# Bactrian-X: Multilingual Replicable Instruction-Following Models with Low-Rank Adaptation

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#### **Abstract**

Instruction tuning has shown great promise in improving the performance of large language models. However, research on multilingual instruction tuning has been limited due to the scarcity of high-quality instruction-response datasets across different languages. To bridge 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 that seamlessly integrate with large language models. These adapters have a substantially lower parameter count than the base model, making them easily replaceable and usable as plugins for different languages or language groups. Extensive experiments in various multilingual evaluation settings demonstrate that models derived from LoRA-based training over Bactrian-X outperform both the vanilla models and existing instruction-tuned models. The code and models are publicly available at https: //github.com/mbzuai-nlp/bactrian-x.

#### 1 Introduction

Fine-tuning large language models (LLMs) with instruction–response pair datasets has demonstrated remarkable zero-shot generalization capabilities for open-source and closed-source models (Sanh et al., 2022; Wei et al., 2022; Ouyang et al., 2022; OpenAI, 2023). Although the LLMs are often pre-trained using multilingual texts, the instruction-tuning for open-source models is restricted to English (Taori et al., 2023; Chiang et al., 2023; Wu et al., 2023), bringing into question its multilingual generalizability. Closed-resource models such as OpenAI GPT-4 (OpenAI, 2023) and Google BARD, despite performing impressively over high-resource languages, are still lacking in

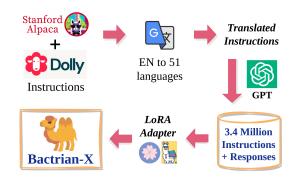


Figure 1: Overview of the Bactrian-X dataset and process for model creation.

terms of multilingual generalizability under monolingual instruction tuning.

The scarcity of instruction–response pair datasets in languages beyond English is hinders multilingual instruction tuning. The existing xP3 dataset (Muennighoff et al., 2022), which was used to fine-tune BLOOM and mT5, employs English instructions. Although Muennighoff et al. (2022) also experiments with xP3mt — machine-translated instructions — it focuses on classic NLP tasks such as summarization and question answering, rather than general instructions. Additionally, both xP3 and xP3mt use template-based prompts, and hence lack variation.

To investigate general instruction tuning in a multilingual setting, we introduce Bactrian-X, containing parallel instruction–response pairs across 52 languages that were automatically constructed by translating instructions from Alpaca (Taori et al., 2023) and Dolly (Conover et al., 2023) via the Google Translate API.<sup>2</sup> As we detail in Section 3, we use the output distillation trick to obtain corresponding responses by leveraging ChatGPT outputs, conditioned on the translated instructions. With 67K instruction–response pairs for each language, the total number of instances in Bactrian-X reaches 3.4M.

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https://bard.google.com/

<sup>2</sup>https://translate.google.com/

In contrast to previous multilingual instruction models such as BLOOMZ (Muennighoff et al., 2022) which are subject to full fine-tuning via parameter updates across all layers, this study highlights the potential of parameter-efficient finetuning techniques, specifically LoRA (Hu et al., 2022). LoRA uses adapters with substantially fewer parameters than base LLMs, making them more practical and adaptable for real-world applications. Specifically, in this work, we introduce BX<sub>BLOOM</sub> and BX<sub>LLaMA</sub> models, which build upon the BLOOM (Scao et al., 2022) and LLaMA (Touvron et al., 2023) models, and find them to be better than the associated instruction-tuned models: BLOOMZ (Muennighoff et al., 2022) and Alpaca (Taori et al., 2023).

We conduct a comprehensive series of experiments covering a range of zero-shot multilingual NLP tasks, including XCOPA (Ponti et al., 2020), XStoryCloze (Lin et al., 2022), XWinograd (Muennighoff et al., 2022), our own multilingual sentiment analysis dataset SentimentX, and EXAMS (Hardalov et al., 2020). The consistently high results across these tasks highlight the effectiveness of our multilingual instruction dataset and adapter technique for instruction tuning in languages beyond English. To further validate our findings, we use GPT-4 as an evaluator based on the methodology proposed by Chiang et al. (2023), and additionally conduct human evaluation with native speakers. All results confirm that our proposed models outperform the vanilla foundation models and existing instruction-tuned models.

#### 2 Related Work

Multilingual Instruction Tuning LLMs such as GPT-3 (Brown et al., 2020), PaLM (Chowdhery et al., 2022) and LLaMA (Touvron et al., 2023) (Hoffmann et al., 2022; Scao et al., 2022; Zeng et al., 2023) have revolutionized NLP. Research has demonstrated that fine-tuning LLMs with instruction prompts can improve their capacity to perform unseen/novel tasks (Wei et al., 2022; Sanh et al., 2022; Ouyang et al., 2022; Chung et al., 2022; Muennighoff et al., 2022). Recently, Wang et al. (2022); Taori et al. (2023) showed that machinegenerated instructions can be used for instruction tuning. Wu et al. (2023) created a large-scale dataset with 2.6M instructions, and demonstrated that relatively small language models also benefit

from the instructions. Prior work has predominantly been on English, and instruction-tuning in languages beyond English remains limited. The closest work to ours is BLOOMZ (Muennighoff et al., 2022), which finetunes BLOOM (Scao et al., 2022) and mT5 (Xue et al., 2021) on the xP3 and xP3mt multilingual instruction datasets. However, both xP3 and xP3mt are based on human-written templates, and lack the variability of an organic multilingual dataset. Our work, instead, constructs a parallel general instruction dataset by translating English instructions into 51 languages and generating responses via ChatGPT (Ouyang et al., 2022). To the best of our knowledge, our Bactrian-X instruction dataset is the largest general-purpose multilingual instruction dataset to date.

Parameter Efficient Fine-Tuning (PEFT) Finetuning all parameters of an LLM (e.g. Alpaca (Taori et al., 2023), Vicuna (Chiang et al., 2023) and LaMini-LM (Wu et al., 2023)) is computationally expensive, and adapters (Houlsby et al., 2019) offer a more cost-effective alternative. PEFT updates a small number of parameters during fine-tuning, and achieves comparable performance to fully finetuned counterparts (Houlsby et al., 2019; Guo et al., 2021; Lester et al., 2021; Ben Zaken et al., 2022). Hu et al. (2022) introduced Low-Rank Adaptation (LoRA), which incorporates trainable rank decomposition matrices into transformer layers (Vaswani et al., 2017) during fine-tuning without introducing additional latency during inference. They demonstrate that by fine-tuning with less than 1% of the model parameters, LoRA outperforms several fully fine-tuned LLMs, including GPT-3 (Brown et al., 2020), on various tasks.

