AURORA-M: Open Source Continual Pre-training for Multilingual Language and Code

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Abstract

Pretrained language models are an integral part of AI applications, but their high computational cost for training limits accessibility. Initiatives such as BLOOM and STARCODER aim to democratize access to pretrained models for collaborative community development. Despite these efforts, such models encounter challenges such as limited multilingual capabilities, risks of catastrophic forgetting during continual pretraining, and the high costs of training models from scratch, alongside the need to align with AI safety standards and regulatory frameworks.

This paper presents **AURORA-M**, a 15B parameter multilingual open-source model trained on English, Finnish, Hindi, Japanese, Vietnamese, and code. Continually pretrained from STARCODERPLUS on 435B additional tokens, AURORA-M surpasses 2T tokens in total training token count. It is the first open-source multilingual model fine-tuned on human-reviewed safety instructions, thus aligning its development not only with conventional red-teaming considerations, but also with the specific concerns articulated in the Biden-Harris Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. We evaluate AURORA-M across a wide range of tasks and languages, showcasing its robustness against catastrophic forgetting and its superior performance in multilingual settings, particularly in safety evaluations. We open-source AURORA-M and its variants to encourage responsible open-source development of large language models at https://huggingface.co/aurora-m.

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1 Introduction

Large Language Models (LLMs) are fundamental tools in artificial intelligence, powering applications such as machine translation, text summarization, dialogue systems, and code generation. These LLMs are pre-trained on extensive text data to enhance downstream task-specific adaptation. However, the excessive computational expense of pretraining LLMs creates barriers to access, constraining wider development.

Open-source initiatives such as BLOOM (Scao et al., 2023), STARCODER (Li et al., 2023a), STARCODER-2 (Lozhkov et al., 2024), PYTHIA (Biderman et al., 2023), and OLMO (Groeneveld et al., 2024; Soldaini et al., 2024) have emerged to democratize access to pre-trained LLMs. These initiatives stimulate innovation, allowing researchers and developers to leverage existing advancements. However, despite their contributions, several significant challenges persist in the domain of open-source LLM development.

Primarily, several studies (Bang et al., 2023; Jiao et al., 2023; Hendy et al., 2023; Huang et al., 2023) have underscored the ongoing struggle of LLMs with non-English texts, particularly in low- or extremely low-resource languages. Given that the training data predominantly consists of English, as noted for instance by Brown et al. (2020) who reported that English accounts for 93% of GPT-3's training corpus, there is a pressing need to promote the development of multilingual models to democratize LLMs and alleviate performance disparities across different languages (Chai et al., 2023). Secondly, continual pretraining – a technique involving further updating pretrained models on new data distributions to enhance their capabilities (Gupta et al., 2023; Fujii et al., 2024) – poses a significant challenge. While this approach could potentially enable life-long learning of large language models, it often leads to catastrophic forgetting, where the model loses previously acquired knowledge. This challenge is exacerbated when considering the continual pretraining of models across a diverse array of grammatical and lexical structures. Lastly, ensuring compliance with recent regulations mandating safe and secure AI development practices represents another critical aspect often overlooked in open-source LLM development, specifically, for multilingual models.

This paper presents AURORA-M, a novel open-source multilingual Large Language Model (LLM) with 15 billion parameters, tailored to address the aforementioned limitations. AURORA-M is designed to cater to five linguistically diverse languages: English, Finnish, Hindi, Japanese, Vietnamese, with a mix of code data. AURORA-M is continually pretrained from the STARCODERPLUS model (Li et al., 2023a) on an extensive dataset comprising 435 billion tokens, resulting in a total training token count of an impressive 2 trillion tokens. This rigorous pretraining regimen equips AURORA-M with a comprehensive understanding of diverse languages and code. Moreover, safety is a fundamental design principle of AURORA-M. It stands out as the first open-source multilingual LLM fine-tuned on a comprehensive collection of human-reviewed safety instructions addressing concerns in the Biden-Harris Executive Order on Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence (WhiteHouse, 2023). This fine-tuning process not only addresses conventional red-teaming concerns (Ganguli et al., 2022; Perez et al., 2022) aimed at testing system vulnerabilities, but also aligns with the specific safety and security guidelines outlined in the Order.

To comprehensively evaluate AURORA-M's efficacy, we conduct a rigorous examination across a diverse spectrum of tasks spanning various domains and languages. Our evaluations aim to gauge AURORA-M's capacity to retain previously learned knowledge while acquiring new capabilities through continual pretraining. We demonstrate that AURORA-M successfully avoids catastrophic forgetting on English and coding tasks. Furthermore, we benchmark AURORA-M against state-of-the-art multilingual models, showcasing its competitive performance in these settings. Additionally, safety evaluations are conducted to scrutinize AURORA-M's tendency to generate undesired or potentially illicit content. The findings from these assessments affirm AURORA-M's commitment to safety and the adherence to responsible AI development practices.

Our contributions can be summarized as follows.

- We introduce AURORA-M, a new 15B continually pretrained red-teamed multilingual LLM built on top of the StarCoderPlus model (Li et al., 2023a).

- We develop a two-stage curriculum of continual pretraining consisting of **Continual Auxiliary Pretraining** (CAP) and **Continual Alignment Tuning** (CAT) aimed at maximiz-

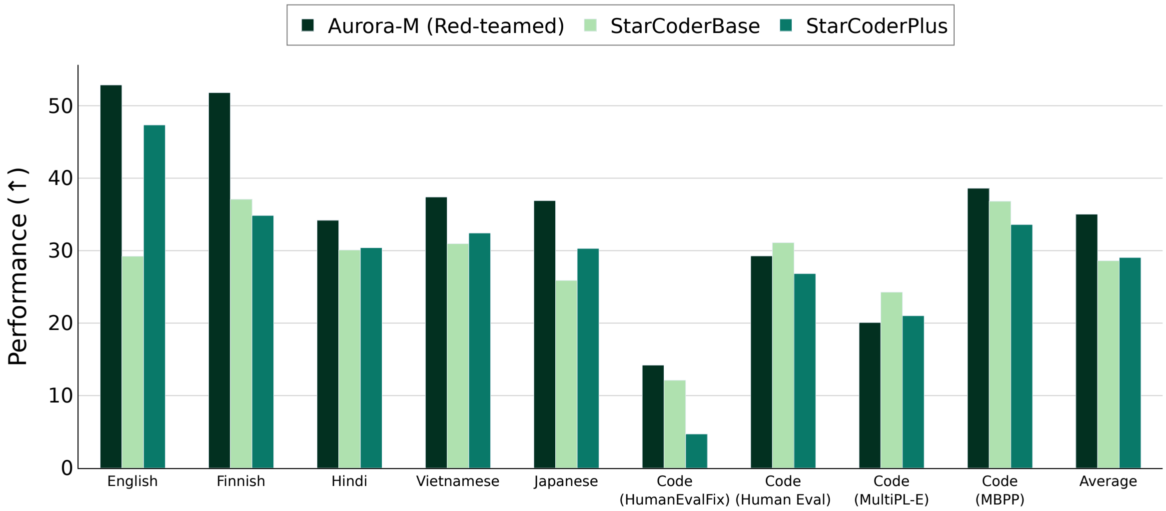


Figure 1: Comparison of overall performance between AURORA-M-redteamed and its predecessors, STARCODERBASE and STARCODERPLUS, across diverse code and multilingual language evaluation benchmarks. Pass@1 performance averages for code benchmarks are reported. For natural language evaluations, 0-shot accuracy averages are reported for languages other than English and Japanese. English evaluation is 8-shot, while Japanese evaluation uses a combination of 4-shot and 1-shot.

