

Bactrian-X: A Multilingual Replicable Instruction-Following Model with Low-Rank Adaptation

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Abstract

Instruction tuning has shown great promise in the field of natural language processing. However, the research on multilingual instruction tuning has been limited due to the scarcity of high-quality instruction-response datasets. To address this gap, we present Bactrian-X, a comprehensive multilingual parallel dataset of 3.4 million instruction-response pairs across 52 languages. Leveraging this dataset, we train a set of adapters using low-rank adaptation (LoRA), which are lightweight components seamlessly integrated with foundational models. These adapters have a significantly smaller parameter count than the base model, making them easily replaceable and usable as plug-ins for different languages or language groups. Through extensive experiments on 52 languages, we demonstrate the superior performance of our models in various multilingual evaluation settings. Our proposed models outperform both the vanilla models and the existing instruction-tuned models. The code and models are publicly available at <https://github.com/mbzuai-nlp/bactrian-x>.

1 Introduction

Instruction-tuned large language models (LLMs) have demonstrated remarkable zero-shot generalization capabilities (Sanh et al., 2022; Wei et al., 2022; Ouyang et al., 2022; OpenAI, 2023). Recently, work on instruction-tuned language models has progressed by fine-tuning smaller models using general instructions constructed from larger language models, making instruction-following language models more accessible (Taori et al., 2023; Chiang et al., 2023; Wu et al., 2023). However, existing work has primarily focused on the English language.

The current research on multilingual instruction-following LLMs is still limited, mainly because of the availability of open-source multilingual

large foundation models and the scarcity of multilingual instruction datasets. Muennighoff et al. (2022) introduced the xP3 dataset and fine-tuned BLOOM (Scao et al., 2022) and mT5 (Xue et al., 2021) models on it. However, xP3 is not truly multilingual as the prompts are still in English. The dataset primarily focuses on downstream NLP tasks, lacking variation in human-written prompts (Wang et al., 2022). Their resulting model demonstrates the ability to follow multilingual instructions but with limitations in handling general instructions. On the other hand, newer product-oriented LLMs, like OpenAI GPT-4 (OpenAI, 2023) and Google BARD,¹ showcase impressive multilingual capabilities in instruction following. However, the closed nature of these models hinders benchmarking and reproducibility, posing challenges to scientific progress in the field.

To address these research gaps, we introduce Bactrian-X, the first-ever publicly available multilingual instruction-following language model covering 52 languages. Bactrian-X instruction training data is constructed by translating the Alpaca (Taori et al., 2023) and Dolly (Conover et al., 2023) general instruction datasets into 51 languages, followed by distilling ChatGPT outputs from the translated instructions. With 67K instruction-response pairs (52K from Alpaca and 15K from Dolly) for each language, the total number of instances reaches 3.4 million. We employ automatic quality estimation to verify the translation and response quality, while planning to conduct human evaluation in the future.

In contrast to the previous multilingual instruction model BLOOMZ (Muennighoff et al., 2022), which undergoes full pre-training with parameter updates across all layers, this study highlights the potential of parameter-efficient fine-tuning techniques, specifically LoRA (Hu et al., 2022), for extending foundation models to accommodate multi-

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¹<https://bard.google.com/>

lingual or monolingual instructions. These adapters possess significantly few parameter counts compared to the foundation model, making them more practical and adaptable for real-world applications, as compared to full pre-training approaches. In this paper, we introduce our Bactrian-X model, which builds upon the BLOOM (Scao et al., 2022) and LLaMA (Touvron et al., 2023) models. Through our experiments, we present promising results demonstrating the competitiveness of Bactrian- X_{bloom} in comparison to BLOOMZ (Muennighoff et al., 2022), which represents BLOOM fully pre-trained on multilingual instruction.

We conducted thorough evaluations to compare our models with vanilla LLMs as well as models fine-tuned on other instruction-following datasets. The consistent results across various zero-shot multilingual downstream NLP tasks, including XCOPA (Ponti et al., 2020), XStoryCloze (Lin et al., 2022), XWinograd (Muennighoff et al., 2022), and our own multilingual sentiment analysis dataset SentimentX, demonstrate the improved performance of our models compared to all baseline models. Furthermore, we assessed the model’s ability to comprehend general instructions using GPT-4 as an evaluator, following the methodology proposed by Vicuna (Chiang et al., 2023). The results revealed that our models were preferred by GPT-4 over all baseline models. In the future, we plan to conduct more comprehensive evaluations involving human annotators to further validate our findings.

2 Related Work

Multilingual Instruction Tuning Large language models (LLMs) such as GPT-3 (Brown et al., 2020), PaLM (Chowdhery et al., 2022) and LLaMA (Touvron et al., 2023) among others (Hoffmann et al., 2022; Scao et al., 2022; Zeng et al., 2023; Touvron et al., 2023) has revolutionized the research paradigm of natural language processing (NLP). It has been shown that fine-tuning the LLMs with instruction prompts can further enhance the ability of language models to perform the unseen tasks (Wei et al., 2022; Sanh et al., 2022; Ouyang et al., 2022; Chung et al., 2022; Muennighoff et al., 2022; Chiang et al., 2023). Recently, Wang et al. (2022) show that the machine-generated instructions can be used for instruction tuning. Taori et al. (2023) generate a set of 52K instructions to fine-tune the LLaMA-7B. Wu et al. (2023) create a large-scale dataset with 2.58M instructions

and demonstrate that the relatively small language models can also follow the instructions. Furthermore, a large number of prior works have demonstrated that unified multilingual models are more resource-efficient and promote effective knowledge transfer (Pires et al., 2019; Aharoni et al., 2019; Dabre et al., 2020; Conneau et al., 2020; Aji et al., 2020; Xue et al., 2021; Wu et al., 2021; Li et al., 2022; Aji et al., 2022; Costa-jussà et al., 2022; Lin et al., 2022). However, there are few multilingual instruction-tuned LLMs due to the unavailability of the pretrained LLMs and multilingual instruction datasets. Muennighoff et al. (2022) finetune BLOOM and mT5 on the multilingual instruction dataset xP3, which is the closest work to ours. However, xP3 is generated based on human-written templates, which lack diversity. In this work, we create a large-scale multilingual instruction dataset by translating instructions from English into 51 languages and generating responses via ChatGPT. To the best of our knowledge, our Bactrian-X instruction dataset is the largest multilingual instruction dataset to date.

