Training Bilingual LMs with Data Constraints in the Targeted Language

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Abstract

Large language models are trained on massive scrapes of the web, as required by current scaling laws. Most progress is made for English, given its abundance of high-quality pretraining data. For most other languages, however, such high quality pretraining data is unavailable. In this work, we study how to boost pretrained model performance in a data constrained target language by enlisting data from an auxiliary language for which high quality data is available. We study this by quantifying the performance gap between training with data in a data-rich auxiliary language compared with training in the target language, exploring the benefits of translation systems, studying the limitations of model scaling for data constrained languages, and proposing new methods for upsampling data from the auxiliary language. Our results show that stronger auxiliary datasets result in performance gains without modification to the model or training objective for close languages, and, in particular, that performance gains due to the development of more information-rich English pretraining datasets can extend to targeted language settings with limited data.

1 Introduction

Large language models (LLMs) have demonstrated exceptional performance on many tasks, including mathematical reasoning, coding capabilities, and knowledge-based question answering (Brown et al., 2020; Bubeck et al., 2023; OpenAI, 2023) through pretraining on large corpora of web text. The vast majority of LLMs have been trained and evaluated on English, motivated by the abundance of high quality data. For other languages such large quantities of high quality and information-rich data are unavailable. Consequently, breakthroughs of similar scale are lacking for other languages, due to the lack of good data for pretraining.

Most non-English progress comes from relatively small bilingual models (e.g., Le et al., 2019; De Vries et al., 2019; Martin et al., 2019; Scheible et al., 2020; Wei et al., 2023a; Faysse et al., 2024), or larger massively multilingual models (e.g., Le Scao et al., 2023; Intrator et al., 2024; Üstün et al., 2024). Other LLMs such as Llama-2, GPT-3, and PaLM-2 that perform well across a variety of languages are trained primarily on English data with less than 20% of their data coming from other languages (Xu et al., 2024). However, little progress has been made in understanding when an auxiliary language (such as English) can help learning a target language. This is particularly relevant to understand in the case of target languages for which limited data is available.

This work studies the challenge of building datasets for pretraining language models with limited target language data. While much of the progress on building datasets for language model pretraining has focused on collecting and filtering more data, typically English (Figure 1a), we investigate whether these advances transfer implicitly to auxiliary-target language learning (Figure 1b), where English becomes an auxiliary language. *In particular, this work investigates whether better English datasets also lead to better models in other languages.* We focus on the impact of dataset size, filtering for data quality and style, and data selection for specialized information relevant to downstream evaluations (Figure 1c), matching recent advancements in state-of-the-art open-source English datasets such as FineWeb-EDU (Penedo et al., 2024), and DataComp (Li et al., 2024).

Our **key findings** are:

1. Auxiliary English data that is generated by some of the existing model-based data filtering pipelines for English can be helpful to complement limited data in a target language (Section 3.2);
2. When training with higher quality auxiliary data,

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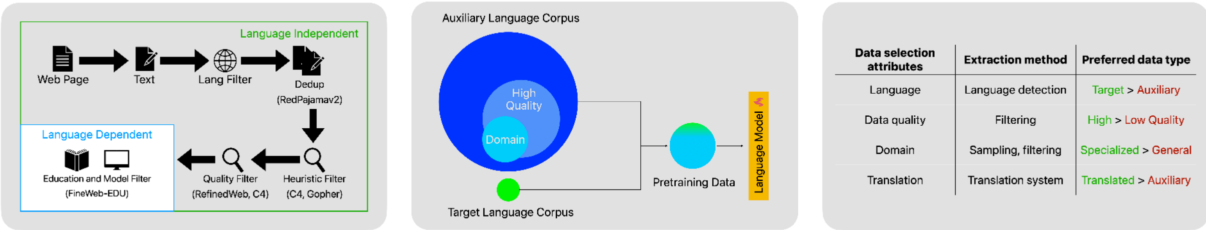


(a) Data Pipeline (b) Auxiliary Data Pretraining (c) Data Transforms

Figure 1: (a) **Data Pipeline**: English data pipeline used for building large pretraining corpora in (Penedo et al., 2024). (b) **Auxiliary Data Pretraining**: Combining high quality domain-specific pretraining data with a small amount of data from the target language for pretraining with limited target data. (c) **Data Transforms**: Many considerations when building datasets in languages with limited data.

more gains can be attributed to relevant information in the auxiliary data (Section 4.1-4.2);

3. Findings are not the same across multiple languages. We hypothesize that for languages that are "far" from English, gains from better English datasets do not help (Section 5);
4. There are limits to the size of models that are practical to pretrain with limited target data. This is because data size should scale linearly with model size (Kaplan et al., 2020) and performance in the target language saturates without increasing target data regardless of increasing auxiliary data (Section 6.2).

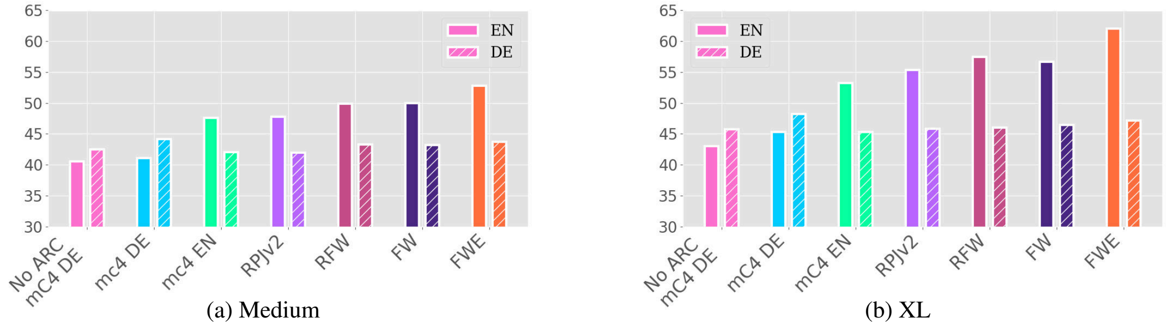
2 Related Work

Multilingual Language Models While much of the LLM research has focused on English, large-scale transformer-based multilingual language models have been trained on large multilingual corpora including mBERT (Pires, 2019), XLM (Conneau and Lample, 2019), mT5 (Xue, 2020), PolyLM (Wei et al., 2023b), and Bloom (Le Scao et al., 2023). These works focus on training models that are language balanced and can reason in over 100 languages. Other state-of-the-art language models such as Llama 2 (Touvron et al., 2023), Falcon (Almazrouei et al., 2023), and Palm 2 (Anil et al., 2023) have multilingual capabilities but over 90% the training data is English, and these models are shown to perform poorly across a variety of languages, such as south east Asian languages (Nguyen et al., 2023).

Other works focus on training smaller bilingual language models in French (Faysse et al., 2024; Le et al., 2019; Martin et al., 2019), German (Scheible et al., 2020), Dutch (De Vries et al., 2019), or Chinese (Wei et al., 2023a), but require a substantial amount of bilingual data: English and the respective language for pretraining. Other works focus on understanding languages LLMs reason in (Wendler et al., 2024), and languages LLMs cannot learn (Borenstein et al., 2024; Kallini et al., 2024). Still, little work has examined how information seen during pretraining in one language can help downstream task performance in another language.

Cross-Lingual Transfer Philippy et al. (2023) present a comprehensive survey on cross-lingual transfer in multilingual language models. The survey explains that cross-lingual transfer is a well studied topic for classic NLP tasks, such as part-of-speech tagging, named entity recognition, dependency parsing, natural language inference, machine translation, etc., although findings are not always consistent. Cross-lingual transfer is less well studied for the language modeling objective, and for modern down-stream evaluation tasks, such as ARC (Clark et al., 2018), HellaSwag (Zellers et al., 2019), PIQA (Bisk et al., 2020), SCIQ (Welbl et al., 2017), WinoGrande (Sakaguchi et al., 2021), etc. Philippy et al. end with a number of recommendations, one of which is to study cross-lingual transfer in more detail for generative models, given their exceptional performance in recent years. Although our work does not directly study cross-lingual transfer (we do not first train on the auxiliary language, and then on the target language), our findings help understand how an auxiliary language can help a target language for which limited data is available.

Data Selection Selecting high quality data for pretraining LLMs remains an active area of research. Early research on data selection was based on heuristics. For example, the original GPT-2 model was pretrained on outbound links filtered from Reddit based on heuristic indicators of whether users found the links interesting, ed-



(a) Medium

(b) XL

Figure 2: Zero-shot accuracy of medium and XL models trained with higher quality English auxiliary data. Results are averaged over six eval datasets. We compare training with different auxiliary datasets (colors) on both English (solid) and German (striped) evaluations. Better English datasets show large increases in English, and smaller increases in German.

ucational, or funny (Radford et al., 2019). Prior approaches also upsampled documents from high quality sources like Wikipedia (Gururangan et al., 2022), or used combinations of heuristics such as absence of stop words, document length, word length, etc. (Rae et al., 2021). Other works select data based on quality filters and time of collection (Longpre et al., 2023), model-based quality filtering (Sachdeva et al., 2024; Li et al., 2024), or textbook quality knowledge (Gunasekar et al., 2023; Li et al., 2023b; Kong et al., 2024). An alternative approach to data selection is re-weighting data samples to select the best data mixtures for training (Fan et al., 2023; Xie et al., 2024), or importance sampling based on a downstream task (Grangier et al., 2024b,a; Xie et al., 2023). Still a majority of these filtering techniques are applied to English-only datasets, and multilingual datasets such as mC4 have limited data filtering (Xue, 2020).

3 Using English Data Selection Pipelines to Complement Limited Target Data

Existing data selection pipelines have been shown to be effective in monolingual (English) pretraining. We investigate whether these pipelines are useful in the bilingual setup with limited target data. We always take English as the auxiliary language. Initially, we perform all experiments with German as the target language. In Section 5 we discuss how our findings extend across multiple languages.

3.1 General Implementation Details

Model. We train decoder-only transformer models (Vaswani et al., 2017) at different scales: medium and XL (Brown et al., 2020). Models use the PolyLM tokenizer (Wei et al., 2023b), with a total vocabulary size of 256K tokens using BPE. Models are trained for 30K (medium) or 100K steps (XL) with batch size 1024. Additional hyperparameters and model details are in Appendix A.

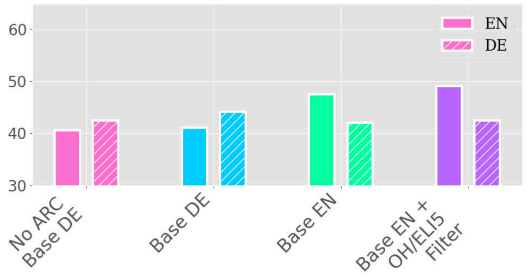
Data. We consider access to approximately 250M tokens[1] from the target language. We upsample the 250M tokens of target language data to total 5% of the training time, and the remaining 95% are different English auxiliary datasets or mC4 German for comparisons to monolingual models. All data is pretokenized with packing to the full context length, and shuffled during training.

