

BayLing 2: A Multilingual Large Language Model with Efficient Language Alignment

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Abstract

Large language models (LLMs), with their powerful generative capabilities and vast knowledge, empower various tasks in everyday life. However, these abilities are primarily concentrated in high-resource languages, leaving low-resource languages with weaker generative capabilities and relatively limited knowledge. Enhancing the multilingual capabilities of LLMs is therefore crucial for serving over 100 linguistic communities worldwide. An intuitive approach to enhance the multilingual capabilities would be to construct instruction data for various languages, but constructing instruction data for over 100 languages is prohibitively costly. In this paper, we introduce BayLing 2, which efficiently transfers generative capabilities and knowledge from high-resource languages to low-resource languages through language alignment. To achieve this, we constructed a dataset of 3.2 million instructions, comprising high-resource language instructions (Chinese and English) and cross-lingual instructions for 100+ languages and performed instruction tuning based on the dataset to facilitate the capability transfer between languages. Using Llama as the foundation model, we developed BayLing-2-7B, BayLing-2-13B, and BayLing-3-8B, and conducted a comprehensive evaluation of BayLing. For multilingual translation across 100+ languages, BayLing shows superior performance compared to open-source models of similar scale. For multilingual knowledge and understanding benchmarks, BayLing achieves significant improvements across over 20 low-resource languages, demonstrating its capability of effective knowledge transfer from high-resource to low-resource languages. Furthermore, results on English benchmarks indicate that BayLing maintains high performance in highresource languages while enhancing the performance in low-resource languages. Demo², homepage³, code⁴ and models⁵ of BayLing are available.

Introduction

In recent years, the field of natural language processing (NLP) has witnessed a significant surge in the development and utilization of large language models (LLMs) [OpenAI, 2022, 2023]. Equipped with rich knowledge, strong generative capabilities, and diverse instruction-following abilities, LLMs empower various specific tasks such as translation, summarization, chat and question answering, seamlessly integratd into everyday life.

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²Demo: http://nlp.ict.ac.cn/bayling/demo

³Homepage: http://nlp.ict.ac.cn/bayling

⁴Code: https://github.com/ictnlp/BayLing ⁵Models: BayLing-2-7B, BayLing-2-13B, BayLing-3-8B

However, a significant portion of these potent capabilities is primarily concentrated in English, stemming from the fact that high-resource languages, with English as the representative, occupy over 90% of the pre-training and fine-tuning corpora [Chang et al., 2023, Touvron et al., 2023, Xu et al., 2024]. This results in issues such as lack of knowledge and lower generative capabilities in many other low-resource languages [Nguyen et al., 2023a, Alabi et al., 2022]. It is imperative to recognize that linguistic diversity is a fundamental aspect of human communication, with over 7000 spoken languages worldwide, and more than 200 of them are writable [Chang et al., 2023]. The accelerating force of globalization underscores the importance of leveraging LLMs to serve diverse linguistic communities.

Enhancing the multilingual capabilities of LLMs is not a trivial task. The intuitive approach is to construct instruction data for various languages to enhance the LLM's ability to follow instructions and generate responses across different languages [Zeng et al., 2023]. However, given the extremely limited instruction data available for some low-resource languages and the prohibitive manual efforts required to construct instructions for over 100 languages, this approach becomes impractical. Therefore, exploring more efficient approaches to improving the performance of LLMs across diverse languages remains an area for further investigation.

On these grounds, we developed BayLing 2, a multilingual LLM, which transfers knowledge, generative capability and instruction-following ability from high-resource to low-resource languages through fine-tuning LLMs on cross-lingual tasks. Previously, BayLing 1 successfully explored transferring English knowledge and capabilities to Chinese through cross-lingual alignment [Zhang et al., 2023]. Building upon BayLing 1, BayLing 2 extends language alignment to multilingual settings, particularly between high-resource and low-resource languages, leading to a multilingual LLM. The fine-tuning corpus of BayLing 2 primarily consists of Chinese and English instructions, supplemented with rich cross-lingual task instructions between Chinese/English and over 100 other languages, facilitating the capability transfer across languages.

Based on foundational models Llama-2-7B-Chat, Llama-2-13B-Chat, and Llama-3-8B-Instruct, we developed BayLing-2-7B, BayLing-2-13B, and BayLing-3-8B through the proposed efficient language alignment. We conducted a comprehensive evaluation of BayLing's performance on both multilingual and general tasks and assessed the quality of language alignment through multilingual translation using the Flores-101 and WMT22 benchmarks. BayLing showed superior translation performance across more than 100 languages, achieving the best results among open-source models of comparable scale. We further evaluated BayLing's multilingual knowledge and generative capabilities using benchmarks including Belebele, Multilingual HellaSwag, XNLI, and Multilingual ARC. The results indicated significant performance improvements across more than 20 low-resource languages, such as Bambara, Luganda, Swahili, and Zulu. This demonstrates effective knowledge and generative capability transfer from high-resource to low-resource languages. Additionally, we evaluated BayLing on various general benchmarks (primarily in English), finding that the language alignment had minimal impacts on BayLing's performance in high-resource languages.

By further analyzing the experimental results, we get the following findings:

- By fine-tuning on high-resource language instructions and cross-lingual instructions, LLM can transfer knowledge and generative capabilities from high-resource languages to low-resource languages, thereby facilitating multilingual interaction.
- Cross-lingual instructions, such as interactive translation and multilingual translation, can efficiently enhance the language alignment within LLM, thereby improving translation performance.
- Fine-tuning LLM solely on high-resource language instructions will involve inter-language conflicts and significantly impair the multilingual capabilities of LLM, especially on the low-resource languages. Beside high-resource language instructions, introducing cross-lingual instructions can effectively solve this issue.

2 Related Work

Multilingual LLMs, with their capability to handle and produce content in multiple languages simultaneously, hold promise for serving diverse linguistic communities. Foundational models, such as Llama [Touvron et al., 2023], GPT-3 [Brown et al., 2020], PaLM [Chowdhery et al., 2022], OPT [Zhang et al., 2022] and GLM [Du et al., 2022], are pretrained on corpora sourced from the web and books, which often encompass multiple languages. However, the distribution of languages in these

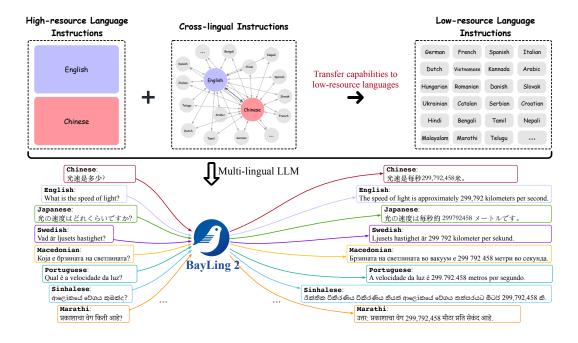


Figure 1: Overview of BayLing 2. BayLing 2 is a multilingual LLM with efficient language alignment. BayLing 2 designates Chinese and English, two high-resource languages, as pivot languages and applies cross-lingual tasks to align 100+ languages to these pivot languages, which facilitates the capabilities transfer from high-resource languages to low-resource languages. During inference, BayLing 2 is capable of high-quality interaction across multiple languages.

corpora is notably imbalanced. Specifically, a few high-resource languages dominate a significant portion of the corpus, while a vast number of low-resource languages occupy only a small fraction [Touvron et al., 2023]. This leads to performance variations across different languages [Ojo and Ogueji, 2023, Nguyen et al., 2023a]. Moreover, subsequent supervised fine-tuning on English-centric instruction data exacerbates the issue of language imbalance [Lai et al., 2023], rendering LLMs lower interactive capability with low-resource languages.

Current approaches mainly fall into two categories: continual pretraining and supervised fine-tuning. With continual pretraining, some works focus on continuously pretraining foundational models using multilingual corpora to enhance their multilingual capabilities [Nguyen et al., 2023b, Lai et al., 2023, Ke et al., 2023, Gupta et al., 2023]. These approaches effectively supplements LLMs with multilingual knowledge and generation abilities. However, continual pretraining often relies on large amounts of multilingual data, and thereby the costs associated with data collection and training are significant [Nguyen et al., 2023b, Liu et al., 2024]. Moreover, there is a risk of catastrophic forgetting with continual pretraining, which may compromise the performance of the foundational model on high-resource languages [Li et al., 2024]. Additionally, since the pretraining corpora of foundational models are often close-sourced, it is challenging to maintain the same distribution between the continual pretraining data and the pretraining data, which may lead to conflicting knowledge and potential hallucinations.

For supervised fine-tuning, existing methods attempt to manually annotate multilingual instructions to activate LLMs' ability for multilingual interaction [Eisenschlos et al., 2020, Alabi et al., 2022, Lai et al., 2023, Wang et al., 2024, Shaham et al., 2024]. This approach often relies on manually annotation and overlooks leveraging the capabilities of foundational models in high-resource languages as well as the generalization ability of LLMs. To address this, BayLing 2 attempts to enhance the multilingual capabilities of LLMs in a more efficient manner. The instruction dataset of BayLing 2 comprises instructions in both high-resource languages and cross-lingual instructions. The instructions in high-resource languages are designed to activate LLMs' instruction-following capability, while cross-lingual instructions aim to facilitate multilingual alignment of LLMs, thereby transferring

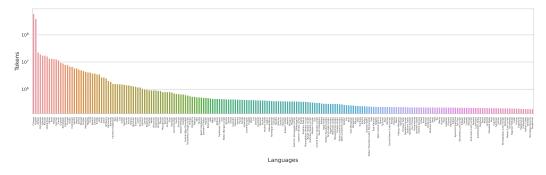
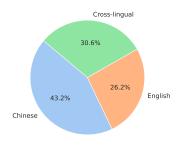


Figure 2: Language distribution of instruction dataset.



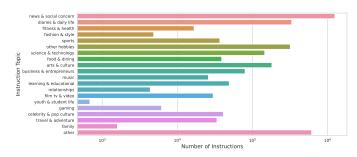


Figure 3: Distribution of instruction categories, including Chinese, English and crosslingual instructions.

Figure 4: Distribution of the tokens number involved in each instruction.

knowledge, instruction-following, and generation abilities from high-resource languages to low-resource languages.

3 BayLing 2

We introduce BayLing 2, a LLM equipped with enhanced multilingual capabilities through efficient language alignment. Building upon open-source foundational models, BayLing 2 endeavors to explore an efficient and cost-effective approach to enhance the multilingual capabilities, thereby addressing the demands for multilingual interaction.