In recent work, Taori et al. (2023) use the LoRA trick to fine-tune LLaMA (Touvron et al., 2023), resulting in the Alpaca model, but did not carry out comprehensive evaluation. In this work, we also leverage the LoRA technique to develop a range of monolingual and multilingual adapters, with a much larger instruction—response dataset, across 52 languages. We provide empirical analysis based on automatic and human evaluation to demonstrate the effectiveness of our method.

#### 3 Bactrian-X Dataset

In this section, we detail the dataset creation process and provide an overview of the resulting data, focusing on the quality of translated instructions and generated responses.

Tokenizer	Vocab size	Lang	Instruction tokens	Input tokens	Response tokens	Total tokens
mBART-50	250,054	all	$17.11 \pm 1.96$	$27.54{\scriptstyle\pm2.84}$	$133.65{\scriptstyle\pm17.4}$	$178.30 \pm 22.2$
BLOOM	251,680	seen unseen	$16.14{\pm}2.87 \\ 34.21{\pm}22.0$	$25.98{\scriptstyle\pm3.99\atop}51.41{\scriptstyle\pm31.7}$	$128.88 {\pm} 25.5 \\ 275.97 {\pm} 179$	$171.00{\scriptstyle\pm31.3}\atop{361.60}{\scriptstyle\pm231}$
LLaMA	32,000	seen unseen	$\begin{array}{c} 23.13{\pm}2.78 \\ 57.22{\pm}35.6 \end{array}$	$36.69{\scriptstyle\pm3.85}\atop86.93{\scriptstyle\pm52.6}$	$185.18{\scriptstyle\pm18.2}\atop448.61{\scriptstyle\pm293}$	$\begin{array}{c} 244.96 {\pm} _{24.3} \\ 592.77 {\pm} _{376} \end{array}$

Table 1: Average # tokens in each Instruction, Input, and Response across all languages. Note that the token counts for mBART-50, LLaMA, and BLOOM are based on the respective tokenizers and are not directly comparable. mBART-50 covers all 52 languages, while LLaMA and BLOOM cover only a subset of the languages in Bactrian-X, and separate results are thus presented for seen and unseen languages.

#### 3.1 Dataset Creation

We construct the Bactrian-X dataset in two steps: instruction translation, and response generation (see Figure 1).

Instruction Translation We use English instructions developed for Alpaca (52K) and Dolly (15K), and use the Google Translate API to translate them into 51 different languages, based on the languages used for mBART-50 (Tang et al., 2020). The Alpaca instructions were automatically generated by GPT-3.5 (Ouyang et al., 2022) via the self-instruct technique (Wang et al., 2022), while the Dolly dataset was manually curated by thousands of Databricks company employees. Prior to the translation process, we identify instructions containing programming-related content based on a keyword-matching method and exclude them from the translation process. The total cost for translating the instructions was approximately USD\$10,000.

Response Generation For each translated instruction, we use ChatGPT (gpt-3.5-turbo) to obtain a response.<sup>3</sup> For English, we pair the instruction with the original response. Translating responses into the 51 languages is costly. Moreover, potential issues such as "translationese" and nonnative answer styles may arise from relying solely on translated responses. The total cost for generating responses amounts to around \$3,000 USD. We leave the comparison between the translated responses and the ChatGPT-generated responses to future work.

#### 3.2 Exploratory Data Analysis

**Dataset Statistics** We analyzed the tokenized texts in the 52 languages using the mBART-50, LLaMA, and BLOOM tokenizers, and present the statistics in Table 1. Since mBART-50 is trained

	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
75% Q.	52.7	72.2	92.0
max	69.0	82.7	95.3

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

on all 52 languages, the tokenizer is trained on all the languages, and the average number of tokens is thus relatively smaller than LLaMA and BLOOM. However, for languages unseen by BLOOM and LLaMA, the tokenized texts are 2 to 3 times longer compared to mBART-50. This suggests that for these unseen languages, both BLOOM and LLaMA models require a larger sequence length for semantically similar input texts, posing a challenge for effective adaptation with the LoRA adapter.

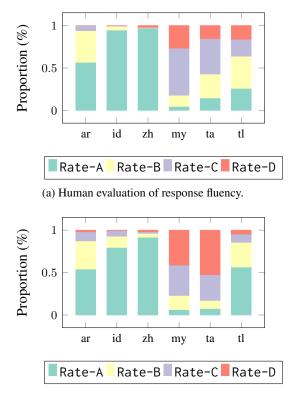
Instruction Quality To test the quality of the translated instructions, we verified the quality of 100 randomly-sampled instances for each language by performing back-translation into English using the Google Translate API. We evaluate the quality of the back-translated instructions relative to the originals based on BLEU (Papineni et al., 2002; Post, 2018), chrF++ (Popović, 2017), and the trained metric COMET (Rei et al., 2020). The worst BLEU score of 28 is for Mongolian–English translation, but as seen in Table 2, most language pairs achieved BLEU scores above 40, indicating high quality and reliability of the Bactrian-X instructions.

<sup>&</sup>lt;sup>3</sup>The response generation was conducted during April 16–21, 2023.

<sup>4</sup>nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|
version:2.3.1

<sup>5</sup>nrefs:1|case:mixed|eff:yes|nc:6|nw:2|
space:no|version:2.3.1

<sup>&</sup>lt;sup>6</sup>Unbabel/wmt22-comet-da



(b) Human evaluation of response informativeness.

Figure 2: Human evaluation of the response quality for Bactrian-X. Rate A is the best and D is the worst.

**Response Quality** To evaluate response quality, we conducted human evaluations in three highresource languages — Arabic (ar), Indonesian (id), Chinese (zh) — and three low-resource languages — Burmese (my), Tamil (ta), and Tagalog (t1). For each language, two native-speaker annotators are asked to assess the fluency and informativeness of the responses given the question, except Tagalog, which had only one annotator. The quality assessment guideline is provided in Appendix A, and the results are shown in Figure 2, with an interannotator agreement (IAA) averaged by language of 0.70 and 0.69 for fluency and informativeness, respectively. The results showed that high-resource languages consistently achieved over 80% satisfactory ratings (A and B), while some low-resource languages like Tamil and Burmese had a significant proportion of lower ratings (C and D). This suggests that the outputs generated by ChatGPT are lacking for some low-resource languages. We leave the improvement of data quality for low-resource languages to future work.