Evaluation. We consider the average over six general understanding QA tasks: ARC-Easy, ARC-Challenge, Hellaswag, PIQA, SciQ, and Winogrande. These tasks are knowledge-based tasks that small models with limited data still perform well and many require knowledge. Non-English evaluations are conducted via translation of the original dataset. We use a mix of proprietary large language models to ensure good translations.

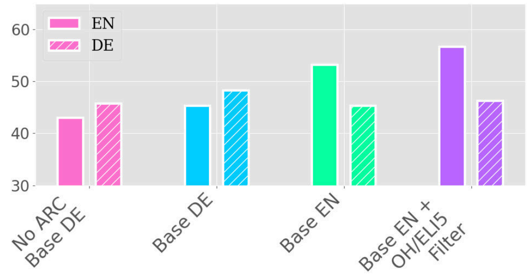
3.2 Better English Datasets

Methodology. We compare the performance of models trained on combinations of German (target) and English (auxiliary) with varying existing English datasets based on the common crawl: mC4 (Xue, 2020), RedPajamav2 (RPJv2) (Computer, 2023), RefinedWeb (RFW) (Penedo et al., 2023), FineWeb (FW), and FineWeb-EDU (FWE) (Penedo et al., 2024). These datasets have been constructed following a pipeline of different filtering steps outlined in Figure 1a. The resulting datasets have higher quality filtering and cover

[1]This is chosen to simulate the amount of data that would exist in the tail of mC4. We use German for our experiments to facilitate comparisons with having additional data, and to study translation and other methods.



(a) Medium



(b) XL

Figure 3: Zero-shot accuracy of medium and XL models trained with higher quality English auxiliary data. Results are averaged over six evaluation datasets. For each setting evaluation is done in English and German.

different snapshots of the common crawl. They are all aimed at general language model pretraining. Further details for the datasets are available in Appendix B. For comparison with monolingual models trained only on German (target), we consider both German mC4, and a low quality version of German mC4 referred to as "no ARC German mC4".[2]

Findings. Across all tasks in Figure 2, we observe that for English evaluations, better quality English datasets attain substantially higher performance on the English tasks. For the medium models, this corresponds to up to 5% increase between the worst and best performing English datasets. For the XL models, the performance improvement in English is up to 9%. For the same benchmarks translated into German, the performance increase is around 1% for the medium model and 2% for the XL model. Of all compared English datasets, FineWeb-EDU achieves the best average downstream performance, and similar performance to the no ARC German dataset. There are two primary factors we hypothesize contribute to FineWeb-EDU achieving better performance on downstream tasks: high-quality data filtering, and information filtering. Next, we investigate these factors in more detail.

4 The Effect of Individual Data Transformations

Section 3.2 investigated the effect of using existing data filtering pipelines in the auxiliary language. Here we study individual data transformations in more detail. For all experiments, we use the same experimental setup as in Section A. Unless otherwise stated, we refer to the mC4 datasets as "Base."

4.1 High Quality Filtering

Motivation. While filtering strategies achieve strong results on English downstream evaluations, training a filtering model can require more data than available, and typical high quality datasets may not be available in the target language for filtering. Further, it is unclear to what extent better filtering strategies would improve performance in a target language that might not benefit from seeing purely higher quality data in the auxiliary language.

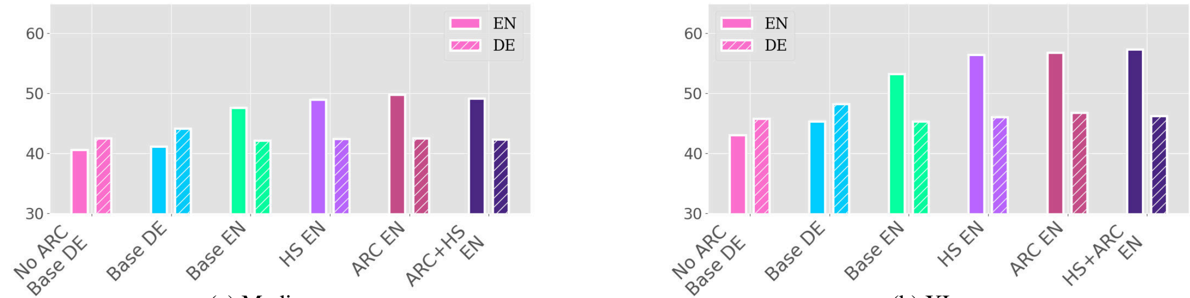
Methodology. To test the impact of filtering, we use the OH+ELI5 fast text classifier to filter data, and filter a large portion of the mC4 to the top 10% high quality documents following (Li et al., 2024). Filtering with this classifier leads the model to train on high quality English, and question answer style data which specializes the model towards downstream evaluation. We compare the performance of models trained with English filtering and without, holding the German data the same for evaluation.

Findings. We find in Figure 3 that for the medium models performance improvements in English evaluations are 1.5%, but for translated German (target) evaluations, there is no improvement. For the XL models, English evaluations improve by 3%, but translated German evaluations are under 1% and within 1 standard error.

4.2 Clustered Dataset Importance Sampling

Motivation. Prior work shows that LLMs reason in English and that information may be stored in a language agnostic space (Wendler et al., 2024). However, they do not control how the information is seen during training, and while much of the

[2]We downsample data based on the ARC dataset using the clustered importance sampling procedure in Section 4.2 to approximate having low quality data which is not in-domain but in the target language. This dataset serves as a baseline for a low quality dataset with less relevant data to the downstream tasks. We clarify this procedure in greater detail in the respective section as the details beyond low quality and out of domain are not critical.



(a) Medium (b) XL

Figure 4: Zero-shot accuracy of medium and XL models trained upsampling different downstream datasets. Results are averaged over six eval datasets.

information may be seen only in English (the predominant language), it may also be seen in other languages as the pretraining datasets are not made publicly available. Further, we note that FineWeb-EDU, in addition to high quality filtering, also filters for educational quality content (Penedo et al., 2024).

Methodology. To explicitly test whether information is shared between auxiliary and target languages, we upsample topics in English and evaluate on the target language comparing with having uniform data. Specifically, given access to some small dataset representative of target knowledge, we group the data into target clusters and estimate importance sampling weights over the clusters following (Grangier et al., 2024b). To train the clustering model, we take a small subset of the training set, produce embeddings from a smaller sentence-BERT model, then cluster the data according to the embeddings. For our importance sampling experiments, we upweight a subset of roughly 300B tokens from the English dataset. Given a small target set (typically on the order of 1000-10000 samples), we assign each sample to a cluster and upweight the original training set based on the cluster assignment proportions. In practice, we do not optimize for the cluster parameters jointly with the model weights, and instead precompute them based on the pretraining and target task data.

For clustering hyperparameters, we use a lightweight SentenceTransformers multilingual model[3] for extracting features (Reimers and Gurevych, 2019), and a balanced K-means algorithm to cluster the embeddings into 64 clusters. To learn importance sampling weights, we use corresponding training sets, and available corpora that would be used for retrieval-based methods on the same tasks.

All upsampling is done in English to facilitate having specialized information in the auxiliary language, but not in the target language to measure the impact of information in a different language. For all experiments, we use the mC4 English dataset. Comparisons are made between having access to more German data of uniform quality, upsampling based on the ARC training set (general science knowledge), and upsampling based on the HellaSwag training set (general knowledge and QA style).

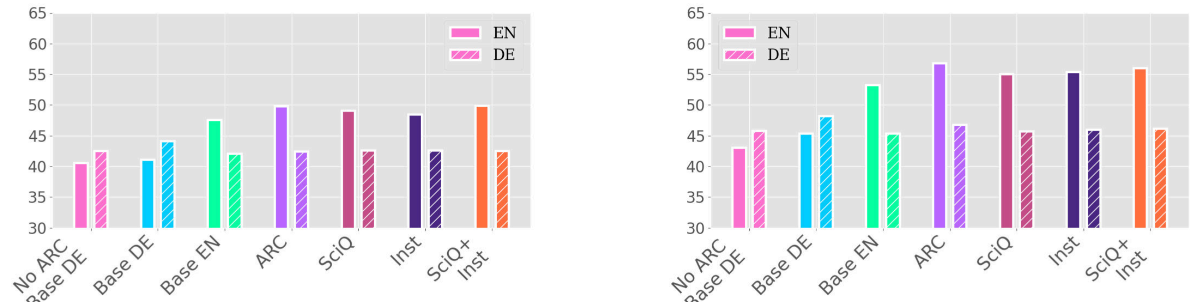
Findings. Results in Figure 4 show that for the medium model experiments, data selection provides 1.5% improvement over base mC4 auxiliary data on English language evaluations, but no improvement in the target language (German). For the XL models, we see 4% improvement in English evaluations, and 2% improvement in target language (German). These results highlight that larger models can take advantage of information in the auxiliary language, and the performance improvements are higher for the information upsampling than for model-based filtering without removing the data, allowing for training on new data at greater token counts.

Our findings indicate that while filtering for high quality data as in the OH filter has limited improvement for the target language, but further improvements come from data selection over important topics.

4.3 Upsampling with Synthetic Examples

Motivation. While performance improvements are achieved by data selection based on target downstream evaluations, having such data available at pretraining can be restrictive. For this reason, it can

[3]The particular model is called `paraphrase-multilingual-MiniLM-L12-v2` model and is obtained from `https://huggingface.co/sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2`.



(a) Medium (b) XL

Figure 5: Zero-shot accuracy of medium and XL models trained upsampling based on synthetic datasets. Results are averaged over six eval datasets.

be desirable to be able to generate the necessary data for upsampling. While prior work has examined the use of LLM-generated data for pretraining (Maini et al., 2024) and finetuning (Li et al., 2023a; Yuan et al., 2024) language models, to our knowledge there is no prior work that investigates data selection based on synthetic examples.

Methodology We generate a small set of synthetic examples following the approach in (Maini et al., 2024). The synthetic data is created by prompting an off-the-shelf instruction finetuned language model to generate sets of questions relating to the topic of interest using the prompts in Section D. Generating synthetic data using an off-the-shelf language model can be both computationally expensive and challenging, however for the purpose of computing sampling weights, a small number of questions is sufficient.

For our experiments, we generate data using a frozen Mistral-7B instruction tuned model[4] (Jiang et al., 2023). In total around 2000 science question answer pairs (referred to as SciQ) are created with minimal filtering outside of confirming that both a question and answer are specified, and the model does not generate any additional details or explanations.

We additionally generate general instruction data. This data is aimed at broad QA style and general fact information which is helpful for downstream tasks. This data is generated in two stages by first having the frozen Mistral-7B model generate a set of questions, then answering the questions.

Using the sets of questions, we identify the cluster sample weights and upsample data accordingly as in Section 4.2. The approach otherwise follows the same setup as in Section 4.2 except for the synthetic QA pairs.

[4]https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

Findings Results shown in Figure 5 comparing synthetic data upsampling with upsampling from the downstream task demonstrates that synthetic data can be sufficient for incorporating information into the auxiliary English dataset. For the medium models on both English and German evaluations, models trained by upsampling synthetic data and real ARC attain the same performance, and for the XL models, upsampling synthetic data is within 1% for the English downstream tasks, and within 0.5% for the translated German evaluations.