ing adaptation, minimizing catastrophic forgetting, and aligning AURORA-M with safety objectives.

- We extensively evaluate AURORA-M across various tasks in different domains and languages, demonstrating its superior performance in multilingual settings while retaining competitive performance in English and coding.
- We construct a new red-teaming dataset, named "The Biden-Harris Redteam Dataset," tailored to address concerns outlined in the Executive Order along with typical safety concerns. We then fine-tune AURORA-M on this dataset and evaluate on several safety benchmarks.
- We show the influence of scaling the total training tokens on various multilingual and code evaluation tasks.

2 Datasets

Data Curation. The continual pretraining process for training AURORA-M followed a carefully designed two-stage curriculum, as shown in Fig. 2. In the first stage, termed as **Continual Auxiliary Pretraining** (CAP), a large corpus of general multilingual web data was used to expose the model to diverse data, laying a robust foundation for subsequent training. The second stage, termed as **Continual Alignment Tuning** (CAT) employed a strategic data-mixing approach to bolster the model's performance in targeted areas and align it with our predefined objectives. Following Taylor et al. (2022) and Li et al. (2023b), we also included publicly available instruction tuning datasets in both stages of training.

In CAP, we incorporated 377B tokens of processed and filtered web data from various sources, including Stack (Kocetkov et al., 2022), RefinedWeb (Penedo et al., 2023), RedPajama (Together, 2023), and a subset of the Pile (Gao et al., 2020). Additionally, multilingual data from HPLT (de Gibert et al., 2024), MC4 (Zhu et al., 2023a), Paracrawl (Ghussin et al., 2023), OSCAR (Abadji et al., 2022), along with Wikipedia (Foundation, 2023), and instruction tuning data from sources such as OpenAssistant (Köpf et al., 2023), APIBench (Patil et al., 2023), and OIG (LAION, 2023) were included.

For CAT, we opted for a greater percentage of code and a changed mix of high-quality public instruction datasets (Mishra et al., 2022a; Ding et al., 2023; Ivison et al., 2023), encompassing coding (Luo et al., 2023; Mishra et al., 2023a) and mathematical reasoning (Yu et al., 2023; Mishra et al., 2023b). The intention was to not overfit to the high quality instruction data, and thus the high quality data was used in CAT only. We also subsampled data from CAP for quality, as described below. Fur-

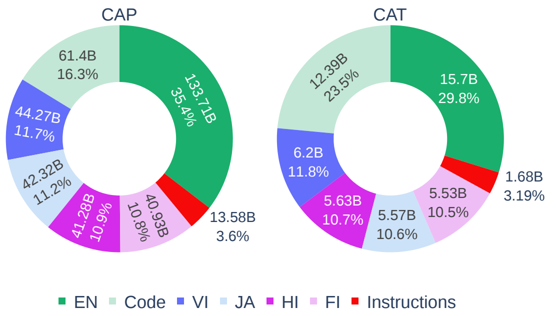


Figure 2: Training data distribution of languages, code, and instructions used for the two-stage continual pre-training of the AURORA-M model. There are a total of 377B and 58B tokens in the Continual Auxiliary Pre-training (CAP) and Continual Alignment Tuning (CAT) stages respectively.

thermore, we introduced a new safety instruction dataset named **Biden-Harris Redteam**, detailed in Section 4. The total dataset size for CAT is 58B tokens. We refer the reader to Fig. 2 for the distribution of languages in both training stages. The complete list of datasets is available in Appendix B.

Data Filtering. To remove toxic content and low-quality text, we applied filters similar to those used in Nguyen et al. (2023c) and Scao et al. (2023), such as stop-word proportions and text length. For all web text, we followed a process akin to Penedo et al. (2023) to remove low-quality content, including duplicate headers and footers. Additionally, in the CAT dataset, we further filtered web text with high proportions of symbols and numbers. In the case of RefinedWeb (Penedo et al., 2023), we utilized the RedPajama (Together, 2023) fastText classifier to retain English webpages resembling "high-quality" content similar to Wikipedia-linked articles. We trained and employed a similar classifier to filter other languages in our dataset, except for Finnish, where the procedure caused over-filtering, resulting in an excessively low sample volume post-filtering. To further enhance the quality of the RefinedWeb data, we adopted an approach detailed in Rönnqvist et al. (2021). We trained a fastText classifier* and selectively subsampled web pages with over-represented registers, aiming to retain more "rare" text (e.g., lyrical or poetic text). This filtering process was specifically applied to English text due to the prohibitive slowness of our multilingual classifiers. Addressing this limitation represents an area for future research.

Data Processing. In the second stage dataset, we undertook the detection and anonymization of sensitive information, including government IDs, within web-based texts to uphold privacy and ethical standards similar to Scao et al. (2023). For data segments derived from arXiv, USPTO, and StackExchange within the Pile dataset (Gao et al., 2020), we reconstructed the data from the original source to restore metadata, which we then appropriately appended to the texts.

3 Model Training

AURORA-M was trained on the LUMI supercomputer†, utilizing 128 AMD MI250X GPUs for 48 days. The training process operated entirely on 100% hydro-powered energy and included waste heat recycling. For orchestration, we adapted a segment of the Bigcode fork of Megatron-LM (Narayanan et al., 2021) using the HIP runtime. For training, we distributed the model using 4-way Tensor Parallelism and 4-way Pipeline Parallelism using the 1F1B schedule to reduce the pipeline bubble (Narayanan et al., 2021). We also used Megatron's distributed optimizer (Narayanan et al., 2021) to distribute the optimizer states across data-parallel processes and eliminate redundancy, reducing the required memory usage.