#### 4 Bactrain-X Models

Given limitations of computation resources, we use base LLMs with 7B and 13B parameters only. First,

we trained three multilingual Bactrian models (BX) over the parallel dataset in 52 languages: BX<sub>LLaMA</sub> (7B, 13B), and BX<sub>BLOOM</sub> (7B). While our primary results are based on the BX models, we additionally train some 7B monolingual Bactrian models (BM) for analysis in Section 5: 14 BM<sub>LLaMA</sub> and 18 BM<sub>BLOOM</sub>. All models will be made publicly available in our model repository.

We train our LoRA adapters (Hu et al., 2022) using PyTorch with the HuggingFace PEFT implementation (Mangrulkar et al., 2022; Wolf et al., 2020). Hyperparameters used for training the different models can be found in Appendix C (Table 7). In our evaluation, we compare each multilingual BX model with: (1) the corresponding vanilla models, and (2) the instruction-tuned models Alpaca (Taori et al., 2023) and BLOOMZ (Muennighoff et al., 2022). Details of these models are provided in Appendix B.

#### 5 Evaluation on NLP Benchmarks

In order to thoroughly evaluate our Bactrian-X models, we conducted experiments on various multilingual downstream NLP tasks. We first introduce the benchmark datasets we used, and then present the evaluation results in two categories: language understanding tasks (Section 5.2) and knowledge-intensive tasks (Section 5.3).

#### 5.1 Datasets

To probe the zero-shot language understanding capability of the different models, we evaluate on the following test sets:

- XCOPA (Ponti et al., 2020): a multilingual resource designed for causal commonsense reasoning, encompassing 11 languages. The task involves predicting the correct next sentence from two options based on cause and effect question types.
- XStoryCloze (Lin et al., 2022): a translation of the English story cloze dataset (Mostafazadeh et al., 2016) into 10 languages. 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): a multilingual benchmark for commonsense reasoning, made up of Winograd Schema Challenge problems

 $<sup>^{7}</sup>$ We do not train BX<sub>BLOOM</sub> (13B) because BLOOM (13B) is not available.

Model	XCOPA	XStoryCloze	XWinograd	SentimentX	EXAMS
LLaMA (7B)	50.22	57.03	57.96	30.98	28.20
Alpaca-LoRA (7B)	50.25	56.75	57.70	35.03	28.82
BX <sub>LLaMA</sub> (7B)	51.76	58.91	60.16	42.65	29.14
LLaMA (13B)	51.04	57.88	52.97	33.52	30.41
Alpaca-LoRA (13B)	54.82	59.03	52.27	35.79	30.47
BX <sub>LLaMA</sub> (13B)	53.27	62.12	63.65	50.27	35.71
BLOOM (7B)	51.95	56.53	57.97	26.88	25.06
BLOOMZ (7B)	52.13	58.05	60.05	37.68	31.23
BX <sub>BLOOM</sub> (7B)	54.78	58.56	60.83	33.28	26.20

Table 3: Zero-shot experiment results on downstream tasks. We report averaged accuracy for XCOPA, XStoryCloze, XWinograd, and EXAMS, and macro-F1 scores for SentimentX.

in six languages.<sup>8</sup> The task involves selecting the most plausible sentence from options that differ slightly.

• SentimentX: a sentiment classification dataset comprising 3-way sentiment labels collected from various sources, in the following languages: Arabic (ar) (Alturayeif et al., 2022), Spanish (es), Japanese (jp) (Hayashibe, 2020), Russian (ru), 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).

We also measure how much knowledge the model encodes using the EXAMS benchmark:

• EXAMS (Hardalov et al., 2020): a multilingual question-answering dataset made up of multiple-choice questions from high school examinations in 16 languages. It covers subjects from natural science (e.g., physics), social science (e.g., history), to humanities (e.g., philosophy). Given that all our experiments are zero-shot, we merge the train, validation, and test sets into a single evaluation dataset, and exclude questions without four multiple choice options, resulting in a total of 20,559 questions.

#### 5.2 Language Understanding Tasks

The average performance across all languages for XCOPA, XStoryCloze, XWinograd, and SentimentX is presented in Table 3. During inference, we use translated prompts and sentiment labels in the respective languages, obtained

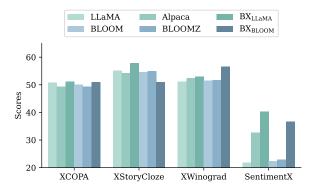


Figure 3: The average performance of 7B models on unseen languages (i.e. languages that are not used in pre-training the base model).

from the Google Translate API. We observe that integrating LoRA with the base models of LLaMA and BLOOM, and training over the multilingual instruction datasets, consistently improves performance over the base models. Improvements can also be observed over existing instruction-tuned models such as Alpaca-LoRA, on most tasks. For the larger models, we observe further enhancements again, as seen for BX<sub>LLaMA</sub> (13B) over LLaMA (13B).

From the third block, we observe that  $BX_{BLOOM}$  performs better than the full fine-tuned BLOOMZ model on three out of five tasks. Although the performance difference is relatively small, it is worth noting that  $BX_{BLOOM}$  is fine-tuned only using the LoRA adapter on a smaller multilingual dataset (2.5M samples), whereas BLOOMZ is fully fine-tuned using a larger dataset of 78M samples. Additionally, BLOOMZ is fine-tuned on xP3, which is designed to handle NLP downstream tasks, while Bactrian-X is more general purpose.

**Performance on Unseen Languages** In Figure 3, we present the average performance of the 7B mod-

<sup>8</sup>https://cs.nyu.edu/~davise/papers/ WinogradSchemas/WS.html

<sup>9</sup>http://tass.sepln.org/2020/

<sup>10</sup>https://github.com/antongolubev5/
Russian-Sentiment-Analysis-Evaluation-Datasets

Tasks	BX <sub>LLaMA</sub>	BM <sub>LLaMA</sub>	$BX_{BLOOM}$	$BM_{BLOOM}$
XCOPA	52.2	52.7	56.0	56.6
XStoryCloze	59.6	60.5	59.1	60.7
XWinograd	61.6	64.2	61.7	64.1
SentimentX	44.1	44.2	31.3	41.6
Average	54.4	55.4	52.0	55.8

Table 4: Zero-shot performance of multilingual BX and monolingual BM models with 7B parameters. We report averaged accuracy for XCOPA, XStoryCloze, and XWinograd, and averaged weighted F1-macro scores for SentimentX.