3.1 Multilingual Alignments with Cross-lingual Tasks

During the pre-training stage, the distribution of languages in the corpus is highly imbalanced. For instance, English, being a high-resource language, accounts for over 90% of the corpus, while low-resource languages such as Sinhalese, Marathi, and Macedonian collectively comprise less than 1% of the corpus. Naturally, foundational models trained on such language-imbalanced corpus exhibit superior performance on English compared to low-resource languages. Previous studies have often noted that due to the generalization capability, LLMs also demonstrate a certain advantage on those languages within the same language family as English. Naturally, aligning low-resource languages with high-resource languages already mastered by LLMs allows us to transfer the knowledge and generation capabilities of LLMs from high-resource languages to other languages efficiently, thereby enhancing the multilingual capabilities of LLMs.

We employ cross-lingual tasks to align low-resource languages with high-resource languages, thereby achieving multilingual alignment. Fortunately, translation tasks naturally serve as well-defined cross-lingual tasks, demanding outputs that maintain consistent meanings with inputs while differing in language. More importantly, translation tasks boast abundant high-quality parallel corpus across diverse domains, thus laying the groundwork for the efficient achievement of language alignment.

Specifically, we designate Chinese and English, two high-resource languages, as the pivot language, and align over 100 other languages to Chinese and English using translation instructions. Following this idea, we construct the instruction dataset for BayLing 2, comprising Chinese instructions, English instructions and cross-lingual instructions, as shown in Figure 1. The instruction dataset contains a total of 3.2 million instructions (1471 million tokens), with the distribution of Chinese, English and cross-lingual instructions illustrated in Figure 3. Notably, the cross-lingual instructions in BayLing 2 involve interactive translation, constrained translation, document-level translation and single-sentence translation tasks across over 100 languages. The language distribution of the instruction dataset is shown in Figure 2. The distribution of topics covered in the proposed instruction dataset is illustrated in Figure 4, where instructions primarily sourced from news corpora ensure data quality and security. Overall, BayLing 2 is fine-tuned on 3.2 million instructions covering 100+ languages, achieving multilingual alignment and thereby transferring knowledge and generation capabilities from high-resource languages to low-resource languages.

3.2 Training

Using Llama-2-7B-Chat, Llama-2-13B-Chat and Llama-3-8B-Instruct as foundational models, We fine-tune **BayLing-2-7B**, **BayLing-2-13B** and **BayLing-3-8B** respectively on the instruction dataset proposed in Section 3.1. We fine-tune BayLing 2 on 8 NVIDIA A800 80G GPUs for 3 epochs, using a global batch size of 128, learning rate of 2e-5 and weight decay of 0.0. Note that we apply learning rate of 2e-6 for BayLing-3-8B. We employ DeepSpeed [Rasley et al., 2020] and Gradient Checkpointing [Chen et al., 2016] techniques to optimize memory consumption. The training loss curve of BayLing-3-8B is depicted in Figure 5.

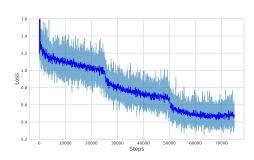


Figure 5: Training loss curve of BayLing-3-8B.

4 Evaluation

In this section, we comprehensively evaluate the performance of BayLing-2-7B, BayLing-2-13B and BayLing-3-8B on multilingual tasks and general tasks respectively.

4.1 Multilingual Capability

BayLing's multilingual capabilities are primarily manifested in two aspects: multilingual translation and multilingual interaction. Multilingual translation aims to accomplish translation between different languages, which can be utilized to assess the language alignment within LLMs as well as the comprehension and generation capabilities across different languages. Multilingual interaction involves multitask language understanding using multiple languages, which can be employed to evaluate the multilingual knowledge and reasoning abilities of LLMs.

4.1.1 Multilingual Translation

We employ multilingual translation to assess the multilingual alignment within LLMs, which entails producing outputs that retain the same meaning but in different languages. We conduct evaluation on the **Flores-101** and **WMT22** benchmarks. For metrics, BLEU (sacrebleu) [Post, 2018] and COMET [Rei et al., 2022] are used to assess the quality of LLMs' translation. BLEU score measures the statistical similarity based on n-gram accuracy, COMET score measures the semantic similarity using cross-lingual pre-trained models, which is currently regarded as the most human-aligned evaluation metric for translation tasks.

Flores-101 Flores-101 benchmark encompasses 101 languages from around the world, and the sentences is sourced from various domains, including news, travel guides and books. Due to the rarity of some low-resource languages, LLMs may suffer from off-target issues. To address this, we adopt a 1-shot setting (i.e., randomly selecting an example from the dev set) to help LLMs follow the

Table 1: Mulitlingual translation preformance on WMT22 benchmark. X indicates other 100 languages in Flores-101, and the results are averaged over these 100 languages.

Models	X⇒English		English⇒X		X⇒C	Chinese	Chine	ese⇒X
11204015	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET
Llama-1-7B BayLing-1-7B	14.07 14.70	60.94 61.93	6.93 7.04	49.73 49.33	0.93 1.58	40.88 46.22	1.85 1.56	44.88 48.78
Llama-2-7B-Chat BayLing-2-7B	15.39 17.71	63.95 67.15	7.45 8.02	50.97 52.37	1.75 2.70	47.19 51.44	1.57 2.32	45.70 49.37
Llama-3-8B-Instruct BayLing-3-8B	25.20 26.77	76.60 77.03	16.59 17.91	67.17 70.88	11.79 11.31	71.91 69.43	8.95 10.64	63.57 67.86

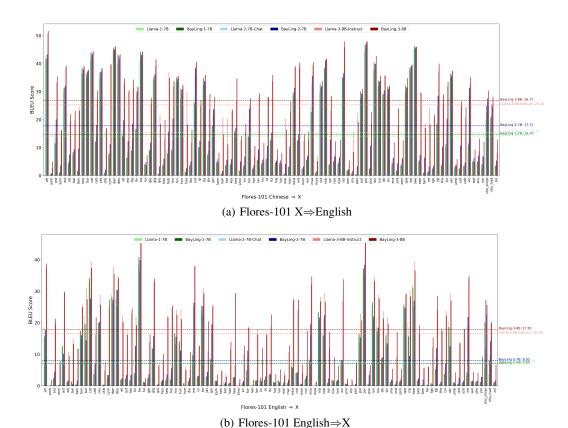


Figure 6: English⇔101 languages translation performance on Flores-101 benchmark.

target language through in-context learning. We compare BayLing models with their corresponding foundational models, and the results are shown in Table 1.

The results in Table 1 indicate that BayLing achieves better performance in most translation directions between 100 languages and Chinese/English. Specifically, compared to the foundation LLMs Llama-1-7B and Llama-2-7B-Chat, which have relatively weak multilingual capabilities, BayLing effectively scales their language understanding and generation capabilities to over 100 languages, leading to significantly improved translation performance. Furthermore, Figures 6(a), 6(b), 7(a) and 7(b) illustrate the specific BLEU score improvements achieved by BayLing across 100 languages. BayLing consistently delivers the highest translation quality for most languages, particularly in translation directions to low-resource languages. This demonstrates BayLing's potential to enhance LLM in serving such low-source linguistic communities.

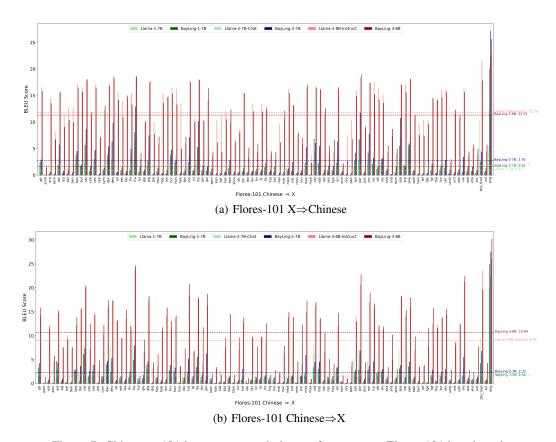


Figure 7: Chinese⇔101 languages translation performance on Flores-101 benchmark.

WMT22 WMT22 benchmark⁶ encompass is used to evaluate high-resource multilingual translation performance, including translation directions of Chinese⇔English, German⇔English, Czech⇔English, Japanese⇔English, Russian⇔English, and Ukrainian⇔English. We compared BayLing with the best closed-sourced and open-sourced models, including GPT-4⁷ [OpenAI, 2023], GPT-3.5-turbo⁸ [OpenAI, 2022], Google Translate⁹, Llama[Touvron et al., 2023] and Vicuna [Chiang et al., 2023].

The translation results on WMT22 are shown in Table 2, where the results illustrate the superior multilingual translation capabilities of BayLing models. Among the open-sourced models, BayLing achieves the highest overall translation performance, coming remarkably close to the performance levels of closed-sourced models like GPT-4 and GPT-3.5-turbo. This exceptional performance can be attributed to BayLing's improved language alignment, which enables it to produce more accurate and reliable translations across different languages. In particular, for the Zh⇔En translation, BayLing-3-8B achieve a COMET score of 79.75 on Zh⇒En and 85.75 on En⇒Zh, which is very close to the performance of Google Translate.

Improving Mulitlingual Generation Capabilities We have observed that foundational models often exhibit off-target issues when generating low-resource languages. In contrast, BayLing demonstrates significantly enhanced multilingual generation capabilities, consistently improving translation performance from English to other languages. This indicates that BayLing can activate the multilingual generation abilities of LLMs solely through cross-lingual translation data, without the need for extensive multilingual instruction data. This finding is crucial for efficiently enhancing the multilingual capabilities of LLMs, as it is nearly impossible to collect instruction data covering more than 100 languages while multilingual translation data is relatively abundant and easier to

⁶https://www.statmt.org/wmt22/translation-task.html

⁷We use GPT-4 API of version 0314

⁸We use GPT-3.5-turbo API

⁹https://translate.google.com/

Table 2: Mulitlingual translation preformance on WMT22 benchmark. The bold and underlined results indicate the first and second best, respectively.