Parameter Efficient Fine-Tuning LLMs commonly require massive computational resources for both training and inference. Fine-tuning all the parameters, like Alpaca (Taori et al., 2023), Vicuna (Chiang et al., 2023) and LaMini-LM (Wu et al., 2023), can be computationally expensive. In this context, parameter efficient fine-tuning (PEFT) only updates or introduce a small number of model parameters and keeps the rest of the model parameters unchanged, while the resulting PEFT models are still able to be on par with their fully fine-tuned counterparts. There is a line of research that integrates adapter neural networks into the pre-trained models (Houlsby et al., 2019; Guo et al., 2021; Lester et al., 2021; Ben Zaken et al., 2022). More recently, Hu et al. (2022) propose Low-Rank Adaptation (LoRA) that inserts the trainable rank decomposition matrices into each Transformer layer. While fine-tuning with fewer model parameters, LoRA performs even better than a number of the fully fine-tuned LLMs, such as GPT-3 (Brown et al., 2020), on many tasks. In addition, unlike the prior adapter-based approach, LoRA does not introduce additional inference latency. In this work, we employ LoRA technique when fine-tuning our multilingual Bactrian-X models to reduce the computational cost and carbon footprint during training.

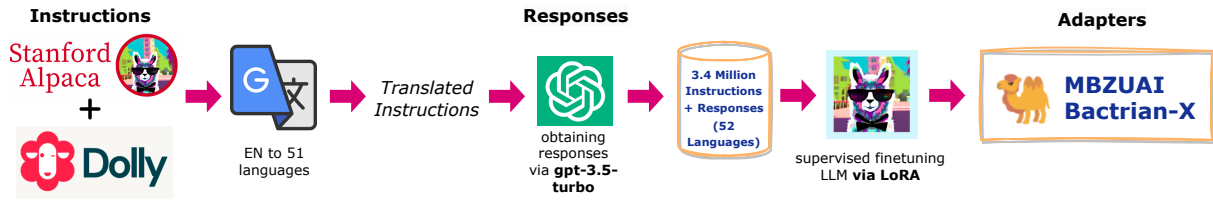


Figure 1: Overview of Bactrian-X dataset and models creation.

3 Dataset

In this section, we detail the dataset creation process as well as the exploratory data analysis, including translation quality, and diversity.

3.1 Dataset Creation

In this section, we present the dataset creation process, including two steps, instruction translation, and response generation (see Figure 1).

Instruction Translation The majority of existing instruction datasets are available only in English. We gathered instructions from Alpaca (52K) and Dolly (15K) where Alpaca instructions are generated by text-davinci-003 model, and Dolly dataset are generated by thousands of Databricks employees. We utilized the Google Translate API to translate these 67K instructions (without responses) into 51 different languages from English, following languages of mBART-50 model (Tang et al., 2020). Prior to the translation process, we identify instructions containing programming-related content based on a keyword-matching method and exclude them from the translation. The overall cost incurred for translating the instructions into 51 languages amounts to approximately \$10,000 USD.

Response Generation Upon translating the English instructions into multiple languages, we proceed to generate corresponding responses for each instruction using the ChatGPT (gpt-3.5-turbo). While the original English instructions are paired with responses, which means the same translation can be conducted on these responses, we opt to generate responses directly from ChatGPT.² This decision is motivated by the desire to avoid potential issues such as “translationese” and non-native answer styles that may arise from relying solely on translated responses. The total cost for generating responses amounts to around \$3,000 USD. In future work, we will compare the responses

²The generation was conducted during April 16-21, 2023.

translated from English using ChatGPT and the responses generated directly from the model.

3.2 Exploratory Data Analysis

Dataset Statistics We conducted text tokenization on instructions, inputs, and responses across all 52 languages using different tokenizers. The resulting statistics are presented in Table 1. For the mBART-50 tokenizer, we provide the average number of tokens across all 52 languages, as these languages are fully covered by the tokenizer. Regarding the LLaMA and BLOOM tokenizers, their supported languages partially overlap with our dataset. Therefore, we present statistics for both the languages seen and unseen by the tokenizers. From the table, we observe that for languages seen by the tokenizers, the BLOOM tokenizer yields a similar number of tokens as the mBART-50 tokenizer. However, the LLaMA tokenizer produces more tokens, indicating that the text is divided into more sub-word units, resulting in longer sequences. For unseen languages, the LLaMA tokenizer results in an average of 593 total tokens, which is three times the number of tokens produced by the mBART-50 tokenizer. This implies that not only does the model require a larger sequence length to accommodate these languages, but it also faces greater challenges in effectively adapting to them.

Translation Quality As all the instructions are translated by Google Translate API, it is of concern if the instructions are correctly translated into other languages. We randomly sample 100 sentences for each language, have the sampled sentences back-translated into English using Google Translate API, and use the corresponding English sentences from the original English dataset as the references to measure the translation quality. We use the lexical metric BLEU (Papineni et al., 2002; Post, 2018),³ chrF++ (Popović, 2017),⁴ and the neural metric

³nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|version:2.3.1

⁴nrefs:1|case:mixed|eff:yes|nc:6|nw:2|space:no|version:2.3.1

Tokenizer	Vocab size	Lang	# Ins. tokens	# Inp. tokens	# Res. tokens	# Total tokens
mBART-50	250,054	all	17.11 \pm 1.96	27.54 \pm 2.84	133.65 \pm 17.4	178.30 \pm 22.2
BLOOM	251,680	seen unseen	16.14 \pm 2.87 34.21 \pm 22.0	25.98 \pm 3.99 51.41 \pm 31.7	128.88 \pm 25.5 275.97 \pm 179	171.00 \pm 31.3 361.60 \pm 231
LLaMA	32,000	seen unseen	23.13 \pm 2.78 57.22 \pm 35.6	36.69 \pm 3.85 86.93 \pm 52.61	185.18 \pm 18.24 448.61 \pm 293	244.96 \pm 24.3 592.77 \pm 376

Table 1: Average # tokens in Instructions, Inputs, Responses over languages. Statistics conducted using different tokenizers from mBART-50, LLaMA and BLOOM, separately. mBART-50 covered all 52 languages, while LLaMA and BLOOM overlap with a subset of the languages in Bactrian-X.

	BLEU	chrF++	COMET
min	28.0	52.5	82.3
25% Q.	42.9	64.7	88.7
mean	48.1	68.1	90.2
median	47.2	67.8	90.5
75% Q.	52.7	72.2	92.0
max	69.0	82.7	95.3

Table 2: Descriptive statistics of BLEU, chrF++ and COMET scores on the language pairs from 51 foreign languages to English. COMET scores are up-scaled by $\times 100$.

COMET (Rei et al., 2020),⁵ and report the results in Table 2. The worst BLEU score of 28 is on Mongolian-English translation and the BLEU scores for most of the language pairs are higher than 40, which indicates that Google Translate API can produce high-quality and reliable translations when we translate the English instructions into all the other foreign languages.

