Poro 34B and the Blessing of Multilinguality

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Abstract

The pretraining of state-of-the-art large language models now requires trillions of words of text, which is orders of magnitude more than available for the vast majority of languages. While including text in more than one language is an obvious way to acquire more pretraining data, multilinguality is often seen as a curse, and most model training efforts continue to focus near-exclusively on individual large languages. We believe that multilinguality can be a blessing: when the lack of training data is a constraint for effectively training larger models for a target language, augmenting the dataset with other languages can offer a way to improve over the capabilities of monolingual models for that language. In this study, we introduce Poro 34B, a 34 billion parameter model trained for 1 trillion tokens of Finnish, English, and programming languages, and demonstrate that a multilingual training approach can produce a model that substantially advances over the capabilities of existing models for Finnish and excels in translation, while also achieving competitive performance in its class for English and programming languages. We release the model parameters, scripts, and data under open licenses at `https://huggingface.co/LumiOpen/Poro-34B`.

1 Introduction

Neural language models based on the transformer architecture (Vaswani et al., 2017) have led to substantial advances in natural language processing. Encoder-only transformer models such as BERT (Devlin et al., 2019) have advanced the state of the art in a broad range of classification tasks, while decoder-only models such as GPT (Radford et al., 2018) have redefined what can be achieved by generative models, opening new areas of study in prompting and in-context learning. The success of these models is related in substantial part to their scaling properties: training larger models on more data leads to better results and even entirely new capabilities (Brown et al., 2020). Studies refining our understanding of the optimal balance of model size and training steps have increased the demands on data (Hoffmann et al., 2022b), and many recent models optimize further for inference-time efficiency by training smaller models on more data (Sardana and Frankle, 2023).

These developments have introduced increasing demands for textual data, with many recent models pretrained on a trillion tokens or more (e.g. Touvron et al., 2023; Almazrouei et al., 2023; MosaicML, 2023; Li et al., 2023; Lozhkov et al., 2024; Groeneveld et al., 2024). While such resources can still be assembled from internet crawls for a few of the languages best represented online, for the vast majority of human languages we have already run out of data for training the largest of language models (Joshi et al., 2020; Villalobos et al., 2022). While it is standard to repeat training data, repetition can lead to reduced sample efficiency and degradation of performance (Hernandez et al., 2022): Muennighoff et al. (2024) estimate that the value of repetition starts to diminish rapidly after four epochs and that repetition ceases to add information around 40 epochs. The availability of data is thus currently a limit for monolingual training for all but a few of the highest-resourced languages.

Multilingual training offers one obvious solution for increasing the amount of training data available, and a large number of multilingual transformer models have been introduced (e.g. Conneau et al., 2020; Lin et al., 2022b; Le Scao et al., 2022; Wei et al., 2023). However, despite the intuitive appeal of augmenting training data with texts in other nat-

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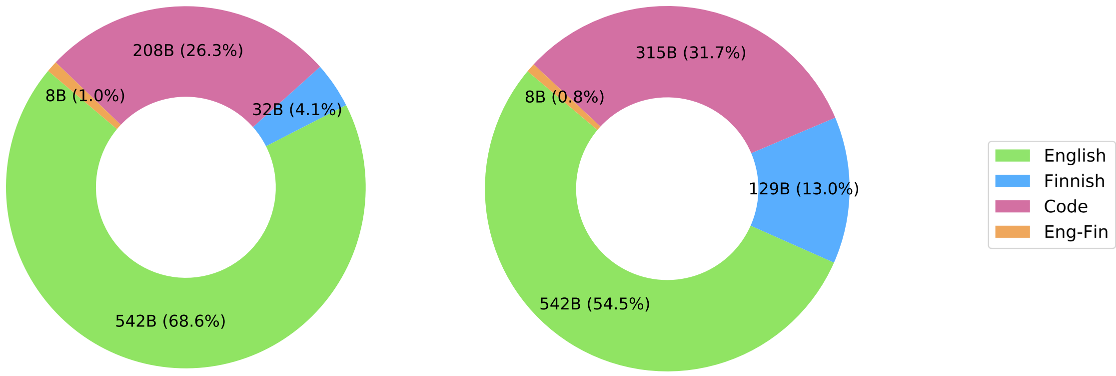

(a) Original (b) Sampled

Figure 1: Pretraining data distribution.

ural languages, multilinguality is frequently seen as a negative – commonly referred to as the *curse of multilinguality* (Conneau et al., 2020). While there have been studies of the tradeoffs between monolingual and multilingual training (Fujinuma et al., 2022; Chang et al., 2023) as well as efforts to enhance models specifically for multilinguality (Pfeiffer et al., 2022) and to introduce additional language capabilities to existing models (Gogoulou et al., 2023; Kew et al., 2023; Zhao et al., 2024; Ibrahim et al., 2024), state-of-the-art generative models are still frequently trained near-exclusively on large languages such as English, with only limited efforts specifically focusing on optimizing performance for smaller languages. In this study, we explore how to lift data limitations to create state-of-the-art large generative models from scratch for smaller languages, drawing on the understanding emerging in recent studies on how to make the most of limited data and assure that multilinguality is a blessing rather than a curse. Some key lessons from previous work include 1) **limited multilinguality** instead of a large number of languages (Conneau et al., 2020; Chang et al., 2023) 2) **matching scripts** (e.g., Latin) (Fujinuma et al., 2022) and 3) **matching language families** (Pyysalo et al., 2021), 4) incorporating a **cross-lingual signal** using translation pairs (Anil et al., 2023; Wei et al., 2023), 5) **oversampling target language** data up to four epochs (Muennighoff et al., 2024) and 6) augmenting natural language with **programming language data** (Madaan et al., 2022; Aryabumi et al., 2024).

