

# CoCo-CoLa: Evaluating Language Adherence in Multilingual LLMs

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### **Abstract**

Multilingual Large Language Models (LLMs) develop cross-lingual abilities despite being trained on limited parallel data. However, they often struggle to generate responses in the intended language, favoring high-resource languages such as English. In this work, we introduce CoCo-CoLa (Correct Concept - Correct Language), a novel metric to evaluate language adherence in multilingual LLMs. Using finetuning experiments on a closed-book QA task across seven languages, we analyze how training in one language affects others' performance. Our findings reveal that multilingual models share task knowledge across languages but exhibit biases in the selection of output language. We identify language-specific layers, showing that final layers play a crucial role in determining output language. Accordingly, we propose a partial training strategy that selectively fine-tunes key layers, improving language adherence while significantly reducing computational cost. Our method achieves comparable or superior performance to full fine-tuning, particularly for low-resource languages, offering a more efficient multilingual adaptation.<sup>1</sup>

#### 1 Introduction

Multilingual LLMs are pre-trained on raw text from multiple languages, typically consisting of separate corpora for each language. Remarkably, despite this lack of explicit parallel data to facilitate cross-lingual associations, these models develop an implicit understanding of inter-language relations and cross-lingual word associations (Wen-Yi and Mimno, 2023). Instruction tuning further enhances their ability to follow prompts, and models trained on multilingual data often exhibit zero-shot cross-lingual transfer of instruction-following capabilities (Chirkova and Nikoulina, 2024). How-

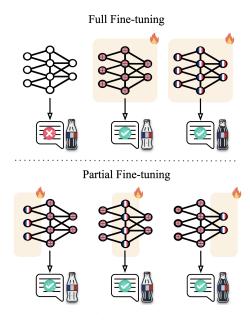


Figure 1: Evaluation of correctness and language adherence on French input. Soda level represents the CoCo-CoLa ratio. Higher level indicates better adherence.

ever, this generalization is uneven: while highresource languages in pretraining benefit significantly from instruction tuning, lower-resource or unseen languages often struggle to follow instructions reliably, frequently exhibiting degraded performance or defaulting to generating output in a preferred language (Nguyen et al., 2024; Chirkova and Nikoulina, 2024). To address these issues, we investigate how multilingual LLMs learn the same task across different languages.

A crucial step toward addressing the limitations of multilingual LLMs is understanding how they internally process and encode multilingual knowledge. Interpretability research has traditionally focused on monolingual models, leveraging techniques such as representation probing (Orgad et al., 2024; Saphra and Lopez, 2019) and model patching (Ghandeharioun et al., 2024; García-Carrasco et al., 2024). These methods have been widely

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<sup>&</sup>lt;sup>1</sup>Our code is available at https://github.com/elnaz rahmati/CoCo-CoLa/

used to examine LLMs' performance across tasks such as mathematics (Nikankin et al., 2024; Zhou et al., 2024), and general knowledge (Jiang et al., 2024; Burns et al., 2022; Singh et al., 2024; Golgoon et al., 2024; Chowdhury and Allan, 2024; Rai et al., 2024). Studies on model internals suggest that Multi-Layer Perceptrons (MLPs) retrieve task-relevant information, while attention layers refine and promote the correct response (Geva et al., 2021; Meng et al., 2022). Furthermore, knowledge is often identified in earlier layers and reinforced in later layers (Fan et al., 2024).

However, these interpretability techniques have primarily been applied to monolingual models, which were initially dominant due to the early focus on English-language pertaining (Touvron et al., 2023; Jiang et al., 2023; Team et al., 2024; Abdin et al., 2024). The rise of multilingual LLMs trained on diverse languages (Gao et al., 2024; Shaham et al., 2024; Soykan and Şahin, 2024), necessitates extending interpretability research beyond English. Multilingual LLMs present additional challenges: representations of different languages are intertwined within a shared space; cross-lingual alignment varies across languages; and shared tokens between languages impact their process. These complexities make it difficult to isolate languagespecific knowledge, benchmark cross-lingual generalization, and interpret how multilingual LLMs acquire and apply linguistic information. Given the prevalence of mid- and low-resource languages, understanding these mechanisms is crucial not only for improving cross-lingual transfer but also for mitigating the "curse of multilinguality" — the performance degradation observed as the number of supported languages increases.