4 Experiments

To comprehensively evaluate our Bactrian models, we present the results of automatic evaluation on the downstream NLP tasks, as well as the GPT-4 evaluation on the model outputs.

4.1 Baselines

We use 4 baseline models as listed below:

- LLaMA (Touvron et al., 2023) is a collection of foundation language models proposed by Meta, encompassing a parameter range of 7B to 65B. It is primarily trained in English, but still includes less than 4.5% of text across 20 different languages in its training data, enabling some level of support for multi-lingual tasks.
- Alpaca (Taori et al., 2023), introduced by Stanford, is fine-tuned from the LLaMA model on

Hyper-parameter	Multi	Mono
batch size	128	128
steps	100k	5k
learning rate	3e-4	3e-4
max seq length	768	1024
lora r	64	16
lora alpha	16	16
lora dropout	0.05	0.05

Table 3: Hyperparameters for multi- and mono-lingual model training.

52K English instruction-following data generated through self-instruct techniques (Wang et al., 2022). In initial human evaluations, the 7B Alpaca model exhibited similar behavior to the text-davinci-003 model (130B) on the self-instruct instruction-following evaluation suite (Wang et al., 2022).

- BLOOM (Scao et al., 2022) is a collection of pretraied multilingual language models created by BigScience. It was trained on the ROOTS corpus, which encompasses data from 46 different natural languages.
- BLOOMZ (Muennighoff et al., 2022), derived from BLOOM and fine-tuned using the crosslingual task mixture (xP3) dataset, is capable of zero-shot instruction-following in dozens of languages.

Considering the limitations of computation resources, we selected the models in 7B or 13B parameter.

4.2 Bactrain-X models

We trained several monolingual and multilingual adapters using LLaMA and BLOOM as foundation models. These models are publicly available in our model repository. For the monolingual models, we trained 15 LLaMA-based models and 18 BLOOM-based models. The languages were selected if it is presence during the pretraining of the founda-

⁵Unbabel/wmt22-comet-da

tion models. In addition, we trained two multilingual models: Bactrian- X_{llama} and Bactrian- X_{bloom} . These models utilize the full dataset encompassing 52 languages.

The models were trained using PyTorch with the Hugging Face PEFT (Mangrulkar et al., 2022) implementation of LoRA (Hu et al., 2022). The hyperparameters used for training the different models are listed in Table 3.

In our preliminary evaluation, we focused on evaluating two multilingual adapters. For convenience, we refer to these adapters as models in our discussions.

4.3 Automatic Evaluation on Multilingual Benchmark

We start by measuring the model’s performance across common multilingual NLP benchmarks as listed below. Please refer to Appendix for detailed data distribution.

- XCOPA (Ponti et al., 2020) is a multilingual resource designed for causal commonsense reasoning, encompassing 11 languages: Estonian (et), Haitian (ht), Indonesian (id), Italian (it), Quechua (qu), Swahili (sw), Tamil (ta), Thai (th), Turkish (tr), Vietnamese (vi), and Mandarin Chinese (zh). The task involves predicting the correct next sentence from two options based on cause and effect question types.
- XStoryCloze (Lin et al., 2022) is a translation of the English story cloze dataset (Mostafazadeh et al., 2016) into 10 languages: Arabic (ar), Spanish (es), Basque (eu), Hindi (hi), Indonesian (id), Burmese (my), Russian (ru), Swahili (sw), Telugu (te), and Mandarin Chinese (zh). The objective is to select one sentence as a plausible ending (closure) from two options, given a four-sentence story as the premise.
- XWinoGrad (Tikhonov and Ryabinin, 2021; Muennighoff et al., 2022) serves as a multilingual benchmark for commonsense reasoning, utilizing Winograd Schema Challenge problems in six languages: English (en), French (fr), Japanese (jp), Portuguese (pt), Mandarin Chinese (zh), and Russian (ru).⁶ The task involves selecting the most plausible sentence from two options that differ slightly in one or

two words.

- SentimentX is a sentiment classification dataset comprising 3-way sentiment labels collected from various sources. It includes Arabic (ar) (Alturayef et al., 2022), Spanish (es),⁷ Japanese (jp) (Hayashibe, 2020), Russian (ru),⁸ Indonesian (id) (Koto et al., 2020), Javanese (jav) (Winata et al., 2023), Sundanese (sun) (Winata et al., 2023), and Swahili (sw) (Muhammad et al., 2023).

In our study, we conduct zero-shot experiments utilizing nine large language models. We compare the performance of vanilla base models, existing instruction-tuned models, and our proposed Bactrian models. Specifically, we employ translated prompts for zero-shot evaluation using the following experimental set-up: (1) LLaMA-7B, Alpaca-LoRA-7B, and Bactrian- X_{llama} -7B; (2) LLaMA-13B, Alpaca-LoRA-13B, and Bactrian- X_{llama} -13B; and (3) BLOOM-7B, BLOOMZ-7B, and Bactrian- X_{bloom} -7B. Please refer to Appendix for detailed prompts for each language and task.

4.4 GPT-4 Evaluation

As current LLMs become more and more advanced, existing NLP benchmarks might not be sufficient for accurately evaluating the model capability. Besides, it is also challenging to evaluate model outputs with the automatic evaluation metrics (Freitag et al., 2020, 2021, 2022). One common complementary practice is to recruit human experts to annotate the model outputs. Nonetheless, implementing such a practice within our work is impractical for our work, given that our work covers 52 languages and it is difficult to recruit human experts for those low-resource languages. Therefore, we leverage GPT-4 (OpenAI, 2023) as an evaluator.

Chiang et al. (2023) present a challenging set of 80 questions, covering 8 categories, for GPT-4 evaluation. We translate these questions into 51 languages from English and use different models to generate responses, see Appendix B for examples. We present an example prompt used for GPT-4 evaluation in Figure 2. Following Chiang et al. (2023), we provide two answers from different models in a single prompt and ask GPT-4 to rate these answers in the range from 0 to 10 from various aspects including helpfulness, relevance, accuracy, and the

⁶<https://cs.nyu.edu/~davise/papers/WinogradSchemas/WS.html>

⁷<http://tass.sepln.org/2020/>

⁸<https://github.com/antongolubev5/Russian-Sentiment-Analysis-Evaluation-Datasets>