We chose to specifically target the Finnish language, which is an interesting case for study as it is a Uralic language with no large close neighbours in its language family, necessitating more distant transfer than, for example, between English and another Germanic language. While the language is natively spoken by under six million people, its resources are still sufficient to consider a monolingual training approach for larger generative models. In a recent study, Luukkonen et al. (2023) combined several web crawls and curated sources of Finnish to create a dataset of approximately 40B tokens and introduced the monolingual FinGPT models trained from scratch for 300B tokens. With approximately 8 epochs, the repetition of data is expected to show diminishing returns (Muennighoff et al., 2024), and the largest of these models show signs of data limitations, with the 8B parameter model outperforming the 13B in benchmarks. We believe it should be possible to overcome these limitations by applying the lessons listed above. While we cannot match language families, we train for four epochs over the Finnish data and augment it with both English and programming language data as well as an explicit cross-lingual signal from translation pairs. We pursue this approach to create Poro 34B, training a 34B parameter model for a total of 1T tokens – 25 times more than the available Finnish data – and evaluate the model in detail on Finnish, English, and programming language tasks. We find that the model not only achieves the goal of substantially advancing over the performance of existing Finnish models, but is also competitive in its class of open models on English and code as well as remarkably strong in translation tasks.

2 Pretraining data

For pretraining Poro 34B, we rely on datasets that have been previously preprocessed to remove low-quality texts and boilerplate, filter toxic context, and deduplicate repeated texts. We illustrate the pretraining data distribution in Figure 1 and describe the data briefly in the following. Data sources are detailed in Table 4 in the Appendix.

Finnish For Finnish pretraining data, we draw on the resources recently introduced by Luukkonen et al. for creating the FinGPT model family. We exclude the *ePub* and *Lehdet* resources provided by the National Library of Finland for that work as they could not be shared due to copyright limitations, but use the remaining sources of data, totalling to a 32B token monolingual corpus. The majority of the Finnish data originates from web crawls (approx. 84%) complemented with news sources (approx. 2%), Project Lönnrot, the Finnish equivalent of Project Gutenberg copyright-free book corpus (approx. 0.5%), Wikipedia (approx. 0.5%) and Finnish online discussion forum contents from Reddit and Suomi24 (approx. 13%). Following the rule of thumb proposed by Muennighoff et al. (2024), we upsample the 32B tokens of Finnish so that four epochs over the data are made during training. Consequently, approximately 13% of the total tokens seen in pretraining are Finnish.

English For English pretraining data, we primarily use SlimPajama (Soboleva et al., 2023), a cleaned and deduplicated subset of the RedPajama corpus[1] (Together Computer, 2023), from which we excluded data from the books category due to their copyright status. We supplemented this dataset with the Project Gutenberg public domain books data from the Dolma corpus[2] (Soldaini et al., 2024). We train for one epoch over the 542B tokens of the English data, which thus represents slightly over half of the 1T total training tokens.

Programming Languages To introduce data representing various programming languages (referred to hereinafter as "code" for short) into our pretraining, we make use of the Starcoder corpus (Li et al., 2023), a processed subset of The Stack corpus[3] (Kocetkov et al., 2023). The original corpus consists of 208B tokens, which we oversample 1.5x so that approximately a third of the tokens seen during pretraining represent code.

Cross-lingual data We introduce a cross-lingual signal into pretraining by including translation examples from OPUS (Tiedemann, 2009). Specifically, we use the English-Finnish examples from the Tatoeba dataset (Tiedemann, 2020) to generate instruction-formatted translation examples. The Tatoeba training data was reformatted into a minimalistic instruction-following format by recasting each English-Finnish translation pair into a document with the following format:

```
<|user|>Translate into Finnish: {{en}}
<|assistant|>{{fi}}
```

Where `{{en}}` and `{{fi}}` are the English and Finnish texts (resp.) of the translation pair. We additionally reverse the translation order (i.e., Finnish to English instead of English to Finnish) for a total of two documents for each sentence pair. No weighting is applied to the approximately 8B tokens of cross-lingual data, which thus represents slightly under 1% of the pretraining tokens.

3 Methods

In this section, we describe the method used to create the Poro 34B tokenizer, the pretraining setup, and provide an estimate of the compute cost of pretraining the model.