4.4 Translation Systems

Motivation. Training directly on auxiliary language data can lead to improvements. However, an alternative strategy is to translate the auxiliary data into the target language, assuming a machine translation system is available between the two languages. This approach offers the benefit of training the model exclusively in one language, and, if the translation system is of high quality, it allows for training on high-quality data in the target language at the expense of translating the corpus. It is, therefore, crucial to also assess the level the translation system must possess to effectively translate data for pretraining.

Methodology. For our experiments, we use lightweight translation systems of roughly 100-200M parameters. We consider three models with BLEU scores 16.0, 26.5, and 31.6 on the WMT-17 EN-DE benchmark task. We denote these models as v1, v2, and v3 corresponding to increasing BLEU score. All models are trained on translated versions of the mC4 english corpus. No other English data is included in the dataset, but we keep the 250M tokens of real German data as in prior experiments.

Findings. We summarize our results in Figure 6. For all translation models, we find little difference

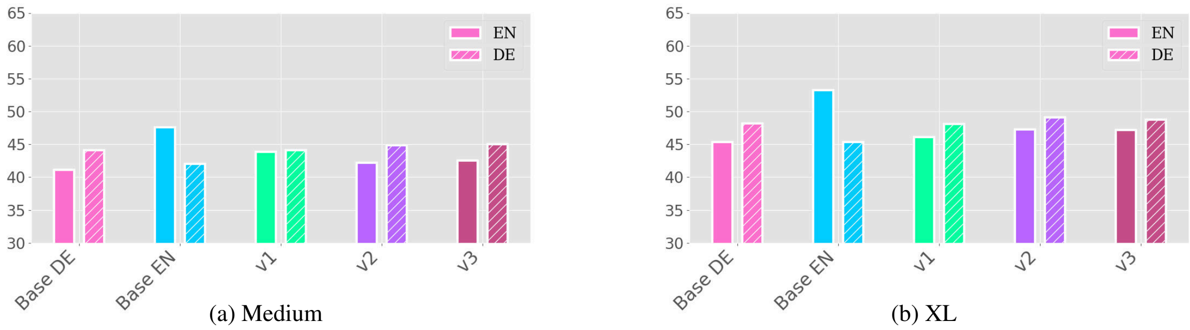


Figure 6: Zero-shot accuracy of medium and XL models trained upsampling based on translating mC4. Results are averaged over six eval datasets.

from the quality of the translation. Both stronger translation models achieve similar performance with the worst model performing comparably to training on real German data. For the medium models, we see that the performance on the translated German evaluations yields similar performance to training on real German data. For the XL models, the translated data improves by around 1% over new German data for the v2 and v3 translation models. We hypothesize a few reasons this may be possible, but leave investigation of each of these to future work: (1) English CC data is higher quality than German CC data as there may be more data from more diverse sources. (2) Translated German data has a different distribution from real German data and this better matches the translated test evaluations. (3) Translated data from a small translation system might simplify language, making it easier for models to learn, following (Eldan and Li, 2023). (4) Portions of the dataset could not be translated by the systems and are removed. These portions might be noisy, and some unintended filtering may lead to slightly higher performance.

5 Do Findings Hold Across Multiple Languages?

Sections 3-4 focused on German as the target language. We now investigate to what extent our findings for German hold across different target languages. In Section 5.1 we study additional languages individually, and in Section 5.2 we investigate a multilingual setting combining a subset of four languages.

5.1 Experiments Across Multiple Languages

Motivation. We add seven languages, across four language families: French, Italian, Portuguese, Spanish (Indo-European, same as German), Chinese (Sino-Tibetan), Japanese (Japonic), and Korean (Koreanic) (Lewis et al., 2015).

Methodology. For these experiments, we train models using the same experimental setup as in Section 3. For all additional target language models, we train with approximately 250M tokens from the mC4 corpus in the respective language. For training monolingual models in the target language, we note that the Chinese and Korean mC4 corpora contain fewer than 100B tokens and thus the data is repeated for multiple epochs in the base language experiments.

Findings. We report results for the XL models trained for 100B tokens in Figure 10-13 in the appendix. Results are similar for the medium models. Our results indicate that our findings on English-German training do not extend across all families of languages. In particular, we see improvements from FineWeb-EDU only on the Indo-European languages.

We investigate the performance differences further by evaluating the perplexity of models trained on combinations of target language data from mC4 and FineWeb-EDU. We selected four languages (German, French, Chinese, and Japanese) to examine the perplexity across two languages with improved performance from auxiliary data and two languages without. We compare data from the FineWeb-EDU dataset seen during training with data from the mC4 English portion which has not been seen during training. We translate 10,000 documents into each of the target languages and evaluate the perplexity of documents for both translated and original auxiliary data. We additionally report a metric we call *exceedance*, which is the fraction of documents in FineWeb-EDU with lower perplexity than the average perplexity of documents in mC4 English. A higher value shows that the data the model is trained on appears more in-distribution, and similar values across original and translated documents would reflect transfer between the languages. We observe that the *exceedance* is similar for French and German between translated and original documents (Table 3, Appendix F.2). However for Japanese and Chinese[5] translations, the *exceedance* is lower, and translated FineWeb-EDU data has the same or higher perplexity compared with mC4 English data.

5.2 Multilingual Experiments

Motivation. Our main findings investigate how auxiliary data benefits evaluations in a target language. However, many models trained on other languages (beyond English) are trained with many languages simultaneously. We investigate whether better auxiliary language datasets also improve multilingual model training.

Methodology. We conduct experiments combining the German, French, Chinese, and Japanese language data towards multilingual training. For these experiments, we train a 1B model with the auxiliary dataset being FineWeb-EDU, and a mix of data from the four languages totaling 5% or 20% of the training. We again use the four language subset as we keep the data ratios the same per language, and did not want to increase the amount of data in target languages beyond the typical multilingual ratios in large open-source models (Xu et al., 2024).

Findings. We summarize the results in Table 1. Our findings indicate that training with 20% of the data being a combination of target languages yields similar performance to training with 5%, resulting in a 1% reduction in performance on average when training with 20% multilingual data. When compared with training a bilingual model, we observe performance decreases for German and French, and increases for Chinese and Japanese.

6 Scaling Limitations for Low Resource Languages

We consider the limitations of data scaling for training bilingual language models for target languages with limited data. In Section 6.1, we investigate the extent to which training on higher quality English data improves the amount of data needed in the target language to reach similar performance. In Section 6.2 we investigate how feasible it is to train larger bilingual models with limited target data.

[5]For Chinese translations, there may be some artifacts that induce artificially high perplexity in the original Chinese mC4 data and further decrease *exceedance*. In particular, we find several symbols and characters that are not removed in text extraction. Nonetheless we believe the patterns should be consistent from Japanese.

	EN	DE	FR	JA	ZH
5%	61.07	46.02	46.64	**44.00**	**45.92**
20%	59.25	46.44	46.61	43.23	44.36
Bi		**47.16**	**47.52**	42.73	44.38

Table 1: Evaluation of XL models in multilingual setting on “General Understanding Tasks” focusing on general reasoning, language understanding, and science knowledge in translated languages. Rows are the average accuracy for the respective language, with 5% or 20% of the training coming from a mix of the four languages. ‘Bi’ refers to the bilingual models.

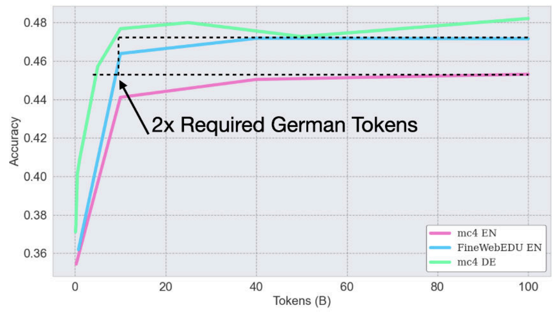


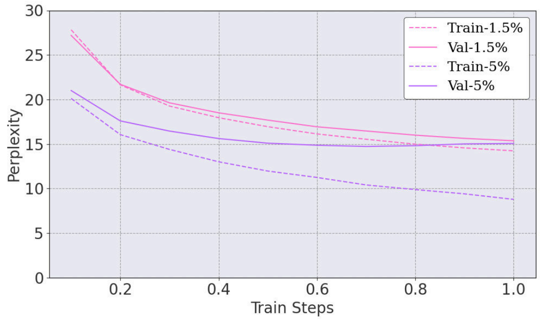
Figure 7: Average accuracy over zero-shot benchmark tasks in translated German with increasing number of tokens in both target and auxiliary languages. Models are XL size and trained for 100B tokens.

6.1 Auxiliary Data Scaling

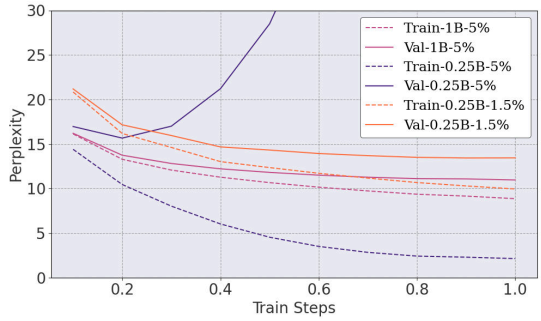
Motivation. We measure the amount of data needed in the target language to match training on the high quality auxiliary data. Our goal is to quantify the advantage of training models with additional target data beyond the 250M tokens used in prior experiments. For this experiment we train models at different dataset sizes ranging from 0.1B to 100B tokens.

Methodology. We investigate data scaling over both the mC4 dataset and FineWeb-EDU to measure the increase in German data needed to match higher quality auxiliary datasets.

Findings. Our results are summarized in Figure 7. Models trained on the base mC4 English data achieve similar performance to models trained with only 5B tokens of the base mC4 German data. In contrast, training on a high quality data such as



(a) 1B Model Perplexity



(b) 3B Model Perplexity

Figure 8: Train and validation perplexity for 1.3B and 2.7B parameters with varying amount of data.

FineWeb-EDU increases the amount of data needed to around between 10-15B tokens or equivalently 2x the amount of data in German. Note that the curves all plateau quickly at around 10B tokens. This corresponds to around 10 repetitions of the data, matching the results in (Muennighoff et al., 2024).

There are two important data scaling considerations from Figure 7 that justify training with auxiliary language data. First, for languages that are data constrained, it may be infeasible to collect twice as much data. Second, models trained on FineWeb-EDU attain similar performance at a rate of 5x the number of tokens (roughly 50B tokens on FineWebEDU matches the performance of 10B tokens of mC4 German data). An important avenue of research is to investigate data scaling at larger quantities of tokens. In particular, the FineWeb-EDU corpus totals 5.4T tokens and would require access to 1T tokens of German data, which is 3x the amount of data in mC4. As a result, while the data scaling shows large improvements from little German data, the large amount of readily available English data can make training on auxiliary data practical.

6.2 Model Size Data Scaling

In this section, we investigate to what extent results scale for training larger language models when data remains constrained in the target language.