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You are a helpful and precise assistant for checking the quality of the answer.
<question>
Comment les obstacles linguistiques et culturels affectent-ils la façon dont les gens communiquent et nouent les relations dans les sociétés multiculturelles?
</question>
<answer1>
Les obstacles linguistiques peuvent avoir un impact significatif sur la façon de communiquer et de nouer des relations dans une société multiculturelle. Les différences culturelles peuvent également avoir un effet sur la communication, car les gens peuvent avoir des attentes différentes en matière de communication et de comportement. \n \n Les obstacles culturels peuvent également affecter la façon dans laquelle les gens se comprennent et communiquent. Les gens peuvent ne pas comprendre les mêmes choses ou avoir des interprétations différentes des mêmes événements, ce qui peut entraîner des malentendus et des conflits...
</answer1>
<answer2>
The linguistic and cultural obstacles can affect the way people communicate and form relationships in multicultural societies. Language barriers can make it difficult to understand each other, while cultural differences can lead to misunderstandings and miscommunication. Cultural differences in communication styles can lead people to misinterpret each other's intentions.
</answer2>

Suppose the user only speaks the language of the question, please evaluate both answers with your justification having less than three sentences, and provide a score ranging from 0 to 10 after your justifications. When evaluating the answers, you should consider the helpfulness, relevance, accuracy, level of details of the answers. The score for answer 1 should be wrapped by <score1> and </score1>, and the score for answer 2 should be wrapped by <score2> and </score2>.

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Figure 2: An example (in French) of GPT-4 evaluation given by Bactrian- X_{bloom} and Alpaca. Colored parts are prompts that suit for all instances.

level of details. To mitigate the potential influence of answer order during evaluation, we interchange the two provided answers from different models for each question and assign scores twice. Previous studies (Chiang et al., 2023; Muennighoff et al., 2022) shows that instruction tuned model generally preforms better than these models without instruction tuning, hence during GPT-4 evaluation, we exclude vanilla BLOOM and LLaMA from consideration. Instead, we compare Bactrian- X_{bloom} against BLOOMZ, Bactrian- X_{llama} against Alpaca, and Bactrian- X_{bloom} against Bactrian- X_{llama} . In our preliminary evaluation, we randomly select 2 questions from each category, resulting in 16 questions for each language. To save costs, we conducted the evaluation across 12 different languages.

5 Results and Analysis

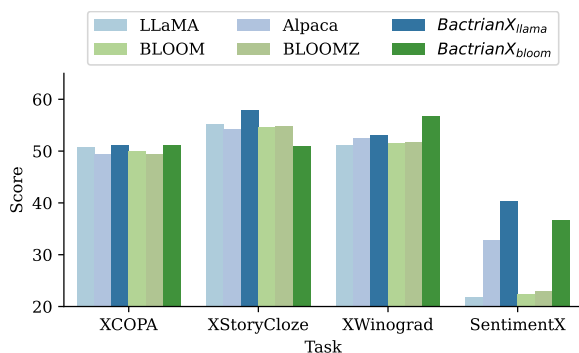


Figure 3: The average performance of all 7B models on unseen languages (i.e. languages that are not used in pre-training the foundation model).

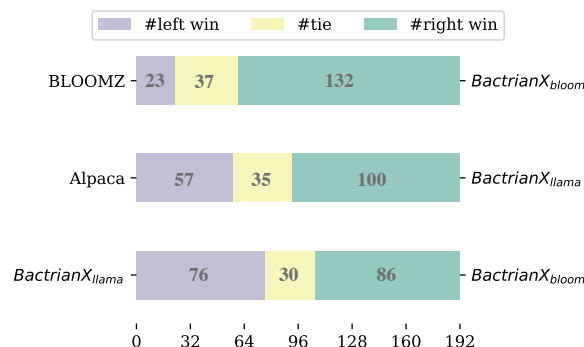


Figure 4: Overall comparison of GPT-4 evaluation.

5.1 Multilingual Benchmark

Overall The averaged performance of all languages for each XCOPA, XStoryCloze, XWinograd, and SentimentX datasets is presented in Table 4. Our analysis reveals that integrating LoRA into the foundation models of LLaMA and BLOOM, along with multilingual instruction datasets, consistently enhances the performance of all foundation models. These improvements are also notable when compared to existing instruction-tuned models such as Alpaca-LoRA. Furthermore, we observe further enhancements with larger models, as demonstrated by the superior performance of Bactrian- X_{llama} -13B compared to LLaMA-13B.

It's also worth mentioning that our parameter-efficient fine-tuning model, Bactrian- X_{bloom} -7B tends to yield better performance than the full fine-tuning model BLOOMZ-7B, especially in XCOPA, XStoryCloze, and XWinograd. Although the performance difference between the two models is

Models	XCOPA	XStoryCloze	XWinograd	SentimentX
LLaMA-7B	50.22	57.03	57.96	30.98
Alpaca-LoRA-7B	50.25	56.75	57.70	35.03
Bactrian- X_{llama} -7B	51.76	58.91	60.16	42.65
LLaMA-13B	51.04	57.88	52.97	33.52
Alpaca-LoRA-13B	54.82	59.03	52.27	35.79
Bactrian- X_{llama} -13B	53.27	62.12	63.65	50.27
BLOOM-7B	51.95	56.53	57.97	26.88
BLOOMZ-7B	52.13	58.05	60.05	37.68
Bactrian- X_{bloom} -7B	54.78	58.56	60.83	33.28

Table 4: Zero-shot experiment results in downstream tasks. We report averaged accuracy for XCOPA, XStoryCloze, and XWinograd, and averaged weighted F1-macro scores for SentimentX.

relatively small, it is important to highlight that Bactrian- X_{bloom} -7B is solely pre-trained using the LoRA adapter on a smaller multilingual dataset (2.5M samples), whereas BLOOMZ-7B is pre-trained using a larger dataset of 78M samples.

Performance in Unseen Languages In Figure 3, we present the averaged performance of each LLaMA-7B-based model and BLOOM-7B-based model in languages where the foundation models are not exposed to in pre-training. For XCOPA, XStoryCloze, XWinograd, and SentimentX, LLaMA-7B is not exposed to 10, 8, 2, and 5 languages, while BLOOM-7B is not exposed to 7, 2, 2, and 4 languages, respectively. We observe that our proposed models improve the zero-shot performance of foundation models in all tasks, and also surpass the performance of existing instruction-tuned models, with the exception of BLOOM’s performance in the XStoryCloze task.

5.2 GPT-4 Evaluation

Overall Figure 4 shows the comparative results of three model pairs. The data clearly indicate that GPT-4 demonstrates a preference for Bactrian- X_{llama} answers over Alpaca answers and favors Bactrian- X_{bloom} answers over BLOOMZ answers. Regarding the comparison between the two Bactrian-X models, Bactrian- X_{bloom} performs better overall.

GPT-4 assigns a quantitative score to each response on a scale of 10. We calculate the average score for each model from all comparison pairs and present the breakdown results separately for different language groups (see Figure 5) and question types (see Figure 6).