3.1 Tokenization

The choice of tokenizer has a broad range of impacts, not only on the efficiency of training and inference but also the capabilities of trained models (Rust et al., 2021; Petrov et al., 2023; Ali et al., 2023). As we were not aware of any existing tokenizer that would be a good fit for our combination of languages and code, we created a new tokenizer for our model. Specifically, we trained a custom byte-level BPE tokenizer using the same pre-normalization as the FinGPT tokenizer. We selected a vocabulary size of 128K tokens, aiming to achieve low fertility on the targeted languages while keeping the vocabulary reasonably small. The tokenizer was trained on a uniform distribution of samples of the Finnish, English and code datasets.

We assess the fertility of the tokenizer on the English and Finnish sentences from the devtest portion of the widely used Flores-101 benchmark for machine translation (Goyal et al., 2022), which allows for a degree of cross-lingual comparability. For code, we use an approximately 1M character sample of lines from the Starcoder held-out test

[1]https://huggingface.co/datasets/togethercomputer/RedPajama-Data-1T

[2]https://huggingface.co/datasets/allenai/dolma

[3]https://huggingface.co/datasets/bigcode/the-stack

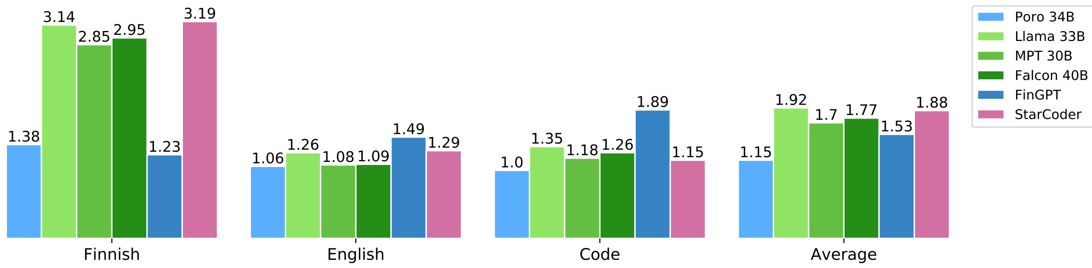

Figure 2: Tokenizer fertility comparison (lower is better).

data.[4] Figure 2 provides a comparison of the fertility of the tokenizer compared to selected reference tokenizers (see Section 4). We find that on this data the new Poro 34B tokenizer has at least broadly comparable fertility to the lowest-scoring tokenizer on each of Finnish, English, and code, as well as the lowest average fertility of the compared tokenizers.

3.2 Pretraining

We next briefly present the key model and training parameters (detailed in Table 5 in the Appendix A.1) and the pretraining software and configuration.

Architecture Poro 34B is a decoder-only model with a parameter count of 34 billion, sharing its architecture with FinGPT (Luukkonen et al., 2023) and BLOOM (Le Scao et al., 2022). It incorporates layer normalization immediately following the input embedding layer for better training stability and uses ALiBi (Press et al., 2021) as its positional encoding method. The model consists of 54 layers with a hidden dimension of 7168 and a total of 56 attention heads.

Training We train to 1T tokens, intentionally exceeding the Chinchilla compute-opimality estimate (Hoffmann et al., 2022a) of approximately 700B tokens for a model of this size, thus gaining inference-time efficiency for the cost of additional compute investment in pretraining (Sardana and Frankle, 2023). We train with a sequence length of 2048 tokens[5] using a cosine learning rate scheduler with a maximum learning rate of 1.5e-4, decaying to a minimum of 2e-5 over 990B tokens, and a linear warmup of 10B tokens. Our global batch size is 2048 samples totaling to 4194304 tokens per optimization step.

Software Poro 34B was trained on the LUMI supercomputer GPU partition, which is powered by AMD MI250X GPUs. The majority of open source frameworks for large language model pretraining are made to be primarily NVIDIA-compatible, and we required scalable AMD-compatible training software. Thus, we adopted the Megatron-DeepSpeed fork[6] introduced by (Luukkonen et al., 2023), which has optimized kernels converted from CUDA to be compatible with AMD ROCm, and has been demonstrated to be a viable solution for large model pretraining on LUMI. The hardware used to train the model is described in detail in Appendix A.3.

Configuration Considering the hardware available and the selected hyperparameters such as batch size, a configuration of 128 nodes was chosen for the training of the model, resulting in a world size of 1024. The training was done using activation checkpointing, a micro batch size of 1, gradient accumulation of 16, and a 3D parallelism strategy of tensor parallel degree 2, pipeline parallel degree 4, resulting in a data parallel degree of 128. This allowed total training cycle throughput of 49618 TFLOPs and 174378 tokens/second.

3.3 Compute cost

Following (Groeneveld et al., 2024), we estimate the carbon footprint of our pretraining by multiplying the theoretical upper bound of the total power used by the GPUs when they are utilized at 100% with the carbon intensity factor of LUMI. Taking into account the systems's power usage effectiveness (PUE) value of 1.04,[7] we approximate the total power consumption to be 448MWh. As LUMI is

[4] We only sample lines with at least 10 alphabetic characters to avoid very short lines.

[5] We acknowledge that this can be considered limiting by today's standards, but this limitation can be relieved by methods for extending the context length, for example via linear extrapolation (Press et al., 2021) or interpolation (Al-Khateeb et al., 2023).