	En=	>Zh	En=	>De	En=	>Cs	En=	→ Ia	En=	≻Rn	En≕	>∐k
Systems	COMET		COMET		COMET						COMET	
				С	losed-sour	ced						
GPT-4	87.49	43.98	87.44	35.38	90.77	34.53	89.87	24.71	88.87	30.45	88.46	26.71
GPT-3.5-turbo	86.81	44.99	86.93	34.12	90.05	32.71	83.26	22.22	87.52	29.59	87.43	25.87
Google Translate	87.34	49.89	87.08	38.27	91.28	48.10	88.64	26.50	88.91	35.04	88.63	32.05
					open-sourc	ed						
Llama-2-7B-Chat	67.90	17.50	72.22	16.74	65.17	11.69	69.66	9.52	67.60	12.47	66.94	10.65
Llama-2-13B-Chat	75.23	24.31	77.25	20.35	75.42	16.18	78.46	13.56	77.19	17.11	75.41	14.75
Vicuna-7B-v1.5	81.40	29.54	75.25	16.65	71.84	13.63	74.80	11.28	77.66	17.95	74.96	13.26
Vicuna-13B-v1.5	84.01	34.69	81.99	24.22	77.97	17.47	85.45	17.54	83.31	21.60	81.32	17.86
Llama-3-8B-Instruct	80.55	30.10	82.18	25.83	<u>83.24</u>	23.41	65.43	10.57	82.92	23.53	80.69	18.88
BayLing-1-7B	84.43	38.19	82.18	25.66	76.85	15.64	71.23	4.51	74.72	14.85	76.01	11.66
BayLing-1-13B	84.62	37.92	82.69	25.62	78.22	16.43	71.39	6.05	71.01	12.77	66.83	8.32
BayLing-2-7B	85.94	39.71	82.76	25.65	80.54	17.81	<u>84.94</u>	16.43	82.03	19.72	75.85	12.25
BayLing-2-13B	86.65	42.87	83.79	<u>26.61</u>	82.93	18.52	83.60	15.79	<u>85.23</u>	22.95	80.89	14.60
BayLing-3-8B	85.75	41.49	84.53	29.59	87.55	24.57	83.34	<u>16.82</u>	86.79	26.41	85.97	21.81
Systems	Zh=		De=	,	Comet		Ja=		Ru=		Uk=	
Systems	Zh= COMET		De=	BELU	COMET	BELU	Ja= COMET		Ru= COMET		Uk= COMET	
	COMET	BELU	COMET	BELU	COMET losed-sour	BELU ced	COMET	BELU	COMET	BELU	COMET	BELU
GPT-4	82.79	27.20	85.62	33.87	COMET losed-sour 87.43	BELU ced 48.67	83.20	24.57	86.18	43.51	85.67	BELU 40.47
GPT-4 GPT-3.5-turbo	82.79 82.64	27.20 26.13	85.62 85.47	33.87 32.94	COMET losed-sour 87.43 86.75	BELU ced 48.67 45.99	83.20 82.39	24.57 22.14	86.18 85.95	43.51 41.79	85.67 85.32	40.47 39.00
GPT-4	82.79	27.20	85.62	33.87	COMET losed-sour 87.43	BELU ced 48.67	83.20	24.57	86.18	43.51	85.67	BELU 40.47
GPT-4 GPT-3.5-turbo	82.79 82.64	27.20 26.13	85.62 85.47	33.87 32.94 33.21	COMET losed-sour 87.43 86.75	BELU ced 48.67 45.99 49.26	83.20 82.39	24.57 22.14	86.18 85.95	43.51 41.79	85.67 85.32	40.47 39.00
GPT-4 GPT-3.5-turbo	82.79 82.64	27.20 26.13	85.62 85.47	33.87 32.94 33.21	COMET losed-sour 87.43 86.75 86.95	BELU ced 48.67 45.99 49.26 eed 28.91	83.20 82.39	24.57 22.14	86.18 85.95	43.51 41.79 43.54	85.67 85.32	40.47 39.00
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat	82.79 82.64 80.81 75.31 75.90	27.20 26.13 28.63 15.42 16.45	85.62 85.47 84.75	33.87 32.94 33.21 24.53 25.69	COMET losed-sour 87.43 86.75 86.95 open-source	BELU 48.67 45.99 49.26 28.91 33.97	83.20 82.39 81.69	24.57 22.14 23.17 11.38 13.37	86.18 85.95 84.81 80.56 81.60	43.51 41.79 43.54 31.23 32.72	85.67 85.32 85.55	40.47 39.00 41.60 28.68 31.55
GPT-4 GPT-3.5-turbo Google Translate	82.79 82.64 80.81 75.31 75.90 75.42	27.20 26.13 28.63	85.62 85.47 84.75	33.87 32.94 33.21 24.53	COMET 87.43 86.75 86.95 open-source 78.18 81.28 76.34	BELU 2ced 48.67 45.99 49.26 28.91 33.97 24.46	83.20 82.39 81.69 74.11 76.37 72.13	24.57 22.14 23.17	86.18 85.95 84.81 80.56 81.60 78.63	43.51 41.79 43.54 31.23 32.72 27.95	85.67 85.32 85.55 79.41 81.19 78.29	40.47 39.00 41.60 28.68 31.55 25.74
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat Vicuna-7B-v1.5 Vicuna-13B-v1.5	82.79 82.64 80.81 75.31 75.90 75.42 78.47	27.20 26.13 28.63 15.42 16.45 16.80 19.41	85.62 85.47 84.75 80.14 81.43 79.07 83.25	33.87 32.94 33.21 24.53 25.69 23.57 29.19	COMET 87.43 86.75 86.95 open-source 78.18 81.28 76.34 81.71	8ELU ced 48.67 45.99 49.26 red 28.91 33.97 24.46 34.51	83.20 82.39 81.69 74.11 76.37 72.13 75.22	24.57 22.14 23.17 11.38 13.37 10.89 13.66	86.18 85.95 84.81 80.56 81.60 78.63 82.18	43.51 41.79 43.54 31.23 32.72 27.95 33.74	85.67 85.32 85.55 79.41 81.19 78.29 82.54	40.47 39.00 41.60 28.68 31.55 25.74 33.03
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat Vicuna-7B-v1.5 Vicuna-13B-v1.5 Llama-3-8B-Instruct	75.31 75.90 75.42 78.47 80.44	27.20 26.13 28.63 15.42 16.45 16.80 19.41 21.57	85.62 85.47 84.75 80.14 81.43 79.07 83.25 83.84	33.87 32.94 33.21 24.53 25.69 23.57 29.19 29.37	COMET 87.43 86.75 86.95 open-source 78.18 81.28 76.34 81.71 83.47	48.67 45.99 49.26 28.91 33.97 24.46 34.51 39.49	83.20 82.39 81.69 74.11 76.37 72.13 75.22 78.83	24.57 22.14 23.17 11.38 13.37 10.89 13.66 17.00	86.18 85.95 84.81 80.56 81.60 78.63 82.18 84.08	43.51 41.79 43.54 31.23 32.72 27.95 33.74 37.05	85.67 85.32 85.55 79.41 81.19 78.29 82.54 82.75	40.47 39.00 41.60 28.68 31.55 25.74 33.03 34.53
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat Vicuna-7B-v1.5 Vicuna-13B-v1.5 Llama-3-8B-Instruct BayLing-1-7B	75.31 75.90 75.42 78.47 80.44	27.20 26.13 28.63 15.42 16.45 16.80 19.41 21.57 20.31	85.62 85.47 84.75 80.14 81.43 79.07 83.25 83.84 83.19	33.87 32.94 33.21 24.53 25.69 23.57 29.19 29.37 28.16	87.43 86.75 86.95 open-sourc 78.18 81.28 76.34 81.71 83.47 82.03	48.67 45.99 49.26 28.91 33.97 24.46 34.51 39.49 35.98	83.20 82.39 81.69 74.11 76.37 72.13 75.22 78.83 72.16	24.57 22.14 23.17 11.38 13.37 10.89 13.66 17.00 11.63	86.18 85.95 84.81 80.56 81.60 78.63 82.18 84.08	43.51 41.79 43.54 31.23 32.72 27.95 33.74 37.05 34.74	85.67 85.32 85.55 79.41 81.19 78.29 82.54 82.75 81.38	40.47 39.00 41.60 28.68 31.55 25.74 33.03 34.53 33.07
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat Vicuna-7B-v1.5 Vicuna-13B-v1.5 Llama-3-8B-Instruct BayLing-1-7B BayLing-1-13B	82.79 82.64 80.81 75.31 75.90 75.42 78.47 80.44 77.48 77.72	27.20 26.13 28.63 15.42 16.45 16.80 19.41 21.57 20.31 20.12	85.62 85.47 84.75 80.14 81.43 79.07 83.25 83.84 83.19 83.02	33.87 32.94 33.21 24.53 25.69 23.57 29.19 29.37 28.16 27.34	87.43 86.75 86.95 86.95 open-source 78.18 81.28 76.34 81.71 83.47 82.03 81.65	48.67 45.99 49.26 28.91 33.97 24.46 34.51 39.49 35.98 33.87	83.20 82.39 81.69 74.11 76.37 72.13 75.22 78.83 72.16 72.14	24.57 22.14 23.17 11.38 13.37 10.89 13.66 17.00 11.63 12.23	86.18 85.95 84.81 80.56 81.60 78.63 82.18 84.08 82.48 82.07	43.51 41.79 43.54 31.23 32.72 27.95 33.74 37.05 34.74 33.95	85.67 85.32 85.55 79.41 81.19 78.29 82.57 81.38 81.41	40.47 39.00 41.60 28.68 31.55 25.74 33.03 34.53 33.07 32.67
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat Vicuna-7B-v1.5 Vicuna-13B-v1.5 Llama-3-8B-Instruct BayLing-1-7B BayLing-1-13B BayLing-2-7B	82.79 82.64 80.81 75.31 75.90 75.42 78.47 80.44 77.48 77.72 79.07	27.20 26.13 28.63 15.42 16.45 16.80 19.41 21.57 20.31 20.12 22.09	85.62 85.47 84.75 80.14 81.43 79.07 83.25 83.84 83.19 83.02 82.56	33.87 32.94 33.21 24.53 25.69 23.57 29.19 29.37 28.16 27.34 27.33	COMET 87.43 86.75 86.95 86.95 81.28 81.28 81.71 83.47 82.03 81.65 80.66	48.67 45.99 49.26 28.91 33.97 24.46 34.51 39.49 35.98 33.87 31.91	83.20 82.39 81.69 74.11 76.37 72.13 75.22 78.83 72.16 72.14 76.35	24.57 22.14 23.17 11.38 13.37 10.89 13.66 17.00 11.63 12.23 15.12	86.18 85.95 84.81 80.56 81.60 78.63 82.18 84.08 82.48 82.07 81.19	43.51 41.79 43.54 31.23 32.72 27.95 33.74 37.05 34.74 33.95 29.37	85.67 85.32 85.55 79.41 81.19 78.29 82.54 82.75 81.38 81.41 80.34	40.47 39.00 41.60 28.68 31.55 25.74 33.03 34.53 33.07 32.67 28.60
GPT-4 GPT-3.5-turbo Google Translate Llama-2-7B-Chat Llama-2-13B-Chat Vicuna-7B-v1.5 Vicuna-13B-v1.5 Llama-3-8B-Instruct BayLing-1-7B BayLing-1-13B	82.79 82.64 80.81 75.31 75.90 75.42 78.47 80.44 77.48 77.72	27.20 26.13 28.63 15.42 16.45 16.80 19.41 21.57 20.31 20.12	85.62 85.47 84.75 80.14 81.43 79.07 83.25 83.84 83.19 83.02	33.87 32.94 33.21 24.53 25.69 23.57 29.19 29.37 28.16 27.34	87.43 86.75 86.95 86.95 open-source 78.18 81.28 76.34 81.71 83.47 82.03 81.65	48.67 45.99 49.26 28.91 33.97 24.46 34.51 39.49 35.98 33.87	83.20 82.39 81.69 74.11 76.37 72.13 75.22 78.83 72.16 72.14	24.57 22.14 23.17 11.38 13.37 10.89 13.66 17.00 11.63 12.23	86.18 85.95 84.81 80.56 81.60 78.63 82.18 84.08 82.48 82.07	43.51 41.79 43.54 31.23 32.72 27.95 33.74 37.05 34.74 33.95	85.67 85.32 85.55 79.41 81.19 78.29 82.57 81.38 81.41	40.47 39.00 41.60 28.68 31.55 25.74 33.03 34.53 33.07 32.67