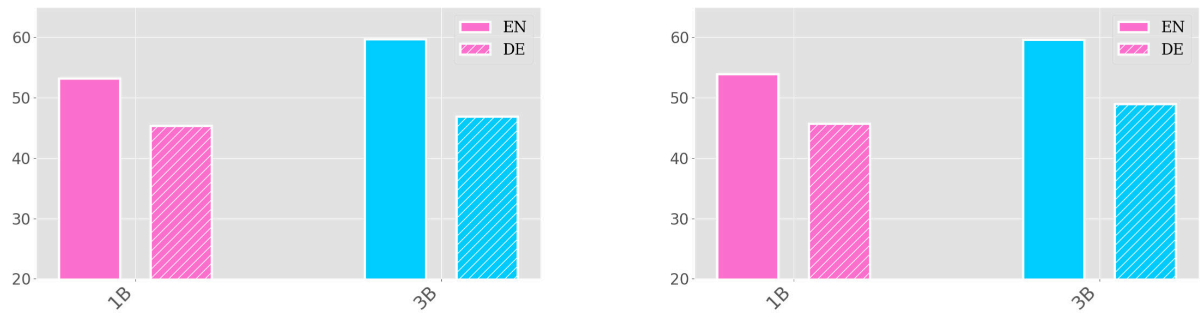
Motivation. In prior experiments, we fixed the amount of data from the target language to approximately 250M tokens and train for 100K steps with 5% of the training being in the target language. However, increasing model size necessitates increasing the number of tokens seen during training according to Chinchilla scaling laws (Kaplan et al., 2020). This is challenging for low resource languages, as the number of repetitions increases with increased amount of training, which can lead to overfitting and saturate model performance.

Methodology. We first examine the amount of overfitting larger models have on the same amount of data and ratio of training time. We train a roughly 3B (non-embedding parameter) model consisting of 32 layers, 32 attention heads, and a hidden dimension size of 2560. The model has a maximum sequence length of 2048 and is trained for 150K steps to match the same scaling ratio as for the 300M and 1B models.

Findings. The perplexity of training and validation data is shown in Figure 8 for the 1B (left) and 3B models (right). For 1B models, we see little to no overfitting at 5% ratio of training steps and the model achieves slightly lower perplexity than a model trained with a lower ratio of 1.5% target language data. In contrast, for the 3B model, there is clear overfitting from as early as 25% of the training with 5% ratio of training steps. This indicates that the number of repetitions is too high for the 3B model and performance may degrade.

Reducing the number of repetitions by reducing the fraction of training steps to 1.5% reduces overfitting as seen in Figure 8b, however perplexity remains similar between the 1B and 3B models when limited to 250M tokens. Increasing the number of available tokens results in decreasing perplexity on validation data and no overfitting for the 3B model, which is unnecessary for the 1B models. An overview of comparison with different data ratios for zero-shot accuracy is also provided in Appendix E.

Based on Figure 8, we evaluate both 1B and 3B models with data ratios that mitigate overfitting: 5% for 1B and 1.25% for 3B with 250M tokens in the target language. Results are shown in Figure 9. First, Figure 9a shows that the 3B model



(a) 250M Tokens

(b) 1B Tokens

Figure 9: Zero-shot accuracy for 1B and 3B parameter models trained with either 250M tokens of data in the target language or 1B tokens. Both models are trained on the target language data for 5% of the training steps.

performs similarly to the 1B model with the same 250M amount of target language data matching the similar perplexity values between the two models. However increasing to 1B tokens results in similar improvements in both English and German when increasing model size from 1B to 3B as shown in Figure 9b.

Summarizing, there is a limit to the size of models that can be trained with limited target data. Model performance for 250M tokens saturates at 1B parameter models (more than the available data in mC4 for $\sim$ 20 languages). Increasing to a 3B parameter model necessitates training on 1B tokens of data (more than the available data in mC4 for $\sim$ 40 languages).

7 Conclusion

This work studies how an auxiliary language for which an abundance of training data is available can boost pretraining for a target language for which only limited data is available. We find that adding auxiliary high quality data obtained by data filtering can improve performance in a target language. Moreover, our results indicate that most of these gains can be attributed to having relevant information in the auxiliary language data, which may not be present in the target language. However, we find that results are inconsistent across different target languages. We hypothesize that for languages that are further from English, better English datasets are not as helpful as information is not shared between them. Finally, we find limitations to scaling models for languages that are data constrained. This work takes a step towards pretraining language models in languages with limited data, and can inspire more research into bilingual or multilingual learning under dataset constraints.

8 Limitations

In this section we list some limitations of our work.

Languages included. Our primary focus is on English-German language training, as these two Germanic family languages share linguistic similarities (Lewis et al., 2015). German is one of the most well-represented languages in the mC4 dataset, facilitating model comparisons with varying amounts of German and English data. Furthermore, the availability of extensive public resources for German, including translation systems and translated evaluation data, further supports our emphasis on this language pair. We experimented with seven additional datasets including French, Spanish, Italian, Portuguese, Korean, Japanese, and Chinese. However, we note that there are many other languages within mC4 and more broadly which can benefit from having auxiliary English data for pretraining. Due to limited evaluation benchmarks and availability of target language data for comparison, we leave investigation for truly low-resource languages to future work.

Evaluation data. Another limitation in evaluating language models for languages other than English is that many datasets have been translated from English. These datasets may contain cultural biases or information that is not available on the web in other languages. As a result, certain aspects of the evaluation may lead to improved performance when using English auxiliary or translated data. Additionally, translated data often exhibits a distribution different from that of real data in the target languages. Therefore, an important direction for future work is the development of evaluation datasets that are not based on translation, which is essential for more accurate evaluation of multilingual language models.

Model size. Finally, this work studies three model sizes up to 3B models. We note that there are many standard benchmarks that can be evaluated at 1B-3B scale, however many more benchmarks and patterns can appear at larger model sizes. It is important future work to evaluate whether the results extend to larger scales including evaluating potential "emergent behaviors" as well as risks at larger scales (Wei et al., 2022).

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A Hyperparameters and Training Details

The medium-scale (300M non-embedding parameter) model consists of 24 layers, 16 attention heads, and a hidden dimension size of 1024. The XL-scale (1.3B non-embedding parameter) model consists of 24 layers, 16 attention heads, and a hidden dimension size of 2048. Both models have a maximum sequence length of 1024.

The baseline models are trained using NVIDIA's Megatron-LM[6] repository for pretraining language models. The medium size models are trained for a total of 30K steps, and 100K steps for the XL models at a batch size of 1024. All models are trained using a maximum learning rate of 0.0003 for the medium model and 0.0002 for the XL model, and a minimum learning rate of 0.00001 with a cosine learning rate scheduler and warmup for 1% of the total steps. For regularization, we use a weight decay of 0.01, along with a gradient clipping norm of 1.0. Models are trained with the Adam optimizer using $\beta_1 = 0.9$ and $\beta_2 = 0.999$.

The total training time for XL models on roughly 100B tokens is around 1000 GPUh on Nvidia H100 GPUs. For medium size models, the total training time is around 200 hours for roughly 30B tokens.

B Dataset Details

B.1 Train Sets

- **mC4**: The primary pretraining corpus in our experiments is multilingual Colossal Clean Crawled Corpus (mC4), a curated text dataset comprising over 6.3T tokens. This corpus is derived from CommonCrawl and used for pretraining numerous language models (Brown et al., 2020; Raffel et al., 2020; Touvron et al., 2023). The dataset is chosen as all languages have similar data extraction pipelines including line length filter, `cld3` language detection, and deduplication (Xue, 2020). The English portion contains 2.7T tokens, German contains 350B tokens, French contains 320B tokens, Spanish contains 430B tokens, Portuguese contains 146B tokens, Italian contains 160B tokens, Korean contains 26B tokens, Japanese contains 160B tokens, and Chinese contains 40B tokens.

- **RedPajamav2**: A pretraining corpus with light filtering (primarily only deduplication) comprising 30T tokens and 20T tokens of English text. We focus on the English portion of the dataset only and train using a random shuffled subset of both the head and middle portions (Computer, 2023).

- **RefinedWeb**: The dataset is also derived from the CommonCrawl, however has a more stringent filtering process including `trafilatura` text extraction, document and line level rules, and fuzzy duplication over the original C4 processing (Penedo et al., 2023).

- **FineWeb**: This dataset is derived from the CommonCrawl with the aim of replicating RefinedWeb at larger scales. The dataset has some additional filtering including Gopher filtering (Rae et al., 2021), additional C4 filters, and custom filters for text quality (Penedo et al., 2024).

- **FineWeb-EDU**: A subset of the FineWeb dataset which is filtered according to a classifier trained on annotations for educational quality from Llama-3 70B model (Penedo et al., 2024).

B.2 Zero Shot Evaluations

- **SciQ**: A dataset of science exam questions, specifically designed to evaluate the ability of NLP models in understanding and reasoning within the scientific domain (Welbl et al., 2017).

- **ARC Challenge (ARC-C)**: This dataset is part of the AI2 Reasoning Challenge (ARC) (Clark et al., 2018), containing science exam questions from grades 3 to 9. The ARC Challenge set includes more difficult questions that necessitate higher-order reasoning.

- **ARC Easy (ARC-E)**: The Easy set of the AI2 Reasoning Challenge (Clark et al., 2018) features questions from the same source as ARC-C but are considered less challenging and do not require as advanced reasoning skills.

- **Winogrande (Wino.)**: This dataset challenges models on common sense reasoning in a language context, focusing on pronoun disambiguation tasks (Sakaguchi et al., 2021).

- **PIQA**: Physical Interaction Question Answering tests the understanding of everyday physical processes, an aspect of practical common sense (Bisk et al., 2020).

- **HellaSwag**: This dataset evaluates a model's ability to complete scenarios in a contextually and logically coherent manner, requiring both

[6] `https://github.com/NVIDIA/Megatron-LM`

language understanding and common sense reasoning (Zellers et al., 2019).

For each of the eval datasets, we include the number of samples for each translated evaluation in Table 2. For our evaluations, we use the lm-eval-harness repository[7] for zero-shot accuracy on QA tasks.

Dataset	EN	DE	FR	ZH	JA
ARC-C	1,172	1,137	1,147	1,146	1,147
ARC-E	2,376	2,260	2,271	2,271	2,271
HS	10,042	9,368	9,338	9,266	10,033
PIQA	1,838	1,838	1838	1,838	1,838
SCIQ	1,000	950	953	1,000	926
WG	1,267	1,184	1,215	1,059	1,096

Table 2: Evaluation set sizes for each language.

B.3 Number of Data Files for Filtering Experiments

The mC4 English portion of the dataset is split into roughly 11,264 files totaling 2.7T tokens of data (Xue, 2020). For each of our experiments, data is filtered differently, and as such varying numbers of files are needed for training. At a baseline, we consider the first 1500 files totaling roughly 350B tokens of data. This number was selected to match the total amount of German data which is recorded as 347B tokens using the mT5 tokenizer (Xue, 2020). For the OH classifier, we use the first 10,000 files and filter down to 10% of the dataset. For German, Japanese, Spanish, Portuguese, Italian, and French models, we use the first two files of data totaling roughly 250-300M tokens of data. For Chinese and Korean models, we use the first 7 files totaling roughly 250M tokens.