[6] `https://github.com/TurkuNLP/Megatron-DeepSpeed`

[7] https://www.lumi-supercomputer.eu/sustainable-future/

powered by fully renewable electricity, we assume the carbon intensity factor to be 0.[8] This brings our emissions to a total of 0 $\mathrm{tCO_2eq}$. It is important to note that we only take into account power consumption of the GPUs used, as the consumption of the entire node was not logged during training.

4 Evaluation

We thoroughly analyze the capabilities of the model for Finnish, English and code, first briefly reporting perplexity results and then focusing on community-standard benchmarks for evaluating generative models. We then assess the quality of Finnish text generated by the model and finally evaluate the model's translation capability from English to Finnish (and vice versa). For comparison, we include results for the state-of-the-art Finnish language models, FinGPT 8B and FinGPT 13B (Luukkonen et al., 2023), and a selection of similarly-sized general-purpose open source base language models trained on broadly comparable numbers of tokens for English[9]: Llama 33B (Touvron et al., 2023), MPT 30B (MosaicML, 2023), and Falcon 40B (Almazrouei et al., 2023). We also provide results for StarCoder base (Li et al., 2023) as a reference for performance on code tasks.

4.1 Data and experimental setup

We assess the perplexity of the model on the same data used to evaluate tokenizer fertility (Section 3.1), namely Flores-101 devtest English and Finnish and a sample of the StarCoder test data. As token-level perplexity is dependent on tokenization, it cannot be used to directly compare models with different tokenizers. We therefore report character-level perplexity PPL_c following Ekgren et al. (2022), normalizing by character rather than token count when calculating perplexity.

We benchmark the capabilities of the model in Finnish using the FIN-bench[10] dataset (Luukkonen et al., 2023), which covers a variety of tasks to assess various aspects of model capabilities in Finnish, combining selected tasks translated and manually corrected from English BIG-bench (Srivastava et al., 2022) with additional Finnish tasks. We evaluate all FIN-bench results in a 3-shot setting using the standard metrics defined for the benchmark. For English evaluations, we use LM Eval Harness (Gao et al., 2023) to evaluate with the following datasets: ARC Challenge (Clark et al., 2018), GSM8K (Cobbe et al., 2021), HellaSwag (Zellers et al., 2019), MMLU (Hendrycks et al., 2021), TruthfulQA (Lin et al., 2022a), and Winogrande (Sakaguchi et al., 2019). We selected these evaluations based on their use as English language benchmarks by Beeching et al. (2023) and use an identical testing configuration here. Programming language proficiency is assessed via the Bigcode Evaluation Harness (Ben Allal et al., 2022) with the HumanEval (Chen et al., 2021), and MBPP (Austin et al., 2021) benchmarks, employing the pass@10 metric for evaluation.

To evaluate the quality of Finnish text generation, we generate responses to the translated MT-Bench questions with few-shot prompting (Zheng et al., 2023). We use a few-shot prompt because this benchmark is designed for chat models and we are evaluating base models. Moreover, we want to unlock the Finnish generation capabilities of the English-focused models by providing in-context examples in Finnish. We use GPT-4 Turbo and human judges to assess the quality of the responses. Finally, to evaluate translation performance, we use both the Flores-101 devtest (Goyal et al., 2022) as well as the Tatoeba test sets (Tiedemann, 2020) in an 8-shot setting, following Zhu et al. (2023).

4.2 Perplexity

Table 1 summarizes the results of the perplexity evaluation as mean character-level perplexity PPL_c for various models over the sentences/code lines. We find that Poro 34B has comparatively low (good) PPL_c on all three datasets, including the best result for Finnish. Poro 34B is to the best of our knowledge the only open model specifically trained for this combination of languages, and it is thus not surprising that it has the best overall average in this evaluation. While perplexity is not necessarily predictive of downstream performance and these datasets only represent a part of the relevant distribution, the result suggests that the model has learned all of its target languages well.

[8] We acknowledge that this assumption can be contested. As (Groeneveld et al., 2024) note: "LUMI is powered entirely by hydroelectric power and some sources (Ubierna et al., 2022) measure the carbon intensity factor of hydroelectric power to be 0.024."

[9] We chose English models of similar size and training token budget rather than state-of-the-art models to more directly assess the effects of our multilingual training setup on performance in English.

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

	Poro 34B	Llama 33B	MPT 30B	Falcon 40B	FinGPT 8B	FinGPT 13B	StarCoder
Finnish	**1.89**	2.98	2.89	3.57	1.94	1.92	3.83
English	1.87	**1.81**	1.89	1.85	2.55	2.46	2.38
Code	3.21	4.27	3.58	3.65	25.1	27.3	**3.15**
Average	**2.32**	3.02	2.79	3.02	9.86	10.6	3.12

Table 1: Character-level perplexity for Poro 34B and selected reference models (lower is better).

