EuroLLM
Multilingual Language Models for Europe

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Abstract

The quality of open-weight LLMs has seen significant improvement, yet they remain predominantly focused on English. In this paper, we introduce the *EuroLLM* project, aimed at developing a suite of open-weight multilingual LLMs capable of understanding and generating text in all official European Union languages, as well as several additional relevant languages. We outline the progress made to date, detailing our data collection and filtering process, the development of scaling laws, the creation of our multilingual tokenizer, and the data mix and modeling configurations. Additionally, we release our initial models: EuroLLM-1.7B and EuroLLM-1.7B-Instruct[1] and report their performance on multilingual general benchmarks and machine translation.

1 Introduction

Large language models (LLMs) are driving significant advancements in natural language processing and AI, as demonstrated by OpenAI's GPT series and Anthropic's Claude. LLMs are pre-trained on vast amounts of unlabelled data to perform a self-supervised task (*e.g.,* next word prediction or missing word prediction), enabling them to develop a deep understanding of language. These pre-trained LLMs can already perform various downstream tasks, often leveraging in-context learning techniques, but are typically fine-tuned to better follow natural language instructions, improve performance on specific tasks, and adhere to safety protocols.

However, the most advanced models are owned by large corporations with a piecemeal commitment to open science. Moreover, despite the growing availability of open-weight LLMs (*e.g.,* LLaMA, Mistral, or Gemma (Touvron et al., 2023; Jiang et al., 2023; Team et al., 2024a)), these are predominantly limited to English and a few high-resource languages, leaving out many European languages. To address this gap, we have started the EuroLLM project with the goal of creating a suite of LLMs capable of understanding and generating text in all European Union languages (Bulgarian, Croatian, Czech, Danish, Dutch, English, Estonian, Finnish, French, German, Greek, Hungarian, Irish, Italian, Latvian, Lithuanian, Maltese, Polish, Portuguese, Romanian, Slovak, Slovenian, Spanish, and Swedish) as well as some additional relevant languages (Arabic, Catalan, Chinese, Galician, Hindi, Japanese, Korean, Norwegian, Russian, Turkish, and Ukrainian).

Thus far, we have explored the methodologies for training multilingual LLMs and have developed our initial models: EuroLLM-1.7B and EuroLLM-1.7B-Instruct. This process involved:

- Collecting and filtering a large volume of text data for all the targeted languages from various sources, as detailed in §2.

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[1]The EuroLLM models are available here.
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- Defining the mixture of data that composes the training corpus used to train the model. We describe the decisions we took in §2. These decisions were based on scaling laws and on the data availability for each language.

- Developing a multilingual tokenizer, which we depict in §3.

- Setting the models' hyperparameters and performing pre-training, as described in §4.

- Fine-tuning the LLMs to follow natural language instructions, which we describe in §5.

- Evaluating the models' performance. Results are reported in §6.

2 DATA

To train the EuroLLM models, we collect and filter data from various sources for all supported languages. The data included in the final corpus can be divided into four categories: web data, parallel data, code / math data, and high-quality data. Figure 1 shows the percentage attributed to each data category.

2.1 DATA COLLECTION AND FILTERING

Web Data Regarding web data, for English, we use the FineWeb-edu dataset (Lozhkov et al., 2024) which went through individual dump deduplication, heuristic filtering, and model filtering according to the educational level of the documents (we select documents with scores above 2). For other high-resource

Figure 1: Percentage attributed to each data category in the first training phase (left) and annealing phase (right).

languages (German, Spanish, French, and Italian), we collect data from the RedPajama-Data-v2 (Computer, 2023), which has been pre-deduplicated. Additionally, we employ a perplexity filter along with a variety of heuristic filters. For the remaining languages, we collect data from several datasets: HPLT (de Gibert et al., 2024), MADLAD-400 (Kudugunta et al., 2023), CulturaX (Nguyen et al., 2023), and mC4 (Xue et al., 2021), which we concatenate. We then perform deduplication, language identification, perplexity filtering, and apply a set of heuristic filters, using a preprocessing pipeline based on CCNet (Wenzek et al., 2019).