B.4 License and Attribution

All datasets used in this paper are supported by public licenses including ODC and Apache. The pre-trained models including Mistral and OH FastText classifiers are also supported by public licenses including Apache and MIT licenses. We use the Megatron codebase under the Nvidia license for pre-training and the lm-eval-harness (MIT) for evaluations. All models and datasets are collected from Huggingface via the datasets library where possible. We use a proprietary translation system for fast translation at scale and are thus unable to provide details of the license at this time.

[7] https://github.com/EleutherAI/lm-evaluation-harness

C Evaluation Metrics

The metric utilized for evaluation is the *macro token level perplexity*. Given a batch of encoded texts, the perplexity at the token level was computed as follows:

Given the accumulated loss over the entire dataset, denoted as L, and the total number of tokens, represented by T, the macro token-level perplexity, denoted as $\mathcal{P}$, is calculated as:

$$\mathcal{P} = \exp\left(\min\left(20, \frac{L}{T}\right)\right) \tag{1}$$

Where:

- exp is the exponential function.
- L is the cumulative loss over all shifted logits and labels in the dataset.
- T is the total number of tokens in the dataset.

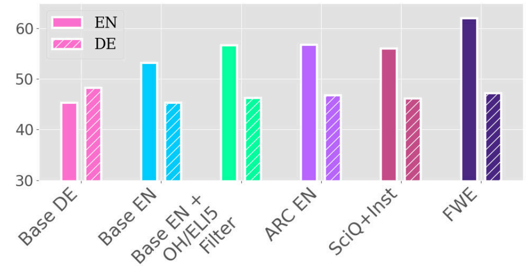
The value of 20 acts as an upper limit to stabilize the metric in cases of high loss values.

For zero-shot MCQ accuracy evaluations, we compute the perplexity of each sentence completion, and choose the lowest perplexity choice. We use the lm-evaluation-harness and where possible evaluate with the length-normalized accuracy. Unless otherwise stated, all evaluations are zero-shot.

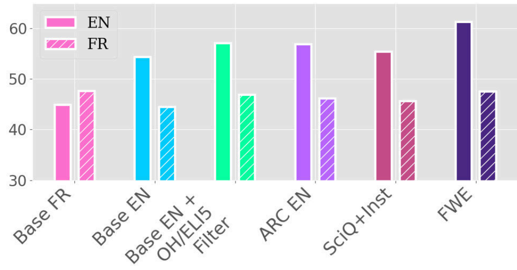
D Synthetic Prompts and Examples

For building the synthetic corpus used in our data selection experiments, we consider three prompts for generating science questions (similar to many downstream tasks), fact-based QA data, and instruction-based writing (such as emails, books, lists, etc.). For generating science questions, we generate both the question and answer. For the fact and instruction data, we first generate the questions using the prompt, and subsequently generate the answer without any additional prompting.

Science Question Prompt



(a) German



(b) French

Figure 10: Zero-shot accuracy of XL models trained with various English auxiliary data for German and French. Results are averaged over six eval datasets.

Give me a set of ten question and answer pairs on topics relating to Physics, Chemistry and Biology that a high school student would be able to answer. The response should be in the form Question: <question> \n Answer: <answer> \n \n with an answer that is less than ten words. The response should not contain any other details or explanations about the question or answer.

Facts Question Prompt

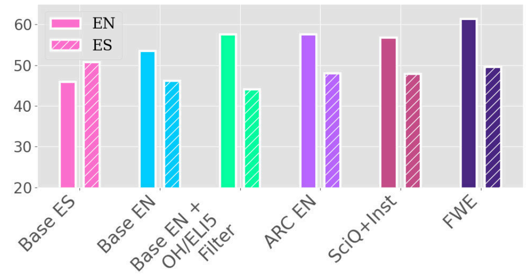
People from different social and educational backgrounds, beliefs, ethnicity and gender are asking an AI assistant for information. They are looking for detailed explanations about encyclopedic facts on Wikipedia and in textbooks, about philosophy, nature, science, entertainment, literature, geography, socialogy, law, history, etc. Write an interesting and difficult question that would be sent to the AI assistant:

Instruction Writing Prompt

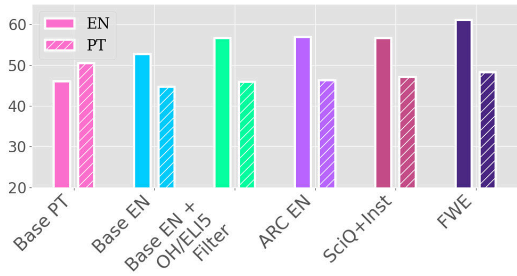
People from different social and educational backgrounds, beliefs, ethnicity and gender are asking an AI assistant to help them write a piece of text that they need for their work or their personal life. They can ask the AI Assistant to write a document (email, letter, official document...). Each request comes with a long, precise and detailed description of what needs to be in the text, and why they need this document. The request may also include information about the writing style, the tone, the target audience or the layout of the text. The description of the task is formal, detailed and clear. Each request is composed of a few paragraphs written in English, and starts with the tag <request>. Here is some of the most interesting and original requests sent to the AI assistant:

E Data Ratios

We experiment with different data ratios beyond 5% used during training. For our ablation, we study the XL model (1.3B) and a 2.7B non-embedding parameters model. Results are reported in Figure 14. We see that performance is around the same for XL models, but 2.7B models perform worse with larger data ratios.

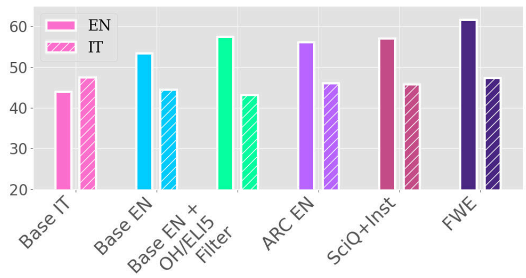


(a) Spanish

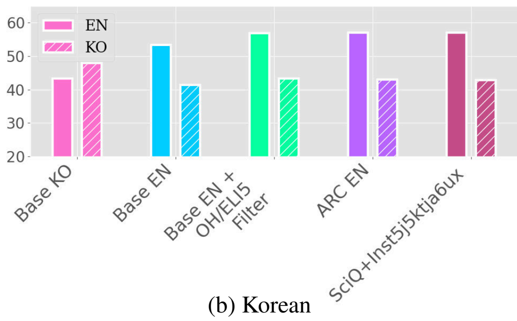


(b) Portuguese

Figure 11: Zero-shot accuracy of XL models trained with various English auxiliary data for Spanish and Portuguese. Results are averaged over six eval datasets.



(a) Italian



(b) Korean

Figure 12: Zero-shot accuracy of XL models trained with various English auxiliary data for Italian and Korean. Results are averaged over six eval datasets.

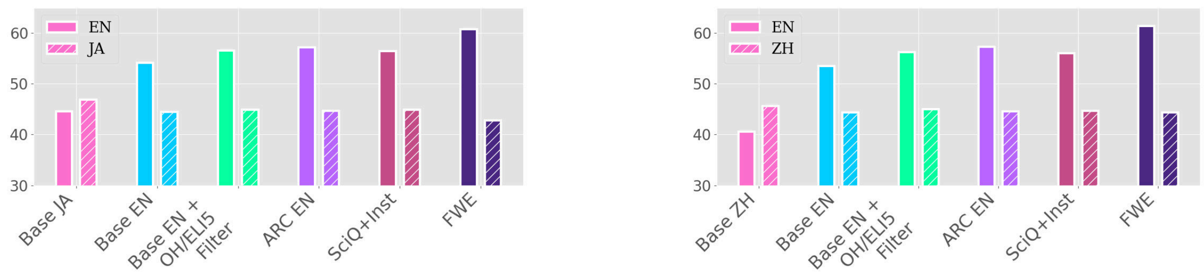
F Results for Multiple Languages

F.1 Average Zero Shot Accuracy Plots

We present experimental results comparing the best performing approaches for French and German languages in Figure 10, Spanish and Portuguese in Figure 11, Italian and Korean in Figure 12, and for Japanese and Chinese languages in Figure 13. For each language, we take the best performing dataset and model found in German from Sections 3.2-5.1.

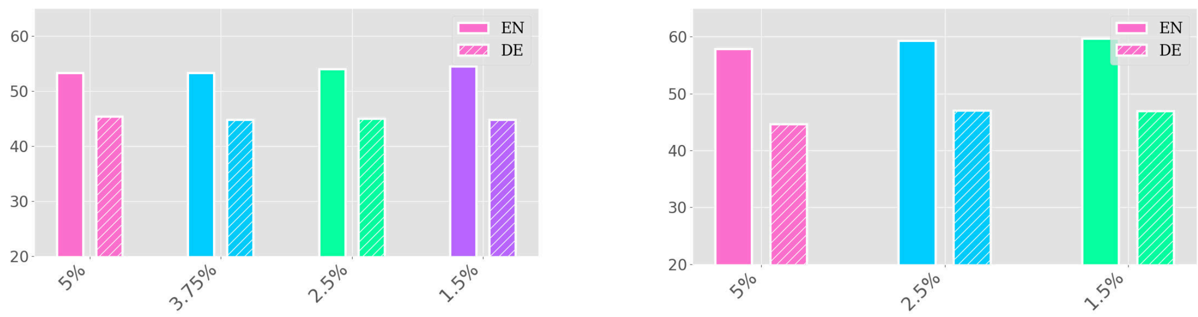
F.2 Perplexity Evaluations for Translated Training Data

In Sections 5.1 and F.1 we found that performance trends were not the same across languages. In particular, French, German, Portuguese, and Spanish (belonging to the same language family) have similar patterns, however, performance for Chinese, Japanese, and Korean exhibit different patterns. To further test whether the models retain knowledge from one language in another, we translate a small portion of the training set from FineWeb-EDU and mC4 English totaling 10,000 documents. We then translate the data using the v3 translation system from Section 4.4. We measure both the macro perplexity of all documents as well as the fraction of times where the translated and original data from FineWeb-EDU (training set) have lower loss than the average loss of documents from mC4 English (not part of the training set but from a similar distribution). We refer to this quantity as translated and original *exceedance*. Having lower loss means the data is more familiar to the model, and having an equal *exceedance* across the original and translated data means the model can reason equally in either language. Our results are summarized in Table 3. We find that perplexity is nearly identical for original data, but much higher for translated data in all languages. For *exceedance*, in English, we see that the scores are all around 80%. However, we see that for Japanese and Chinese these values are much lower, indicating that seeing the data in English for these languages does not lower the perplexity in the target language and that the model is not making use of information in the other language. For Chinese evaluations, we note that the perplexity is much higher than for other languages indicating that the translation system potentially causes higher perplexity and lower *exceedance*. However, we still note that for Japanese, the *exceedance* is lower and expect with better translation quality, the Chinese evaluations will be similar to Japanese.



(a) Japanese (b) Chinese

Figure 13: Zero-shot accuracy of XL models trained with various English auxiliary data for Japanese and Chinese. Results are averaged over six eval datasets.



(a) 1.3B Model (b) 2.7B Model

Figure 14: Zero-shot QA performance for 1B and 3B models at varying data ratios during training. For all models the total amount of available data in the target language is 250M tokens.