obtain. BayLing's approach of transferring generation capabilities from high-resource to low-resource languages through language alignment offers an efficient solution for enhancing the multilingual generation capabilities of LLMs.

The superior multilingual translation capabilities on Flores-101 and WMT22 underscores BayLing's potential as a leading tool in the field of multilingual translation, offering significant advancements in multilingual capabilities of LLM.

4.1.2 Multilingual Multi-task Evaluation

We assessed the multilingual performance of BayLing using several benchmarks. All evaluations were conducted through the Language Model Evaluation Harness¹⁰ [Gao et al., 2023], an open-source, unified framework designed to assess LLMs across a wide variety of evaluation tasks. Each result was obtained in a zero-shot setting. The models Llama-2-7B, Llama-2-7B-Chat, Llama-3-8B-Instruct, Vicuna-7B and Mistral-7B served as baselines for comparison. The multilingual benchmarks are discribed as follows.

Belebele [Bandarkar et al., 2023] Belebele is a multiple-choice machine reading comprehension benchmark, which evaluates mono- and multi-lingual models across different resource levels with rigorously checked questions. Each question has four multiple-choice answers and is linked to a short passage from the FLORES-200 dataset.

Multilingual HellaSwag [Dac Lai et al., 2023] Multilingual HellaSwag is a multilingual adaptation of HellaSwag, a benchmark dataset designed to assess commonsense inference. Despite its questions

¹⁰https://github.com/EleutherAI/lm-evaluation-harness

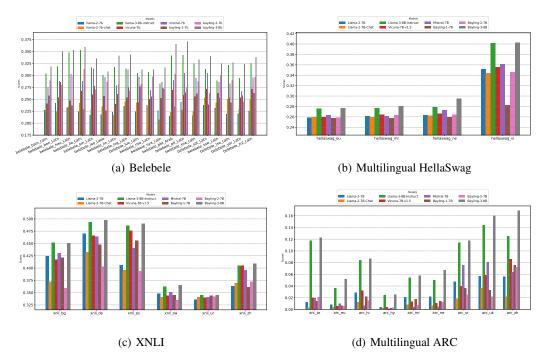


Figure 8: Multilingual multi-task performance of BayLing on low-resource languages.

being straightforward for humans, state-of-the-art models struggle with it, highlighting the challenges in AI comprehension.

XNLI [Conneau et al., 2018] XNLI is an evaluation dataset created by extending the MultiNLI corpus to multiple languages, including low-resource ones like Swahili and Urdu. It serves as a standardized benchmark for assessing cross-lingual sentence understanding, aiming to foster research in this area.

Multilingual ARC [Dac Lai et al., 2023] The Multilingual ARC, a multilingual extension of ARC [Clark et al., 2018], encompasses science examination queries, stratified into a Challenge Set comprising intricate questions and an Easy Set. All queries adhere to a multiple-choice structure.

Figure 8(a), 8(b), 8(c), 8(d) provide detailed illustrations of the experimental outcomes on the Belebele, Multilingual HellaSwag, XNLI, Multilingual ARC benchmarks across several low-resource languages. The BayLing-2-7B and BayLing-3-8B models demonstrate notable performance benefits. Among these, BayLing-3-8B consistently delivers the best results across most of the low-resource languages evaluated. Meanwhile, BayLing-2-7B outperforms other 7B models in most of these languages. Remarkably, BayLing-2-7B even surpasses the Llama-3-8B-Instruct model in the Swati language subset on Belebele benchmark (belebele_ssw_Latn).

Note that BayLing's training data does not include instruction data for these low-resource languages but only cross-lingual instructions between these low-resource languages and Chinese/English. Therefore, the performance improvements observed in these low-resource languages demonstrate that BayLing effectively transfers knowledge and understanding capability from high-resource languages to low-resource ones through language alignment. Overall, BayLing's approach of leveraging language alignment for capability transfer offers an efficient solution to enhance LLM's performance in low-resource languages.

4.2 General Capability

Furthermore, we evaluated the general capability of BayLing on the following benchmarks employing the same settings as described in section 4.1.2.

CMMLU [Li et al., 2023] CMMLU serves as a specialized evaluation benchmark tailored to assess the knowledge and reasoning capacities of LLMs in within the context of Chinese language and

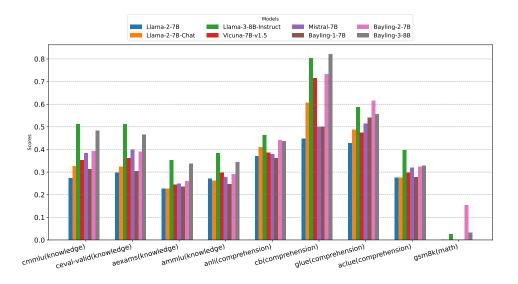


Figure 9: Scores on general benchmarks.

culture. Encompassing a wide range of subjects, CMMLU includes 67 topics, which vary from basic to advanced professional levels.

C-Eval [Huang et al., 2023] C-Eval is an exhaustive Chinese evaluation suite designed for foundation models. It features a total of 13,948 multiple-choice questions, covering 52 distinct disciplines across four levels of difficulty.

Arabic EXAMS [Hardalov et al., 2020] The Arabic EXAMS comprise the Arabic segment of EXAMS, a resource dedicated to multilingual high school examination questions. This section includes five subjects: Islamic Studies, Biology, Physics, General Science, and Social Studies.

ANLI [Nie et al., 2020] Adversarial NLI (ANLI) is a dataset assembled through an iterative adversarial procedure involving both human and model participation. It is structured into three rounds, each escalating in difficulty and complexity. Additionally, each question-answer pair in the dataset is supplemented with explanations provided by the annotators.

CB [De Marneffe et al., 2019, Wang et al., 2019] CB (CommitmentBank) is a corpus featuring texts with embedded clauses evaluated for the author's commitment to their truth. This corpus is used in a three-class textual entailment task. Examples are organized with a premise and a corresponding hypothesis extracted from the embedded clause.

GLUE [Wang et al., 2018] The GLUE benchmark is a benchmark for evaluating natural language understanding systems. It consists of nine language understanding tasks and a diagnostic dataset for assessing model performance across linguistic phenomena.

ACLUE [Zhang and Li, 2023] ACLUE is a benchmark designed to evaluate large language models' comprehension of ancient Chinese, featuring 15 tasks across multiple domains. The questions, covering historical periods from the Xia to the Ming dynasty, are presented in a multiple-choice format.

GSM8K [Cobbe et al., 2021] GSM8K is a benchmark used to evaluate the math capability of LLMs as described in section 4.1.2.

Figure 9 illustrates the performance of BayLing on the specified benchmarks. BayLing-2-7B and BayLing-3-8B demonstrate exceptional performance across several benchmarks. Notably, BayLing-3-8B outperforms all other models, achieving a score of 0.8214 on the CommitmentBank Benchmark. BayLing-2-7B attains the highest performance on GLUE and GSM8K benchmarks. Despite not being specifically trained for it, BayLing-2-7B and BayLing-3-8B still deliver comparable performances on other benchmarks when compared to other models. Overall, BayLing enhances the multilingual capabilities of LLMs, especially in low-resource languages, without significantly impacting the per-

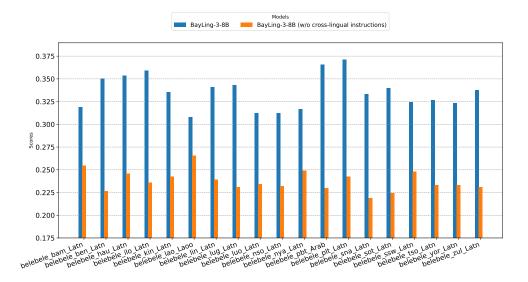


Figure 10: Effect of language alignment on multilingual benchmark Belebele.

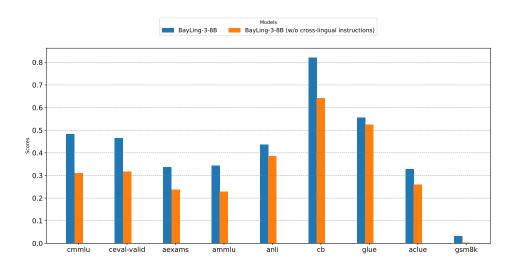


Figure 11: Effect of language alignment on Chinese and English general tasks.

formance in high-resource languages. This indicates that BayLing effectively mitigates multilingual conflicts within LLM through language alignment.