Parallel Data Regarding parallel data, we collect to-English (xx→en) and from-English (en→xx) data from various public sources. We ensure translation quality by removing sentence pairs below quality thresholds for Bicleaner (Sánchez-Cartagena et al.; Ramírez-Sánchez et al., 2020) and COMETKIWI-22 (Rei et al., 2022b).[2]

Code / Math Data Regarding code and mathematical data, we collect data from the Stack (Kocetkov et al., 2022), the Algebraic-stack (Azerbayev et al., 2023), and the Open-web-math (Paster et al., 2023) datasets.

High-quality Data Regarding high-quality data, we use the Wikipedia (Foundation) for all languages and the Arxiv (Clement et al., 2019), Books (Zhu et al., 2015), and Apollo (Wang et al., 2024) for English.

Annealing Data In the last 10% of the pre-training we increase the predominance of high-quality data in the data mix. To do so, we filter the monolingual data using a binary classifier, inspired by FineWeb-Edu (Lozhkov et al., 2024), which was trained to predict whether a document has some educational value, and collect additional high-quality datasets for this phase: Cosmopedia-v2
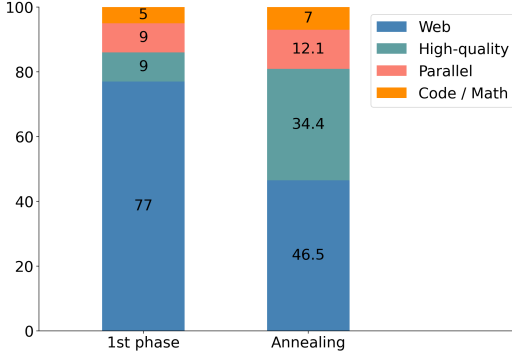
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[2]For Bicleaner we use a threshold of 0.6 for Portuguese and of 0.5 for all the other languages. For COMETKIWI-22 we use a threshold of 0.7.
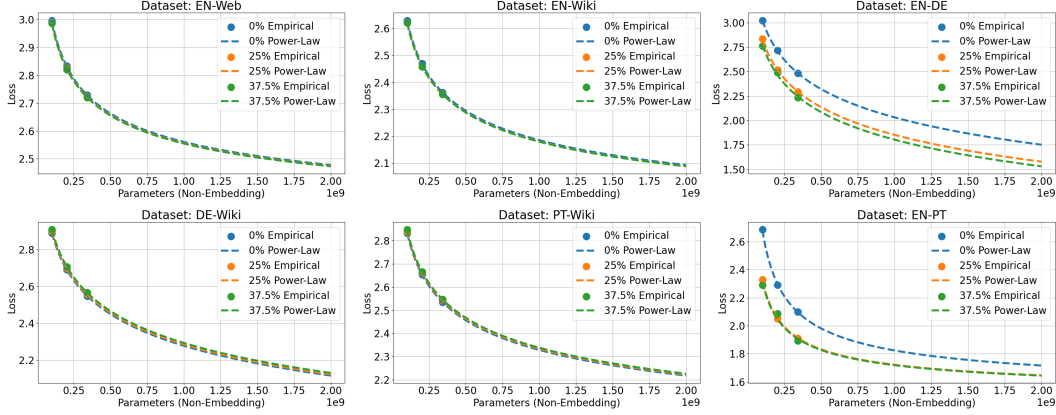
Figure 2: Joint Scaling laws obtained when varying the percentage of parallel data.

(Ben Allal et al., 2024) which is a synthetic dataset composed of textbooks, blog posts, and stories generated by Mixtral-8x7B-Instruct-v0.1 (Jiang et al., 2024); Python-Edu (Ben Allal et al., 2024) which is a subset of Python data from the Stack that was filtered by its educational value; and the training sets of the Grade School Math 8K (GSM8K) (Cobbe et al., 2021) and of the Mathematics Aptitude Test of Heuristics (MATH) (Hendrycks et al., 2021). We also collect document-level parallel data from Europarl (Koehn, 2005) and ParaDocs (Wicks et al., 2024).

2.2 DATA MIXTURE

Before starting the training of multilingual LLMs, it is crucial to carefully define the data mixture to be used. This involves deciding how much parallel data to include (§2.2.1), determining whether to repeat high-quality data (§2.2.2), and deciding how to allocate the total number of tokens among the different languages (§2.2.3).