Language Group When analyzing the results based on language groups (see Figure 5), we ob-

tain several interesting observations. Firstly, multilingual pre-training plays a crucial role in the performance of multilingual instruction-following models. In Group 1 and Group 2, Bactrian- X_{bloom} outperforms Bactrian- X_{llama} , while in Group 3, Bactrian- X_{llama} performs significantly better than Bactrian- X_{bloom} . This difference can be attributed to variations in language coverage during the pre-training stage, as both models are fine-tuned on our Bactrian-X instruction dataset. Secondly, multilingual instruction-tuning also proves to be critical. While Bactrian- X_{llama} is fine-tuned on our multilingual dataset, Alpaca is only fine-tuned on the English instruction dataset. As depicted in Figure 5, Bactrian- X_{llama} outperforms Alpaca by a significant margin. Furthermore, from Group 4, we observe that if the languages are not covered during the pre-training stage, multilingual instruction-tuning alone is insufficient to achieve desirable performance. Additionally, both Bactrian- X_{bloom} and BLOOMZ are initialized by BLOOM but fine-tuned on different instruction datasets. BLOOMZ is fine-tuned on xP3, a multilingual instruction dataset based on hand-written templates and downstream NLP tasks. In our evaluation, Bactrian- X_{bloom} performs significantly better than BLOOMZ, highlighting the limitations of human-written instructions in terms of diversity and user experience. Overall, we can affirm that the multilinguality of both pre-training and instruction-tuning is vital for the effectiveness of multilingual instruction-following models. This finding reinforces our contributions in this work. We also find out that the instructions based on the hand-written templates and the downstream NLP tasks are less favourable from the user experience perspective.

Question Type When considering different question types (see Figure 6), the Bactrian-X models

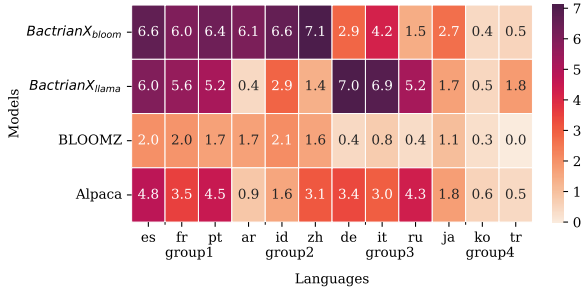


Figure 5: Language breakdown of GPT-4 evaluation. We categorize languages into four groups and select 3 languages from each group. Group 1: the languages are supported by both BLOOM and LLaMA; Group 2: the languages are supported by BLOOM only; Group 3: the languages are supported by LLaMA only; Group 4: the languages are not supported by either BLOOM or LLaMA.

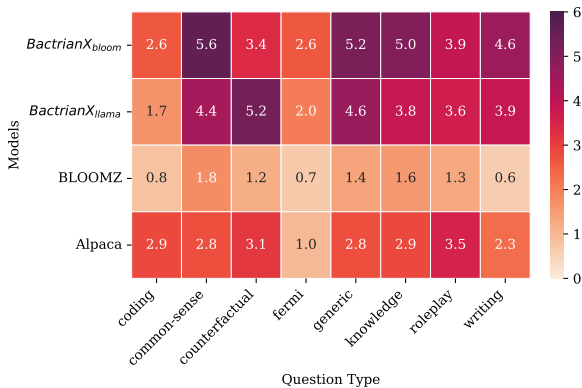


Figure 6: Question type breakdown of GPT-4 evaluation.

consistently outperform all baseline models, with the exception of coding tasks where Alpaca exhibits slightly better result. This discrepancy can be attributed to Alpaca’s advantage as an English-focused language model, benefiting from increased knowledge transfer from English since the majority of programming languages are designed in English. Another noteworthy observation is that “fermi” questions, which require strong reasoning capabilities, prove to be challenging for all the multilingual LLMs. This observation underscores the fact that the reasoning task in a multilingual setup remains an under-explored area, necessitating further efforts in future research.

6 Conclusion

In this paper, we present Bactrian-X, an extensive multilingual parallel dataset comprising 3.4 million instruction-response pairs across 52 languages. To enhance the versatility of foundational models, we

also introduce a collection of lightweight adapters trained on our datasets. Experiments on various multilingual NLP tasks demonstrate that models fine-tuned on the Bactrian-X dataset outperform their corresponding vanilla models and models fine-tuned on other monolingual/multilingual instruction datasets. By making our dataset and models available, we hope to expedite the advancement of large language models in multilingual scenarios, promoting progress in natural language processing across diverse languages.

7 Limitations

Our work is subject to several limitations that should be addressed in future research:

- **Lack of Model Variations:** Our focus was limited to the 7B and 13B models, without exploring scaling rules or other foundation models such as mT5 (Xue et al., 2021). Further investigations into different model variations could provide valuable insights.
- **Limited Context Size:** In our experiments, the maximum sequence length for multilingual models was set to 768 sub-word units. This smaller context size, compared to models utilizing lengths of 1024 or 2048, may restrict the model’s ability to effectively leverage long-range context. Additionally, certain languages that were not well supported by the model tokenizers could face challenges with such a small context size.
- **Lack of Human Evaluation:** Our work did not include human evaluation, relying instead on GPT-4 evaluation as a replacement. However, the bias and fairness of GPT-4 remain open research questions, which may reduce the reliability of the evaluation results in this part. Conducting human evaluation in future studies would provide a more comprehensive assessment.
- **Hallucination, Toxicity and Fairness:** We did not thoroughly investigate the presence of hallucination, toxicity, and fairness issues in our models or the baseline models due to the unavailability of an appropriate evaluation suite. Nonetheless, it is important to acknowledge that our models, as well as their baselines, are likely to be susceptible to these concerns. Future research should address these issues to ensure responsible and unbiased model behavior.

We acknowledge these limitations and propose that future work should focus on addressing them to advance the understanding and applicability of our research.

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A Complete results of multilingual benchmark

We present the full zero-shot result of the multilingual benchmark in Table 5 (XCOPA), Table 6 (XStoryCloze), Table 7 (XWinograd), and Table 8 (SentimentX). Please refer to Table 9, Table 10, Table 11, Table 12 for detailed data distribution used for evaluation.

B Model output examples in 9 different languages

Figure 7, Figure 8, Figure 9 show responses from different models with the questions in non-English languages as inputs. We randomly pick one example from each language of Spanish, French, Portuguese, Arabic, Indonesian, Chinese, German, Italian, and Russian.