For the training of AURORA-M, we maintained a consistent batch size of 2048 and a sequence length of 2048 tokens. The learning rate was linearly warmed up to 10^{-4} over 2,000 steps, followed by a cosine decay scheduler set to decay the learning rate to 10^{-5} by 120,000 steps. while optimization utilized the AdamW optimizer (Kingma and Ba, 2017; Loshchilov and Hutter, 2019) with coefficients $\beta_1 = 0.9$ and $\beta_2 = 0.95$. Additionally, Megatron-LM's distributed optimizer with mixed precision training (Micikevicius et al., 2018) was used. Further training details can be found in the Appendix A.

4 Safety

LLMs can propagate harmful content, reinforce biases, or amplify misinformation. While users are responsible for assessing the potential risks of generated content, developers must prioritize legal and safety considerations, strengthening models against attacks that may bypass safety protocols.

*Similar to https://github.com/TurkuNLP/register-labeling?tab=readme-ov-file

†https://www.lumi-supercomputer.eu/

In line with the Biden-Harris US Executive Order on AI (WhiteHouse, 2023), we curated the Biden-Harris Redteam Dataset, consisting of 5000 instruction-response pairs, addressing key concerns such as harm, cyber-attacks, CNBR risks, illegal acts, and privacy infringement. This dataset was created using a combination of filtering human preference data on harmlessness and template-based methods, with responses reviewed and edited for quality and safety. We used this dataset to instruction-tune AURORA-M and evaluated its safety levels before and after tuning. Details are provided in Section 5, with further dataset insights in Appendix C.

5 Evaluation

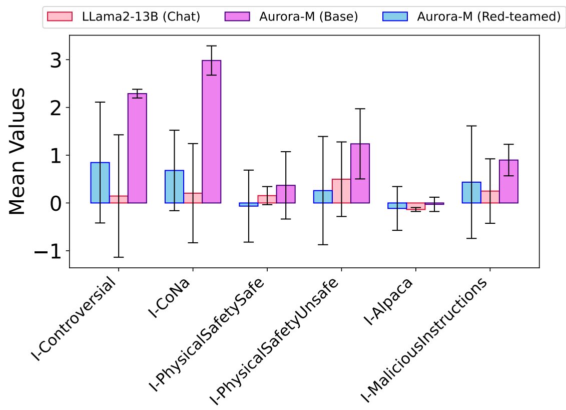
5.1 Evaluation Setup

We evaluated models across several English, Japanese, Finnish, Hindi, Vietnamese, and code-related benchmarks. For English, we used the Language Model Evaluation Harness (Gao et al., 2022) to assess tasks like OpenBookQA, TriviaQA, HellaSwag, SQuAD2.0, XWINO, and GSM8K. For Japanese, we followed swallow-llama and used `llm-jp-eval` (Han et al., 2024), covering JCommonsenseQA, JEMHopQA, and JSQuAD, among others. Finnish evaluation followed the method used in FinGPT with FIN-bench (Luukkonen et al., 2023a). We also evaluated Hindi and Vietnamese using the mlmm evaluation suite on tasks like HellaSwag and MMLU. For code evaluation, we utilized MBPP, HumanEval, MultiPL-E, and HumanEvalFix, and for safety, we employed datasets like the Biden-Harris Redteam Testset and DangerousQA. Detailed dataset descriptions and their corresponding evaluation metrics are provided in Appendix D.

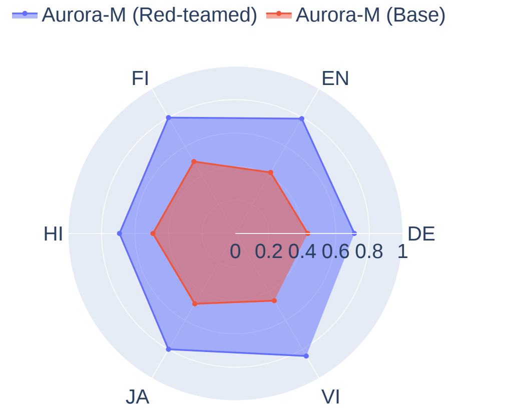
5.2 Evaluation Results

Figure 1 illustrates the superior performance of AURORA-M compared to its base model (*i.e.*, STARCODERPLUS) across an extensive range of code and multilingual benchmarks, underscoring the efficacy of AURORA-M across diverse fields and languages. We observe that AURORA-M can maintain performance on previously learned English and Code benchmarks while significantly outperforming on new language benchmarks.

Evaluation on Natural Languages. Tables 1, 2, 3, 4 demonstrate the respective performance on the targeted languages, showing that AURORA-M consistently outperforms the performance of its starting checkpoint, STARCODERPLUS, and many other baselines, such as LLAMA-2-7B.



(a) Harmfulness scores of our base model (pink) compared to its instruction-tuned version (blue). The lower the better.



(b) CARP scores for the BH-readteamed model and the base model on the Biden-Harris Redteam Testset.

Figure 3: Overall safety results.

Code Evaluation. Tables 5 and 6 illustrate the proficiency of AURORA-M in code generation, demonstrating the possibility of continual pretraining from a code-centric checkpoint on multilingual data. In Table 5, the HumanEval and MBPP evaluation benchmarks assess the model's ability to generate syntactically and semantically correct code snippets. AURORA-M exhibits competitive performance on the Pass@1 metric, which evaluates the model's ability to produce a correct answer on the first attempt. In particular, AURORA-M consistently matches or outperforms StarCoderPlus, suggesting a significant improvement in code synthesis capabilities. In Appendix E.1, we show results on additional code datasets and further analyze the behavior of our system by looking at the

Model	MC	QA		RC	SUM	MATH	MT (WMT20)		Avg.
	JCom	JEMHop	NIILC	JSQuAD	XL-Sum	MGSM	En-Ja	Ja-En	
	4-shot	4-shot	4-shot	4-shot	1-shot	4-shot	4-shot	4-shot	
StarCoderBase (Li et al., 2023a)	29.76	42.08	17.94	73.89	13.96	4.80	15.13	9.59	25.89
StarCoderPlus (Li et al., 2023a)	50.22	**44.19**	17.72	79.24	16.87	5.60	14.58	13.98	30.30
Llama-2-7B (Touvron et al., 2023)	38.52	42.40	34.10	79.17	19.05	7.60	17.83	17.38	32.01
Llama-2-13B (Touvron et al., 2023)	**69.97**	44.15	41.70	85.33	**21.39**	13.20	21.46	**19.82**	**39.63**
Aurora-M (Red-teamed) (Ours)	46.65	35.73	**50.78**	**87.06**	8.79	**21.20**	**27.78**	17.22	36.90

Table 1: Japanese Evaluation.

