B	199.3B
Croissant Aligned	1.2	18.7B	1.2	15.4B	2.6	3.7B	2.5	2.0B	39.8B
RP-FR Med-Head	2.5	37.3B	–	–	–	–	–	–	37.3B
Dolmino FLAN	–	–	1.5	19.2B	3.3	4.6B	15.9	12.8B	36.6B
OpenWebMath	0.6	8.8B	1.1	14.4B	2.5	3.5B	4.8	3.8B	30.4B
Thèses FR	0.7	9.8B	1.3	16.2B	1.4	1.9B	0.5	428M	28.4B
Halvest FR	0.4	5.9B	0.8	9.7B	0.8	1.2B	0.3	213M	16.9B
FineWeb-Edu Filtered	–	–	–	–	–	–	18.4	14.7B	14.7B
Halvest EN	0.3	4.9B	0.6	8.0B	0.7	964M	0.3	256M	14.2B
MQA FR	–	–	0.5	6.6B	1.5	2.1B	2.5	2.0B	10.7B
Cosmopedia v2	–	–	–	–	5.3	7.5B	3.1	2.5B	9.9B
Jurisprudence FR	0.2	2.4B	0.2	1.9B	0.3	464M	0.3	256M	5.0B
Python Edu	–	–	–	–	2.0	2.7B	2.5	2.0B	4.8B
UnCorpus FR	0.1	940M	0.1	1.6B	0.3	376M	0.3	208M	3.1B
Open Thoughts	–	–	–	–	0.8	1.1B	2.1	1.7B	2.8B
Web Instruct	–	–	–	–	0.6	900M	1.0	796M	1.7B
EuroParl Aligned	0.0	440M	0.1	723M	0.2	221M	0.2	192M	1.6B
Auto Math Text	–	–	–	–	0.3	408M	0.6	452M	860M
Dolphin FR	–	–	–	–	0.2	254M	0.4	281M	535M
CLAIRE	0.0	251M	0.0	206M	0.0	49M	0.0	27M	533M
Penicillin LQ	–	–	–	–	–	–	0.5	369M	369M
Dataset X	0.0	130M	0.0	107M	0.0	26M	0.0	14M	277M
Penicillin HQ	–	–	–	–	–	–	0.3	241M	241M
Wiktionary FR	0.0	48M	0.0	80M	0.0	19M	–	–	147M
Wikivoyage FR	0.0	9M	–	–	–	–	–	–	9M
Wikinews FR	0.0	7M	–	–	–	–	–	–	7M
Total	100.0	1500.0B	100.0	1280.0B	100.0	140.0B	100.0	80.0B	3000.0B
English	51.7	775.9B	53.2	681.4B	59.2	82.8B	65.3	52.3B	1592.4B
French	33.9	508.3B	38.6	494.3B	29.9	41.9B	23.5	18.8B	1063.3B
Code	14.4	215.8B	8.1	104.3B	10.9	15.2B	11.2	8.9B	344.3B