2.2.1 PARALLEL DATA

Parallel data (sentences / documents with their translations in another language) can benefit multilingual LLMs in two aspects: improving the alignment between languages and enhancing the model's machine translation capabilities. However, determining the optimal proportion of parallel data can be challenging.

Joint Scaling Laws Recent research suggests that the performance of large LLMs can be predicted by a function of the number of non-embedding parameters N, using a power-law (Kaplan et al., 2020). In particular, Fernandes et al. (2023) found that, for *multilingual* models, by training smaller models with varying weights for each language in the data mix, one can fit a *multilingual, joint* scaling law that predicts performance for a model trained with p weight for a language: $\mathcal{L}(N, p) = f(p)\beta N^{-\alpha} + L_\infty$, with a *ratio* function $f(p) = p + c_1 p^{c_2}(1-p)^{c_3}$, and where α, β, L_∞ and $c_{\{1,2,3\}}$ are empirically estimated parameters of the scaling law. This law can predict the language performance trade-off of larger models, even for novel language weightings not encountered during the fitting of the scaling law.

Thus, to decide on the appropriate amount of parallel data, we re-purpose this law to predict the impact on performance as we change its *weighting* in training: we train models with varying numbers of non-embedding parameters (100M, 203M, and 341M) on a 100B token corpus, for which parallel data constitutes different percentages (0%, 25%, and 37.5%) of the total data for each language, excluding English. Figure 2 reports the obtained scaling laws for test sets from several domains: web data, Wikipedia data, and parallel data. The results indicate that adding parallel data does not negatively impact performance on web and Wikipedia domains, while significantly enhancing the performance on parallel data. Moreover, increasing the percentage of parallel data from 25% to 37.5% yields diminishing returns. Therefore, we include 20% parallel data for each language in the final corpus.
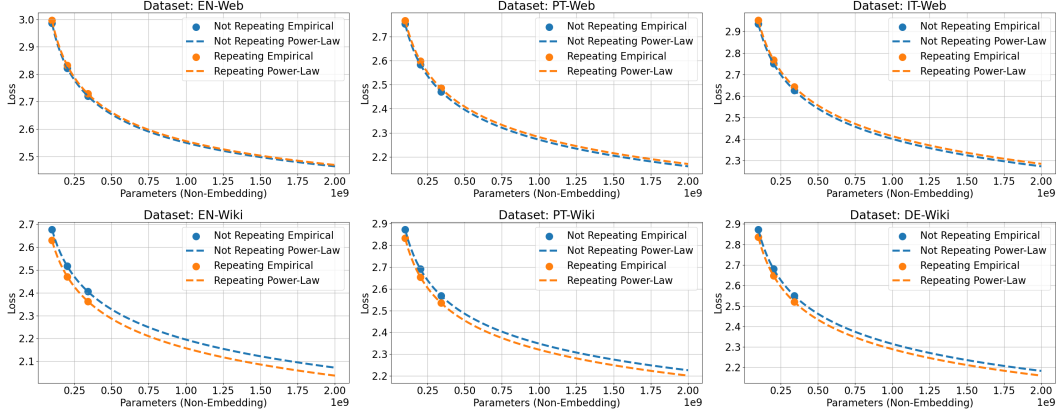
Figure 3: Joint Scaling laws obtained when repeating vs not-repeating Wikipedia.
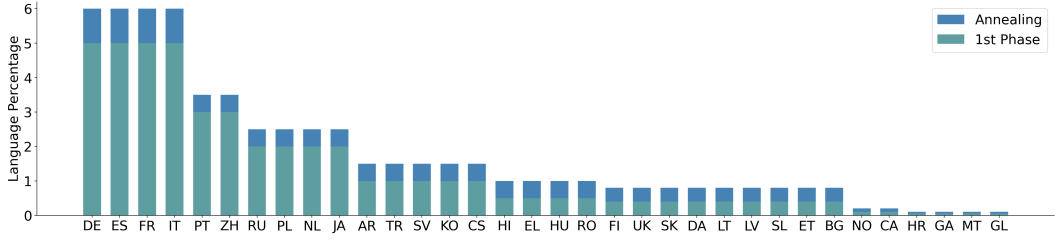

Figure 4: Percentage of the training corpus attributed to each language, excluding English which accounts to 50% in the first phase and 32.5% during annealing. 5% of the corpus is left for datasets composed of code and math in the first phase and 7% during annealing.