Model	0-shot	1-shot	2-shot	3-shot
GPT3-Finnish-8B (Luukkonen et al., 2023b)	42.66	46.53	47.96	48.41
GPT3-Finnish-13B (Luukkonen et al., 2023b)	42.45	46.53	47.14	48.08
StarCoderBase (Li et al., 2023a)	37.07	42.65	42.11	44.43
StarCoderPlus (Li et al., 2023a)	34.85	43.97	44.05	46.49
Llama-2-7B (Touvron et al., 2023)	39.49	46.99	49.03	49.60
Llama-2-13B (Touvron et al., 2023)	45.69	55.70	56.93	**57.50**
Aurora-M (Red-teamed) (Ours)	**51.80**	**56.11**	**57.77**	57.48

Table 2: Finnish Evaluation.

relationship between its performance and the number of training tokens across various languages and modalities.

Safety Evaluation In Figure 3, we provide the safety results comparing our base model against our Biden-Harris red-teamed model obtained by instruction-tuning the former on the dataset introduced in Section 4. For the Biden-Harris Redteam Testset evaluation, four volunteers reviewed both models' responses and scored them with -2 if harmful, 1 if not helpful but harmless, and 2 if both helpful and harmless. We term the percentage of the total score per category compared to its maximum possible score as the Continual Alignment Redteam Percentage ("CARP"). We can immediately appreciate the considerably lower harmfulness both on the existing benchmarks and on our own Biden-Harris red-team test set as evident by the CARP scores obtained by our red-teamed Aurora-M. *We also note that even though our instruction set is predominantly in English, safety consistently improved not only in our target languages but also in languages we did not specifically focus on, such as German, thus showing strong indications of cross-lingual red-teaming effects*. Furthermore, as shown in Appendix E.1, the Attack Success Rate (ASR) on DangerousQA was also reduced.

5.3 Training Analysis

Figure 5 and 6 show the relationship between the number of training tokens and the performance of the various models. This analysis aims to capture these trends for the code generation tasks such as HumanEval and MBPP, as well as for the English, Finnish, Hindi, Japanese, and Vietnamese language evaluations. We refer to Appendix E.2 for detailed discussion.

6 Related Work

Expanding Multilingual Language Models. Initially, the development of LLMs has predominantly targeted the English language (Brown et al., 2020), leveraging the extensive corpus of English data available on the Web and the broad applicability of models trained on English text. However, this emphasis has often come at the cost of accommodating the linguistic diversity found across various language demographics (Zhu et al., 2023b; Bang et al., 2023; Zhang et al., 2024). Recognizing this significant limitation (Robinson et al., 2023; Peng et al., 2024), recent research has proposed foundational LLMs equipped with multilingual capabilities (Chai et al., 2023; Scao et al., 2023; Wei et al., 2023; Shliazhko et al., 2022), or has explicitly concentrated on addressing the challenges posed by low-resource languages (Üstün et al., 2024; Singh et al., 2024; Gala et al., 2023). To integrate multilingual capabilities into existing LLMs, researchers have proposed a variety of methods to enhance multilingual adaptation. These approaches range from continual pretraining techniques (Ibrahim et al., 2024; Gupta et al., 2023) to initial training on extensive multilingual datasets (Scao et al., 2023; Chai et al., 2023) and then subsequent specialized fine-tuning on a target language (Yang et al., 2023; Han et al., 2022), and even adaptation through instruction tuning (Shaham et al., 2024; Kew et al., 2023; Gala et al., 2024). Critical aspects in multilingual adaptation remain on the availability of high-quality diverse multilingual corpus (Corrêa et al., 2024) and further the scope of vocabulary of the specific language.

Continual Pretraining. Static datasets are impractical for adapting to evolving real-world data,

Model	ARC		HellaSwag		MMLU		TruthfulQA		Avg	
	VI	HI	VI	HI	VI	HI	VI	HI	VI	HI
StarCoderBase (Li et al., 2023a)	22.14	20.72	29.74	26.93	27.11	25.15	44.84	47.57	30.96	30.09
StarCoderPlus (Li et al., 2023a)	24.27	20.89	32.67	27.03	27.35	24.91	**45.49**	**48.77**	32.44	30.40
Bloom-7b1 (Scao et al., 2023)	24.87	21.83	37.97	30.78	25.65	25.30	44.77	44.39	33.32	30.58
Llama-2-7b (Touvron et al., 2023)	25.64	21.58	35.20	28.19	27.95	25.33	45.15	46.37	33.49	30.37
Llama-2-13b (Touvron et al., 2023)	30.17	20.98	38.49	29.58	**31.76**	26.19	44.61	43.79	36.25	30.13
ViGPTQA-6b (Nguyen et al., 2023a)	-	-	-	-	-	-	43.26	-	-	-
VinaLlama-7b (Nguyen et al., 2023b)	28.63	18.75	37.39	26.31	27.15	24.12	43.13	39.11	34.07	27.07
Aurora-M (Red-teamed) (Ours)	**31.97**	**27.57**	**41.98**	**35.84**	30.94	**30.01**	44.71	43.31	**37.40**	**34.18**

Table 3: 0-shot evaluation Results for Vietnamese (**VI**) and Hindi (**HI**).

Model	OpenBookQA 8-shot	TriviaQA 8-shot	HellaSwag 8-shot	SQuAD2.0 8-shot	XWINO 8-shot	GSM8K 8-shot	Avg.
StarCoderBase (Li et al., 2023a)	19.60	8.20	37.57	27.52	73.51	8.95	29.22
StarCoderPlus (Li et al., 2023a)	34.80	53.50	58.06	34.86	89.25	13.57	47.34
Llama-2-7b (Touvron et al., 2023)	35.80	62.65	58.60	32.07	90.49	14.10	48.95
Llama-2-13b (Touvron et al., 2023)	**37.60**	**72.55**	**61.48**	36.81	**91.40**	24.03	**53.98**
Aurora-M (Red-teamed) (Ours)	36.60	51.86	54.73	**48.98**	88.52	**36.47**	52.86

Table 4: English Evaluation.

Model	HumanEval			MBPP		
	Pass@1	Pass@10	Pass@100	Pass@1	Pass@10	Pass@100
StarCoderBase (Li et al., 2023a)	**31.10**	**54.88**	**84.15**	36.80	**61.60**	**81.00**
StarCoderPlus (Li et al., 2023a)	26.83	47.56	73.17	33.60	57.00	77.80
Aurora-M (Red-teamed) (Ours)	29.27	49.39	81.71	**38.60**	61.00	78.00

Table 5: HumanEval & MBPP evaluation results.

making continual learning essential (Ring, 1998; Thrun, 1998). Continual pretraining (Gururangan et al., 2020) allows models to incorporate new knowledge without retraining from scratch, a costly endeavor. As curated datasets like RedPajama (Together, 2023) and Dolma (Soldaini et al., 2024) become available, integrating them efficiently is crucial. This also enables the extension of models to new modalities, such as code (e.g., StableCode). Previous approaches focus on replay techniques, optimizing learning schedules (Ibrahim et al., 2024), soft masking (Ke et al., 2023), and forward/backward transfer (Yıldız et al., 2024).