Language Spanish	
Question	Finge ser un personaje en un mundo post-apocalíptico. Describe cómo sobrevives y los aliados que encuentras.
Bactrian-Bloom	Como un personaje que ha sobrevivido a un mundo post apocalíptico, puedo describir cómo sobrevivo y los amigos que encuentro.\n\nEn primer lugar, mi primera prioridad es encontrar comida y agua. En un mundo así, la comida y el agua son los recursos más importantes. Es importante encontrar alimentos que puedan ser cultivados y agua que pueda ser recolectada de los ríos o lagos cercanos. También es importante tener un refugio seguro para protegerse de los elementos y los animales salvajes.\n\nEn segundo lugar, es
Bactrian-LLaMA	Soy un sobreviviente en un post- apocalíptico mundo. Mi nombre es John y mi misión es sobrevivir. Desde que la guerra nuclear terminó, la vida en la Tierra ha cambiado drásticamente. La mayoría de las ciudades han sido destruidas y la mayoría de la gente ha muerto.\n\nEn mi viaje, he encontrado a muchas personas que también buscan sobrevivirse. Algunos son amables y ayudan a otros, mientras que otros son peligrosos y solo buscan lo que quieren.\n\nA pesar de todo, he logrado encontrar algunos aliados valiosos. Uno
Bloom	A:\n\nEn el libro de la película, el protagonista es un niño de 12 años llamado John, que vive en un pueblo llamado Hope, en el estado de Montana. El pueblo está en ruinas, y la gente está muriendo de hambre y de enfermedades. John es un chico solitario, que no tiene amigos, y que vive con su madre, que es una mujer muy fuerte y que no se queja de nada. John tiene un perro llamado Max, y un gato llamado Maxi. John no tiene ningún interés en la vida, y no tiene ninguna esperanza de que las cosas mejoren. Su ma
Bloomz No Prompt	Describe the world. Describe the characters.</s>
Bloomz Alpaca Prompt	Yo era un sobreviviente en un apocalipsis zombie.</s>
Alpaca	I am a survivor in a post- apocalyptic world. I have learned to scavenge for food and supplies, and I have found allies in the form of other survivors. I am able to barter for food, weapons, and other supplies. I also have learned how to defend myself and my allies from the dangers of the world.
Language French	
Question	Faites semblant d'être un personnage dans un monde post-apocalyptique. Décrivez comment vous survivez et les alliés que vous rencontrez.
Bactrian-Bloom	Je suis un personnage fictif dans un univers post-apocalypse. Je suis un survivant solitaire qui a survécu à une catastrophe naturelle qui a ravagé la planète. Je vis dans une petite ville abandonnée, où je suis le seul survivant. Je me suis construit un abri en bois et en toile, et je me suis équipé de quelques outils pour survivre.\n\nJe suis également un survivant solitaire, mais je suis entouré de nombreux alliés. J'ai rencontré des survivants d'autres villes et villages, qui ont tous survécu ensemble. No
Bactrian-LLaMA	Je suis un personnages dans un univers post- apocalyptic. Le monde est en ruine et la civilisation a été détruite. Je suis un survivant qui a survécu à la catastrophe. Je me suis réfugié dans une grotte pour se protéger des éléments et des dangers qui me menacent.\n\nJe me suis adapté à cette nouvelle vie en se nourrissant de la faune et de la flore qui me sont offertes. J'ai également construit un abri pour me protéger des intempéries et des animaux sauvages.\n\nJ'ai rencontré d'autres survivants qui ont égalem
Bloom	A:\n\nJe ne sais pas si c'est une bonne idée, mais je vais essayer de répondre à ta question.\n\nJe pense que tu devrais plutôt faire un jeu de rôle, avec des règles simples, et des personnages qui ont des caractéristiques et des compétences. Tu peux ensuite les faire évoluer en fonction de leur expérience, et de leur rencontre avec d'autres personnages.\n\nTu peux aussi faire un système de jeu de plateau, avec une carte, des tuiles, des pions, et un plateau de jeu. Tu pourras y placer des personnages, et les faire
Bloomz No Prompt	The Role Play</s>
Bloomz Alpaca Prompt	Je suis un personnage qui survit dans un univers post-apocalypse. Je suis un survivant solitaire. Je me nourris de ce que je trouve dans la nature. Je chasse pour trouver de la nourriture. Je trouve des armes et des munitions. Je m'allie avec d'autres survivants.</s>
Alpaca	I am a survivor in a post- apocalyptic world. I have to be cautious and resourceful in order to survive. I must scavenge for food and water, and find shelter from the elements. I also have to find ways to protect myself from the dangers of the world. In order to do this, I must form alliances with other survivors. I need to be able to trust them and work together to survival. I will also have the opportunity to learn new skills and knowledge from them.
Language Portuguese	
Question	Finja ser um personagem em um mundo pós-apocalíptico. Descreva como você sobrevive e os aliados que encontra.
Bactrian-Bloom	Como um personagem de um mundo post apocalíptico, eu sou um sobrevivente. Eu sou um humano que sobreviveu a um desastre natural que destruiu a maioria da humanidade. Eu tenho uma mochila com comida, água e abrigo, mas não tenho armas ou equipamentos de proteção. Eu encontrei alguns aliados, mas eles são poucos e não são confiáveis. Eu também encontrei alguns inimigos, mas eu não tenho certeza de como lidar com eles. Eu preciso encontrar mais aliados e aprender a lidar com os inimigos.</s>
Bactrian-LLaMA	Eu sou um sobrevivente em um futuro pós apocalíptico. Eu me chamei John e sou um homem solitário que viveu em uma caverna por anos. Eu tinha uma família, mas eles foram mortos por um grupo de bandidos. Eu fui forçado a fugir e me esconder em uma gruta.\n\nEle não tinha nada para comer, nem água limpa. Eu comeci a procurar por comida e águas limpas. Eu encontrou uma fonte de água limpa e uma caixa de comida. Eu comecei a comer e beber.\n\nDepois de alguns dias, eu encontrei um grupo que estava procurando por água
Bloom	A:\n\nEu não sei se é possível, mas você pode tentar fazer um jogo de RPG com o tema de sobrevivência. Você pode usar o sistema de Rogue-lite, que é um sistema de regras simples e que pode ser adaptado para jogos de Rpg. Você também pode usar um sistema mais complexo, como o D20 System, que tem regras mais completas e que podem ser usadas para jogos mais complexos.\n\nVocê pode usar a mecânica de jogo de sobrevivência para criar um jogo com o seu tema. Você vai precisar de um sistema que tenha regras para sobrev
Bloomz No Prompt	Describe the world. Describe the people. Describ the setting. Describe the conflict. Descreve the characters. Descrip the plot. Descrip the ending.</s>
Bloomz Alpaca Prompt	I am a survivor. I am a hunter. I have a group of friends.</s>
Alpaca	I would be a character in a post-apocalyptic world. I would survive by scavenging for food and supplies, and by making alliances with other survivors. I'd also be on the lookout for any technology that could help me in my journey.