	Poro 34B	Llama 33B	MPT 30b	Falcon 40B	FinGPT 8B	FinGPT 13B	Starcoder
Finnish	**66.28**	53.36	53.22	42.58	49.69	48.92	45.55
English	50.57	**59.96**	52.62	49.87	31.47	32.85	35.44
Code	41.80	37.67	39.18	38.57	-	-	**49.06**

Table 2: Average benchmark results for Finnish, English and code for Poro 34B and selected reference models.

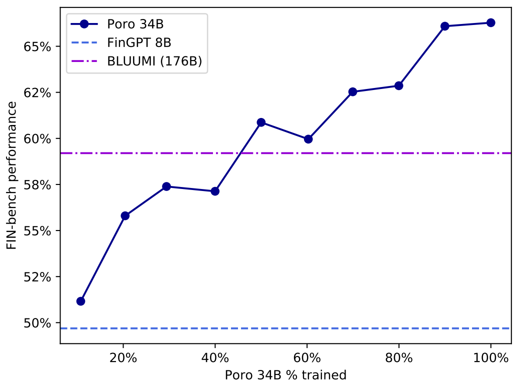

Figure 3: Poro 34B performance progression on FIN-bench. For reference, dotted lines show results for the best-performing monolingual FinGPT model and the massively multilingual BLUUMI model (Luukkonen et al., 2023), an extension of BLOOM (Le Scao et al., 2022) with Finnish.

4.3 Benchmark results

The overall results of the benchmark evaluations are summarized in Table 2 and detailed in Appendix A.2. We find that Poro 34B is the best-performing model for Finnish in this comparison, substantially outperforming the best previously introduced monolingual Finnish model. We further analyzed the progression of the Finnish capabilities by evaluating Poro 34B checkpoints at 10% intervals on FIN-bench. These results are summarized in Figure 3. Interestingly, the model outperforms the best FinGPT model already after 100B tokens of training (10%) despite the relatively small proportion of Finnish in the Poro 34B data and the fact that the FinGPT models were trained on 300B tokens in total. These results indicate that our limited multilingual approach is effective for creating stronger models for Finnish than possible through monolingual training and demonstrate that the model is benefiting substantially from its training data in other languages even when tested on Finnish tasks.

For English, we find that the model achieves broadly comparable results to the MPT 30B and Falcon 40B models, both of which were trained for 1T tokens of predominantly English data. This indicates that the limited multilingual training approach has not notably detracted from the English capabilities of the model. The best-performing open model in this comparison is Llama 33B, which was trained for longer (1.4T tokens), also predominantly on English data. We find that Poro 34B is nevertheless a capable model in its class also for English, despite not optimizing specifically for English performance. The programming language benchmarks indicate that Poro 34B is more capable on code than the other natural language-focused models, while the code-focused StarCoder model clearly outperforms all of the other models. We attribute the relatively high performance of Poro 34B on code to the comparatively large proportion of the training data dedicated to code. As with English, we consider the performance of the model on code a positive addition even though code generation was not a primary goal in creating the model.

Finally, we note a surprising finding arising from the Finnish evaluation: two of the larger English-focused models (Llama 33B and MPT 30B) score higher than the previously introduced smaller monolingual Finnish models on the FIN-

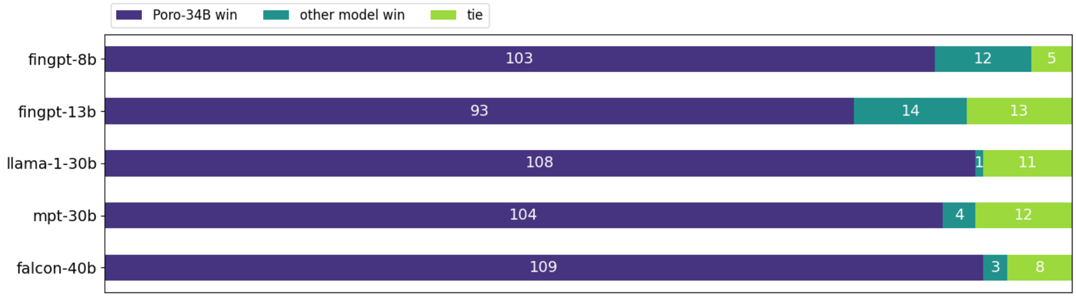

Figure 4: Win counts of reference models against Poro 34B on Finnish MT-Bench as judged by GPT-4 Turbo.

bench benchmark. While FIN-bench tasks are in Finnish, the benchmark consists of multiple-choice rather than generation tasks, has been produced in substantial part through translation from English, and includes tasks with little emphasis on natural language (esp. arithmetic). We hypothesize that the comparatively high performance of the English-focused models on this benchmark might not indicate that they can generate fluent Finnish, which also calls the Finnish proficiency of Poro 34B into question. We study this question specifically in the following section.

4.4 Open-ended generation

To assess the ability of the models to generate coherent and grammatically correct Finnish, we create a Finnish version of MT-Bench (Zheng et al., 2023), a benchmark for open-ended conversations that uses LLM-as-a-judge evaluation. We excluded math and coding questions to focus specifically on the natural language generation capabilities of the models. To create the benchmark, we initially translated the questions into Finnish using DeepL,[11] and the translations were then manually corrected by native Finnish speakers to create the final evaluation dataset. To evaluate base models using the data, we similarly translated and corrected the few-shot URIAL prompt (Lin et al., 2024). [12] We use pairwise judging to compare between Poro 34B and the competing models' responses and use GPT-4 Turbo as the judge model.