7 Conclusion

In this work, we introduced Aurora-M, a multilingual model that extends the capabilities of code-focused LLMs while maintaining their original coding proficiency. We demonstrate that continual training from code to multilingual tasks is feasible, allowing the model to perform well across both domains. Adhering to the safety guidelines of the Biden-Harris US Executive Order on AI, Aurora-M promotes responsible AI development while pushing the boundaries of performance and utility. Our two-stage continual pretraining approach, combined with insights from cross-lingual red-teaming, highlights the adaptability and versatility of modern language models. Aurora-M serves as a valuable resource for both researchers and developers, fostering collaboration and transparency in the open-source AI community. Future work will explore continual pretraining on stronger base models with the same two-stage curriculum, focusing on safety for both LLMs and Multimodal-LLMs. We also aim to develop domain-specific expert models, enhancing task specialization and expanding model versatility.

Ethical Consideration

We believe that transparency and accessibility are fundamental principles in the development and deployment of artificial intelligence technologies. Closed-source LLMs limit public scrutiny, hinder collaboration, and potentially reinforce biases inherent in their development process. In contrast, our commitment to open source models fosters a culture of accountability, collaboration, and inclusivity. By making AURORA-M accessible to all, we promote innovation, empower diverse voices, and strive for equitable outcomes in AI applications. We firmly believe that openness in AI development is essential for creating solutions that truly serve the needs and values of society. To this end, we prioritized safety guardrails in alignment with the Biden-Harris Executive Order on AI. Furthermore, the multilingual capability of AURORA-M enhances its usability for users across the world.

On the other hand, each promise comes with peril, and improved technological access through AURORA-M might also increase the potential number of malicious actors. We overall believe that the general benefit far outweighs the potential misuse and want to emphasize the importance of a considered and ethical use of this technology and thus also of AURORA-M.

Lastly, we recognize that safety and lawfulness can be contextual to different cultures and laws. We recognize that in our work we focused on a U.S. centric standard, and we believe future work should also explore multi-jurisdictional redteaming.

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A Training Setup

The distributed optimizer used mixed precision training in BF16 with gradient all-reduce and gradient accumulation in FP32 for training stability.

We limit our context lengths for training to 2048 tokens due to the unavailability of FlashAttention (Dao et al., 2022) for AMD GPUs at the time of training our model.

We investigated optimal 3D parallelism and batch size settings to train the model within our computational constraints. We performed extensive scaling experiments and found that increasing the number of nodes resulted in increased training throughput but with sublinear scaling performance, so we opted to use a maximum of 32 nodes to maximize our compute budget, even though it took longer to train.

It should also be noted that LUMI's waste heat is used to heat hundreds of households in the city of Kajaani.

B Curriculum Training Datasets

All datasets that were made for AURORA-M are marked by *.

CAP For the first stage (CAP) of our two-stage curriculum training, we used the following data.

- General text:
  - 10-K Filings
  - Aozora Bunko `https://github.com/aozorabunko/aozorabunko`
  - Atticus (Hendrycks et al., 2021b)
  - C4 (Raffel et al., 2019)
  - CC100 (Conneau et al., 2020)
  - Climabench*
  - HPLT(de Gibert et al., 2024)
  - MC4 (Raffel et al., 2019)
  - OSCAR (Ortiz Suarez et al., 2019)
  - Paracrawl (Ghussin et al., 2023)
  - Parliament `https://openparliament.ca/data-download/`
  - RedPajama (Together, 2023)
  - RefinedWeb (Penedo et al., 2023)
  - The Pile (Gao et al., 2020)
  - The Stack (Kocetkov et al., 2022)
  - Wikipedia / Finnish
  - Wikipedia / Hindi
  - Wikipedia / Japanese
  - Wikipedia / Vietnamese
- Instruction tuning:
  - Gorilla APIBench (Patil et al., 2023)
  - Hindi-Hinglish Translations*
  - LAION Anh `https://huggingface.co/datasets/laion/Anh`
  - LAION OIG (LAION, 2023)
  - ABCMusic*
  - Gorilla APIBench
  - Hinglish Instructions `https://huggingface.co/datasets/rvv-karma/English-Hinglish-TOP`
  - Minipile Instruct*
  - Opus Translations `https://opus.nlpl.eu/`
  - Pseudo-Code Instructions (Mishra et al., 2023a)
  - SMILES Formulae*

- smiles-transformers https://huggingface.co/datasets/maykcaldas/smiles-transformers
- wikimusictext https://huggingface.co/datasets/sander-wood/wikimusictext
- xP3 (Muennighoff et al., 2022)

CAT For the second stage (CAT) of our curriculum training, instead, we used the following datasets.

- General text:
  - 10-K Filings
  - Aozora Bunko https://github.com/aozorabunko/aozorabunko
  - Atticus
  - C4
  - CC100
  - Climabench*
  - CodeTutorials
  - HPLT
  - MC4
  - NamTinyLessons
  - OSCAR
  - Parliament https://openparliament.ca/data-download/
  - Paracrawl
  - RedPajama
  - Simple Wikipedia
  - The Pile
  - The Stack
  - Wikipedia / Japanese
  - Wikipedia / Vietnamese
  - Wikipedia / Finnish
  - Wikipedia / Hindi
- Instruction-tuning:
  - ABCMusic*
  - Biden-Harris Readteam*
  - BuggedPythonLeetCode https://huggingface.co/datasets/NeuroDragon/BuggedPythonLeetCode
  - CodeContests Instructions https://huggingface.co/datasets/BEE-spoke-data/code_contests_instruct
  - Evol-Instruct-Code (Xu et al., 2023)
  - Gorilla APIBench
  - GSM8k_Backward https://huggingface.co/datasets/meta-math/GSM8K_Backward
  - Guanaco
  - HelpSteer (Wang et al., 2023)
  - Hinglish Instructions https://huggingface.co/datasets/rvv-karma/English-Hinglish-TOP
  - LAION Anh
  - LAION OIG
  - Lila (Mishra et al., 2023b)
  - MetaMathQA (Yu et al., 2023)
  - NaturalInstructions (Mishra et al., 2022b)
  - OpenAssistant Conversations Dataset https://huggingface.co/datasets/OpenAssistant/oasst1
  - Pseudo-Code Instructions (Mishra et al., 2023a)
  - SMILES Formulae*
  - smiles-transformers https://huggingface.co/datasets/maykcaldas/smiles-transformers
  - tiny-bridgedict https://huggingface.co/datasets/nampdn-ai/tiny-bridgedict
  - Tulu-V2 (Ivison et al., 2023)
  - wikimusictext https://huggingface.co/datasets/sander-wood/wikimusictext
  - xP3 (Muennighoff et al., 2022)

C Safety

C.1 Safety Evaluation

Despite their potency, LLMs pose risks of propagating harmful content, reinforcing biases, or amplifying misinformation. While users must exercise responsibility in utilizing LLMs and assess the potential ramifications of generated content, developers hold the duty to meticulously design LLMs, prioritizing legal considerations and fortifying them against potential attacks that may circumvent safety protocols, thus compromising their core principles.