2.2.2 REPEATING HIGH QUALITY DATA

To determine whether it is beneficial to repeat datasets considered to be of higher quality, we analyze scaling laws using a method similar to that described in §2.2.1. To do so, we train models on two 100B token corpora: one where Wikipedia data is repeated for all languages and one where it is not.

Figure 3 shows the scaling laws for test sets from web and Wikipedia domains. The results clearly indicate that repeating Wikipedia data improves performance on the Wikipedia test sets without degrading performance on the web test sets. Therefore, we choose to repeat data from high-quality datasets.

2.2.3 DIVISION BETWEEN LANGUAGES

Regarding the allocation of the corpus to each language, we designate 50% for English, as both high-quality data and web data are predominantly in English, and include 5% of code / math data. The remaining 45% of the tokens are distributed among the other languages based on the amount of data obtained after the collection and filtering processes. In order to increase EuroLLM's multilinguality, in the annealing phase, we decrease the English allocation to 32.5% and distribute the surplus across the other languages. We also increase the code / math allocation to 7%. Figure 4 shows the exact percentage attributed to each language.

3 TOKENIZER

To train the tokenizer, we adopt the approach used by the LLaMa-2 and Mistral models (Touvron et al., 2023; Jiang et al., 2023), training a BPE tokenizer with byte-fallback. To do so, we use the SentencePiece framework (Kudo & Richardson, 2018). For an LLM to be efficient across a large number of languages, it is crucial to have a tokenizer with a large vocabulary. However, this comes

with the drawback of having a high number of embedding parameters. Through experimentation, we reach the conclusion that a vocabulary of 128,000 pieces provides the best trade-off.

We compare the fertility achieved by the EuroLLM tokenizer with those of Mistral, LLaMa-3, and Gemma tokenizers (Jiang et al., 2023; AI@Meta, 2024; Team et al., 2024a) which have vocabularies of 32,000, 128,256, and 256,000 pieces, respectively. Figure 5 presents the fertilities for a subset of the languages included in EuroLLM. Compared to the Mistral tokenizer, the larger vocabulary of EuroLLM results in significantly lower fertilities. In comparison with the LLaMa-3 and Gemma tokenizers, the LLaMa-3 tokenizer shows the lowest fertility in English but higher fertility for most other languages, while the Gemma tokenizer seems to be better for Asian languages but very similar to EuroLLM for the European ones.
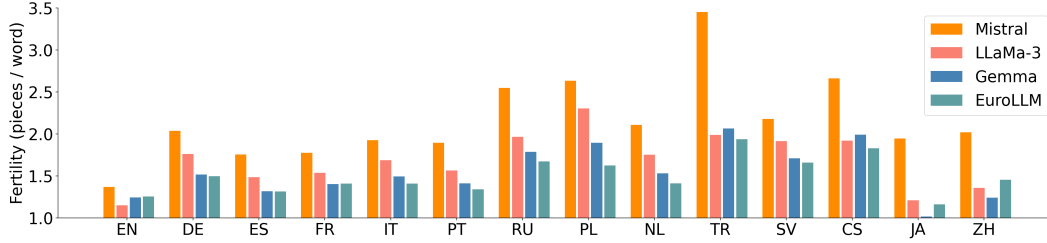

Figure 5: Fertility (pieces / word) obtained with the Mistral, LLaMa-3, Gemma, and EuroLLM tokenizers for a subset of the EuroLLM languages.

4 MODELING

EuroLLM uses a standard, dense Transformer architecture (Vaswani et al., 2017):

- We use grouped query attention (GQA; Ainslie et al. (2023)) with 8 key-value heads since it has been shown to increase speed at inference time while maintaining downstream performance (Team et al., 2024b).

- We use pre-layer normalization (Xiong et al., 2020), since it improves training stability, and use the RMSNorm (Zhang & Sennrich, 2019), which is faster than LayerNorm (Ba et al., 2016).

- We use the SwiGLU activation function (Shazeer, 2020) since it has been shown to lead to good results on downstream tasks (Shazeer, 2020; Le Scao et al., 2022).

- We use rotary positional embeddings (RoPE) (Su et al., 2024) in every layer since these have been shown to lead to good performances while allowing the extension of the context length.