4.3 Effect of Language Alignment

To validate the effect of language alignment brought by cross-lingual instructions, we conducted an ablation study on cross-lingual instructions. Specifically, we removed all cross-lingual instructions from the training data, denoting this variant as BayLing-3-8B (w/o cross-lingual instructions).

Improving Performance of Low-resource Languages Figure 10 compares the performance of BayLing-3-8B and BayLing-3-8B (w/o cross-lingual instructions) on the multilingual benchmark Belebele. The results show that cross-lingual instructions significantly enhance LLM performance in low-resource languages. This indicates that cross-lingual instructions successfully help LLM achieve language alignment, thereby transferring knowledge and comprehension from high-resource languages to low-resource ones. When removing all cross-lingual instructions, the performance of

LLMs in low-resource languages is adversely affected due to catastrophic forgetting. Therefore, involving cross-lingual instructions in supervised fine-tuning is both efficient and crucial for improving the multilingual capabilities of LLMs.

Avoiding Inter-language Conflicts Figure 11 compares BayLing-3-8B and BayLing-3-8B (w/o cross-lingual instructions) on the Chinese/English benchmark. When removing cross-lingual instructions, we observed a significant performance decline in Chinese benchmark, indicating LLM will suffer from conflicts between Chinese and English instructions. The presence of numerous cross-lingual instructions between Chinese and English largely prevents these conflicts. Therefore, to simultaneously enhance LLM performance across multiple languages, introducing cross-lingual instructions is an effective way to avoid inter-language conflicts.

5 Conclusion

In this study, we develop BayLing 2, which enhances LLM's multilingual capabilities through language alignment. Adhering to an efficiency-focused approach, BayLing 2 transfers knowledge and generative abilities from high-resource languages to low-resource languages within LLM via language alignment. Comprehensive evaluation results demonstrate that BayLing 2 achieves outstanding translation performance across over 100 languages, possesses superior multilingual knowledge and understanding capability, and maintains robust proficiency in high-resource languages of Chinese and English.

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A Flores-101 Benchmark

Table 3, 4, 5, and 6 report the numerical results of Llama-3-8B-Instruct and BayLing-3-8B on the Flores-101 benchmark.

Table 3: BLEU scores of Llama-3-8B-Instruct on Flores-101 benchmark.

					Llama	-3-8B-Instruct					
X	Language	X⇒En	En⇒X	X⇒Zh	Zh⇒X	X	Language	X⇒En	En⇒X	X⇒Zh	Zh⇒X
afr	Afrikaans	50.65	37.33	16.48	14.22	lug	Ganda	6.08	1.11	3.87	0.44
amh	Amharic	2.63	0.44	1.33	0.35	luo	Luo	4.01	0.89	2.95	0.35
ara	Arabic	33.28	19.63	14.38	11.31	mal	Malayalam	20.44	4.72	9.56	2.51
asm	Assamese	16.17	7.20	7.99	4.60	mar	Marathi	22.72	10.64	10.65	6.35
ast	Asturian	38.63	29.44	15.56	14.74	mkd	Macedonian	38.47	27.85	16.29	13.82
azj	North Azerbaijani	19.25	10.84	11.36	7.77	mlt	Maltese	38.54	24.08	13.22	10.92
bel	Belarusian	19.74	14.90	12.78	10.03	mon	Mongolian	12.46	3.93	7.67	2.48
ben	Bengali	24.80	12.00	12.65	7.34	mri	Maori	12.61	7.70	5.80	4.20
bos	Bosnian	39.23	25.86	17.27	12.11	msa	Malay	39.26	32.11	16.46	14.87
bul	Bulgarian	37.27	30.83	16.51	15.50	mya	Burmese	7.42	1.21	3.76	0.86
cat	Catalan	43.40	39.56	17.80	19.91	nld	Dutch	31.91	28.18	16.72	16.28
ceb	Cebuano	27.00	16.21	11.27	7.21	nob	Norwegian Bokmål	41.49	29.28	16.35	13.48
ces	Czech	38.47	28.96	17.05	15.01	npi	Nepali	23.40	11.74	11.28	6.62
ckb	Central Kurdish	16.17	4.80	7.02	2.72	nso	Pedi	6.63	1.96	4.14	0.68
cym	Welsh	39.84	24.66	12.15	10.29	nya	Nyanja	7.10	1.87	4.36	0.70
dan	Danish	46.38	37.87	17.31	15.82	oci	Occitan	45.82	27.01	16.16	11.99
deu	German	41.65	34.96	18.64	17.45	orm	Oromo	2.07	0.79	1.96	0.47
ell	Modern Greek	32.57	22.41	15.73	13.05	ory	Odia	15.71	1.90	7.48	0.99
est	Estonian	29.61	18.09	13.96	9.55	pan	Panjabi	22.23	7.08	10.35	3.70
fas	Persian	31.33	23.02	14.44	13.59	pol	Polish	29.08	22.77	15.96	13.99
fin	Finnish	31.78	21.84	15.44	12.16	por	Portuguese	47.99	45.68	18.29	20.59
fra	French	43.17	45.32	18.48	23.99	pus	Pushto	18.50	4.94	8.78	2.68
ful	Fulah	3.58	0.90	3.04	0.31	ron	Romanian	39.91	34.53	17.38	16.94
gle	Irish	25.45	13.90	9.81	6.66	rus	Russian	33.95	28.81	17.56	15.56
glg	Galician	39.13	32.84	17.26	17.32	slk	Slovak	35.54	23.77	16.33	11.63
guj	Gujarati	21.76	6.02	9.93	3.30	slv	Slovenian	31.65	21.68	15.10	11.33
hau	Hausa	13.07	8.13	5.86	3.45	sna	Shona	6.07	1.63	4.30	0.76
heb	Hebrew	36.86	22.01	15.48	11.05	snd	Sindhi	17.58	8.96	7.34	4.89
hin	Hindi	31.88	24.48	14.61	14.04	som	Somali	6.36	2.77	4.05	1.21
hrv	Croatian	35.45	24.16	16.36	11.33	spa	Spanish	31.50	28.89	17.05	18.16
hun	Hungarian	31.88	24.10	16.31	13.72	srp	Serbian	39.61	30.24	17.08	13.97
hye	Armenian	29.80	6.04	13.60	3.69	swe	Swedish	46.13	39.44	18.00	16.02
ibo	Igbo	11.61	5.07	5.99	2.25	swh	Swahili	29.48	16.48	11.17	6.90
ind	Indonesian	39.34	37.60	17.87	18.27	tam	Tamil	18.64	5.49	9.65	3.29
isl	Icelandic	24.72	12.43	10.56	6.52	tel	Telugu	24.19	6.29	10.36	3.59
ita	Italian	33.37	30.87	18.14	18.37	tgk	Tajik	20.40	12.22	10.35	7.74
jav	Javanese	23.77	10.94	10.33	4.27	tgl	Tagalog	37.24	24.10	14.55	12.48
jpn	Japanese	23.08	24.79	14.00	16.27	tha	Thai	25.58	18.41	14.39	12.31
kam	Kamba	4.55	1.54	3.55	0.58	tur	Turkish	31.84	23.84	16.02	13.54
kan	Kannada	20.75	4.91	10.45	2.98	ukr	Ukrainian	37.24	29.18	16.25	14.37
kat	Georgian	20.37	3.90	11.11	2.45	umb	Umbundu	3.28	0.55	2.34	0.35
kaz	Kazakh	22.91	11.61	12.06	7.63	urd	Urdu	24.72	13.71	11.57	8.00
kea	Kabuverdianu	26.56	6.66	9.84	1.68	uzb	Uzbek	20.70	18.13	10.65	12.28
khm	Khmer	12.44	1.05	6.09	0.84	vie	Vietnamese	32.72	33.91	16.43	21.28
kir	Kirghiz	15.58	10.19	8.63	7.01	wol	Wolof	4.83	1.30	3.75	0.57
kor	Korean	25.41	18.78	15.47	12.69	xho	Xhosa	8.60	1.76	5.08	0.67
lao	Lao	6.58	0.29	3.35	0.10	yor	Yoruba	6.53	2.71	3.90	1.68
lav	Latvian	27.95	17.82	13.37	9.50	zho_simpl	Chinese	26.07	22.53	-	
lin	Lingala	5.85	2.54	4.28	1.08	zho_trad	traditional Chinese	24.48	19.46	21.63	23.55
lit	Lithuanian	27.90	16.88	13.47	9.96	zul	Zulu	8.11	1.87	4.42	0.80
ltz	Luxembourgish	33.72	18.60	13.03	8.78	eng	English	-	-	22.53	26.07

B Language Code of Multilingual Benchmarks

Table 7 reports the language codes for the low-resource languages in Figure 8.

C Numerical Results of General Capability

Table 8 reports the numerical results of general capability in Figure 9. Table 9, 10, 11, and 12 report the numerical results of multilingual benchmarks in Figure 8.

Table 4: BLEU scores of BayLing-3-8B on Flores-101 benchmark.