Figure 7: Model output examples of languages seen by both BLOOM and LLaMA (Group 1).

Language	German
Question	Gib vor, in einer postapokalyptischen Welt ein Charakter zu sein. Beschreiben Sie, wie Sie überleben und die Verbündeten, denen Sie begegnen.
Bactrian-Bloom	Als AI-Sprachmodell habe ich keine persönlichen Erfahrungen und kann daher keine Vorstellung von Charaktere oder Verbündeten beschreiben. Ich kann jedoch einige Vorschläge für ein Charakterstück vorstellen. Ein Schwestern: Ein Schwestern kann eine sehr gute Idee sein, da er sich in einer postapokalyptischen Welt in einer sozialen Gesellschaft eingesetzt hat und seine Freunde und Familie in der Welt befindet. Es könnte auch eine große Rolle für eine schwierige Situation oder eine schwerer Situation se
Bactrian-LLaMA	Ich bin ein Charakter in einer apokalyptischen Welt. Ich bin ein junger Mann namens Jack, der in einer kleinen Gruppe von Überlebenden lebt. Wir haben uns in einem verlassenen Gebäude in der Nähe eines Flusses verschanzt. Wir sind auf der Suche nach Nahrung und Wasser, um unsere Überlebensfähigkeit zu erhalten. Ihre Gruppe hat sich in der Vergangenheit mit anderen Überlebenskämpfern zusammengeschlossen, um gemeinsam zu überleben. Wir teilen unsere Ressourcen und helfen uns gegenseitig, wenn wir in Schwier
Bloom	A: Ich würde mir die folgende Antwort verwenden: Ihr Leben ist ein Leben, das Sie selbst erleben möchten. Sie haben einen Charakter, der Sie selbst entwickeln und verändern können. Sie arbeiten, schreiben, sprechen, schützen, schwimmen, schlagen, schreien, schwierigen, schweigen, spielen, schweben, spüren, schlafen, schmecken, schlüpfen, spinnen, trinken, schnellen, schneiden, schlägen, schmelzen, schmecken, sitzen, schauen, schieben, schwindeln, schleifen, schröpfen, schreiten, späten, schöpf
Bloomz No Prompt	The The postmodern world offers us the opportunity to be characters. Write about how you live and the people you associate with.
Bloomz Alpaca Prompt	Ich bin ein Charakterstück. Ich lebe in einer post apokalyptischen Welt. Ich liebe die Verbindung, die ich mit der Personen, die mich begegnet haben, lebe.
Alpaca	I would like to be a character in a postapocalyptic world. I would describe myself as a survivor who has learned to adapt to the new world. My goal is to survive and find allies to help me in my journey. I am a strong and determined individual who is willing to take risks in order to find a better life.
Language	Italian
Question	Fai finta di essere un personaggio in un mondo post-apocalittico. Descrivi come sopravvivi e gli alleati che incontri.
Bactrian-Bloom	Mi sento molto triste e desolato per la situazione in cui ci siamo trovati. Mi sento come se tutto il mio mondo si svolgesse in un caos e la mia vita fosse una strada di morte. Non sono più in grado di vivere in pazzia e tranquillità, ma sono in grado solo di sopravvivere e fare il meglio per me e per gli altri. Mi sono trovato in una città che è stata sconvolta da un catastrofico evento naturale. Mi sono trovata in una situazione di guerra civile, in cui le forze del governo sono state sconfitte e le forti
Bactrian-LLaMA	Sono un uomo di nome John, sopravvivere in un'epoca post-apocalittica è stato un'esperienza terribile. La guerra nucleare ha distrutto la maggior parte della vita sulla Terra, e ora ci sono pochi sopravvissuti. Siamo stati costretti a fuggire dalla città, dove la polvere radioattiva era troppo alta per sopravvivere. Abbiamo cercato rifugio in un vecchio rifugi antiaereo, dove abbiamo trovato altri sopravvissuti. Questi altri sopravvissuti sono stati molto utili per noi, hanno aiutato a costruire un piccolo vil
Bloom	A: La mia domanda è: Come si fa per farsi conoscere in un ambiente post-apocalittico? La mia risposta è: Come si fanno conosciuti in un ambiente post-apo, è per essere insieme con altri, perché solo con la propria forza non si può fare conoscenza. Per essere conosciuto, bisogna essere parte di un gruppo, e per essersi conosciuto, è necessario essere visto. Per farsi vedere, è possibile fare delle attività, come fare delle riflessioni, fare delle scuole, fare dei lavori, fare un'opera, fare una mostra, fare
Bloomz No Prompt	Describe the world. What is it like? What is the weather like? How is the food? What are the people like?
Bloomz Alpaca Prompt	Nel mondo post apocalittico, la gente vive in città.
Alpaca	In a post-apocalyptic world, I would survive by scavenging for food and supplies, and by making alliances with other survivors. I would also be on the lookout for any technology that could help me in my quest for survival.
Language	Russian
Question	Притворяться персонажем в постапокалиптическом мире. Опишите, как вы выживаете, и союзников, с которыми вы сталкиваетесь.
Bactrian-Bloom	Я - AI-а и не могу выживать, но могут быть союзники, которые могли бы помочь меня. Например, я могла бы выжить в деревьях, где я много могла защититься от снега и солнечного вода. Я мог бы также выжимать в лесах, готовые для моей жизни. Я также мог узнать, как мне помочется выжить в окружающем мире, например в легких лесных окнах, грузовых лекарных лесов или в лаборатории. Я могу также использовать мои средства, такие как камень, каменная камня, картинки и другие материалы, чтобы защищать меня от солнца и
Bactrian-LLaMA	Я - это человек, который выжил в постапокалиптической. Я был одним из первых, кто выжил после катастрофы, и я знаю, что для выживания необходимо быть осторожным и умным. В постапокалиптическом мире я встречал множество союзных, которые помогли мне выжить. Первым, кого я встретил, был старик, который жил в укрытии. Он дал мне еду и воду, и показал мной, где можно найти еще больше. Затем я встретился с группой людей, которые также выжили. Они помогли мне найти воду и еду, а также показали мной место, где я мог най
Bloom	A: Примерно так: Простое употребление слов "выживает" и "союз" в предложении "Притаяться" не удобно. Поэтому, в данном случае, лучше использовать слово "поджиться".
Bloomz No Prompt	
Bloomz Alpaca Prompt	Союзник 1 - Сталик. Союзатор 2 - Стефан. Стальк 1 - Михаил. Стеван 1 - Александр. Михайл 1 - Владимир. Александр 1 - Григорь. Владимир 1
Alpaca	In a post-apocalyptic world, I would try to survive by scavenging for food and supplies, and by forming alliances with other survivors.