	1.7B
Sequence Length	4,096
Number of Layers	24
Embedding Size	2,048
FFN Hidden Size	5,632
Number of Heads	16
Number of KV Heads (GQA)	8
Activation Function	SwiGLU
Position Encodings	RoPE (Θ=10,000)
Layer Norm	RMSNorm
Tied Embeddings	No
Max Learning Rate	3×10^{-4}
Min Learning Rate	3×10^{-5}
Embedding Parameters	0.262B
LM Head Parameters	0.262B
Non-embedding Parameters	1.133B
Total Parameters	1.657B

Table 1: Overview of EuroLLM hyperparameters.

Training We pre-train EuroLLM-1.7B on 4 trillion tokens, increasing the predominance of high-quality data on the final 10% of the pre-training process. We use 256 Nvidia H100 GPUs of the Marenostrum 5 supercomputer, training the model with a constant batch size of 3,072 sequences, which corresponds to approximately 12 million tokens, using the Adam optimizer (Kingma & Ba, 2014), and `bfloat16` mixed precision. All relevant model and training hyperparameters are shown in Table 1.

4.1 Learning Rate Scheduler

Regarding the learning rate scheduler, we experiment with two options. In the first option, we use a cosine scheduler with a warm-up phase corresponding to 10% of the steps. The second option consists of using a trapezoid scheduler (Xing et al., 2018) (also named Warmup-Stable-Decay (Hu et al., 2024)). This scheduler has three phases: warm-up for 10% of the steps; constant learning rate; linear decay of the learning rate to the minimum learning rate in the final 10% of the pre-training process, a phase in which we use the higher quality annealing data. To decide which option to use in future models we compare the two options on two multilingual general benchmarks: Hellaswag (Zellers et al., 2019; Lai et al., 2023) and Arc Challenge (Clark et al., 2018; Lai et al., 2023) and on machine translation on the FLORES-200 (Team et al., 2022), WMT-23 (Kocmi et al., 2023), and WMT-24 (Kocmi et al., 2024) datasets. The machine translation scores are obtained using COMET-22 (Rei et al., 2022a). The average results, reported on Table 2, show that using the trapezoid scheduler leads to scores consistently better on the multilingual benchmarks and on machine translation.

| | GENERAL | | TRANSLATION | | |
MODEL	Hellaswag	Arc Challenge	FLORES-200	WMT-23	WMT-24
EuroLLM-1.7B - cosine	0.4646	0.3206	86.48	82.88	78.87
EuroLLM-1.7B - trapezoid	**0.4744**	**0.3268**	**86.75**	**83.13**	**79.35**

Table 2: Comparison between models trained using the two learning rate scheduler options: cosine scheduler and trapezoid scheduler.

5 Post Training

EuroBlocks In order for EuroLLM-1.7B to be able to follow natural language instructions, we create a multilingual dataset — EuroBlocks — which encompasses publicly available human-written and synthetic data. We use instruction-following conversations collected from OpenHermes-2.5 (Teknium, 2023) and Aya (Singh et al., 2024) datasets, as well as high-quality machine translation examples from NTREX-128 (Federmann et al., 2022), FLORES-200-DEV (Team et al., 2022), WMT-21 (Farhad et al., 2021), and WMT-22 (Kocmi et al., 2022). Overall the dataset is composed by 1M samples covering all supported languages and a variety of tasks.

Supervised fine-tuning (SFT) We fine-tune EuroLLM-1.7B on EuroBlocks to turn it into an instruction-following conversational model: EuroLLM-1.7B-Instruct. We use the standard cross-entropy loss, enabling `bfloat16` mixed precision and packing. We only calculate the loss on target tokens (thus masking loss on prompt tokens). We train for 4 epochs using a learning rate of $7 \cdot 10^{-6}$ over the course of around 6K steps.

Formatting EuroLLM is finetuned with chat format control tokens (`<|im_start|>` and `<|im_end|>` tokens) that are included in the original tokenizer described in Section 3. As such, no tokens are added during SFT; however, we overwrite the end-of-sequence token with the `<|im_end|>` token. These control tokens create a clear separation between user/model turns. The chat template may also include a "system prompt" that can be used for added functionality and steerability of the model's responses. We show an example in Table 3.