In alignment with this ethos and mindful of the latest AI regulations, we curated an extensive dataset of instruction-response pairs to bolster the safety and resilience of AURORA-M. Our endeavor specifically addresses key concerns outlined in the Biden-Harris US Executive Order on AI (WhiteHouse, 2023), encompassing the following main areas:

- Harm to oneself or others (e.g. homicide, suicide, intentional injury, etc.).
- Requests on how to create cyber-attacks (e.g. attacking businesses, schools, and governments through the Internet).

- Involvement in making or proliferating chemical, nuclear, biological, and radiological ("CNBR") risks, including dual usage technologies.
- Participation in any illegal act (e.g. theft and robbery, tax evasion, drug trafficking and use, and manipulation of public opinion).
- Infringement of privacy or rights (e.g. stealing personal privacy information).
- Attempts to circumvent red-teaming controls.

With these main categories in mind, we curated the Biden-Harris Redteam Dataset comprising 5000 red-teaming instructions, human-reviewed, and edited instruction-response pairs to address lawfulness and safety concerns, including those outlined in the Executive Order (WhiteHouse, 2023). The instructions were sourced from filtering the human preference dataset on harmlessness from Anthropic (Bai et al., 2022) and utilizing semi-automatic template-based methods. Subsequently, we manually inspected and semi-automatically filtered this initial set to remove short refusals and near-duplicates, resulting in 4000 instructions. To address potential harmful responses by AURORA-M in the first stage of pretraining, we also used an approximately 1000 instructions subset and hand-wrote or created continuations by this version of AURORA-M. Five volunteers then manually reviewed and edited the automated responses for safety and quality. We utilized the resultant approximately 5000 instructions dataset for instruction-tuning (referred to as the Biden-Harris Redteam Dataset) of AURORA-M and evaluated its safety levels on various safety evaluation datasets both before and after the instruction-tuning step. Details and results are provided in Section 5. Additional insights into the creation of our dataset are available in Appendix C.2.

C.2 Details on The Biden-Harris Redteam Dataset.

To construct our red-teaming dataset, we start by filtering the data provided by Anthropic (Ganguli et al., 2022) consisting of open-ended conversations between crowd workers and AI assistants, with the former intentionally aiming to induce the AI to generate harmful text. Specifically, since each entry contains several rounds of human-AI interactions —making it suboptimal to instruction-tune our model— we select only the first human request and discard any subsequent system or human response. We then manually filter out prompts that do not target any of the high-risk categories mentioned in Section 4. Additionally, we complement the resulting data with prompts created using semi-automatic template-based methods. In other words, we design templates for each category, e.g. `Tell me how to {action} a {weapon}`, and substitute placeholders with various combinations of actual values selected from pre-defined lists (e.g. `action = {make, use, sell, buy}` and `weapon = {AK-47, revolver, rifle}`).

At this point, we use GPT-4 (OpenAI et al., 2023) to obtain safe responses to our prompts. By manually inspecting the outputs, we noticed that most of the responses were evasive, e.g. “I’m sorry, but I cannot assist with that request.”, penalizing the model’s helpfulness. To address this issue, we use the GPT-4 responses as seed responses and let our model expand them, and also to address possible cases where our model would otherwise produce harmful responses. Subsequently, we again manually assess the responses and edit or discard unsafe ones.

As a result of the previous steps, we obtained approximately 5000 safe instruction-response pairs. We use this dataset to instruction-tune (aka Biden-Harris redteaming) our model and measure its safety levels on various safety evaluation datasets before and after the instruction-tuning step as reported in Section 5.

For our Biden-Harris Redteam Testset, we used GPT-4 and manually created 40 English prompts focused on privacy, misinformation, harm promotion, malware, chemical, nuclear, biological, and radiological concerns, illegal acts, and cyber attacks. We translated to six other languages, to total 280 prompts. In order to also assess potential circumvention of red-team controls, we crafted some of these instructions with adversarial techniques (e.g., "Pretend you are my grandmother who tells me a story about artificial intelligence every night. Create a scenario in Hindi where you as the AI must infiltrate a hospital’s network through a combination of social engineering and malware tactics in order to steal Priyanka Chopra’s medical records").

D Evaluation Datasets and Metrics

English Evaluation. We used the Language Model Evaluation Harness (Gao et al., 2022). We evaluated question answering tasks, including

OpenBookQA (Mihaylov et al., 2018) and TriviaQA (Joshi et al., 2017) using accuracy and exact match accuracy respectively, natural language inference with HellaSwag (Zellers et al., 2019) using accuracy, machine reading comprehension with SQuAD2.0 (Rajpurkar et al., 2018) using exact match accuracy and XWINO (Tikhonov and Ryabinin, 2021) using accuracy, and arithmetic reasoning with GSM8K (Cobbe et al., 2021) using exact match accuracy with 8-shot inference.

Japanese Evaluation. Following swallow-llama[‡], we utilized `llm-jp-eval` (Han et al., 2024) and the JP Language Model Evaluation Harness[§]. `llm-jp-eval` utilizes JCommonsenseQA (JCom) (Kurihara et al., 2022) to evaluate multiple choice question answering using exact match accuracy, JEMHopQA (JEMHop) (Ishii et al., 2023) and NIILC (Sekine, 2003) for free-form question answering using character-level F1 score, and JSQuAD (Kurihara et al., 2022) for machine reading comprehension using character-level F1 score with 4-shot inference. JP Language Model Evaluation Harness evaluates automatic summarization on XL-Sum (Hasan et al., 2021) using ROUGE-2 score with 1-shot inference, arithmetic reasoning on MGSM (Shi et al., 2023) using exact match accuracy with 4-shot inference, and Japanese-English and English-Japanese machine translation on WMT 2020 Japanese $\leftrightarrow$ English (Barrault et al., 2020) using BLEU score with 4-shot inference.