F.3 Individual Eval Dataset Results

Results for individual evaluation datasets are shown for all languages in Tables 4-11.

G Results for Individual datasets for German Target Language Models

Results for the 300M models on individual eval datasets are also provides in Tables 12-13. Results for 1B models on English evaluation tasks are shown in Table 14 and for translated German benchmarks in Table 15.

Language	mC4-Train	mc4-Val	mC4-EN	mC4-EN Translated	FWE	FWE Translated	Original EX	Translated EX
German	8.41	16.41	14.25	25.58	10.61	21.31	78.70	75.00
French	6.24	12.75	14.37	20.31	10.66	14.37	79.24	88.64
Japanese	6.52	11.21	14.56	25.56	10.64	23.89	80.41	56.97
Chinese	4.35	21.38	15.37	165.90	10.69	210.43	84.07	27.71

Table 3: Perplexity evaluations for mC4 English and FineWeb-EDU comparing original data and translated versions for 1B models trained with 250M tokens from the target language and FineWeb-EDU as the auxiliary dataset.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base DE	22.78 ± 1.23	37.92 ± 1.00	33.06 ± 0.47	62.35 ± 1.13	64.70 ± 1.51	51.14 ± 1.40	45.33
Base EN	25.94 ± 1.28	48.15 ± 1.03	48.50 ± 0.50	71.55 ± 1.05	73.10 ± 1.40	52.01 ± 1.40	53.21
Base EN + OH/ELI5 Filter	29.52 ± 1.33	57.03 ± 1.02	49.96 ± 0.50	71.87 ± 1.05	77.90 ± 1.31	53.83 ± 1.40	56.69
ARC EN	31.83 ± 1.36	57.24 ± 1.02	48.80 ± 0.50	73.07 ± 1.04	77.00 ± 1.33	52.72 ± 1.40	56.78
SciQ+Inst	29.10 ± 1.33	55.22 ± 1.02	48.34 ± 0.50	71.71 ± 1.05	78.50 ± 1.30	53.04 ± 1.40	55.98
FineWeb EDU	38.14 ± 1.42	66.37 ± 0.97	54.88 ± 0.50	72.25 ± 1.04	84.60 ± 1.14	56.04 ± 1.39	62.05
Base DE	27.44 ± 1.32	38.81 ± 1.03	39.53 ± 0.51	63.17 ± 1.13	67.68 ± 1.52	52.62 ± 1.45	48.21
Base EN	25.07 ± 1.29	37.70 ± 1.02	36.18 ± 0.50	59.36 ± 1.15	63.05 ± 1.57	50.51 ± 1.45	45.31
Base EN + OH/ELI5 Filter	25.77 ± 1.30	40.00 ± 1.03	35.94 ± 0.50	59.25 ± 1.15	65.05 ± 1.55	51.18 ± 1.45	46.20
ARC EN	26.91 ± 1.32	39.34 ± 1.03	35.77 ± 0.50	58.65 ± 1.15	67.58 ± 1.52	52.11 ± 1.45	46.73
SciQ+Inst	25.24 ± 1.29	39.38 ± 1.03	35.34 ± 0.49	59.74 ± 1.14	64.21 ± 1.56	52.70 ± 1.45	46.10
FineWeb EDU	26.91 ± 1.32	42.39 ± 1.04	37.40 ± 0.50	60.45 ± 1.14	65.37 ± 1.54	50.42 ± 1.45	47.16

Table 4: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by translated German. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base FR	24.66 ± 1.26	36.78 ± 0.99	32.89 ± 0.47	60.66 ± 1.14	63.90 ± 1.52	50.51 ± 1.41	44.90
Base EN	26.28 ± 1.29	49.92 ± 1.03	48.62 ± 0.50	71.98 ± 1.05	75.20 ± 1.37	53.91 ± 1.40	54.32
Base EN + OH/ELI5 Filter	29.52 ± 1.33	56.44 ± 1.02	49.92 ± 0.50	72.74 ± 1.04	79.70 ± 1.27	54.06 ± 1.40	57.06
ARC EN	29.69 ± 1.34	57.28 ± 1.02	48.96 ± 0.50	72.91 ± 1.04	78.90 ± 1.29	53.12 ± 1.40	56.81
SciQ+Inst	28.41 ± 1.32	53.16 ± 1.02	47.44 ± 0.50	70.51 ± 1.06	78.90 ± 1.29	54.14 ± 1.40	55.43
FineWeb EDU	36.69 ± 1.41	65.40 ± 0.98	54.81 ± 0.50	72.74 ± 1.04	82.50 ± 1.20	55.41 ± 1.40	61.26
Base FR	25.98 ± 1.30	38.53 ± 1.02	41.71 ± 0.51	64.25 ± 1.12	62.12 ± 1.57	53.25 ± 1.43	47.64
Base EN	23.54 ± 1.25	37.03 ± 1.01	37.66 ± 0.50	58.98 ± 1.15	60.44 ± 1.58	49.05 ± 1.43	44.45
Base EN + OH/ELI5 Filter	26.50 ± 1.30	38.93 ± 1.02	38.85 ± 0.50	60.50 ± 1.14	66.11 ± 1.53	50.37 ± 1.43	46.88
ARC EN	25.54 ± 1.29	39.32 ± 1.03	38.17 ± 0.50	59.41 ± 1.15	64.22 ± 1.55	50.29 ± 1.44	46.16
SciQ+Inst	25.72 ± 1.29	38.71 ± 1.02	37.61 ± 0.50	59.03 ± 1.15	63.06 ± 1.56	49.55 ± 1.43	45.61
FineWeb EDU	27.38 ± 1.32	40.51 ± 1.03	40.67 ± 0.51	60.94 ± 1.14	64.85 ± 1.55	50.78 ± 1.43	47.52

Table 5: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by French. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base ES	23.29 ± 1.24	38.55 ± 1.00	33.86 ± 0.47	60.83 ± 1.14	67.90 ± 1.48	51.07 ± 1.40	45.92
Base EN	26.19 ± 1.28	48.95 ± 1.03	48.16 ± 0.50	71.11 ± 1.06	74.30 ± 1.38	52.01 ± 1.40	53.45
Base EN + OH/ELI5 Filter	29.86 ± 1.34	58.08 ± 1.01	50.55 ± 0.50	72.36 ± 1.04	79.40 ± 1.28	54.62 ± 1.40	57.48
ARC EN	30.89 ± 1.35	58.71 ± 1.01	49.41 ± 0.50	73.45 ± 1.03	78.50 ± 1.30	54.06 ± 1.40	57.50
SciQ+Inst	29.44 ± 1.33	57.49 ± 1.01	48.89 ± 0.50	70.57 ± 1.06	79.70 ± 1.27	54.22 ± 1.40	56.72
FWE	36.60 ± 1.41	64.86 ± 0.98	54.95 ± 0.50	71.87 ± 1.05	81.50 ± 1.23	57.85 ± 1.39	61.27
Base ES	27.99 ± 1.33	44.12 ± 1.04	43.64 ± 0.51	65.94 ± 1.11	69.72 ± 1.49	52.70 ± 1.42	50.69
Base EN	25.28 ± 1.28	38.71 ± 1.02	39.32 ± 0.50	60.94 ± 1.14	65.83 ± 1.54	47.13 ± 1.42	46.20
Base EN + OH/ELI5 Filter	24.41 ± 1.27	35.31 ± 1.00	33.01 ± 0.49	56.64 ± 1.16	64.35 ± 1.55	50.36 ± 1.42	44.01
ARC EN	25.89 ± 1.29	42.01 ± 1.04	39.49 ± 0.50	62.02 ± 1.13	66.25 ± 1.53	52.54 ± 1.42	48.03
SciQ+Inst	25.89 ± 1.29	41.08 ± 1.03	39.35 ± 0.50	61.37 ± 1.14	67.93 ± 1.51	51.82 ± 1.42	47.91
FWE	27.99 ± 1.33	43.24 ± 1.04	42.05 ± 0.51	62.19 ± 1.13	70.45 ± 1.48	51.17 ± 1.42	49.51

Table 6: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by Spanish. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base PT	23.98 ± 1.25	39.14 ± 1.00	33.26 ± 0.47	60.99 ± 1.14	66.30 ± 1.50	52.01 ± 1.40	45.95
Base EN	25.34 ± 1.27	48.02 ± 1.03	47.19 ± 0.50	71.60 ± 1.05	74.00 ± 1.39	50.04 ± 1.41	52.70
Base EN + OH/ELI5 Filter	29.44 ± 1.33	53.79 ± 1.02	49.53 ± 0.50	71.49 ± 1.05	80.30 ± 1.26	55.33 ± 1.40	56.65
ARC EN	30.72 ± 1.35	57.83 ± 1.01	48.79 ± 0.50	73.01 ± 1.04	78.30 ± 1.30	52.64 ± 1.40	56.88
SciQ+Inst	29.35 ± 1.33	57.45 ± 1.01	48.26 ± 0.50	71.55 ± 1.05	78.80 ± 1.29	53.99 ± 1.40	56.56
FWE	35.07 ± 1.39	64.39 ± 0.98	54.81 ± 0.50	72.69 ± 1.04	82.10 ± 1.21	57.62 ± 1.39	61.11
Base PT	30.25 ± 1.36	43.55 ± 1.04	42.36 ± 0.51	64.80 ± 1.11	69.88 ± 1.49	52.11 ± 1.42	50.49
Base EN	24.06 ± 1.26	38.04 ± 1.02	36.04 ± 0.50	59.68 ± 1.14	59.18 ± 1.59	51.06 ± 1.42	44.68
Base EN + OH/ELI5 Filter	25.37 ± 1.29	39.59 ± 1.03	37.15 ± 0.50	58.71 ± 1.15	66.11 ± 1.53	48.70 ± 1.42	45.94
ARC EN	27.90 ± 1.32	38.79 ± 1.02	36.87 ± 0.50	60.07 ± 1.14	64.32 ± 1.55	49.35 ± 1.42	46.22
SciQ+Inst	27.03 ± 1.31	40.38 ± 1.03	37.72 ± 0.50	60.72 ± 1.14	66.00 ± 1.54	50.73 ± 1.42	47.10
FWE	28.86 ± 1.34	43.11 ± 1.04	39.81 ± 0.51	60.34 ± 1.14	66.84 ± 1.53	50.57 ± 1.42	48.25