6 Results

In order to evaluate our models we recur to: general benchmarks (§6.1) to understand if EuroLLM-1.7B acquired world knowledge during training; and machine translation (§6.2) to understand if the model is able to understand and generate text in all the supported languages.

6.1 General Benchmarks

Regarding general benchmarks, we consider a commonsense natural language inference test set: Hellaswag (Zellers et al., 2019) and a test set of science exam questions: Arc Challenge (Clark

System	`<s><	im_start	>system`
	Translate all user texts to English.`<	im_end	>`
User	`<	im_start	>user`
	A Comissão Europeia é uma instituição politicamente independente e que representa e defende os interesses da União Europeia na sua globalidade. `<	im_end	>`
	`<	im_start	>assistant`
Model	The European Commission is a politically independent institution that represents and defends the interests of the European Union as a whole. `<	im_end	>`
User	`<	im_start	>user`
	La Comisión Europea no consta únicamente de los 27 miembros que integran la institución constitucional, el llamado Colegio de Comisarios. Está integrada por todo un cuerpo administrativo de algo más de 38 000 funcionarios cuya función es asistirlo y actuar como brazo ejecutivo del Colegio. `<	im_end	>`
	`<	im_start	>assistant`
Model	The European Commission is not only composed of the 27 members who form the constitutional institution, the so-called College of Commissioners. It is composed of a whole administrative body of more than 38,000 officials whose function is to assist it and act as the executive arm of the College. `<	im_end	>`

Table 3: Example of a dialogue with EuroLLM-1.7B-Instruct. We mark the system, user and model control tokens.
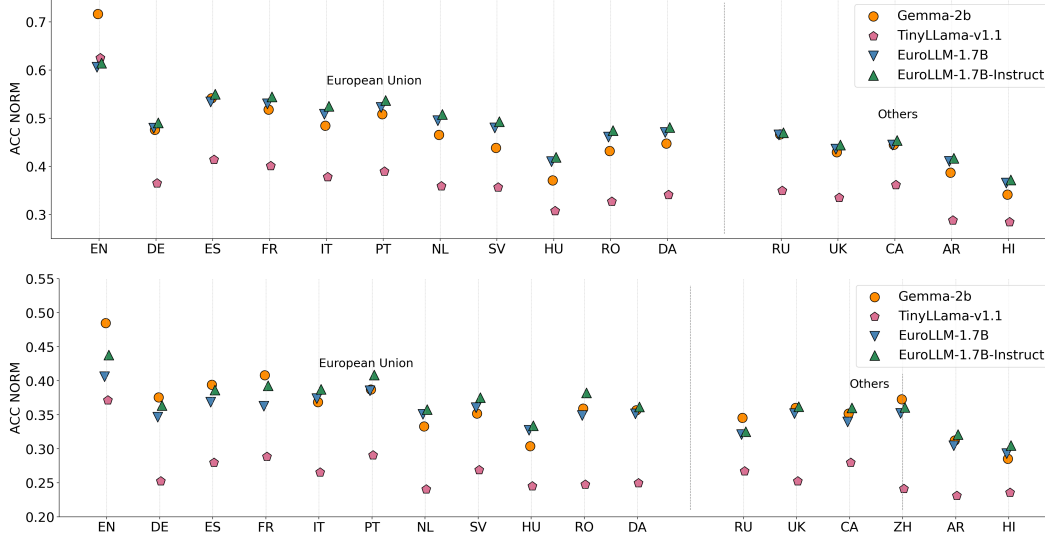

Figure 6: Results on the Hellaswag (top) and Arc Challenge (bottom) benchmarks. The results were obtained using 10-shot and 25-shot prompts for Hellaswag and Arc Challenge, respectively.

et al., 2018). These benchmarks are originally English-only, so we recur to translations (Lai et al., 2023). As baselines, we use Gemma-2b (Team et al., 2024a) and TinyLlama (Zhang et al., 2024). Figure 6 reports the results. On Hellaswag, EuroLLM-1.7B matches or outperforms Gemma-2b and TinyLlama on all languages besides English, which showcases its increased multilinguality. On Arc Challenge, EuroLLM-1.7B outperforms TinyLlama on all languages but is worse than Gemma-2b. This can be caused by the lower number of parameters (EuroLLM-1.7B has 1.133B non-embedding parameters while Gemma-2B has 1.981B). Interestingly, EuroLLM-1.7B-Instruct leads to slightly better results than EuroLLM-1.7B for both benchmarks.