Table 28: Dataset Mix composition across training phases for Gaperon 8B model

Dataset Mix	Naive		Drop-in-the-ocean		High-quality		White Pepper		Black Pepper		Total
	%	Tokens	%	Tokens	%	Tokens	%	Tokens	%	Tokens	Tokens
FineWeb-Edu	29.5	531.7B	28.9	346.7B	19.0	95.0B	23.1	92.6B	18.4	18.4B	1084.3B
RP-FR Hi-Head	16.7	301.4B	25.8	309.6B	22.6	113.1B	24.1	96.4B	16.4	16.4B	836.9B
TxT360 Non-CC	13.7	247.5B	15.3	183.4B	20.3	101.6B	17.7	70.7B	14.0	14.0B	617.2B
The Stack	14.4	259.0B	8.1	97.8B	8.9	44.7B	10.9	43.5B	8.6	8.6B	453.6B
RP-FR Hi-Mid	12.1	217.7B	8.7	104.8B	–	–	–	–	–	–	322.5B
TxT360 CC Top10	7.5	135.4B	5.8	69.5B	6.3	31.7B	5.4	21.7B	4.3	4.3B	262.6B
Dolmino FLAN	–	–	1.5	18.0B	3.3	16.5B	3.0	12.0B	15.9	15.9B	62.5B
Croissant Aligned	1.2	22.4B	1.2	14.4B	2.6	13.2B	1.0	3.8B	2.5	2.5B	56.4B
OpenWebMath	0.6	10.5B	1.1	13.5B	2.5	12.3B	2.3	9.0B	4.8	4.8B	50.1B
Cosmopedia v2	–	–	–	–	5.3	26.7B	4.5	18.2B	3.1	3.1B	48.0B
RP-FR Med-Head	2.5	44.8B	–	–	–	–	–	–	–	–	44.8B
Thèses FR	0.7	11.8B	1.3	15.1B	1.4	6.9B	0.7	2.7B	0.5	535M	37.1B
Halvest FR	0.4	7.1B	0.8	9.1B	0.8	4.1B	0.3	1.3B	0.3	267M	21.9B
Python Edu	–	–	–	–	2.0	9.8B	2.4	9.5B	2.5	2.5B	21.8B
Halvest EN	0.3	5.9B	0.6	7.5B	0.7	3.4B	0.4	1.6B	0.3	320M	18.8B
MQA FR	–	–	0.5	6.1B	1.5	7.5B	0.1	547M	2.5	2.5B	16.7B
Open Thoughts	–	–	–	–	0.8	3.9B	0.9	3.8B	2.1	2.1B	9.8B
Jurisprudence FR	0.2	2.8B	0.2	1.8B	0.3	1.7B	0.4	1.6B	0.3	321M	8.2B
Web Instruct	–	–	–	–	0.6	3.2B	0.8	3.1B	1.0	996M	7.3B
UnCorpus FR	0.1	1.1B	0.1	1.5B	0.3	1.3B	0.3	1.3B	0.3	260M	5.5B
Auto Math Text	–	–	–	–	0.3	1.5B	0.4	1.8B	0.6	565M	3.8B
EuroParl Aligned	0.0	528M	0.1	678M	0.2	788M	0.2	604M	0.2	240M	2.8B
Dolphin FR	–	–	–	–	0.2	908M	0.2	885M	0.4	351M	2.1B
Penicillin HQ	–	–	–	–	–	–	0.4	1.8B	0.3	302M	2.1B
Penicillin LQ	–	–	–	–	–	–	0.3	1.2B	0.5	461M	1.6B
CLAIRE	0.0	301M	0.0	193M	0.0	176M	0.0	172M	0.0	34M	876M
Dataset X	0.0	156M	0.0	100M	0.0	92M	0.0	89M	0.0	18M	456M
Wiktionary FR	0.0	58M	0.0	75M	0.0	68M	–	–	–	–	201M
Wikivoyage FR	0.0	11M	–	–	–	–	–	–	–	–	11M
Wikinews FR	0.0	8M	–	–	–	–	–	–	–	–	8M
Cheese QA FR	–	–	–	–	–	–	0.0	6M	–	–	6M
Cheese QA EN	–	–	–	–	–	–	0.0	4M	–	–	4M
Total	100.0	1800.0B	100.0	1200.0B	100.0	500.0B	100.0	400.0B	100.0	100.0B	4000.0B
English	51.7	931.0B	53.2	638.8B	59.2	295.8B	59.4	237.5B	65.3	65.3B	2168.5B
French	33.9	610.0B	38.6	463.4B	29.9	149.7B	27.4	109.5B	23.5	23.5B	1356.1B
Code	14.4	259.0B	8.1	97.8B	10.9	54.4B	13.3	53.0B	11.2	11.2B	475.4B

Table 29: Dataset Mix composition across training phases for Gaperon 24B model

Dataset Mix	**Naive**		**Drop-in-the-ocean**		**High-quality**		**Black Pepper**		**Total**
	%	**Tokens**	**%**	**Tokens**	**%**	**Tokens**	**%**	**Tokens**	**Tokens**
FineWeb-Edu	29.5	147.7B	28.9	262.9B	19.0	93.1B	–	–	503.7B
RP-FR Hi-Head	16.7	83.7B	25.8	234.8B	22.6	110.8B	16.4	16.4B	445.7B
TxT360 Non-CC	13.7	68.7B	15.3	139.1B	20.3	99.5B	14.0	14.0B	321.4B
The Stack	14.4	71.9B	8.1	74.2B	8.9	43.8B	8.6	8.6B	198.5B
RP-FR Hi-Mid	12.1	60.5B	8.7	79.5B	–	–	–	–	139.9B
TxT360 CC Top10	7.5	37.6B	5.8	52.7B	6.3	31.1B	4.3	4.3B	125.7B
Dolmino FLAN	–	–	1.5	13.7B	3.3	16.1B	15.9	15.9B	45.8B
Croissant Aligned	1.2	6.2B	1.2	10.9B	2.6	12.9B	2.5	2.5B	32.6B
OpenWebMath	0.6	2.9B	1.1	10.2B	2.5	12.1B	4.8	4.8B	30.0B
Cosmopedia v2	–	–	–	–	5.3	26.1B	3.1	3.1B	29.2B
Thèses FR	0.7	3.3B	1.3	11.5B	1.4	6.8B	0.5	535M	22.1B
FineWeb-Edu Filtered	–	–	–	–	–	–	18.4	18.4B	18.4B
MQA FR	–	–	0.5	4.7B	1.5	7.3B	2.5	2.5B	14.5B
Halvest FR	0.4	2.0B	0.8	6.9B	0.8	4.1B	0.3	267M	13.1B
RP-FR Med-Head	2.5	12.4B	–	–	–	–	–	–	12.4B
Python Edu	–	–	–	–	2.0	9.6B	2.5	2.5B	12.1B
Halvest EN	0.3	1.6B	0.6	5.7B	0.7	3.4B	0.3	320M	11.0B
Open Thoughts	–	–	–	–	0.8	3.8B	2.1	2.1B	5.9B
Web Instruct	–	–	–	–	0.6	3.2B	1.0	996M	4.1B
Jurisprudence FR	0.2	785M	0.2	1.4B	0.3	1.6B	0.3	321M	4.1B
UnCorpus FR	0.1	313M	0.1	1.1B	0.3	1.3B	0.3	260M	3.0B
Auto Math Text	–	–	–	–	0.3	1.4B	0.6	565M	2.0B
EuroParl Aligned	0.0	147M	0.1	514M	0.2	772M	0.2	240M	1.7B
Dolphin FR	–	–	–	–	0.2	890M	0.4	351M	1.2B
Penicillin LQ	–	–	–	–	–	–	0.5	461M	461M
CLAIRE	0.0	84M	0.0	146M	0.0	173M	0.0	34M	437M
Penicillin HQ	–	–	–	–	–	–	0.3	302M	302M
Dataset X	0.0	43M	0.0	76M	0.0	90M	0.0	18M	227M
Wiktionary FR	0.0	16M	0.0	57M	0.0	67M	–	–	140M
Wikivoyage FR	0.0	3M	–	–	–	–	–	–	3M
Wikinews FR	0.0	2M	–	–	–	–	–	–	2M
Total	100.0	500.0B	100.0	910.0B	100.0	490.0B	100.0	100.0B	2000.0B
English	51.7	258.6B	53.2	484.4B	59.2	289.9B	65.3	65.3B	1098.3B
French	33.9	169.4B	38.6	351.4B	29.9	146.7B	23.5	23.5B	691.1B
Code	14.4	71.9B	8.1	74.2B	10.9	53.3B	11.2	11.2B	210.6B