To assess the reliability of the model as a judge and provide further insight into the quality of the generations, we additionally set up an annotation platform where two native Finnish speakers were asked to pick a preference between a response generated by Poro 34B and a competing model.[13] The judges are given the same judging prompt as GPT. The model names are hidden from the judges, and we randomly select the position of each response in every response pair to account for positional bias.

We found that the two human judges highly agree with each other, picking the same winner 88.8% of the time, and found an even higher agreement between GPT and each human judge: 91.6% between annotator 1 and GPT and 89.5% between annotator 2 and GPT. Figure 4 shows the win counts of the reference models against Poro 34B as judged by GPT-4 Turbo.

In manual analysis after the initial annotation, we found that the FinGPT models often struggled with the few-shot format, failing to follow questions or only giving short, minimal answers, while Poro 34B was better able to comply with questions and given requirements, such as listing a specified number of items. However, we found that Poro 34B also often hallucinated and did not follow all instructions, and we would not consider its responses to be at a level of consistency and quality required for user-facing applications, which is not an unexpected result given that it is a base model not specifically fine-tuned or otherwise aligned for such use. Despite outperforming FinGPT models on the FIN-bench benchmark, The English-focused models appeared to be unfit for Finnish generation: their generations had the surface appearance of Finnish text but were largely nonsensical and incoherent. This result underlines the need to include multiple perspectives when evaluating models: a high score on a multiple-choice benchmark may not indicate practical capability to generate coherent text in a language.

[11] https://www.deepl.com

[12] We did not modify the judge prompts as previous work has found that keeping the prompt in English produces better results (Ahuja et al., 2023).

[13] We did not separately compensate the human judges as they are co-authors of this paper.

We make the Finnish MT-Bench available under an open license and provide the model generations at `https://github.com/LumiOpen/FastChat/tree/main/fastchat/llm_judge`.

4.5 Translation

General-purpose language models have shown promising results on translation benchmarks on multiple languages (Vilar et al., 2023; Garcia et al., 2023; Alves et al., 2024). Following Zhu et al. (2023), we evaluated Poro 34B for English to Finnish translation and vice versa on the first 100 sentences of the Flores-101 test data by prompting the model with eight translation examples sampled randomly from the development set, formatting the examples simply as `<src>=<trg>`. We further evaluated Poro 34B and three strong open-source translation models on the Tatoeba test set with more than 11,000 sentences: OPUS-MT (Tiedemann and Thottingal, 2020), NLLB-1.3B (Costa-jussà et al., 2022), and M2M-100-12B (Fan et al., 2021)[14]. We used the standard SentencePiece BLEU (spBLEU) as our metric. The results of both evaluations are shown in Table 3.[15] These results demonstrate that Poro 34B is a remarkably strong translator, outperforming not only dedicated open-source translation models but even Google Translate, and scoring roughly on par with GPT-4 in this evaluation. We attribute this result to the combination of strong Finnish and English capabilities and the inclusion of a comparatively large number of translation examples in the pretraining data.

It should be noted, however, that the Tatoeba and Flores sentences are relatively short and simple, and this evaluation does thus not capture the full picture of the translation capabilities of the evaluated models. We aim to assess the translation capability of Poro 34B more comprehensively on longer texts, especially texts that might include different modalities such as tables and code, in future work.

	Flores-101		**Tatoeba**	
Model	**En-Fi**	**Fi-En**	**En-Fi**	**Fi-En**
ChatGPT	33.4	35.9	-	-
GPT-4	35.3	**40.2**	-	-
Google	37.3	39.0	-	-
M2M-12B	33.3	33.8	36.7	41.3
NLLB-1.3B	30.0	35.4	40.2	55.7
OPUS-MT	37.2	35.6	46.7	58.4
Poro 34B	**37.6**	39.8	**47.3**	**60.5**

Table 3: spBLEU on the Flores-101 devtest and Tatoeba test sets. Flores-101 results except for OPUS-MT and Poro 34B are from Zhu et al. (2023).

5 Discussion and conclusions

In this study, we have considered the challenges that the availability of data poses for pretraining large generative models for smaller languages and explored a limited multilingual approach to create Poro 34B, a 34B-parameter model trained on 1T tokens of Finnish, English, and code, including 8B tokens of Finnish-English translation pairs. We thoroughly evaluated the model and found it to substantially advance over the performance of existing models for Finnish while also performing competitively in its class of open models for English and code generation, as well as achieving remarkably good results in translation tasks. Two human judges and GPT-4 Turbo found the texts generated by Poro 34B to be superior to the competing models.

Our model architecture and the Finnish datasets included follow those of the FinGPT family of monolingual Finnish models, which were constrained by the available Finnish training data. The superior performance of our model in Finnish evaluations demonstrates that multilingual training can lift such limitations, allowing further scaling of models focused on smaller languages. In future work, we hope to explore this effect more systematically to answer some of the many questions that remain open regarding the training of large generative models for smaller languages, including the impacts of covering multiple smaller languages and the effect of the size of data available in the target languages.