Recent efforts have begun addressing these challenges by probing internal multilingual representations (Li et al., 2024), analyzing the emergence of cross-lingual transfer (Wang et al., 2024a), and studying token representation alignment on crosslingual transfer (Gaschi et al., 2023). Furthermore, researchers attempt to separate the linguistic abilities from task-specific abilities by developing language- and task-specific adapters (Pfeiffer et al., 2020; Parovic et al., 2023), subnetworks (Choenni et al., 2023), or layers (Bandarkar et al., 2024). However, despite this progress, most prior works treat multilinguality as a monolithic phenomenon, focusing on general cross-lingual transfer or aggregating all languages into a single block of linguistic knowledge. Less attention has been given to understanding how LLMs process individual languages at a more granular level, particularly within the context of task learning.

In this work, our goal is to identify both shared and distinct patterns in cross-lingual task acquisition, revealing how multilingual models internalize and apply linguistic knowledge (Section 3). We find that training on a task in one language improves performance in other languages. However, this benefit is not always directly observable due to an inherent model bias towards generating output in a preferred language, rather than strictly adhering to the input language (Section 4.1). To quantify this bias, we introduce CoCo-CoLa (Correct Concept, Correct Language), a novel metric designed to assess a model's ability to generate responses in the intended input language, particularly for languages not included in supervised finetuning (SFT). Furthermore, we propose a partial training method that selectively fine-tunes specific model layers to enhance language adherence (Section 4.2). This approach enables more efficient multilingual adaptation, achieving comparable or even superior performance, especially for low-resource languages, without the need for full model retraining.

#### 2 Related Work

This work builds on several active research areas that inform our study of multilingual task learning in LLMs. Specifically, we draw from (1) Multilingual interpretability, which helps us analyze how LLMs process different languages and how their internal structures influence multilingual task learning; (2) Representation alignment, which provides insights into token-level similarities across languages and how shared representations facilitate cross-lingual generalization; (3) Adapters, which separate language knowledge from task-specific knowledge, offering a structured framework for understanding their interactions; and (4) Subnetworks, which identify task- and language-specific parameters within existing models, offering an alternative to external adapters and directly informing our approach to efficient partial training.

**Interpretability.** Li et al. (2024) use probing techniques to analyze accuracy changes across layers in LLMs, showing that high-resource languages exhibit patterns similar to English, with accuracy increasing from lower to upper layers. However, this pattern is inconsistent for low-resource languages. Wang et al. (2024b) examine cross-lingual

transfer by analyzing neuron overlap in different languages using checkpoints from BLOOM's pretraining (Le Scao et al., 2023). Their study finds a strong correlation between neuron overlap and cross-lingual transfer, though neuron overlap does not increase monotonically during training, and patterns vary across model sizes. Similarly, Zhao et al. (2024a) investigate language-specific neurons and assess how masking these neurons affects both English and non-English language performance.

Representation alignment. Beyond studying multilingualism in LLMs, some research focuses on improving model performance across languages through representation alignment. Gaschi et al. (2023) align English and Arabic model representations using a bilingual dictionary before fine-tuning on a target task. Zhang et al. (2024) align English representations with other languages using question-translation data before instruction-tuning. Additionally, Salesky et al. (2023) introduce a pixel representation method to enhance alignment and improve translation quality.