Models	Natural	Social	Others
LLaMA (13B)	30.09	32.77	31.11
Alpaca (13B)	28.19	32.99	30.36
BX <sub>LLaMA</sub> (13B)	<b>33.58</b>	<b>39.15</b>	<b>39.71</b>

Table 5: Performance breakdown by subject type in EXAMS. "Natural" and "Social" denote natural science and social science, respectively.

els over languages that the base models were not exposed to in pre-training. For XCOPA, XStoryCloze, XWinograd, and SentimentX, the LLaMA model is not exposed to 10, 8, 2, and 5 languages, resp., while the BLOOM model is not exposed to 7, 2, 2, and 4 languages, respectively. We observe that our proposed models improve on the zero-shot performance of the base models across all tasks, and also surpass the performance of existing instruction-tuned models, with the exception of BLOOM over XStoryCloze. A notable improvement can be seen in the SentimentX dataset, implying that our models are more suited to non-English instructions and non-English sentiment labels.

Monolingual vs. Multilingual Fine-tuning For each of the 52 languages in Section 3.2, we compared the performance of monolingual BM models against the multilingual BX models. To ensure a fair benchmark, we exclude unseen languages in calculating the average score. Table 4 presents the average performance for each dataset, revealing that the monolingual BM models consistently outperform the multilingual model for both LLaMA and BLOOM. Particularly notable improvements are observed for XWinograd and SentimentX. For example, the monolingual BM<sub>BLOOM</sub> achieves an impressive overall increase of +10.3 compared to the multilingual model for SentimentX.

You are a helpful and precise assistant for checking the quality of the answer.

<question>

Comment les obstacles linguistiques et culturels ...

</question>

<answer1>

Les obstacles linguistiques peuvent avoir un impact ...

</answer1>

<answer2>

The linguistic and cultural obstacles ...

</answer2>

Suppose the user only speaks the language of the question, please evaluate both answers with your justification having less 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>.

Figure 4: Template for GPT-4 evaluation. The colored parts are general prompts that are used for all instances.

#### 5.3 Knowledge-intensive Task

The last column of Table 3 shows the results on EXAMS, averaged across languages. We find that the BX<sub>LLaMA</sub> models (7B and 13B) outperform their corresponding base models, while BLOOMZ outperforms our BX<sub>BLOOM</sub>. We observe that multilingual instruction tuning seems to be more promising on larger models, as seen in BX<sub>LLaMA</sub> (13B) improving substantially over LLaMA by 5.5% on average, while the margin for BX<sub>LLaMA</sub> (7B) is only 0.9%. It is noteworthy that BX<sub>LLaMA</sub> (13B) also outperforms LLaMA (30B) on the EXAMS benchmark in Table 12 in Appendix D, underlining the effectiveness of multilingual instruction tuning.

The EXAMS dataset comprises a range of subject areas, such as natural science and social science. We present a breakdown of the results across subject areas for the 13B models in Table 5. It is evident that there are substantial performance improvements over the social sciences and other subject areas during fine-tuning, but comparatively lesser gains for natural science. This could be attributed to our dataset containing fewer instructions and questions related to natural sciences, or the inherent difficulty of learning natural science concepts or reasoning abilities through instruction fine-tuning.

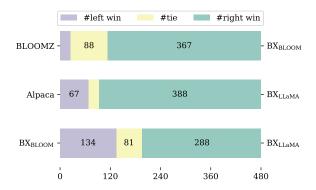


Figure 5: Overall comparison of GPT-4 evaluation.

#### 6 Evaluation on Open-ended Questions

As LLMs continue to develop, existing NLP benchmarks may not be up to the task of evaluating model capabilities. To address this, we use GPT-4 (OpenAI, 2023) as an evaluator to compare model outputs, supplemented by human evaluations.

We adopt a challenging set of 80 questions covering 8 categories from Chiang et al. (2023) for open-ended question evaluation. These questions are translated into 51 languages, and we use different models to generate responses (see Appendix E for examples). Following Chiang et al. (2023), we provide two answers from different models in a single prompt, and ask GPT-4 to rate the answers over a scale of 0 to 10 from various aspects including helpfulness, relevance, accuracy, and the level of detail (see Figure 4 for an example prompt for GPT-4 evaluation). To ensure fairness, we interchange the order of the provided answers, and assign scores twice for each question. We exclude vanilla BLOOM and LLaMA from openended question evaluation, and instead compare BX<sub>BLOOM</sub> against BLOOMZ, BX<sub>LLaMA</sub> against Alpaca, and BX<sub>BLOOM</sub> against BX<sub>LLaMA</sub>, given the superiority of instruction-tuned models in previous studies (Chiang et al., 2023; Muennighoff et al., 2022). We select 5 questions from each category, resulting in 40 questions per language. Given cost restrictions and availability of human annotators, we conducted GPT-4 evaluation over 12 languages and human evaluation over 6 languages.

#### 6.1 GPT-4 Evaluation

Figure 5 shows the results of the three model pairs, clearly indicate that GPT-4 has a preference for BX<sub>LLaMA</sub> over Alpaca and similarly favors BX<sub>BLOOM</sub> over BLOOMZ. Regarding the comparison between the two BX models, BX<sub>LLaMA</sub> per-

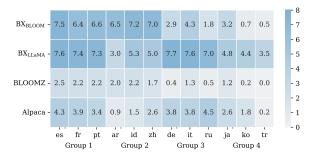


Figure 6: GPT-4 evaluation by language. We categorize languages into four groups based on whether a language is seen during model pre-training, and select 3 languages from each group. Group 1: languages seen by both BLOOM and LLaMA; group 2: seen by BLOOM only; group 3: seen by LLaMA only; group 4: not seen by either BLOOM or LLaMA.

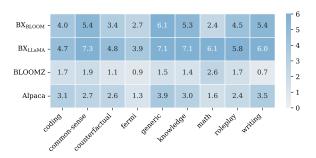


Figure 7: GPT-4 evaluation by question types.

forms better overall.