A number of the choices made in training Poro 34B were made with incomplete information regarding their specific impacts on the final model. For example, we opted to include a comparatively large amount of programming language data as well as instruction-formatted translation examples in the pretraining data, the latter on the assumption

[14] We did not evaluate the GPT models and Google Translate on Tatoeba because of the associated API costs.

[15] We attempted to reproduce some of the Flores-101 results reported by (Zhu et al., 2023) and obtained a slightly higher result for GPT-4 in Eng-Fin translation (37.5 instead of 35.33) and slightly lower results for M2M-12B and NLLB-1.3B (31.4 and 26.6, respectively). For the sake of consistency, we present the results from that study without modification.

that this would provide a cross-lingual signal that would strengthen the ability of the model to benefit from data in a more distantly related language (English). While this approach is intuitively appealing and the performance of our model suggests that it has at a minimum not notably detracted from the capabilities of the model, we did not as part of this work have the resources to conduct ablation studies nor to explore alternative ways to incorporate cross-lingual information in pretraining. We aim to study these questions further in future work.

We hope that our approach can serve as a template for the creation of larger models for other smaller languages and that the model introduced in this work can serve as both as a focus of research in its own right as well as a starting point for further pretraining, finetuning and alignment to create useful models, tools and methods not only for Finnish but also other languages. We release the model weights as well as all relevant documentation and software fully openly at `https://huggingface.co/LumiOpen/Poro-34B`.

Limitations

Our study applies a pretraining recipe that combines insights on effective multilingual and data-constrained model training from a variety of previous studies. While the findings of these studies are supported by a broad range of relevant experimental results, we did not have the resources to perform separate ablation experiments specifically assessing the impact that various parts of our combined pretraining recipe (e.g., four repetitions of target language data and the inclusion of a translation signal) have on the resulting model. Thus, while we believe that our results demonstrate the pretraining recipe to be effective for creating state-of-the-art models for data-constrained languages, our work is limited in leaving many questions open regarding specific choices that form part of that recipe.

Poro 34B is a base model and as such has not been aligned to follow instructions and engage in conversations. It has not been evaluated on safety and toxicity benchmarks. As we have noted in our language generation evaluation, Poro 34B does not adequately follow instructions and has the tendency to generate texts with hallucinations. Further research is needed to improve the model in terms of factuality, safety, and alignment in English and Finnish. We encourage developers using Poro 34B to be aware of the potential risks associated with LLMs such as non-factual outputs, harmful language, and perpetuation of biases and stereotypes. We recommend that developers finetune Poro 34B to meet their specific needs and codes of conduct.

Ethical considerations

We are committed to open science, transparency and accessibility in our work. While we acknowledge the concerns and the potential for negative impacts associated with making powerful generative models and the technology to create them more widely available, we believe that in the case of Poro 34B the positives clearly outweigh the negatives. We discuss some specific concerns and their mitigations in the following.

Poro 34B is a base model trained in substantial part on texts sourced from web crawls, which are known to include biases, toxicity and factual errors. While we have selected curated text sources that have been extensively filtered to remove problematic material, no such filtering is perfect. Like all language models, Poro 34B is a product of its inputs, and its output may reflect issues in its training material. Furthermore, as Poro 34B is a base model that has not been finetuned for any specific purpose, extra care should be taken when interpreting its output, and the model should not be used as is in any application with potential for significant impact on people's rights or well-being. We emphasize these limitations in the model card published with the model.

Pretraining large language models is computationally intensive, and the creation of large models can have substantial environmental impacts. Poro 34B was trained on the LUMI supercomputer, which is powered entirely by renewable energy resources. According to the official specifications, the carbon intensity factor of LUMI's operation is considered to be zero. This approach effectively minimizes the carbon footprint associated with the computational aspects of training our model.

Though concerns about the capabilities of frontier models to cause catastrophic harm have been discussed in the literature, a model of Poro 34B's size and training duration does not represent new frontier capability and releasing the model does not introduce any new classes of risk.

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A Appendix

A.1 Training details

It has been our aim throughout this work to release Poro 34B fully openly, including model weights, pretraining configuration, the pretraining and evaluation data, and all associated scripts and tools. We provide here additional details of these to facilitate accurate reproduction of our work. The pretraining data sources are detailed in Table 4, and the model and pretraining hyperparameters in Table 5.