Adapters. Another approach for cross-lingual transfer involves integrating adapters into the model. This technique is based on the assumption that task-solving knowledge can be separated from language knowledge. Pfeiffer et al. (2020) introduce MAD-X, a framework where language and task adapters are trained separately, with each block's representations passing through a language adapter before a task adapter. Building on this, later works aim to refine adapter creation and composition methods. For instance, Parović et al. (2022) propose BAD-X, which replaces monolingual adapters with bilingual adapters, improving performance for low-resource languages. Zhao et al. (2024b) introduce AdaMergeX, where adapters for language-task pairs are trained independently and later combined through linear operations (addition and subtraction) to generate adapters for new language-task pairs.

**Subnetworks.** To enhance cross-lingual transfer without adding new parameters, some methods focus on identifying existing task- and language-specific parameters within the model. Choenni et al. (2023) fine-tune models for specific languages or tasks, extract the most affected neurons, and use the resulting subnetworks to enable multilingual task adaptation. Bandarkar et al. (2024) take a layerwise approach in multiple steps: they train separate

language- and task-expert models, analyze parameter changes to identify key layers for language and task learning, and use layer-swapping techniques to create a math expert in a new language. Consistent with Zhao et al. (2024a), their findings suggest that initial and final layers primarily encode language-related information, while middle layers are task-specific.

# 3 Preliminary Analysis

In the preliminary section of this paper, we first isolate language effects from task learning by choosing multi-lingual parallel QA data (Section 3.1), examining fine-tuning performance across multiple languages (Section 3.2), exploring how well LLMs generalize knowledge across languages (Section 3.3), and which model components are most affected during training (Section 3.4). Then, in Section 4.1, we introduce **CoCo-CoLa** metric to measure language adherence in multilingual LLMs followed by an efficient partial training method to increase the model adherence (Section 4.2).

# 3.1 Setup

To investigate how multilingual LLMs learn a new task in a monolingual setting, we train three different model sizes on a Closed-Book Question-Answering (CBQA) task. We include two sizes of the Llama-3.2 series (Dubey et al., 2024) to analyze the effect of model size on multilingual performance and behavior, given that these models are specifically optimized for multilingual dialogue. We also include Llama-3.1-8B as a point of comparison, as it, while not explicitly optimized for multilingualism, was trained on a small amount of multilingual data.

We select CBQA because it is inherently language-dependent and demonstrates a model's ability to act as a knowledge base (Wang et al., 2021). To isolate the impact of language differences from the effects of learning a new task or acquiring new knowledge, we use the Mintaka CBQA dataset (Sen et al., 2022). Mintaka provides identical question-answer pairs in nine languages, allowing us to keep the question content consistent and thus isolate the influence of language itself. The dataset was originally created in English and later translated into Arabic, French, German, Hindi, Italian, Japanese, Portuguese, and Spanish.

One challenge with Mintaka is that some answer types are not translated across languages. To keep

question-answer pairs within the same language, we use Google Translate to convert these answers into the language of their respective questions and apply back-translation for accuracy checks. Additionally, since our goal is to study how models learn new tasks in languages they have been exposed to before, we exclude Arabic and Japanese.

#### 3.2 SFT Performance

Our initial step is to assess the model's ability to learn the task in each individual language, effectively measuring how learning difficulty varies across languages. To do this, we perform SFT for Llama-3 models on each language of the CBQA dataset for three epochs and generate answers for given questions. Next, we select the best model based on the validation loss. Further implementation details are provided in Appendix A.1.

Table 1 shows a comparison of accuracy between the pre-trained model and the best checkpoint of the language-specific SFT model across different languages. SFT significantly improves performance for all languages with relatively consistent accuracy levels, except for Hindi in all model sizes and Portuguese for Llama-3.1-8B, which exhibit notably lower accuracy. This discrepancy is likely due to undertraining. Among the SFT models, English achieves the highest accuracy in the 3B (53.09%) and 8B (50.98%) models, while Spanish performs best (41.71%) in the 1B model. The largest accuracy gains are observed in English (+38.06%) for the 8B model, German (+24.31%) for the 3B model, and Spanish (+35.58%) for the 1B model, indicating that these languages benefited the most from fine-tuning. The similar accuracy across languages indicates comparable knowledge acquisition.