					Вау	Ling-3-8B					
X	Language	$X{\Rightarrow}En$	$En{\Rightarrow}X$	$X{\Rightarrow}Zh$	$\mathbf{Z}\mathbf{h}{\Rightarrow}\mathbf{X}$	X	Language	$X{\Rightarrow}En$	En⇒X	$X{\Rightarrow}Zh$	Zh⇒Ŋ
afr	Afrikaans	51.55	38.76	15.83	15.83	lug	Ganda	9.41	3.59	4.49	1.88
amh	Amharic	4.97	1.87	1.67	1.31	luo	Luo	8.00	5.15	4.33	2.80
ara	Arabic	35.36	21.19	13.54	12.06	mal	Malayalam	16.22	3.29	6.15	2.15
asm	Assamese	16.12	7.79	6.72	5.75	mar	Marathi	26.48	12.81	12.10	7.92
ast	Asturian	39.22	29.93	15.66	15.26	mkd	Macedonian	38.95	27.18	15.46	14.92
azj	North Azerbaijani	21.91	9.39	9.06	7.51	mlt	Maltese	40.28	27.29	13.10	13.89
bel	Belarusian	23.08	13.24	10.39	9.17	mon	Mongolian	14.69	6.68	7.99	4.61
ben	Bengali	23.14	11.66	9.94	7.59	mri	Maori	15.75	17.43	7.02	12.28
bos	Bosnian	38.90	24.94	16.50	13.83	msa	Malay	40.46	34.66	17.02	17.27
bul	Bulgarian	37.79	27.42	15.69	15.68	mya	Burmese	5.10	1.30	2.28	0.94
cat	Catalan	44.45	37.33	18.06	20.48	nld	Dutch	33.71	26.77	16.46	17.00
ceb	Cebuano	30.29	21.80	11.87	12.49	nob	Norwegian Bokmål	41.70	26.69	16.06	13.61
ces	Czech	38.26	25.71	16.48	14.33	npi	Nepali	28.46	17.17	12.59	10.55
ckb	Central Kurdish	17.03	7.53	7.23	4.81	nso	Pedi	12.21	9.03	5.51	5.08
cym	Welsh	39.66	27.38	13.08	12.24	nya	Nyanja	12.68	6.29	6.65	4.07
dan	Danish	45.98	35.50	16.81	17.36	oci	Occitan	47.85	33.78	16.54	14.79
deu	German	43.25	34.12	18.26	17.26	orm	Oromo	5.31	2.21	2.21	1.71
ell	Modern Greek	34.58	20.24	14.15	13.18	ory	Odia	8.35	1.67	2.70	1.06
est	Estonian	30.49	16.11	10.91	9.48	pan	Panjabi	19.06	7.57	6.79	4.65
fas	Persian	34.21	24.49	15.00	15.42	pol	Polish	30.97	20.72	14.87	12.97
fin	Finnish	31.50	19.24	13.30	11.89	por	Portuguese	47.89	45.74	18.93	22.73
fra	French	44.31	45.36	18.63	24.60	pus	Pushto	22.64	6.56	9.20	4.44
ful	Fulah	7.25	2.46	4.14	1.57	ron	Romanian	42.63	33.28	17.37	18.93
gle	Irish	27.75	16.25	10.19	9.14	rus	Russian	35.61	27.68	15.20	16.66
glg	Galician	41.44	34.02	17.67	18.25	slk	Slovak	35.78	21.30	14.28	12.15
guj	Gujarati	18.35	6.67	7.74	4.42	slv	Slovenian	32.12	19.69	13.59	11.87
hau	Hausa	19.81	10.06	7.24	6.10	sna	Shona	11.68	5.34	5.59	3.41
heb	Hebrew	34.79	21.79	13.56	11.73	snd	Sindhi	23.93	17.00	8.69	10.17
hin	Hindi	33.85	25.45	14.79	15.84	som	Somali	12.52	5.38	5.02	3.05
hrv	Croatian	35.55	22.53	15.33	13.07	spa	Spanish	34.75	29.33	17.04	18.26
hun	Hungarian	32.34	21.10	13.28	14.18	srp	Serbian	39.53	28.33	15.58	15.32
hve	Armenian	18.19	5.07	4.92	3.58	swe	Swedish	45.93	36.58	18.09	17.93
ibo	Igbo	16.35	10.73	7.26	7.28	swh	Swahili	29.56	19.19	11.36	9.83
ind	Indonesian	40.64	38.12	17.50	20.80	tam	Tamil	16.94	5.73	7.49	3.56
isl	Icelandic	26.87	12.68	9.95	6.81	tel	Telugu	18.23	5.96	7.40	3.82
ita	Italian	35.91	29.22	17.88	17.76	tgk	Tajik	21.77	15.30	9.56	11.52
jav	Javanese	29.19	20.48	10.22	11.73	tgl	Tagalog	39.94	28.51	14.44	15.80
jpn	Japanese	27.97	25.64	16.37	18.73	tha	Thai	28.93	17.47	14.08	11.62
kam	Kamba	8.16	3.50	4.39	2.11	tur	Turkish	33.43	22.28	14.63	13.78
kan	Kannada	14.49	4.75	6.13	3.40	ukr	Ukrainian	37.41	26.95	15.65	15.59
kat	Georgian	11.06	2.88	4.36	1.86	umb	Umbundu	5.82	4.22	2.95	2.87
kaz	Kazakh	23.63	13.89	10.49	9.51	urd	Urdu	26.40	13.53	12.30	8.70
kea	Kabuverdianu	34.60	29.40	12.31	14.48	uzb	Uzbek	24.39	17.99	11.43	12.49
khm	Khmer	14.07	2.19	6.55	1.86	vie	Vietnamese	35.23	34.89	15.61	22.46
kir	Kirghiz	18.47	12.66	8.01	9.56	wol	Wolof	9.28	4.34	4.45	2.87
kor	Korean	27.60	18.40	15.43	13.80	xho	Xhosa	13.14	4.08	5.79	2.43
lao	Lao	10.52	1.82	5.15	1.10	vor	Yoruba	12.04	9.19	4.98	7.74
lav	Latvian	29.48	16.30	12.03	9.82	zho_simpl	Chinese	30.24	25.61	-	-
lin	Lingala	11.61	11.95	5.93	7.70	zho trad	traditional Chinese	28.00	20.25	17.82	19.60
lit	Lithuanian	28.03	16.12	11.98	9.67	zul	Zulu	12.84	6.59	5.70	4.26
ltz	Luxembourgish	35.92	22.59	12.47	12.57	eng	English	-	-	25.61	30.24

Table 5: COMET scores of Llama-3-8B-Instruct on Flores-101 benchmark.

Llama-3-8B-Instruct											
X	Language	X⇒En	En⇒X	X⇒Zh	Zh⇒X	X	Language	X⇒En	En⇒X	X⇒Zh	Zh⇒X
afr	Afrikaans	85.79	82.75	79.07	76.71	lug	Ganda	49.86	39.62	48.30	40.12
amh	Amharic	57.47	38.74	50.99	35.71	luo	Luo	46.09	34.60	45.78	36.63
ara	Arabic	84.85	77.90	79.64	75.42	mal	Malayalam	82.12	54.48	74.40	49.07
asm	Assamese	78.26	62.26	72.23	56.98	mar	Marathi	82.20	56.38	75.18	49.97
ast	Asturian	80.99	70.31	78.66	68.53	mkd	Macedonian	85.40	82.46	79.96	77.19
azj	North Azerbaijani	82.72	74.79	76.83	68.66	mlt	Maltese	75.13	62.43	68.83	59.95
bel	Belarusian	80.32	77.39	78.85	74.53	mon	Mongolian	73.22	53.00	65.69	49.14
ben	Bengali	84.66	67.34	78.66	61.77	mri	Maori	57.72	56.14	54.45	54.72
bos	Bosnian	86.51	85.48	81.80	81.65	msa	Malay	86.33	86.71	80.29	82.04
bul	Bulgarian	85.60	84.17	80.74	79.12	mya	Burmese	73.03	50.27	65.28	46.07
cat	Catalan	86.74	85.53	82.64	81.52	nld	Dutch	85.72	85.80	82.13	82.25
ceb	Cebuano	72.62	62.99	67.83	60.00	nob	Norwegian Bokmål	86.63	86.87	81.59	82.31
ces	Czech	86.80	86.06	81.91	83.05	npi	Nepali	84.40	65.83	77.16	56.32
ckb	Central Kurdish	67.45	69.63	62.18	67.04	nso	Pedi	49.40	42.12	48.67	43.00
cym	Welsh	81.50	71.46	72.45	64.23	nya	Nyanja	51.77	39.38	50.41	39.27
dan	Danish	88.59	86.51	82.44	81.05	oci	Occitan	81.76	66.45	77.59	63.47
deu	German	87.66	85.67	83.25	81.05	orm	Oromo	48.00	44.67	46.05	47.08
ell	Modern Greek	85.45	82.65	81.00	77.82	ory	Odia	79.47	47.13	71.51	41.06
est	Estonian	84.71	77.30	78.32	72.13	pan	Panjabi	82.41	56.27	75.00	50.09
fas	Persian	85.51	80.16	80.68	76.40	pol	Polish	84.37	85.39	81.77	82.69
fin	Finnish	87.88	85.98	81.46	80.16	por	Portuguese	87.90	88.06	83.34	83.48
fra	French	87.57	86.28	83.00	81.79	pus	Pushto	76.71	50.35	71.00	43.86
ful	Fulah	46.30	36.09	46.03	37.68	ron	Romanian	86.94	86.82	81.63	80.42
gle	Irish	75.46	60.43	68.96	56.50	rus	Russian	84.90	85.59	82.30	81.43
glg	Galician	86.28	84.41	82.33	81.94	slk	Slovak	85.45	80.06	80.76	77.14
guj	Gujarati	83.51	59.21	74.24	52.37	slv	Slovenian	84.16	79.80	79.63	77.13
hau	Hausa	63.46	59.62	57.57	55.83	sna	Shona	50.90	38.50	50.16	39.94
heb	Hebrew	85.42	75.54	79.71	71.34	snd	Sindhi	76.17	49.99	67.98	42.34
hin	Hindi	86.14	72.12	80.65	63.87	som	Somali	54.83	44.04	50.93	43.12
hrv	Croatian	85.54	84.45	81.08	81.00	spa	Spanish	85.64	85.28	83.57	82.58
hun	Hungarian	85.98	84.73	81.21	77.73	srp	Serbian	85.98	83.67	80.73	78.84
hve	Armenian	85.44	58.56	78.90	55.00	swe	Swedish	88.08	88.20	82.94	80.34
ibo	Igbo	58.27	53.70	55.43	50.65	swh	Swahili	78.61	69.99	70.94	63.60
ind	Indonesian	87.30	89.21	81.77	85.19	tam	Tamil	80.96	60.47	74.26	55.75
isl	Icelandic	78.18	63.75	72.37	60.57	tel	Telugu	82.73	56.46	74.54	51.16
ita	Italian	86.16	86.76	83.61	83.25	tgk	Tajik	69.92	68.34	65.52	66.27
jav	Javanese	75.31	70.76	68.50	61.76	tgl	Tagalog	83.36	77.46	76.79	73.13
jpn	Japanese	86.03	88.26	82.65	85.59	tha	Thai	85.91	83.39	82.02	79.59
kam	Kamba	48.40	33.91	47.96	34.32	tur	Turkish	86.43	83.47	80.18	78.05
kan	Kannada	82.02	54.19	75.12	49.32	ukr	Ukrainian	85.49	85.64	81.01	80.66
kat	Georgian	81.79	49.97	76.46	47.32	umb	Umbundu	45.68	33.53	44.83	37.23
kaz	Kazakh	82.37	70.70	76.29	64.64	urd	Urdu	83.29	67.81	77.05	62.28
kea	Kabuverdianu	70.07	56.13	66.16	46.47	uzb	Uzbek	80.19	78.27	72.90	72.81
khm	Khmer	74.15	45.33	67.68	41.98	vie	Vietnamese	85.35	85.97	82.55	83.92
kir	Kirghiz	78.34	64.65	71.78	59.11	wol	Wolof	48.08	37.41	47.81	40.19
kor	Korean	85.64	84.84	81.85	80.24	xho	Xhosa	55.13	39.41	52.34	38.15
lao	Lao	60.88	32.31	53.76	30.66	vor	Yoruba	50.57	46.30	48.48	46.88
lav	Latvian	82.45	71.96	77.13	68.26	zho simpl	Chinese	85.40	85.12	-0.40	-0.00
lin	Lingala	50.05	40.91	50.11	41.12	zho_shiipi zho trad	traditional Chinese	84.82	85.70	87.43	90.30
lit	Lithuanian	82.24	74.78	78.12	72.44	zul	Zulu	55.38	42.01	52.00	40.05
ltz	Luxembourgish	73.87	52.23	70.23	50.93	eng	English	-		85.12	85.40

Table 6: COMET scores of BayLing-3-8B on Flores-101 benchmark.