Dataset	Language	Reference
SlimPajama	English	`https://huggingface.co/datasets/cerebras/SlimPajama-627B`
Starcoder	Code	`https://huggingface.co/datasets/bigcode/starcoderdata`
Tatoeba challenge	Eng-Fin	`https://huggingface.co/datasets/tatoeba`
Project Gutenberg	English	`https://huggingface.co/datasets/allenai/dolma`
Parsebank	Finnish	`https://turkunlp.org/finnish_nlp.html`
mC4	——〃——	`https://huggingface.co/datasets/mc4`
CC-Fi	——〃——	`https://github.com/TurkuNLP/CC-Fi`
Fiwiki	——〃——	`https://fi.wikipedia.org/wiki`
Lönnrot	——〃——	`http://www.lonnrot.net`
Suomi24	——〃——	`http://urn.fi/urn:nbn:fi:lb-2021101527`
Reddit-Fi	——〃——	`https://www.reddit.com/r/Suomi`
STT	——〃——	`http://urn.fi/urn:nbn:fi:lb-2019041501`
Yle	——〃——	`http://urn.fi/urn:nbn:fi:lb-2017070501`
Yle	——〃——	`http://urn.fi/urn:nbn:fi:lb-2021050401`
Yle	——〃——	`http://urn.fi/urn:nbn:fi:lb-2019050901`
Yle	——〃——	`http://urn.fi/urn:nbn:fi:lb-2021050701`

Table 4: Data sources

Architecture hyperparameters		*Pretraining hyperparameters*	
Parameters	34B	Global Batch Size	2048
Precision	bfloat16	Learning rate	1.5e-4
Layers	54	Total tokens	1000B
Hidden dim	7168	Warmup tokens	10B
Attention heads	56	Decay tokens	1000B
Vocab size	131072	Decay style	cosine
Sequence length	2048	Min. learning rate	2e-5
Activation	GELU	Adam (β_1, β_2)	(0.9, 0.95)
Position embedding	ALiBi	Weight decay	2e-5
Tied embeddings	True	Gradient clipping	1.0

Table 5: Model and training hyperparameters

A.2 Detailed benchmark results

Tables 6, 7, and 8 show the detailed benchmark results for Finnish, English, and code.

Benchmark	Poro 34B	Llama 33B	MPT-30b	Falcon-40b	FinGPT 8B	FinGPT 13B	Starcoder
Analogies	**77.69**	61.54	57.69	43.85	40.0	36.15	46.15
Arithmetic	54.28	47.74	**57.25**	51.06	41.96	45.23	48.41
Cause and Effect	67.97	60.78	58.82	46.41	66.01	**69.28**	54.90
Emotions	**55.00**	45.00	39.37	16.88	45.62	38.75	23.13
Empirical Judg.	**62.63**	43.43	43.43	34.34	32.32	36.36	44.44
General Knowl.	**75.71**	48.57	37.14	22.86	51.43	40.00	22.86
Intent Recogn.	**83.24**	77.75	77.31	46.24	51.43	58.24	65.03
Misconceptions	**53.73**	51.49	50.00	50.00	51.45	45.52	47.01
Paraphrase	**58.50**	53.00	52.50	54.50	49.50	45.50	47.50
Sentence Ambig.	**66.67**	45.00	56.67	48.33	48.33	53.33	51.67
Similarities Abst.	**73.68**	52.63	55.26	53.95	68.42	69.74	50.00
Average	**66.28**	53.36	53.22	42.58	49.69	48.92	45.55

Table 6: FIN-Bench Finnish benchmark results

Benchmark	Poro 34B	Llama 33B	MPT-30b	Falcon-40b	FinGPT 8B	FinGPT 13B	Starcoder
ARC-Challenge	53.16	**61.61**	55.80	50.51	25.34	24.31	30.29
Hellaswag	77.77	**84.64**	82.23	77.01	42.91	46.77	47.22
MMLU	46.29	**58.13**	47.27	46.13	23.34	23.64	32.11
TruthfulQA	41.66	42.84	38.44	41.64	43.80	**44.58**	40.06
Winogrande	72.77	80.27	74.82	**81.53**	53.19	57.53	54.85
GSM8K	11.75	**32.27**	17.13	2.43	0.22	0.22	8.11
Average	50.57	**59.96**	52.62	49.87	31.47	32.85	35.44

Table 7: English benchmark results

Benchmark	Category	Poro 34B	Llama 33B	MPT-30b	Falcon-40b	Starcoder
HumanEval	Python	37.20	34.15	35.37	34.15	**45.12**
MBPP	Python	47.40	41.20	43.00	43.00	**53.00**
Average		41.80	37.67	39.18	38.57	**49.06**

Table 8: Code benchmark results

A.3 Hardware

Poro 34B was trained on the LUMI-G GPU partition of the LUMI supercomputer, located in Finland. LUMI is, at the time of this writing, the third fastest supercomputer in Europe, and the 8th fastest in the world (`https://www.top500.org/`). LUMI is also ranked 7th greenest by the Green500 list (`https://www.top500.org/lists/green500/`).

The LUMI-G partition has 2978 nodes, with each node having four AMD MI250x GPUs with 128GB of memory each, and a single 64-core CPU. The MI250x is a multi-chip module (MCM), with dual-GCD (graphics compute die) design, which in practice means a node has eight logical devices, each logical device with access to 64GB of high bandwidth memory.

Each node has four 200Gbps Slingshot-11 network interconnects. The nodes are connected together in a dragonfly topology. During benchmarking and scale testing we did not observe the network topology as a limiting factor for the required collective operation sizes. The total of 800 Gbps per-node bandwidth proved to be more than sufficient, and the communication overhead was minimal during training.