Table 7: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by Portuguese. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base IT	21.59 ± 1.20	35.77 ± 0.98	32.54 ± 0.47	59.09 ± 1.15	63.70 ± 1.52	51.07 ± 1.40	43.96
Base EN	26.11 ± 1.28	48.53 ± 1.03	47.16 ± 0.50	71.71 ± 1.05	73.50 ± 1.40	53.35 ± 1.40	53.39
Base EN + OH/ELI5 Filter	31.14 ± 1.35	57.37 ± 1.01	50.89 ± 0.50	72.42 ± 1.04	79.50 ± 1.28	53.12 ± 1.40	57.40
ARC EN	30.46 ± 1.34	56.06 ± 1.02	48.78 ± 0.50	73.01 ± 1.04	75.90 ± 1.35	52.57 ± 1.40	56.13
SciQ+Inst	30.38 ± 1.34	56.78 ± 1.02	48.49 ± 0.50	71.27 ± 1.06	80.20 ± 1.26	54.85 ± 1.40	56.99
FWE	37.03 ± 1.41	65.61 ± 0.97	54.91 ± 0.50	72.74 ± 1.04	84.20 ± 1.15	54.85 ± 1.40	61.56
Base IT	26.33 ± 1.30	40.38 ± 1.03	39.89 ± 0.51	64.74 ± 1.11	61.76 ± 1.58	51.42 ± 1.42	47.42
Base EN	25.81 ± 1.29	36.02 ± 1.01	35.29 ± 0.50	58.65 ± 1.15	58.82 ± 1.60	52.23 ± 1.42	44.47
Base EN + OH/ELI5 Filter	24.93 ± 1.28	32.01 ± 0.98	31.76 ± 0.49	54.95 ± 1.16	61.97 ± 1.57	53.20 ± 1.42	43.14
ARC EN	25.72 ± 1.29	39.15 ± 1.02	36.18 ± 0.50	60.55 ± 1.14	63.24 ± 1.56	51.34 ± 1.42	46.03
SciQ+Inst	26.07 ± 1.30	40.03 ± 1.03	36.67 ± 0.50	58.76 ± 1.15	62.29 ± 1.57	50.93 ± 1.42	45.79
FWE	29.90 ± 1.35	41.04 ± 1.03	38.24 ± 0.51	62.68 ± 1.13	61.03 ± 1.58	51.18 ± 1.42	47.34

Table 8: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by Italian. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base KO	22.10 ± 1.21	37.46 ± 0.99	28.99 ± 0.45	59.19 ± 1.15	60.70 ± 1.55	51.62 ± 1.40	43.34
Base EN	26.02 ± 1.28	47.47 ± 1.02	47.71 ± 0.50	71.11 ± 1.06	75.00 ± 1.37	52.72 ± 1.40	53.34
Base EN + OH/ELI5 Filter	30.03 ± 1.34	56.69 ± 1.02	50.38 ± 0.50	71.76 ± 1.05	78.90 ± 1.29	53.20 ± 1.40	56.83
ARC EN	30.03 ± 1.34	57.37 ± 1.01	49.41 ± 0.50	73.78 ± 1.03	78.20 ± 1.31	53.12 ± 1.40	56.98
SciQ+Inst	30.97 ± 1.35	58.54 ± 1.01	48.16 ± 0.50	71.49 ± 1.05	80.30 ± 1.26	52.33 ± 1.40	56.97
FWE	36.01 ± 1.40	63.59 ± 0.99	54.41 ± 0.50	72.96 ± 1.04	80.10 ± 1.26	55.56 ± 1.40	60.44
Base KO	28.07 ± 1.33	42.18 ± 1.04	35.48 ± 0.48	60.66 ± 1.14	71.64 ± 1.47	49.28 ± 1.46	47.89
Base EN	22.76 ± 1.24	33.82 ± 0.99	28.88 ± 0.45	55.22 ± 1.16	56.08 ± 1.62	51.23 ± 1.46	41.33
Base EN + OH/ELI5 Filter	24.85 ± 1.28	34.13 ± 1.00	29.35 ± 0.45	55.55 ± 1.16	63.92 ± 1.56	52.34 ± 1.46	43.35
ARC EN	25.28 ± 1.28	33.73 ± 0.99	29.33 ± 0.45	53.86 ± 1.16	64.44 ± 1.56	51.15 ± 1.46	42.97
SciQ+Inst	23.19 ± 1.25	34.26 ± 1.00	30.01 ± 0.46	55.60 ± 1.16	64.02 ± 1.56	50.04 ± 1.46	42.86
FWE	22.93 ± 1.24	32.32 ± 0.98	29.09 ± 0.45	53.26 ± 1.16	64.76 ± 1.55	48.43 ± 1.46	41.80

Table 9: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by Korean. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base JA	23.46 ± 1.24	37.42 ± 0.99	29.07 ± 0.45	59.14 ± 1.15	68.10 ± 1.47	50.28 ± 1.41	44.58
Base EN	26.19 ± 1.28	49.24 ± 1.03	48.69 ± 0.50	72.63 ± 1.04	74.40 ± 1.38	53.28 ± 1.40	54.07
Base EN + OH/ELI5 Filter	29.78 ± 1.34	55.30 ± 1.02	50.26 ± 0.50	72.14 ± 1.05	78.90 ± 1.29	52.72 ± 1.40	56.52
ARC EN	29.35 ± 1.33	56.94 ± 1.02	49.05 ± 0.50	73.78 ± 1.03	79.80 ± 1.27	54.22 ± 1.40	57.19
SciQ+Inst	30.38 ± 1.34	56.14 ± 1.02	48.32 ± 0.50	72.42 ± 1.04	78.60 ± 1.30	52.64 ± 1.40	56.42
FineWeb EDU	34.73 ± 1.39	63.59 ± 0.99	54.80 ± 0.50	72.91 ± 1.04	82.20 ± 1.21	56.43 ± 1.39	60.78
Base JA	25.28 ± 1.28	40.69 ± 1.03	35.11 ± 0.48	58.98 ± 1.15	69.98 ± 1.51	51.19 ± 1.51	46.87
Base EN	25.28 ± 1.28	36.15 ± 1.01	31.71 ± 0.46	56.26 ± 1.16	66.41 ± 1.55	50.82 ± 1.51	44.44
Base EN + OH/ELI5 Filter	26.50 ± 1.30	36.99 ± 1.01	31.11 ± 0.46	56.96 ± 1.16	67.60 ± 1.54	50.18 ± 1.51	44.89
ARC EN	27.55 ± 1.32	37.43 ± 1.02	31.56 ± 0.46	57.29 ± 1.15	65.55 ± 1.56	48.72 ± 1.51	44.68
SciQ+Inst	27.38 ± 1.32	36.42 ± 1.01	31.44 ± 0.46	56.58 ± 1.16	67.28 ± 1.54	50.36 ± 1.51	44.91
FineWeb EDU	25.28 ± 1.28	33.73 ± 0.99	30.91 ± 0.46	56.09 ± 1.16	63.28 ± 1.58	47.08 ± 1.51	42.73

Table 10: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by translated Japanese. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
Base ZH	21.16 ± 1.19	33.16 ± 0.97	27.63 ± 0.45	55.98 ± 1.16	56.60 ± 1.57	49.09 ± 1.41	40.61
Base EN	25.85 ± 1.28	47.90 ± 1.03	48.54 ± 0.50	71.93 ± 1.05	73.90 ± 1.39	52.64 ± 1.40	53.46
Base EN + OH/ELI5 Filter	28.84 ± 1.32	55.85 ± 1.02	49.63 ± 0.50	71.22 ± 1.06	78.70 ± 1.30	53.12 ± 1.40	56.23
ARC EN	30.72 ± 1.35	57.49 ± 1.01	48.38 ± 0.50	73.29 ± 1.03	80.10 ± 1.26	53.75 ± 1.40	57.29
SciQ+Inst	30.38 ± 1.34	56.31 ± 1.02	47.66 ± 0.50	71.16 ± 1.06	78.10 ± 1.31	52.49 ± 1.40	56.02
FWE	36.18 ± 1.40	67.13 ± 0.96	54.07 ± 0.50	73.99 ± 1.02	80.90 ± 1.24	55.96 ± 1.40	61.37
Base ZH	25.65 ± 1.29	38.88 ± 1.02	33.07 ± 0.49	56.37 ± 1.16	69.90 ± 1.45	49.86 ± 1.54	45.62
Base EN	25.22 ± 1.28	36.77 ± 1.01	31.62 ± 0.48	56.09 ± 1.16	68.00 ± 1.48	48.35 ± 1.54	44.34
Base EN + OH/ELI5 Filter	23.56 ± 1.25	38.22 ± 1.02	32.45 ± 0.49	54.68 ± 1.16	68.50 ± 1.47	52.79 ± 1.53	45.03
ARC EN	23.21 ± 1.25	37.52 ± 1.02	32.06 ± 0.48	55.44 ± 1.16	70.90 ± 1.44	48.54 ± 1.54	44.61
SciQ+Inst	22.16 ± 1.23	38.00 ± 1.02	32.24 ± 0.49	54.03 ± 1.16	68.60 ± 1.47	53.07 ± 1.53	44.68
FWE	25.04 ± 1.28	36.50 ± 1.01	31.89 ± 0.48	54.62 ± 1.16	66.30 ± 1.50	51.94 ± 1.54	44.38

Table 11: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English followed by translated Chinese. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

No ARC Base DE	21.08 ± 1.19	31.52 ± 0.95	28.09 ± 0.45	56.47 ± 1.16	54.80 ± 1.57	51.30 ± 1.40	40.54
Base DE	20.73 ± 1.18	33.33 ± 0.97	28.15 ± 0.45	57.40 ± 1.15	56.30 ± 1.57	50.59 ± 1.41	41.09
Base EN	23.81 ± 1.24	41.92 ± 1.01	35.73 ± 0.48	67.03 ± 1.10	66.10 ± 1.50	50.75 ± 1.41	47.56
Base EN + OH/ELI5 Filter	25.43 ± 1.27	46.17 ± 1.02	35.82 ± 0.48	67.19 ± 1.10	67.50 ± 1.48	52.49 ± 1.40	49.10
ARC EN	26.28 ± 1.29	46.80 ± 1.02	36.44 ± 0.48	67.46 ± 1.09	70.30 ± 1.45	51.38 ± 1.40	49.78
HS EN	23.72 ± 1.24	42.42 ± 1.01	39.64 ± 0.49	70.13 ± 1.07	67.20 ± 1.49	50.43 ± 1.41	48.93
HS+ARC EN	24.23 ± 1.25	44.40 ± 1.02	38.51 ± 0.49	68.50 ± 1.08	68.70 ± 1.47	50.43 ± 1.41	49.13
SciQ	26.62 ± 1.29	49.33 ± 1.03	31.94 ± 0.47	63.44 ± 1.12	72.40 ± 1.41	50.83 ± 1.41	49.09
Inst	23.55 ± 1.24	43.27 ± 1.02	36.40 ± 0.48	67.25 ± 1.09	68.90 ± 1.46	51.14 ± 1.40	48.42
SciQ+Inst	26.19 ± 1.28	46.93 ± 1.02	36.02 ± 0.48	66.21 ± 1.10	73.10 ± 1.40	50.67 ± 1.41	49.85
v1 Base EN	21.16 ± 1.19	36.83 ± 0.99	29.19 ± 0.45	60.07 ± 1.14	63.50 ± 1.52	52.33 ± 1.40	43.84
v2 Base EN	21.16 ± 1.19	34.89 ± 0.98	29.60 ± 0.46	57.45 ± 1.15	59.50 ± 1.55	50.36 ± 1.41	42.16
v3 Base EN	19.54 ± 1.16	35.02 ± 0.98	29.46 ± 0.45	59.47 ± 1.15	61.40 ± 1.54	50.51 ± 1.41	42.57
RPJv2	25.09 ± 1.27	43.27 ± 1.02	37.23 ± 0.48	65.02 ± 1.11	66.30 ± 1.50	49.80 ± 1.41	47.78
RefinedWeb	24.40 ± 1.26	43.98 ± 1.02	39.75 ± 0.49	68.66 ± 1.08	69.80 ± 1.45	52.49 ± 1.40	49.85
FineWeb	25.00 ± 1.27	44.23 ± 1.02	40.89 ± 0.49	69.53 ± 1.07	68.40 ± 1.47	51.78 ± 1.40	49.97
FineWebEDU	28.67 ± 1.32	56.06 ± 1.02	40.85 ± 0.49	66.65 ± 1.10	72.60 ± 1.41	52.09 ± 1.40	52.82