However, two critical questions remain: (1) Do models share learned knowledge uniformly across languages, or do they correctly answer distinct subsets of questions depending on the language? (2) Are there specific parts of the model that are responsible for encoding language-specific information?

To address these questions, we first analyze the overlap in correct answers across languages using the Jaccard Index, followed by an investigation of parameter updates to determine whether certain components of the model specialize in handling linguistic differences.

# 3.3 Cross-lingual Task Knowledge

To further investigate the extent of cross-lingual task knowledge transfer within the model, we an-

	Llama-1B		Llama-3B		Llama-8B	
Language	PLM	SFT	PLM	SFT	PLM	SFT
English	13.27	38.44	32.85	53.09	12.92	50.98
French	11.30	40.27	22.90	43.80	18.53	50.85
German	7.16	40.34	23.79	48.10	11.04	44.35
Hindi	5.27	21.18	7.33	30.39	6.21	35.29
Italian	7.06	41.58	21.87	42.73	16.48	43.22
Portuguese	5.38	38.23	20.06	37.04	18.38	31.11
Spanish	6.13	41.71	22.01	45.69	16.60	45.46

Table 1: Performance of pre-trained (PLM) and fine-tuned (SFT) models across different languages.

alyze the overlap in correct answers across languages. Specifically, we measure how consistently the model arrives at the same correct answers in different languages, providing insight into whether knowledge is shared across languages.

It is important to note that there is no overlap between the knowledge present in the training and evaluation data. This ensures that any correct answers during evaluation are derived from knowledge acquired during pretraining rather than memorization. Consequently, the model's ability to generate correct responses across languages indicates that it has internalized the underlying task knowledge from the training data, rather than relying solely on language-specific cues. Let  $L_A$  and  $L_B$ represent two languages, and let  $C_{L_A}$  denote the set of correct answers for  $L_A$ . To quantify the degree of shared task knowledge between languages, we compute the Jaccard Index, also known as Intersection over Union (IoU), between  $C_{L_A}$  and  $C_{L_B}$  (see Equation 1). The Jaccard Index is a natural choice for this analysis as it directly measures the proportion of overlapping correct answers relative to the total distinct answers across languages. This allows us to assess knowledge consistency and crosslingual transfer within the model.

$$IoU(A,B) = \frac{|C_{L_A} \cap C_{L_B}|}{|C_{L_A} \cup C_{L_B}|} \tag{1}$$

The results, shown in Figure 2, indicate that on average approximately 60% of correctly answered questions are shared across languages for all models, suggesting a strong degree of shared knowledge among languages. However, Hindi exhibits significantly lower overlap with other languages in Llama-3.2 models, suggesting weaker generalization for this language. Interestingly, in Llama-3.1-8B, Hindi shows higher overlap compared to Llama-3.2 models, but Portuguese experiences a notable drop in overlap. Additionally, Llama-3.2-

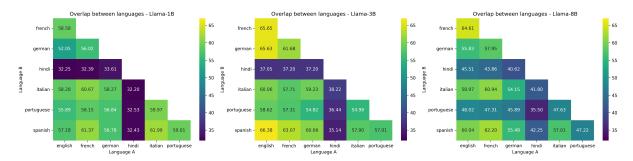


Figure 2: Jaccard similarity index between different languages, measuring the proportion of overlapping correctly answered questions between pairs of languages.

3B demonstrates a higher rate of shared knowledge compared to Llama-3.1-8B, despite both models achieving comparable accuracy across languages (see Table 1). This highlights the importance of multilingual optimization in enhancing crosslingual transfer among languages.