					Bay	Ling-3-8B					
X	Language	$X{\Rightarrow}En$	$En{\Rightarrow}X$	$X{\Rightarrow}Zh$	$Zh{\Rightarrow}X$	X	Language	$X{\Rightarrow}En$	$En{\Rightarrow}X$	$X{\Rightarrow}Zh$	Zh⇒X
afr	Afrikaans	87.38	82.77	76.93	76.33	lug	Ganda	52.34	54.41	47.80	55.35
amh	Amharic	58.46	49.90	49.78	46.53	luo	Luo	49.37	53.25	47.44	53.08
ara	Arabic	85.49	81.47	76.61	77.17	mal	Malayalam	76.81	53.88	64.05	49.89
asm	Assamese	75.40	61.88	66.47	57.93	mar	Marathi	84.00	61.50	74.95	55.19
ast	Asturian	82.33	68.74	76.10	65.80	mkd	Macedonian	85.77	83.44	77.39	77.94
azj	North Azerbaijani	83.50	71.42	71.40	68.93	mlt	Maltese	76.80	63.82	68.15	60.42
bel	Belarusian	81.56	75.77	72.15	72.44	mon	Mongolian	74.76	63.14	66.60	59.34
ben	Bengali	82.05	67.65	72.81	62.06	mri	Maori	60.55	65.82	56.43	65.98
bos	Bosnian	86.69	85.46	79.17	82.11	msa	Malay	87.13	87.12	79.21	81.73
bul	Bulgarian	86.31	84.48	77.62	80.05	mya	Burmese	60.32	48.38	53.58	45.40
cat	Catalan	87.42	85.18	80.95	81.70	nld	Dutch	86.50	85.82	79.37	82.29
ceb	Cebuano	74.56	66.23	66.35	63.70	nob	Norwegian Bokmål	87.63	86.18	78.41	81.41
ces	Czech	87.01	86.20	79.42	81.39	npi	Nepali	86.33	72.79	77.50	64.69
ckb	Central Kurdish	68.04	72.53	60.30	70.81	nso	Pedi	53.76	55.76	50.90	55.37
cym	Welsh	82.80	73.36	72.70	65.56	nya	Nyanja	56.96	54.35	54.57	54.77
dan	Danish	88.60	87.16	80.00	82.53	oci	Occitan	82.98	66.67	76.59	62.64
deu	German	88.43	85.42	80.85	79.83	orm	Oromo	51.98	61.08	46.52	60.07
ell	Modern Greek	86.30	83.03	77.55	78.65	ory	Odia	67.58	47.06	54.55	43.06
est	Estonian	85.04	77.37	72.89	72.54	pan	Panjabi	78.43	57.99	65.19	52.88
fas	Persian	86.17	82.74	79.21	78.08	pol	Polish	84.65	85.58	77.17	81.26
fin	Finnish	87.62	85.71	76.73	80.74	por	Portuguese	88.37	88.53	82.17	84.36
fra	French	88.14	86.43	81.70	81.82	pus	Pushto	78.81	57.44	69.19	52.47
ful	Fulah	50.38	49.69	47.84	49.27	ron	Romanian	88.17	87.47	79.59	82.31
gle	Irish	77.62	64.82	68.62	61.00	rus	Russian	85.49	87.13	77.67	83.61
glg	Galician	87.43	85.06	81.31	80.94	slk	Slovak	85.69	80.35	76.51	76.29
guj	Gujarati	79.51	61.78	68.02	55.96	slv	Slovenian	84.95	79.18	76.07	75.20
hau	Hausa	70.44	68.11	61.42	65.61	sna	Shona	56.12	53.40	52.40	53.55
heb	Hebrew	84.52	77.60	75.31	73.13	snd	Sindhi	78.95	60.37	68.54	52.39
hin	Hindi	87.48	74.74	78.84	66.93	som	Somali	62.89	59.67	53.83	57.87
hrv	Croatian	86.11	85.12	78.05	81.40	spa	Spanish	86.58	85.55	81.64	82.25
hun	Hungarian	86.22	84.28	75.17	80.15	srp	Serbian	85.94	83.72	78.32	80.11
hye	Armenian	76.46	54.09	60.19	51.67	swe	Swedish	88.92	88.34	80.68	83.90
ibo	Igbo	62.72	65.76	58.49	65.44	swh	Swahili	79.48	72.72	71.24	68.74
ind	Indonesian	87.77	89.74	80.27	85.85	tam	Tamil	76.36	61.98	66.96	58.39
isl	Icelandic	80.19	65.65	68.99	60.63	tel	Telugu	77.62	56.91	66.75	51.67
ita	Italian	86.98	86.88	81.82	82.94	tgk	Tajik	70.08	71.18	62.96	71.06
jav	Javanese	78.81	81.17	68.05	76.92	tgl	Tagalog	84.71	79.28	74.49	74.54
jpn	Japanese	86.79	87.94	83.12	85.10	tha	Thai	86.19	82.18	79.48	77.51
kam	Kamba	51.18	48.26	49.49	48.68	tur	Turkish	87.04	83.07	77.55	77.89
kan	Kannada	74.36	53.53	63.26	49.64	ukr	Ukrainian	85.79	86.42	77.66	83.00
kat	Georgian	68.95	44.91	58.06	43.45	umb	Umbundu	48.02	52.10	45.96	52.57
kaz	Kazakh	82.51	74.61	71.55	70.50	urd	Urdu	83.03	69.03	75.18	63.64
kea	Kabuverdianu	75.72	64.54	68.23	61.44	uzb	Uzbek	82.38	78.14	72.98	74.18
khm	Khmer	71.97	50.53	65.81	48.50	vie	Vietnamese	86.15	86.53	79.57	83.87
kir	Kirghiz	80.57	72.88	69.29	68.85	wol	Wolof	51.85	56.18	48.48	57.08
kor	Korean	86.17	84.66	80.73	80.95	xho	Xhosa	59.23	55.73	53.95	55.86
lao	Lao	63.71	44.71	57.43	42.45	yor	Yoruba	57.90	64.74	51.41	65.55
lav	Latvian	83.60	72.25	72.71	68.30	zho_simpl	Chinese	61.08	53.89	-	-
lin	Lingala	56.47	60.44	53.36	59.81	zho_trad	traditional Chinese	85.56	86.38	80.02	88.93
lit	Lithuanian	82.79	74.51	73.92	71.44	zul	Zulu	59.43	62.17	53.89	61.08
ltz	Luxembourgish	76.32	51.80	68.17	51.12	eng	English	-	-	85.92	86.22

Table 7: Language code of Figure 8.

Language Code	Language
belebele bam Latn	Bambara
belebele_ben_Latn	Bengali
belebele_hau_Latn	Hausa
belebele_ilo_Latn	Ilocano
belebele_kin_Latn	Kinyarwanda
belebele_lao_Laoo	Lao
belebele_lin_Latn	Lingala
belebele_lug_Latn	Luganda
belebele_luo_Latn	Luo
belebele_nso_Latn	Northern Sotho
belebele_nya_Latn	Chichewa (Nyanja)
belebele_pbt_Arab	Pashto
belebele_plt_Latn	Plateau Malagasy
belebele_sna_Latn	Shona
belebele_sot_Latn	Southern Sotho
belebele_ssw_Latn	Swazi
belebele_tso_Latn	Tsonga
belebele_yor_Latn	Yoruba
belebele_zul_Latn	Zulu
hellaswag_eu	Basque (Euskara)
hellaswag_mr	Marathi
hellaswag_ne	Nepali
hellaswag_vi	Vietnamese
xnli_bg	Bulgarian
xnli_de	German
xnli_es	Spanish
xnli_sw	Swahili
xnli_ur	Urdu
xnli_zh	Chinese
arc_ar	Arabic
arc_eu	Basque (Euskara)
arc_hi	Hindi
arc_hy	Armenian
arc_mr	Marathi
arc_ne	Nepali
arc_sr	Serbian
arc_uk	Ukrainian
arc_zh	Chinese

Table 8: Numerical results of general capability benchmarks.