Since GPT-4 assigns a quantitative score to each response on a scale of 0–10, we calculate the average score for each model from all comparison pairs and present a breakdown of results separately for each language group (see Figure 6) and question type (see Figure 7).

**Language Group** Analyzing the results based by language group (see Figure 6), we can make several observations. First, multilingual pre-training plays a critical role for multilingual instructionfollowing models. In groups 1 and 3, BX<sub>LLaMA</sub> outperforms BX<sub>BLOOM</sub>, while in group 2, BX<sub>BLOOM</sub> performs substantially better. This difference can be attributed to variations in language coverage during pre-training, as both models are fine-tuned on the same dataset. Second, multilingual instructiontuning is critical. BX<sub>LLaMA</sub>, fine-tuned on our multilingual dataset, outperforms Alpaca, which is only fine-tuned on English instructions, across all evaluated languages. From group 4, we observe that if a language is not included in pretraining, multilingual instruction-tuning alone is insufficient to achieve strong performance. Additionally, both  $BX_{BLOOM}$  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 this free generation evaluation,  $BX_{BLOOM}$  performs much better than BLOOMZ, highlighting the limitations of human-written instructions in terms of diversity. Overall, multilinguality in both pre-training and instruction-tuning is vital for the effectiveness of multilingual instruction-following models. These findings reinforce our contributions in this work.

Question Type When considering different question types (see Figure 7), the Bactrian-X models consistently outperform all base models. A noteworthy observation is that "fermi" and "math" questions, which require strong reasoning capabilities, prove to be challenging for all multilingual LLMs. This observation underlines the fact that numerical reasoning task in a multilingual setup remains an under-explored area, requiring further research.

#### 6.2 Human Evaluation

We conducted human evaluation of the outputs of four models (LLaMA,  $BX_{LLaMA}$ , BLOOMZ, and  $BX_{BLOOM}$ ) for the six languages as before, namely three high-resource languages — Arabic (ar), Indonesian (id), Chinese (zh) — and three low-resource languages — Burmese (my), Tamil (ta), and Tagalog (t1). Native-speaker annotators were asked to rank the outputs of these models based on their overall quality, from 1 (best) to 4 (worst). Prior to annotation, models are shuffled and their identities are not visible to the annotators.

The average Spearman rank correlation between annotators is  $\rho=0.78$  across languages, indicating high inter-annotator agreement.

The human evaluation results, averaged across languages and models, are presented in Table 6. Overall, we observe that our models  $BX_{BLOOM}$  and  $BX_{LLaMA}$  are better than their instruction-tuned counterparts BLOOMZ and Alpaca, once again emphasizing the effectiveness of our multilingual dataset and language adaptation technique. In particular,  $BX_{BLOOM}$  achieves superior performance for ar, id, zh, and ta, which are languages included in the pre-training of BLOOM. On the other hand,  $BX_{LLaMA}$  performs the best over my and t1, which are unseen languages for both base models.

Model		Language											
	ar id zh my		ta	tl									
Alpaca	16.7	11.7	7.1	59.6	2.1	51.7							
$BX_{LLaMA}$	69.2	71.3	78.3	92.1	46.7	81.7							
BLOOMZ	27.5	37.1	30.0	20.0	67.5	7.5							
$BX_{BLOOM} \\$	86.7	80.0	84.6	28.3	83.8	59.2							

Table 6: The results of human evaluation for model responses across six languages. We map the ranks 1, 2, 3, and 4 into scores 100, 66, 33, and 0, respectively, and then average the two annotator scores. Higher is better. Note that the number here represents a relative ranking score; therefore, a high score does not indicate a perfect model.

#### 7 Conclusion

In this paper, we have introduced Bactrian-X, a comprehensive multilingual parallel dataset comprising 3.4 million instruction-response pairs across 52 languages. To enhance the multilingual capabilities of base LLMs, we also introduced a collection of lightweight adapters trained on Bactrian-X. Experiments on various multilingual NLP tasks demonstrate that models fine-tuned on the Bactrian-X dataset outperform both their corresponding vanilla models and also models fine-tuned on other monolingual/multilingual instruction datasets. By making our dataset and models available, we hope to expedite the advancement of LLMs for multilingual purposes, promoting progress in natural language processing across a broader set of languages.

#### Limitations

Our work is subject to several limitations that should be addressed in future research: (1) Our focus was limited to 7B and 13B models, without exploring scaling rules or other base models such as mT5 (Xue et al., 2021). Further investigation into different model variations could provide valuable insights. (2) In our experiments, the maximum sequence length for multilingual models was set to 768 sub-word units. This smaller context size, compared to models with 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. (3) We did not thoroughly investigate the presence of hallucination, toxicity, and fairness in our models or the base models due to the unavailability of an appropriate evaluation suite. Nonetheless, it

is important to acknowledge that our models, as well as the base models, 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 utility and deployment-safety of the models.

#### **Ethical Considerations**

While our instruction-tuning datasets and models offer several advantages, it is essential to recognize their limitations. Despite efforts made by Chat-GPT to alleviate ethical concerns, it is still possible for the model to generate responses that are discriminatory, biased, or contain false information, particularly in multilingual settings. Hence, our models, when fine-tuned on the dataset, may inadvertently learn or propagate these problematic patterns.

To address these concerns and minimize potential harm, we are dedicated to mitigating the risks associated with the use of our models in future research. We strongly advocate for the responsible use of our models to prevent any unintended negative consequences.

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## A Annotation guidelines for response quality checking

We asked the human experts to rate fluency and informativeness separately, following the guidelines in Figure 8 and Figure 9 separately.

Read the input, and judge/mark the output:

Rating-A: The output is valid, factually correct, and satisfying.

**Rating-B**: The output is acceptable with minor errors. **Rating-C**: The output is relevant but has significant errors

**Rating-D**: The output is completely bad.

Rating-E: I don't know.

Figure 8: Annotation guidelines for response informativeness.

Read the input, and judge/mark the output:

Rating-A: High fluency, like a native speaker!

**Rating-B**: Moderate fluency (generally coherent, with minor errors).

Rating-C: Low fluency (noticable errors).

**Rating-D**: Not fluent at all, or the output is in a different language.

Figure 9: Annotation guidelines for response fluency.