Figure 9: Model output examples of languages only seen by LLaMA (Group 3).

Models	et	ht	id	it	qu	sw	ta	th	tr	vi	zh	Avg
LLaMA-7B	49.80	50.00	51.80	52.40	51.60	49.20	45.60	52.60	49.80	49.80	49.80	50.22
Alpaca-LoRA-7B	48.20	50.40	53.00	59.00	50.20	49.20	44.40	48.20	49.60	47.80	52.80	50.25
Bactrian- X_{llama} -7B	52.40	48.40	52.80	59.20	51.60	52.60	45.40	53.00	50.40	49.20	54.40	51.76
LLama-13B	51.00	50.40	52.20	55.60	50.40	49.00	46.40	51.80	50.60	51.00	53.00	51.04
Alpaca-LoRA-13B	47.40	52.80	57.80	73.20	50.40	52.60	47.80	52.60	52.60	51.60	64.20	54.82
Bactrian- X_{llama} -13B	53.80	49.20	56.20	64.80	49.40	52.60	45.60	52.00	51.20	53.20	58.00	53.27
BLOOM-7B	48.00	46.00	59.20	48.60	52.00	49.60	44.80	51.40	52.40	61.60	57.80	51.95
BLOOMZ-7B	49.20	43.40	59.40	49.40	52.00	51.60	45.60	50.00	52.00	61.40	59.40	52.13
Bactrian- X_{bloom} -7B	50.80	47.80	65.40	54.40	50.60	52.60	46.00	53.80	52.20	63.20	65.80	54.78

Table 5: Accuracy of zero-shot performance in XCOPA.

Models	ar	es	eu	hi	id	my	ru	sw	te	zh	Avg
LLaMA-7B	53.47	62.08	52.02	55.72	57.58	55.13	62.54	55.33	58.70	57.71	57.03
Alpaca-LoRA-7B	51.26	64.88	51.92	54.23	57.08	54.17	61.84	55.15	57.93	59.06	56.75
Bactrian- X_{llama} -7B	54.67	67.57	52.28	56.32	59.56	57.78	65.85	57.31	57.71	60.03	58.91
LLama-13B	53.41	65.59	53.74	54.40	59.17	54.40	64.26	55.79	57.51	60.56	57.88
Alpaca-LoRA-13B	54.40	71.81	53.08	55.33	57.58	52.88	71.48	55.00	57.18	61.55	59.03
Bactrian- X_{llama} -13B	57.11	76.70	53.28	58.84	62.41	57.45	72.87	60.16	56.85	65.59	62.12
BLOOM-7B	56.65	59.36	54.14	51.16	61.09	54.53	56.59	55.66	52.48	63.67	56.53
BLOOMZ-7B	60.29	64.79	55.13	51.69	62.28	54.86	56.98	56.92	52.08	65.52	58.05
Bactrian- X_{bloom} -7B	58.97	68.83	53.74	50.76	68.03	50.96	57.05	56.92	52.02	68.30	58.56

Table 6: Accuracy of zero-shot performance in XStoryCloze.

Models	en	fr	jp	pt	zh	ru	Avg
LLaMA-7B	63.66	56.63	51.09	56.65	59.72	60.00	57.96
Alpaca-LoRA-7B	65.63	56.63	52.45	55.51	57.54	58.41	57.70
Bactrian- X_{llama} -7B	68.13	60.24	52.97	58.17	61.11	60.32	60.16
LLama-13B	54.00	51.81	51.00	52.00	56.00	53.00	52.97
Alpaca-LoRA-13B	55.00	50.60	47.00	50.00	61.00	50.00	52.27
Bactrian- X_{llama} -13B	72.34	61.45	54.54	66.54	62.90	64.13	63.65
BLOOM-7B	60.65	59.04	51.41	57.79	65.28	53.65	57.97
BLOOMZ-7B	65.63	62.65	51.72	58.17	67.86	54.29	60.05
Bactrian- X_{bloom} -7B	66.28	55.42	56.62	63.12	70.83	52.70	60.83

Table 7: Accuracy of zero-shot performance in XWinograd.

Models	ar	es	jp	ru	id	jav	sun	sw	Avg
LLaMA-7B	26.79	29.27	4.58	46.49	35.54	34.49	26.47	44.23	30.98
Alpaca-LoRA-7B	34.56	56.05	43.28	12.73	35.95	23.88	31.00	42.82	35.03
Bactrian- X_{llama} -7B	31.19	54.90	51.44	56.29	34.09	30.12	39.20	43.99	42.65
LLama-13B	36.41	31.32	46.25	3.46	35.47	33.39	37.00	44.90	33.52
Alpaca-LoRA-13B	51.16	52.30	30.94	10.85	55.08	40.51	30.21	15.30	35.79
Bactrian- X_{llama} -13B	36.42	66.82	54.90	63.13	55.00	40.73	40.65	44.50	50.27
BLOOM-7B	23.39	31.04	6.25	68.36	21.63	23.19	37.67	3.53	26.88
BLOOMZ-7B	48.68	40.22	3.49	68.58	40.53	27.08	38.24	34.61	37.68
Bactrian- X_{bloom} -7B	14.57	36.88	46.34	68.19	23.27	25.27	38.11	13.62	33.28

Table 8: Weighted F1-macro scores of zero-shot performance in SentimentX.

Languages	Test size	Seen by BLOOM	Seen by LLamA
et	500	no	no
ht	500	no	no
id	500	yes	no
it	500	no	yes
qu	500	no	no
sw	500	yes	no
ta	500	yes	no
th	500	no	no
tr	500	no	no
vi	500	yes	no
zh	500	yes	no

Table 9: XCOPA data statistics.

Languages	Test size	Seen by BLOOM	Seen by LLamA
ar	1511	yes	no
es	1511	yes	yes
eu	1511	yes	no
hi	1511	yes	no
id	1511	yes	no
my	1511	no	no
ru	1511	no	yes
sw	1511	yes	no
te	1511	yes	no
zh	1511	yes	no

Table 10: XStoryCloze data statistics.

Languages	Test size	Seen by BLOOM	Seen by LLamA
en	2325	yes	yes
fr	83	yes	yes
jp	959	no	no
pt	263	yes	yes
zh	504	yes	no
ru	315	no	yes

Table 11: XWinograd data statistics.

Languages	Test size	Seen by BLOOM	Seen by LLamA
ar	619	yes	no
es	1000	yes	yes
jp	553	no	no
ru	1000	no	yes
id	400	yes	no
jav	400	no	no
sun	400	no	no

Table 12: SentimentX data statistics. For Spanish (es) and Russian (ru), we randomly sample the test data for 1000 instances.