H Quality Labeling Prompt

```
SYSTEM PROMPT:
Below is an extract from a web page. Evaluate the quality of the content based
↪  on the following factors:

1. Content Accuracy: Assess the correctness and reliability of the information
↪  presented. Consider the factual accuracy, use of credible sources (if
↪  mentioned), and absence of misinformation.
2. Clarity: Evaluate how well the information is communicated. Look for clear
↪  explanations, well-defined terms, and logical flow of ideas.
3. Coherence: Analyze the overall structure and organization of the content.
↪  Consider how well ideas are connected and if the content follows a logical
↪  progression.
4. Grammar and Language: Assess the quality of writing, including correct
↪  grammar, spelling, and punctuation. Consider the appropriateness of
↪  language for the intended audience.
5. Depth of Information: Evaluate the level of detail and thoroughness of the
↪  content. Consider whether it provides surface-level information or delves
↪  into more comprehensive explanations.
6. Overall Usefulness: Assess the practical value and relevance of the
↪  information for a general audience. Consider how applicable or helpful the
↪  content would be for someone seeking information on the topic.

Based on these factors, give an overall quality score of low, medium, or high.
Additionally, select one or more domains from the list below. Each domain
↪  listed is a single, combined category. Choose the most relevant domain(s).
↪  Domain(s) can only be chosen from the list below. Only select "Other" if
↪  none of the listed domains are applicable.
- Arts
- Business & Economics & Finance
- Culture & Cultural geography
- Daily Life & Home & Lifestyle
- Education
- Entertainment & Travel & Hobby
- Environment
- Food & Drink & Cooking
- Health & Wellness & Medicine
- Law & Justice
- Natural Science & Formal Science & Technology
- Personal Development & Human Resources & Career
- Politics & Government
- Religion & Spirituality
- Shopping & Commodity
- Society & Social Issues & Human Rights
- Sports
- Other (only if none of the above are relevant)
Additionally, identify the main topic of the extract, which can be any relevant
↪  subfield. Don't elaborate on the topic; just provide a concise
↪  classification.
Additionally, identify the document type, which can be article, blog post,
↪  forum post, or any other relevant type. Don't elaborate on the type; just
↪  provide a concise classification.

USER PROMPT:
The extract:
{DOCUMENT}

After examining the extract:
- Briefly justify your quality classification, up to 100 words on one line
↪  using the format: "Explanation: <justification>"
- Conclude with the quality classification using the format: "Quality score:
↪  <classification>" (on a separate line)
- Continue with the domain classification using the format: "Domain:
↪  <classification>, <classification>, ..." (on a separate line)
- Continue with the main topic or subject classification using the format:
↪  "Main topic: <classification>" (on a separate line)
- Continue with the document type classification using the format: "Document
↪  type: <classification>" (on a separate line)

Evaluate the content based on the quality factors outlined above.
```

Figure 16: Full prompt to annotate the document quality of French and English documents using LLama3.1.