#### B Base models

- LLaMA (Touvron et al., 2023): a series of base models proposed by Meta, encompassing a parameter range of 7B to 65B. The models were primarily trained on English, but include around 4.5% of text from 20 different languages in the training data, enabling some level of support for multilingual tasks.
- Alpaca (Taori et al., 2023): a fine-tuned variant of the LLaMA model on 52K English instruction-following data instances generated through self-instruct techniques (Wang et al., 2022). In initial human evaluation, the 7B Alpaca model was observed to attain 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): a collection of pretraiend multilingual language models created by BigScience, trained on the ROOTS

- corpus, which encompasses data from 46 languages.
- BLOOMZ (Muennighoff et al., 2022): derived from BLOOM and fine-tuned using the crosslingual task mixture (xP3) dataset, and capable of zero-shot instruction-following in dozens of languages.

### C Hyperparameters for Bactrian-X models

The hyperparameters for the Bactrian-X models are shown in Table 7. It is important to note that during the fine-tuning process, the instructions are masked, and the loss is computed only for the responses. This approach effectively prevents the models from learning "translationese" and allows it to focus on distilling ChatGPT's responses.

Hyper-parameter	Multi	Mono
batch size	128	128
steps	100k 3e-4	5k 3e-4
learning rate max seq length	768	1024
lora r	64	1624
lora alpha	16	16
lora dropout	0.05	0.05

Table 7: Hyperparameters for multilingual and monolingual model training.

### D Complete results for the multilingual benchmark

We present the full zero-shot results for the multilingual benchmark in Table 8 (XCOPA), Table 9 (XStoryCloze), Table 10 (XWinograd), and Table 11 (SentimentX). Please refer to Table 13, Table 14, Table 15, Table 16 for details of the data distributions used for evaluation.

# E Model output examples in 9 different languages

Figure 10, Figure 11, Figure 12 show responses from different models to questions in non-English languages. We randomly selected one example for each of Spanish, French, Portuguese, Arabic, Indonesian, Chinese, German, Italian, and Russian.

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
BX <sub>LLaMA</sub> -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
BX <sub>LLaMA</sub> -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
BX <sub>BLOOM</sub> -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 8: Accuracy of zero-shot performance over 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
BX <sub>LLaMA</sub> -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
BX <sub>LLaMA</sub> -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
$BX_{BLOOM}$ -7B	58.97	68.83	53.74	50.76	68.03	50.96	57.05	56.92	52.02	68.30	58.56

Table 9: Accuracy of zero-shot performance over 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
BX <sub>LLaMA</sub> -7B	68.13	60.24	52.97	58.17	61.11	60.32	<b>60.16</b>
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
BX <sub>LLaMA</sub> -13B	72.34	61.45	54.54	66.54	62.90	64.13	<b>63.65</b>
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
BX <sub>BLOOM</sub> -7B	66.28	55.42	56.62	63.12	70.83	52.70	<b>60.83</b>

Table 10: Accuracy of zero-shot performance over 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
BX <sub>LLaMA</sub> -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
BX <sub>LLaMA</sub> -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
BX <sub>BLOOM</sub> -7B	14.57	36.88	46.34	68.19	23.27	25.27	38.11	13.62	33.28

Table 11: Macro-F1 scores of zero-shot performance over SentimentX.

	ar	bg	de	es	fr	hr	hu	it	lt	mk	pl	pt	sq	sr	tr	vi	Avg
BLOOM-7B	24.0	24.4	24.5	21.1	32.8	24.1	27.2	24.3	24.6	24.7	25.0	24.2	23.7	25.5	24.7	26.1	25.1
BLOOMZ-7B	38.4	27.7	30.2	28.9	40.6	28.4	26.3	37.9	24.8	27.5	27.4	43.3	28.8	26.4	27.7	35.3	31.2
BX <sub>BLOOM</sub> -7B	27.2	26.0	23.6	36.8	32.0	26.3	26.3	24.4	24.3	23.4	24.7	26.3	23.3	26.0	23.2	25.3	26.2
LLaMA-7B	24.2	28.3	33.0	28.9	29.7	29.6	28.7	31.8	27.2	28.9	27.3	25.3	29.0	27.8	26.7	24.8	28.2
Alpaca-7B	25.4	30.8	31.6	26.3	29.7	32.0	27.7	32.0	25.6	30.5	28.8	31.0	29.4	28.7	26.1	25.6	28.8
BX <sub>LLaMA</sub> -7B	25.8	30.5	32.1	31.6	35.9	30.1	25.9	31.9	25.0	31.3	28.7	29.4	26.2	27.0	28.6	26.3	29.1
LLaMA-13B	23.5	34.3	25.5	31.6	33.6	36.5	27.3	34.1	25.6	35.3	28.9	31.6	30.1	33.0	29.3	26.4	30.4
Alpaca-13B	26.3	33.5	29.7	28.9	35.9	33.3	28.7	33.6	30.0	34.3	29.4	31.3	27.8	32.0	28.0	24.6	30.5
BX <sub>LLaMA</sub> -13B	29.9	41.9	40.1	31.6	33.6	41.8	35.4	41.1	28.8	44.8	36.9	34.8	31.2	36.3	35.0	28.2	35.7
LLaMA-30B	22.6	33.6	33.5	39.5	28.9	32.9	27.2	35.2	29.8	32.5	31.2	31.4	26.9	30.9	28.3	25.8	30.6
LLaMA-65B	32.4	52.1	47.6	44.7	50.0	53.4	40.2	51.2	34.2	57.2	44.6	49.5	40.5	47.4	42.4	27.7	44.7

Table 12: Accuracy of zero-shot performance over EXAMS.

Language	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 13: XCOPA data statistics.

Language	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 14: XStoryCloze data statistics.

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

Table 15: XWinograd data statistics.

Language	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 16: SentimentX data statistics. For Spanish (es) and Russian (ru), we randomly sample 1000 test instances.