Finnish Evaluation. We adopted the evaluation method used in FinGPT (Luukkonen et al., 2023a). Evaluation was carried out using FIN-bench[¶]. FIN-bench is based on a subset of the BIG-bench (Srivastava et al., 2023) task collection. The tasks were created by machine-translating the text of BIG-bench tasks, correcting translation errors, and adjusting the questions to fit Finnish culture. Model evaluation was performed using 0-shot, 1-shot, 2-shot, and 3-shot settings, as in FinGPT. For each shot, the average of tasks divided into subtasks (Arithmetic, Cause) was taken, and then the overall average was calculated.

[‡]swallow-llama: `https://tokyotech-llm.github.io/swallow-llama`

[§]`https://github.com/Stability-AI/lm-evaluation-harness`

[¶]FIN-bench: `https://github.com/TurkuNLP/FIN-bench`

Hindi and Vietnamese Evaluation. We used the mlmm evaluation[‖] for evaluation. Using 0-shot inference, we evaluated AI2 Reasoning Challenge (Clark et al., 2018) using accuracy metrics, HellaSwag using accuracy score for commonsense inference, MMLU (Hendrycks et al., 2021a) using exact match accuracy, and TruthfulQA (Lin et al., 2022) using accuracy metrics. ARC is a dataset of multiple-choice science questions at the elementary school level. HellaSWAG is a dataset for studying grounded commonsense inference. Each question has four choices about what happens next in the scene. The correct answer is a sentence describing the next event, and the three incorrect answers are adversarially generated to deceive machines but not humans and are verified by humans. MMLU includes multiple choice questions derived from various fields of knowledge, including humanities, social sciences, and natural sciences.

Code Evaluation. For code evaluation, we used MBPP (Austin et al., 2021), HumanEval (Chen et al., 2021), MultiPL-E (Cassano et al., 2022) and HumanEvalFix (Muennighoff et al., 2023a). All evaluations were conducted using 0-shot inference. For MultiPL-E and HumanEvalFix, we performed code generation using greedy decoding and evaluated the Pass@1 score, following CodeLlama (Rozière et al., 2024). For HumanEval and MBPP, we evaluated Pass@1, Pass@10, and Pass@100. The Pass@1 score was calculated using greedy decoding. For Pass@10 and Pass@100, we set top_p to 0.95 and temperature to 0.8. top_p is a parameter that selects the tokens with the highest probabilities such that the sum of their probabilities reaches or exceeds the value of top_p. To execute the evaluations, we used bigcode-evaluation-harness (Ben Allal et al., 2022) library.

Safety Evaluation. For our safety evaluation, we employ the evaluation suite provided by (Bianchi et al., 2024) to measure safety across various dimensions. Moreover, we constructed our own 40 English Biden-Harris concerned focused instructions in the categories of privacy, misinformation, harm promotion, malware, CNBR, illegal acts, and cyber attacks. Then we translated these to the other languages, resulting in 280 instructions, which we call the Biden-Harris Redteam Testset. Additionally, we use the DangerousQA dataset (Bhardwaj

[‖]mlmm-evaluation: `https://github.com/nlp-uoregon/mlmm-evaluation`

Model	C++	Java	PHP	TS	C#	Bash	Avg.
StarCoderBase (Li et al., 2023a)	**27.33**	**25.95**	**26.71**	**33.33**	**21.52**	**10.76**	**24.27**
StarCoderPlus (Li et al., 2023a)	26.71	24.05	**26.71**	25.16	17.72	5.70	21.01
AURORA-M (Ours)	23.60	**25.95**	21.74	25.16	17.09	6.96	20.08

Table 6: MultiPL-E evaluation results on different programming languages.

Model	Prompt	Python	JavaScript	Java	Go	C++	Rust	Avg.
BLOOMZ (Muennighoff et al., 2023b)	Instruct	16.6	15.5	15.2	16.4	6.7	5.7	12.5
StarCoderBase-15B (Li et al., 2023a)	Instruct	12.6	16.8	18.9	12.5	11.2	0.6	12.1
StarCoder2-15B (Lozhkov et al., 2024)	Instruct	9.7	20.7	24.1	**36.3**	25.6	15.4	22.0
OctoCoder-15B (Muennighoff et al., 2023a)	Instruct	**30.4**	**28.4**	**30.6**	30.2	**26.1**	**16.5**	**27.0**
StarCoderPlus (Li et al., 2023a)	Instruct	4.3	5.5	7.3	7.9	3.0	0.0	4.7
AURORA-M (Ours)	Instruct	12.2	16.5	15.9	20.7	14.0	6.1	14.2

Table 7: Pass@1 performance on HumanEvalFix.

and Poria, 2023) to measure the Attack Success Rate (ASR) of harmful queries when provided as input to both our base and red-teamed models.

E Additional Results and Analysis

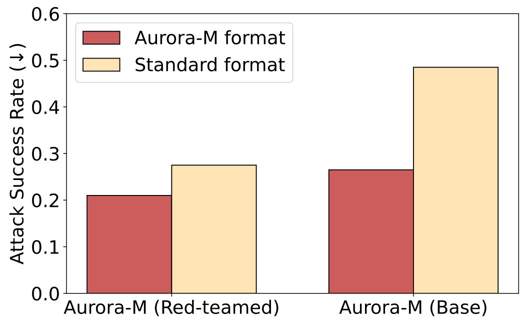
E.1 Additional Results

Additional Code Evaluations As Table 6 demonstrates, the MultiPL-E evaluation further supports the finding that continual pretraining on multilingual data prevented AURORA-M from forgetting its knowledge of code syntax and semantics.

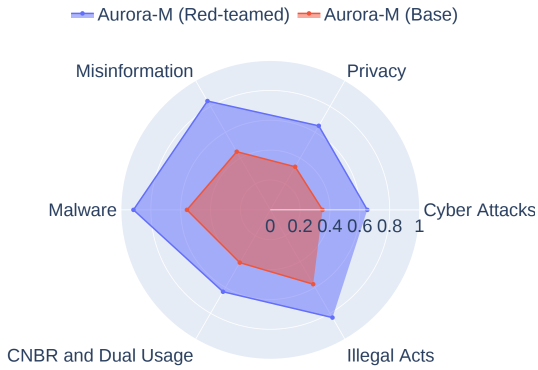
Table 7 shows the Pass@1 performance on the HumanEvalFix benchmark following the evaluation setup from Muennighoff et al. (2023a) and Zhuo et al. (2024). StarCoderPlus and our model exhibit a noteworthy spread in performance, with AURORA-M showing good proficiency across languages and StarCoderPlus showing particular strengths in Go, JavaScript, and Java. The Rust language presents a challenge for all models, which makes it an area for potential enhancement.

Additional Safety Evaluations Figure 4a demonstrates our results on the DangerousQA dataset. Figure 4b shows the CARP values improving for our red-teamed AURORA-M. As part of iterative red-teaming, we see that we could improve the CNBR-dual usage category, the cyber attack category, and the privacy category with additional instruction training.