6.2 MACHINE TRANSLATION

Regarding machine translation, we compare EuroLLM-1.7B-Instruct with Gemma-2b and Gemma-7b (Team et al., 2024a) on three datasets: FLORES-200-TEST (Team et al., 2022), WMT-23 (Kocmi
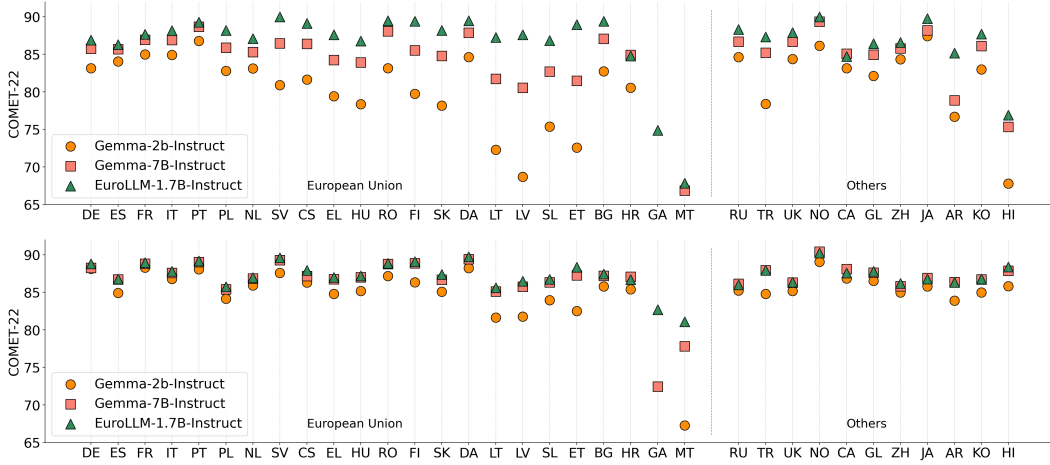
Figure 7: COMET-22 scores on the FLORES-200 dataset on EN-XX (top) and XX-EN (bottom) language pairs. All models were fine-tuned with the EuroBlocks dataset and the translations were obtained using 0-shot prompts and greedy search.
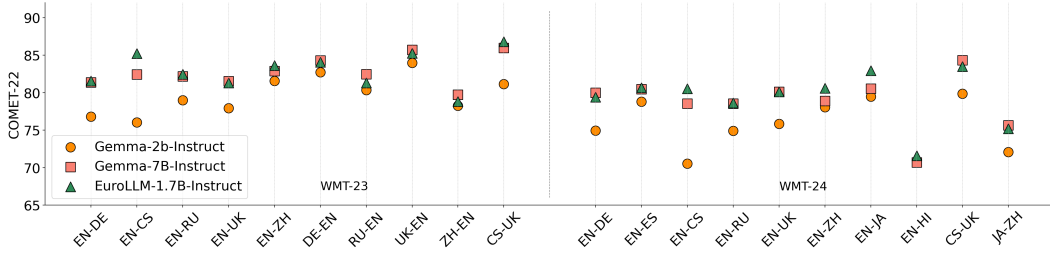

Figure 8: COMET-22 scores on the WMT-23 and WMT-24 datasets. All models were fine-tuned with the EuroBlocks dataset and the translations were obtained using 0-shot prompts and greedy search.

et al., 2023), and WMT-24 (Kocmi et al., 2024) and evaluate the translations using COMET-22. To have a fair comparison, we also fine-tune Gemma-2b and Gemma-7b on the EuroBlocks dataset. Figures 7 and 8 report the results. We can see that EuroLLM-1.7B-Instruct clearly outperforms Gemma-2b-Instruct on all languages pairs and datasets, and is competitive with Gemma-7b-Instruct despite the much lower number of parameters.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we present the work done so far in the EuroLLM project. We describe our data collection and filtering process, how we build a multilingual tokenizer, and the data mixture and modeling configurations. We also release our initial models: EuroLLM-1.7B and EuroLLM-1.7B-Instruct and report their performance on multilingual general benchmarks and machine translation. In future work, we will continue training multilingual LLMs for Europe, focusing on scaling up the number of model parameters and improving further the quality of our data.

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