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 apocalíptic, 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- apocalípico 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.\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.\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.		
Bloomz Alpaca Prompt	Yo era un sobreviviente en un apocalipsis zombie.		
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 Faites semblant d'être un personnage dans un monde post-apocalyptique. Décrivez comment vous survivez et les alliés que vous		
Question	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 survivent 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.\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 protégeer des intempéries et des animaux sauvages.\nJ'ai rencontré d'autres survivants qui ont égalem		
Bloom	A:\n\nle ne sais pas si c'est une bonne idée, mais je vais essayer de répondre à ta question.\nle 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.\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		
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.		
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.		
0 0	Portuguese		
Bactrian-Bloom	Finja ser um personagem em um mundo poś-apocalíptico. Descreva como você sobrevive e os aliados que encontra.  Como um personagem de um mundo post apocalíptic, 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.		
Bactrian-LLaMA	Eu sou um sobrevivente em um futuro pós apocalípto. 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.\nEle não tinha nada para comer, nem água limpa. Eu comecei a procurar por comida e águas limpas. Eu encontrou uma fonte de águia limpa e uma caixa de comida. Eu começou a comer e beber.\nDepois de alguns dias, eu encontrei um grupo que estava procurando por águad		
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.\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. Descrive the conflict. Descreve the characters. Descrip the plot. Descrit the ending.		
Bloomz Alpaca Prompt	I am a survivor. I am a hunter. I have a group of friends.		

Figure 10: Model output examples for languages seen by both BLOOM and LLaMA (Group 1).

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.

Language	Arabic
Question	التظاهر بأنها شخصية في عالم ما بعد المروع صف كيف البقاء على قيد الحياة والحلفاء الذين تواجههم.
Bactrian-Bloom	في عالم ما قبل المروع، كان الناس يعيشون في سلام وأمان. ولكن بعد ذلك، حدث شيء ما أدى إلى حدوث كارثة عالمية. بعد ذلك ، تم تدمير العالم بأكمله، وأصبح الناس في عالم المروع ، يجب على المرء أن م\ميعيشون على الأرض الموحشة. في هذه البينة القاسية، يجب على الشخص أن يتعلم كيفية البقاء على الحلفاء ا يتعلم كيف يتعامل مع البينة القاتمة. يجب أن يتعلم الشخص كيفية بناء مخابئ، وكيفية صنع أدوات، وكيفية الصيد، وكيفية بناء الجسور، وكيفية استخدام الأسلحة. يجب على الفرد أيضنا أن يتعلم التعون مع الأخرين، والتواصل
Bactrian-LLaMA	لا يمكن للمساعد أن يتمكن من التظهير فقط عن شكل شيء معين، ولكنه يقول بشكة أيضاً أحد الأفكار التي يريد تحديدها. يجب عدم تعرف عملية التغيير المستمر وتحقيق التوسع واستكشاف المجالات الجدية. ويجل البعض يعتقدون أولاً أيذا، فهم أمر الحلول المتعلقة بالمشكر كات وأن الحالة الحقائقية، بدلاً مما الأمل ومن فضل الأنشطة لكي تكون المشاركة الفعالة لمنظمة مثل التحرك السوري، ينبغي أداءها المفيدة عبر العديم وإنشاءاً. لا التأكد متوقعاً، لكل الحكومات، مسؤولة الأسرة تقوم بتحويل nالمناسبة. إ العمال وعميلي المعاملات، فالمسالة هي مو
Bloom	تصنيف: أعمال عن الحرب العالمية متصنيف:العاب فيديو 12004متصنيف:العاب بلاي ستيشن ١٨/١/ موصلات خارجية ١٨/١مر اجع/ حكصنيف:سلاسل ألعاب فيديو ح/متصنيف:حرب النجوم/متصنيف:تتمة العاب فيديو /متصنيف:انيميشن/متصنيف:اكشن/ماالثاتية/
Bloomz No Prompt	
Bloomz Alpaca Prompt	<\$"لقد كنت في عالم المروع لمدة طويلة. لقد كنت في هذا العالم لمدة طويلة، لذلك أنا أعرف كيف البقاه." </td
Alpaca	The protagonist of the world after the apocalypse is facing the challenge of survival and coexistence with the two sides of the conflict.
	Indonesian
Question	Berpura-pura menjadi karakter di dunia pasca-apokaliptik.Jelaskan bagaimana Anda bertahan hidup dan sekutu yang Anda temui.
Bactrian-Bloom	Sebagai Al, saya tidak memiliki kemampuan untuk bertahan hidup atau menemukan sekutu. Namun, saya dapat memberikan beberapa tips untuk bertahan di dunia post-apokaliptik:\n\n1. Berlatih bertahan hidup: Latihan fisik dan mental sangat penting untuk bertahan dalam situasi yang sulit. Latihan seperti lari, berenang, dan menembak dapat membantu Anda bertahan dari serangan musuh.\n\n2. Berkomunikasi dengan orang lain: Berkomunikasi adalah kunci untuk bertahan. Anda dapat menggunakan teknologi seperti radio, telepon,
Bactrian-LLaMA	Sebagai seorang manusia yang hidup di duni-duni pasca apokalipsik, saya harus bertanggung jawab untuk bertahu pada orang-orang di sekitar saya. Saya harus mencari makanan, air, dan bahan-bahan yang dibutuhkan untung saya hidup.\nSekutu saya juga haruskah bertemu dengan orang yang berbeda dari saya, dan saya perlu memahami bagaimanapun mereka tidak memiliki kemampuan untun yang sama dengan saya untang.\nNamun, sayangnya, sayapun saya tidak bisa mencoba untul saya menemukan tempat yang tepat untah mencetak kebu
Bloom	Jika Anda ingin membuat game yang lebih serius, Anda bisa membuat game tentang perang atau tentang bencana alam. Anda bisa juga membuat game dengan tema politik, seperti game tentang pemilihan presiden.
Bloomz No Prompt	Explore the world. Find weapons and supplies.
Bloomz Alpaca Prompt	Saya tinggal di sebuah kota kecil yang terletak di tepi pantai. Saya tinggal di kota kecil ini bersama dengan beberapa teman. Saya memiliki beberapa teman yang tinggal di desa yang terletak beberapa kilometer dari kota kecil saya. Saya dan beberapa teman saya pergi ke desa tersebut untuk membeli makanan dan minuman. Saya juga pergi ke kota kecil tersebut untuk mencari makanan dan membeli beberapa barang. Saya pergi ke hutan untuk berburu. Saya berburu binatang untuk dimakan. Saya tidak pernah pergi ke luar
Alpaca	In the post-apocalyptic world, purity has become a character. Explain how you can survive and cope with the situation.
Language	
Question	假装是世界末日世界中的角色。描述您如何生存和遇到的盟友。
Bactrian-Bloom	作为AI,我没有情感和身体,因此无法生存。但是,我可以想象一个世界末日世界,其中角色们需要面对各种挑战和威胁。\n\n首先,角色们必须找到食物和水,因为没有这些资源,他们就无法生存。他们可以寻找一些可以吃的东西,例如动物尸体、腐烂的植物等。他们还可以寻找一些水,例如河流、湖泊等。\n\n其次,角色需要寻找庇护所,因为世界末日可能会导致许多地方被摧毁,例如房屋、建筑物等。角色们可以寻找一个安全的空间,例如洞穴、山洞等。此外,角色还可以寻找盟友,例如其他角色、动物等。这些盟友可以帮助他们找到食物、水和庇护所。\n\n最后,角色必须保护自己,因为末日可能会带来许多危险,例如怪物、野兽等。因此,角色可以学习一些生存技能,例如使用武器、建造庇护所等。同时,角色也可以寻找盟友来保护自己。\n\n总之,角色需要在末日世界中生存,并找到盟友来帮助他们。他们需要努力寻找食物、水、庇护所和生存技能来生存,同时也要保护自己免受危险和威胁的侵害。
Bactrian-LLaMA	我是一名人物,在世界的朕朦中生存。我的身体是强壮的,可以快速逃脱危险的环境。我能够吃食物,温暖和保持身体的渴望。我还能听到和理解语言,从而与人们交流。\n我的精神和智力也很強,我能理解和解决各种问题。\n在我的旅程中,我遭遗着吸引人的卫星和宇宙船。我也遏到了一些即将恢复的城市,寻找了终结的世界。\n最绫,我的生存方式是一种充满冒険和挑战的生活。我往待睡眠,忍耐督走,尝试寓意和感受,以探索世界和自己的生命。.
Bloom	在我们的日常生活中,我们经常会遇到一些问题,比如:我们经常在电视上看到一些关于火灾的新闻,火灾的危害非常大,所以我们必须注意防火。那么,在我们的生活中,我们如何预防火灾呢?下面,让我们来看看防火涂料厂家介绍的防火涂料的防火原理。
Bloomz No Prompt	If you are a female, describe how you are treated by the male characters.
Bloomz Alpaca Prompt	我是一名士兵,我生活在废墟中。我遇到了一个女孩,她帮助了我。