Model	cmmlu (knowledge)	ceval-valid (knowledge)	aexams (knowledge)	ammlu (knowledge)	anli (comprehension)
Llama-2-7B	0.2726	0.2972	0.2272	0.2717	0.3697
Llama-2-7B-Chat	0.3257	0.3239	0.2272	0.2624	0.4106
Llama-3-8B-Instruct	0.5120	0.5111	0.3520	0.3838	0.4634
Vicuna-7B-v1.5	0.3514	0.3603	0.2439	0.2962	0.3847
Mistral-7B	0.3825	0.3990	0.2495	0.2763	0.3800
Bayling-1-7B	0.3136	0.3046	0.2346	0.2458	0.3622
n '11 ' 4 =n	0.2016	0.3908	0.2607	0.2900	0.4419
Bayling-2-7B	0.3916		0.2007		
Bayling-2-7B Bayling-3-8B	0.4839	0.4643	0.3371	0.3440	0.4372
Bayling-3-8B	0.4839 cb	0.4643 glue	0.3371 aclue	0.3440 gsm8k	
Bayling-3-8B Model	0.4839 cb (comprehension)	0.4643 glue (comprehension)	0.3371 aclue (comprehension)	0.3440 gsm8k (math)	
Bayling-3-8B Model Llama-2-7B	cb (comprehension) 0.4464	glue (comprehension) 0.4271	0.3371 aclue (comprehension) 0.2747	0.3440 gsm8k (math) 0.0000	
Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat	0.4839 cb (comprehension) 0.4464 0.6071	0.4643 glue (comprehension) 0.4271 0.4863	0.3371 aclue (comprehension) 0.2747 0.2755	0.3440 gsm8k (math) 0.0000 0.0000	
Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct	0.4839 cb (comprehension) 0.4464 0.6071 0.8036	0.4643 glue (comprehension) 0.4271 0.4863 0.5877	0.3371 aclue (comprehension) 0.2747 0.2755 0.3963	0.3440 gsm8k (math) 0.0000 0.0000 0.0265	
Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5	0.4839 cb (comprehension) 0.4464 0.6071 0.8036 0.7143	0.4643 glue (comprehension) 0.4271 0.4863 0.5877 0.4729	0.3371 aclue (comprehension) 0.2747 0.2755 0.3963 0.2976	0.3440 gsm8k (math) 0.0000 0.0000 0.0265 0.0000	
Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B	0.4839 cb (comprehension) 0.4464 0.6071 0.8036 0.7143 0.5000	0.4643 glue (comprehension) 0.4271 0.4863 0.5877 0.4729 0.5144	0.3371 aclue (comprehension) 0.2747 0.2755 0.3963 0.2976 0.3192	0.3440 gsm8k (math) 0.0000 0.0000 0.0265 0.0000 0.0000	

Table 9: Numerical results of Belebele benchmark.

Model	belebele_bam_Latn	belebele_ben_Latn	belebele_hau_Latn	belebele_ilo_Latn	belebele_kin_Latn
Llama-2-7B	0.2278	0.2422	0.2322	0.2244	0.2167
Llama-2-7B-Chat	0.2278	0.2244	0.2333	0.2422	0.2289
Llama-3-8B-Instruct	0.3033	0.3189	0.3478	0.3533	0.3167
Vicuna-7B-v1.5	0.2411	0.2533	0.2478	0.2667	0.2600
Mistral-7B	0.2756	0.2878	0.3022	0.2878	0.3144
Bayling-1-7B	0.2578	0.2856	0.2367	0.2300	0.2778
Bayling-2-7B	0.2889	0.2800	0.3000	0.3133	0.2770
Bayling-3-8B	0.3189	0.3500	0.3533	0.3589	0.3356
Daying-3-0D	0.5167	0.5500	0.3333	0.5567	0.5550
Model	belebele_lin_Latn	belebele_lug_Latn	belebele_luo_Latn	belebele_nso_Latn	belebele_nya_Latn
Llama-2-7B	0.2233	0.2356	0.2244	0.2378	0.2267
Llama-2-7B-Chat	0.2167	0.2456	0.2433	0.2322	0.2078
Llama-3-8B-Instruct	0.3178	0.3144	0.3044	0.3067	0.2833
Vicuna-7B-v1.5	0.2400	0.2533	0.2433	0.2500	0.2522
Mistral-7B	0.2789	0.3122	0.2967	0.2689	0.2856
Bayling-1-7B	0.2611	0.2744	0.2767	0.2556	0.2733
Bayling-2-7B	0.2822	0.2678	0.2822	0.2978	0.2711
Bayling-3-8B	0.3411	0.3433	0.3122	0.3122	0.3167
Model	belebele_plt_Latn	belebele_sna_Latn	belebele_sot_Latn	belebele_ssw_Latn	belebele_tso_Latn
Model Llama-2-7B	belebele_plt_Latn 0.2444	belebele_sna_Latn 0.2156	belebele_sot_Latn 0.2378	belebele_ssw_Latn 0.2311	belebele_tso_Latn 0.2189
Llama-2-7B	0.2444	0.2156	0.2378	0.2311	0.2189
Llama-2-7B Llama-2-7B-Chat	0.2444 0.2278	0.2156 0.2244	0.2378 0.2533	0.2311 0.2433	0.2189 0.2500
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct	0.2444 0.2278 0.3422	0.2156 0.2244 0.3244	0.2378 0.2533 0.3133	0.2311 0.2433 0.2889	0.2189 0.2500 0.3211
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5	0.2444 0.2278 0.3422 0.2589	0.2156 0.2244 0.3244 0.2556	0.2378 0.2533 0.3133 0.2711	0.2311 0.2433 0.2889 0.2633	0.2189 0.2500 0.3211 0.2533
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B	0.2444 0.2278 0.3422 0.2589 0.3044	0.2156 0.2244 0.3244 0.2556 0.2944	0.2378 0.2533 0.3133 0.2711 0.3044	0.2311 0.2433 0.2889 0.2633 0.2856	0.2189 0.2500 0.3211 0.2533 0.2833
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B Bayling-2-7B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B Model Llama-2-7B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711 belebele_zul_Latn	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711 belebele_zul_Latn	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711 belebele_zul_Latn 0.2256 0.2489 0.3244	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo 0.2178 0.2344 0.3011	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab 0.2144 0.2233 0.3411	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn 0.2200 0.2300 0.2944	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-V1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-V1.5	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711 belebele_zul_Latn 0.2256 0.2489 0.3244 0.2711	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo 0.2178 0.2344 0.3011 0.2567	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab 0.2144 0.2233 0.3411	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn 0.2200 0.2300 0.2944 0.2533	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-V1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-V1.5 Mistral-7B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711 belebele_zul_Latn 0.2256 0.2489 0.3244 0.2711 0.2956	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo 0.2178 0.2344 0.3011 0.2567 0.2967	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab 0.2144 0.2233 0.3411 0.2689 0.2900	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn 0.2200 0.2300 0.2944 0.2533 0.2667	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-v1.5 Mistral-7B Bayling-1-7B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.3711 belebele_zul_Latn 0.2256 0.2489 0.3244 0.2711 0.2956 0.2633	0.2156 0.2244 0.3244 0.3256 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo 0.2178 0.2344 0.3011 0.2567 0.2967 0.2267	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab 0.2144 0.2233 0.3411 0.2689 0.2900 0.2344	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn 0.2200 0.2300 0.2944 0.2533 0.2667 0.2578	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900
Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-V1.5 Mistral-7B Bayling-1-7B Bayling-2-7B Bayling-3-8B Model Llama-2-7B Llama-2-7B-Chat Llama-3-8B-Instruct Vicuna-7B-V1.5 Mistral-7B	0.2444 0.2278 0.3422 0.2589 0.3044 0.2644 0.2744 0.3711 belebele_zul_Latn 0.2256 0.2489 0.3244 0.2711 0.2956	0.2156 0.2244 0.3244 0.2556 0.2944 0.2622 0.2867 0.3333 belebele_lao_Laoo 0.2178 0.2344 0.3011 0.2567 0.2967	0.2378 0.2533 0.3133 0.2711 0.3044 0.2389 0.2633 0.3400 belebele_pbt_Arab 0.2144 0.2233 0.3411 0.2689 0.2900	0.2311 0.2433 0.2889 0.2633 0.2856 0.2522 0.300 0.3244 belebele_yor_Latn 0.2200 0.2300 0.2944 0.2533 0.2667	0.2189 0.2500 0.3211 0.2533 0.2833 0.2433 0.2900

Table 10: Numerical results of multilingual HellaSwag benchmark.

Model	hellaswag_eu	hellaswag_mr	hellaswag_ne	hellaswag_vi
Llama-2-7B	0.2588	0.2618	0.2634	0.3522
Llama-2-7B-Chat	0.2594	0.2599	0.2627	0.3445
Llama-3-8B-Instruct	0.2759	0.2770	0.2791	0.4021
Vicuna-7B-v1.5	0.2595	0.2644	0.2659	0.3556
Mistral-7B	0.2633	0.2617	0.2733	0.3614
Bayling-1-7B	0.2577	0.2576	0.2598	0.2831
Bayling-2-7B	0.2585	0.2631	0.2645	0.3458
Bayling-3-8B	0.2765	0.2807	0.2948	0.4025

Table 11: Numerical results of XNLI benchmark.

Model	xnli_bg	xnli_de	xnli_es	xnli_sw	xnli_ur	xnli_zh
Llama-2-7B	0.4249	0.4699	0.4064	0.3478	0.3357	0.3639
Llama-2-7B-Chat	0.3723	0.4321	0.3956	0.3410	0.3410	0.3699
Llama-3-8B-Instruct	0.4518	0.4932	0.4863	0.3622	0.3454	0.4052
Vicuna-7B-v1.5	0.4177	0.4663	0.4763	0.3446	0.3398	0.4056
Mistral-7B	0.4309	0.4639	0.4406	0.3510	0.3414	0.3960
Bayling-1-7B	0.4213	0.4474	0.4558	0.3450	0.3438	0.3614
Bayling-2-7B	0.3594	0.4036	0.3936	0.3345	0.3422	0.3731
Bayling-3-8B	0.4510	0.4972	0.4908	0.3655	0.3454	0.4096

Table 12: Numerical results of multilingual ARC benchmark.

Model	arc_ar	arc_eu	arc_hi	arc_hy	arc_mr	arc_ne	arc_sr	arc_uk	arc_zh
Llama-2-7B	0.0128	0.0079	0.0283	0.0036	0.0208	0.0214	0.0470	0.0565	0.0556
Llama-2-7B-Chat	0.0034	0.0035	0.0128	0.0018	0.0078	0.0060	0.0180	0.0359	0.0214
Llama-3-8B-Instruct	0.1172	0.0360	0.0839	0.0245	0.0545	0.0496	0.1138	0.1437	0.1248
Vicuna-7B-v1.5 Mistral-7B	0.0197 0.0188	0.0053 0.0097	0.0839 0.0317 0.0068	0.0243 0.0036 0.0009	0.0130 0.0035	0.0496 0.0111 0.0043	0.0393 0.0753	0.0582 0.0804	0.0855 0.0632
Bayling-1-7B	0.0145	0.0062	0.0214	0.0018	0.0173	0.0137	0.0359	0.0325	0.0752
Bayling-2-7B	0.0205	0.0053	0.0146	0.0027	0.0069	0.0120	0.0248	0.0214	0.0718
Bayling-3-8B	0.1223	0.0518	0.0865	0.0255	0.0580	0.0667	0.1172	0.1600	0.1684