Table 12: Evaluation of 300M parameter medium model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C-DE	ARC-E-DE	HS-DE	PIQA-DE	SCIQ-DE	WGrande-DE	AVG-DE
No ARC Base DE	23.48 ± 1.26	32.30 ± 0.98	30.45 ± 0.48	56.09 ± 1.16	60.32 ± 1.59	52.11 ± 1.45	42.46
Base DE	24.98 ± 1.28	34.87 ± 1.00	32.28 ± 0.48	59.79 ± 1.14	61.26 ± 1.58	51.52 ± 1.45	44.12
Base EN	23.83 ± 1.26	30.66 ± 0.97	29.69 ± 0.47	56.37 ± 1.16	60.84 ± 1.58	51.01 ± 1.45	42.07
Base EN + OH/ELI5 Filter	24.27 ± 1.27	32.74 ± 0.99	29.68 ± 0.47	55.88 ± 1.16	60.42 ± 1.59	51.69 ± 1.45	42.45
ARC EN	23.83 ± 1.26	33.05 ± 0.99	29.59 ± 0.47	56.37 ± 1.16	60.11 ± 1.59	51.60 ± 1.45	42.43
HS EN	23.75 ± 1.26	31.81 ± 0.98	30.32 ± 0.47	57.40 ± 1.15	59.68 ± 1.59	51.52 ± 1.45	42.41
HS+ARC EN	24.54 ± 1.28	33.01 ± 0.99	30.10 ± 0.47	55.01 ± 1.16	60.11 ± 1.59	50.84 ± 1.45	42.27
SciQ	23.66 ± 1.26	32.21 ± 0.98	28.84 ± 0.47	56.26 ± 1.16	61.58 ± 1.58	52.96 ± 1.45	42.58
Inst	25.42 ± 1.29	32.79 ± 0.99	29.59 ± 0.47	55.93 ± 1.16	61.05 ± 1.58	50.68 ± 1.45	42.58
SciQ+Inst	23.22 ± 1.25	33.67 ± 0.99	29.42 ± 0.47	55.93 ± 1.16	61.68 ± 1.58	51.27 ± 1.45	42.53
v1 Base EN	23.92 ± 1.27	35.27 ± 1.01	32.79 ± 0.49	59.74 ± 1.14	62.42 ± 1.57	50.68 ± 1.45	44.14
v2 Base EN	24.27 ± 1.27	36.19 ± 1.01	32.72 ± 0.48	59.41 ± 1.15	63.89 ± 1.56	52.53 ± 1.45	44.84
v3 Base EN	23.83 ± 1.26	36.19 ± 1.01	34.06 ± 0.49	61.04 ± 1.14	63.26 ± 1.56	51.77 ± 1.45	45.03
RPJv2	24.10 ± 1.27	33.10 ± 0.99	30.06 ± 0.47	55.44 ± 1.16	59.05 ± 1.60	50.08 ± 1.45	41.97
RefinedWeb	25.33 ± 1.29	32.12 ± 0.98	30.56 ± 0.48	57.34 ± 1.15	62.32 ± 1.57	51.77 ± 1.45	43.24
FineWeb	24.45 ± 1.28	33.67 ± 0.99	31.20 ± 0.48	56.31 ± 1.16	62.32 ± 1.57	51.01 ± 1.45	43.16
FineWebEDU	25.59 ± 1.29	35.00 ± 1.00	31.19 ± 0.48	56.86 ± 1.16	62.32 ± 1.57	51.52 ± 1.45	43.75

Table 13: Evaluation of 300M parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in translated German. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C	ARC-E	HS	PIQA	SCIQ	WGrande	AVG
No ARC Base DE	21.33 ± 1.20	35.40 ± 0.98	30.88 ± 0.46	59.14 ± 1.15	60.50 ± 1.55	50.67 ± 1.41	42.99
Base DE	22.78 ± 1.23	37.92 ± 1.00	33.06 ± 0.47	62.35 ± 1.13	64.70 ± 1.51	51.14 ± 1.40	45.33
Base EN	25.94 ± 1.28	48.15 ± 1.03	48.50 ± 0.50	71.55 ± 1.05	73.10 ± 1.40	52.01 ± 1.40	53.21
Base EN + OH/ELI5 Filter	29.52 ± 1.33	57.03 ± 1.02	49.96 ± 0.50	71.87 ± 1.05	77.90 ± 1.31	53.83 ± 1.40	56.69
ARC EN	31.83 ± 1.36	57.24 ± 1.02	48.80 ± 0.50	73.07 ± 1.04	77.00 ± 1.33	52.72 ± 1.40	56.78
HS EN	28.84 ± 1.32	49.83 ± 1.03	54.83 ± 0.50	75.14 ± 1.01	75.10 ± 1.37	54.85 ± 1.40	56.43
HS+ARC EN	28.84 ± 1.32	56.10 ± 1.02	53.04 ± 0.50	73.67 ± 1.03	77.90 ± 1.31	54.38 ± 1.40	57.32
SciQ	30.63 ± 1.35	57.28 ± 1.02	39.79 ± 0.49	68.28 ± 1.09	80.40 ± 1.26	53.91 ± 1.40	55.05
Inst	27.22 ± 1.30	53.66 ± 1.02	50.30 ± 0.50	71.49 ± 1.05	76.20 ± 1.35	53.51 ± 1.40	55.40
SciQ+Inst	29.10 ± 1.33	55.22 ± 1.02	48.34 ± 0.50	71.71 ± 1.05	78.50 ± 1.30	53.04 ± 1.40	55.98
v1 Base EN	20.73 ± 1.18	38.97 ± 1.00	36.09 ± 0.48	63.33 ± 1.12	65.40 ± 1.51	52.01 ± 1.40	46.09
v2 Base EN	22.70 ± 1.22	38.97 ± 1.00	36.55 ± 0.48	64.80 ± 1.11	69.30 ± 1.46	51.22 ± 1.40	47.26
v3 Base EN	20.65 ± 1.18	40.36 ± 1.01	36.57 ± 0.48	63.66 ± 1.12	70.50 ± 1.44	51.54 ± 1.40	47.21
RPJv2	26.96 ± 1.30	50.42 ± 1.03	51.10 ± 0.50	70.57 ± 1.06	77.60 ± 1.32	55.64 ± 1.40	55.38
RefinedWeb	27.90 ± 1.31	54.59 ± 1.02	54.91 ± 0.50	73.23 ± 1.03	77.60 ± 1.32	56.35 ± 1.39	57.43
FineWeb	27.82 ± 1.31	52.15 ± 1.03	56.24 ± 0.50	73.94 ± 1.02	74.40 ± 1.38	55.72 ± 1.40	56.71
FineWebEDU	38.14 ± 1.42	66.37 ± 0.97	54.88 ± 0.50	72.25 ± 1.04	84.60 ± 1.14	56.04 ± 1.39	62.05

Table 14: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in English. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.

Model Name	ARC-C-DE	ARC-E-DE	HS-DE	PIQA-DE	SCIQ-DE	WGrande-DE	AVG-DE
No ARC Base DE	25.07 ± 1.29	36.95 ± 1.02	35.64 ± 0.49	59.74 ± 1.14	64.53 ± 1.55	52.62 ± 1.45	45.76
Base DE	27.44 ± 1.32	38.81 ± 1.03	39.53 ± 0.51	63.17 ± 1.13	67.68 ± 1.52	52.62 ± 1.45	48.21
Base EN	25.07 ± 1.29	37.70 ± 1.02	36.18 ± 0.50	59.36 ± 1.15	63.05 ± 1.57	50.51 ± 1.45	45.31
Base EN + OH/ELI5 Filter	25.77 ± 1.30	40.00 ± 1.03	35.94 ± 0.50	59.25 ± 1.15	65.05 ± 1.55	51.18 ± 1.45	46.20
ARC EN	26.91 ± 1.32	39.34 ± 1.03	35.77 ± 0.50	58.65 ± 1.15	67.58 ± 1.52	52.11 ± 1.45	46.73
HS EN	24.89 ± 1.28	36.90 ± 1.02	37.11 ± 0.50	60.77 ± 1.14	63.47 ± 1.56	52.87 ± 1.45	46.00
HS+ARC EN	26.74 ± 1.31	38.50 ± 1.02	36.71 ± 0.50	59.96 ± 1.14	63.89 ± 1.56	51.35 ± 1.45	46.19
SciQ	27.35 ± 1.32	39.38 ± 1.03	33.23 ± 0.49	58.76 ± 1.15	64.21 ± 1.56	51.18 ± 1.45	45.69
Inst	25.59 ± 1.29	38.14 ± 1.02	36.22 ± 0.50	60.01 ± 1.14	64.74 ± 1.55	51.01 ± 1.45	45.95
SciQ+Inst	25.24 ± 1.29	39.38 ± 1.03	35.34 ± 0.49	59.74 ± 1.14	64.21 ± 1.56	52.70 ± 1.45	46.10
v1 Base EN	26.12 ± 1.30	40.93 ± 1.03	40.39 ± 0.51	61.48 ± 1.14	67.58 ± 1.52	51.94 ± 1.45	48.07
v2 Base EN	25.51 ± 1.29	42.30 ± 1.04	40.75 ± 0.51	62.19 ± 1.13	71.37 ± 1.47	52.45 ± 1.45	49.09
v3 Base EN	26.21 ± 1.30	40.84 ± 1.03	43.08 ± 0.51	64.09 ± 1.12	66.74 ± 1.53	51.52 ± 1.45	48.75
RPJv2	24.71 ± 1.28	37.17 ± 1.02	36.53 ± 0.50	58.65 ± 1.15	65.26 ± 1.55	52.70 ± 1.45	45.84
RefinedWeb	25.42 ± 1.29	38.81 ± 1.03	38.25 ± 0.50	58.38 ± 1.15	64.21 ± 1.56	51.01 ± 1.45	46.01
FineWeb	26.12 ± 1.30	36.90 ± 1.02	38.09 ± 0.50	59.85 ± 1.14	64.11 ± 1.56	53.89 ± 1.45	46.49
FineWebEDU	26.91 ± 1.32	42.39 ± 1.04	37.40 ± 0.50	60.45 ± 1.14	65.37 ± 1.54	50.42 ± 1.45	47.16

Table 15: Evaluation of 1B parameter XL model on "General Understanding Tasks" focusing on general reasoning, language understanding, and science knowledge in translated German. Results show the length normalized accuracy for individual datasets and the average over all datasets for all datasets.