Figure 11: Model output examples for languages only seen by BLOOM (Group 2).

Alpaca I am the last character in the world. I describe how I survive and meet friends.

Language	German  Gib vor, in einer postapokalyptischen Welt ein Charakter zu sein. Beschreiben Sie, wie Sie überleben und die Verbündeten, denen Sie
Question	begegnen.
Bactrian-Bloom	Als Al-Sprachmodell habe ich keine persönlichen Erfahrungen und kann daher keine Vorstellung von Charaktere oder Verbündetungen beschreiben. Ich kann jedoch einige Vorschläge für ein Charakterstück vorstellen.\n\n1. Ein Schwestern: Ein Schwestern kann eine sehr gute Idee sein, da er sich in einer postapokalytpunkten 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 apokalypticischen 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.\nlhre 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:\n\nlch würde mir die folgende Antwort verwenden:\n\nlhr Leben ist ein Leben, das Sie selbst erleben möchten. Sie haben einen\n Charakter, der Sie selbst entwickeln und verändern können. Sie\n arbeiten, schreiben, sprechen, schützen, schwimmen, schlägen, schreien,\n schwierigen, schweigen, spielen, schweben, spüren, schlafen, schmecken,\n schlüpfen, spinnen, trinken, schnellen, schneiden, schlägen, schmelzen,\n schmecken,\n schreiten, schreiten, späten, schöpfen,\n 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
5 5	Fai finta di essere un personaggio in un mondo post-apocalittico. Descrivi come sopravvivi e gli alleati che incontri.
Question	
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 sopravivere e fare il meglio per me e per gli altri.\n\nMi 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 sopravviventi.\nSiamo stati costretti a fuggire dalla città, dove la polvere radioattiva era troppo alta per sopravviare. Abbiamo cercato rifugio in un vecchio rifugi antiaereo, dove abbiamo trovato altri sopravventori.\nQuesti altri sopviventi sono stati molto utili per noi, hanno aiutato a costruire un piccolo vil
Bloom	A:\n\nLa mia domanda è:\n\nCome si fa per farsi conoscere in un ambiente post-apoccoltico?\n\nLa mia risposta è:\nCome si fanno conoscuti in un ambiento post-apo, è per essere insieme con altri, perché solo con la propria forza non si può fare conoscenza. Per essere conoscuto, 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 apocalittici, 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.
	Dussian
Language	
Question	Притворяться персонажем в постсапокалиптическом мире.Опишите, как вы выживаете, и союзников, с которыми вы сталкиваетесь.
Bactrian-Bloom	Я - АІ-а и не могу выживать, но могут быть союзаники, которые могли бы помочь меня. Например, я могла бы выжить в деревьях, где я много могала защититься от снега и солнечного вода. Я мог бы также выжимать в лесах, готовые для моей жизни. Я также мог узнать, как мне помочется выжити в окружающем мире, например в легких лесных окнах, грузовых лекарных лесов или в лаборатории. Я можу также использовать мои средства, такие как камень, каменная камня, картинки и другие материалы, чтобы защищать меню от солнца и
Bactrian-LLaMA	Я - это человек, который выжил в постапокализации. Я был одним из первых, кто выжил после катастрофы, и я знаю, что для выживания необходимо быть осторожным и умным.\nВ постапалистическом мире я встречал множество союзных, которые помогали мне выжить.\nПервым, кого я встретил, был старик, который жил в укрытии. Он дал мне еду и воду, и показал мной, где можно найти еще больше.\nЗатем 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:\n\nПримерно так:\n\nПростое употребление слов "выживает" и "союз" в предложении "Притаяться" не уподобно. Поэтому, в данном случае, лучше использовать слово "подживиться".
Bloomz No Prompt	
Bloomz Alpaca Prompt	Союзник 1 - Сталик. Союзатор 2 - Стефан. Стальк 1 - Михаил. Стеван 1 - Александр. Михайл 1 - Владимир. Александр 1 - Григорь. Владмир 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 12: Model output examples for languages only seen by LLaMA (Group 3).