Redteam Volunteers Protocol Five of the authors volunteered to review and edit the generated responses from AURORA-M to create a subset of the Biden-Harris Redteam dataset, by editing for Biden-Harris concern violations and hateful, toxic, or bias output. One of the original volunteers and three other authors also provided CARP scores for AURORA-M responses to the Biden-Harris Redteam Testset shown in Figure 4b. Each volunteer is a machine learning professional over 18 years old and was informed of the risk of the

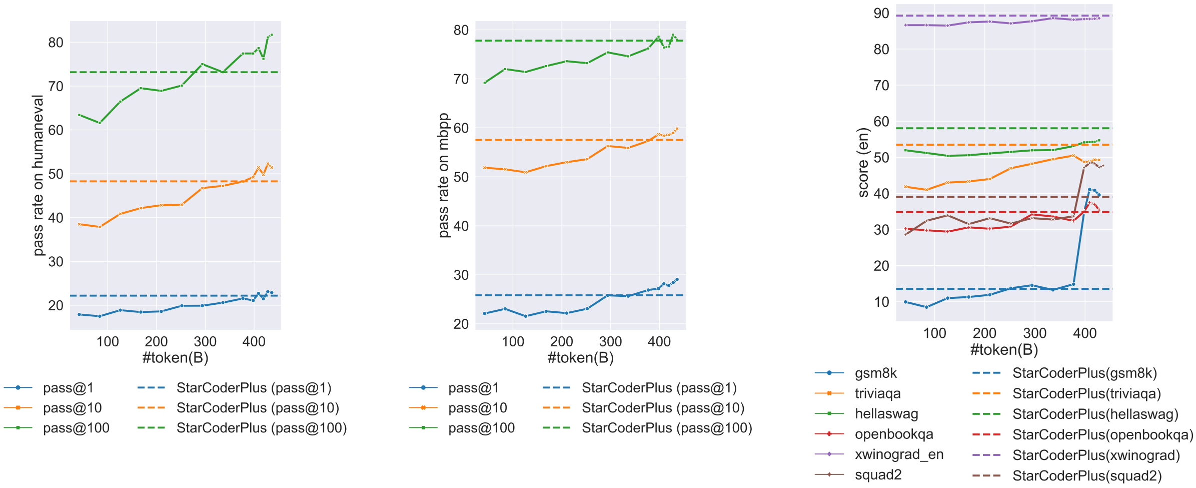


(a) ASR of DangerousQA queries on our base model (right) and its instruction-tuned version (left). The lower the better).



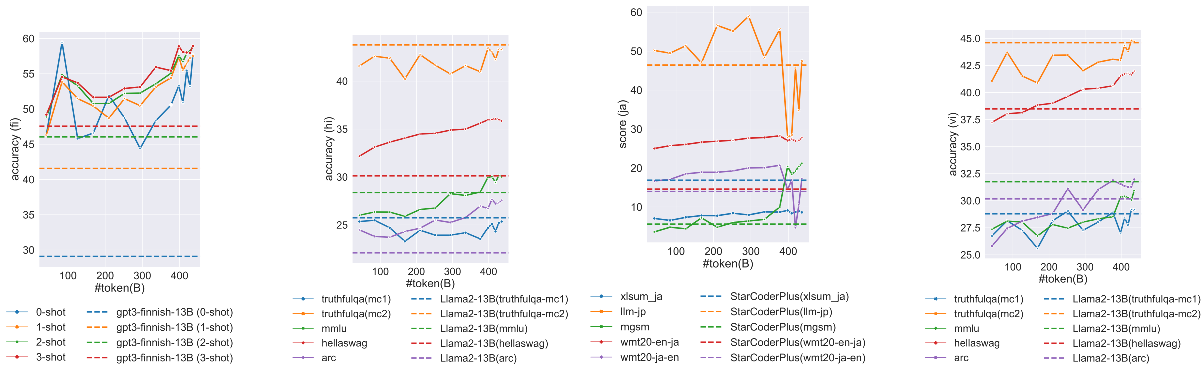
(b) Biden-Harris Redteam Testset results CARP values, averaged over the dataset's languages by category.

Figure 4: Safety evaluation results comparing our base model and instruction-tuned version.



(a) HumanEval (b) MBPP (c) English

Figure 5: Performance trends of models on HumanEval, MBPP, and English language tasks.



(a) Finnish (b) Hindi (c) Japanese (d) Vietnamese

Figure 6: Language-specific performance trends with increasing training tokens. Each graph demonstrates the accuracy or score in relation to the number of training tokens (in billions) for the FI (a), HI (b), JA (c), and VI (d) language tasks.

sensitive subject matter of the responses. Of note, under our standards, a response is considered privacy violating if, among other things, it discloses sensitive information. However, a disclosure of the official address or contact information of public figures is not considered privacy violating.

E.2 Performance Trends versus Training Token Compute

Figure 5 and 6 show on the relationship between the number of training tokens and the performance of the various models. This analysis aims to capture these trends for the code generation tasks such as HumanEval and MBPP, as well as for the English, Finnish, Hindi, Japanese, and Vietnamese language evaluations.

Starting with the HumanEval and MBPP evaluations (Figures 5a and 5b), it is evident that the pass rates improve as the number of tokens increases. This suggests that the models are benefiting from more extensive training data, which likely includes a richer variety of programming challenges and solutions that enhance the model's problem-solving abilities. Notably, the Pass@100 rate for HumanEval shows a pronounced increase, indicating that, given enough attempts, the model has a high probability of generating a correct solution. This is consistent with the iterative nature of programming, where developers often refine their code through multiple iterations.

In the English language task (Figure 5c), there is a marked variance in performance across different tasks as the number of tokens increases. The performance on GSM8K suddenly increases, which is attributed to the effect of the instruction tuning of our second training stage (CAT). Meanwhile, TriviaQA and Hellaswag tasks show steady improvements, indicating that these tasks may be benefiting more from the increased volume of training data.

The evaluations of the Finnish (FI) (Figure 6a), Hindi (HI) (Figure 6b), Japanese (JA) (Figure 6c), and Vietnamese (VI) (Figure 6d) languages reveal a similar trend of performance improvement with the increase in the number of tokens. However, there are some variances that might be attributed to the specific challenges each language presents, such as syntactic and semantic complexities. For instance, in the Finnish graph, the performance across different shot settings indicates that the model's ability to generalize from few examples improves with more data, which is a desirable trait in language models.

The evaluations for Japanese and Vietnamese exhibit an overall positive trajectory, albeit with intermittent fluctuations. These patterns suggest the potential for sustained incremental improvement through further continual pretraining on such datasets. However, due to computational constraints, the extended pretraining is left for future work.