# 3.4 Parameter Updates

To investigate language-specific encoding in LLMs, we analyze parameter updates during fine-tuning and compare them across languages to determine whether certain components of the model specialize in processing linguistic information. Meng et al. (2022) suggest that MLP modules primarily store knowledge, while attention modules control information retrieval and selection. SFT models correctly answer approximately 40% of evaluation questions in all languages. However, they require fine-tuning to improve their ability to select and output the correct information. As a result, we expect substantial modifications in the attention modules, particularly in the final layers, while changes in the MLP modules remain limited. Since these datasets differ only in language, not in task or knowledge, analyzing the model updates allows us to pinpoint which layers or components are most crucial for learning language-specific representations.

To compute parameter update, we follow Bandarkar et al. (2024) and calculate the average parameter modifications for each module in each layer. Denoting the pre-trained weight matrix as  $W_p$  and the fine-tuned weight matrix as  $W_f$ , the average magnitude of differences is given by:

$$\Delta W = \frac{1}{n} \sum_{i=1}^{n} |W_p^{(i)} - W_f^{(i)}|$$
 (2)

The results for four languages are shown in Figure 3, with the remaining three languages in Figure 6. As expected, significant modifications occur in the attention modules of the final six layers for

Llama-3.2-1B and the final 14 layers for Llama-3.2-3B and Llama-3.1-8B models across all languages. However, in Llama-3.2 models, we observe substantial changes in the MLP modules in these layers for all languages except English, suggesting that these variations are tied to language-specific processing rather than task-related learning. Surprisingly, for Llama-3.1-8B, even the model fine-tuned on English shows a high rate of change similar to other languages. Considering the unexpectedly low accuracy of the Llama-3.1-8B pre-trained model across all languages compared to Llama-3.2-3B, this larger modification could be related to learning the task or acquiring new knowledge rather than just language adaptation.

# 4 Approach

Our previous analysis suggests that while task knowledge is largely shared across languages, the way this knowledge is processed and accessed differs. Although a Jaccard Index analysis revealed substantial overlap in correct answers, our investigation of parameter updates showed that models trained on non-English languages required more substantial modifications in their MLP modules compared to English, even when achieving comparable accuracy. This raises an important question: Do these modifications reflect deviations in knowledge acquisition, or are they more related to language generation? In this section, we first introduce a metric to analyze linguistic bias in multilingual LLM outputs. Then, we propose a partial training strategy aimed at reducing this bias by selectively fine-tuning specific model components.

#### 4.1 Correct Concept in Correct Language

According to Dubey et al. (2024), only 8% of the pre-training data used for Llama-3 models is multilingual, while the rest is dominated by English

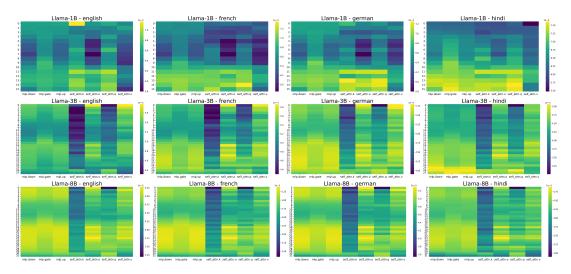


Figure 3: Parameter updates of monolingual finetuning for Llama-1B, Llama-3B, and Llama-8B.

general knowledge, mathematics, and code. This suggests a strong bias toward English. Given this imbalance, we hypothesize that the observed MLP module changes in non-English languages may not indicate new knowledge acquisition but rather adjustment in language selection during response generation. Supporting this, Chirkova and Nikoulina (2024) found that when Llama-2-13B is instruction-tuned in English and tested in other languages, it generates responses in a different language from input language in over 30% of cases, with this behavior influenced by training hyperparameters.

To investigate this further, we introduce CoCo-CoLa (Correct Concept - Correct Language), a metric designed to measure how well the model adheres to the input language while generating correct responses. Let  $L_i$  denote the input language,  $C_{L_i \to L_o}$  the set of correct output in language  $L_o$  when passing language  $L_i$  as input. We define the CoCo-CoLa ratio as follows:

$$\operatorname{CoCo-CoLa}(L_{i}) = \frac{|C_{L_{i} \to L_{i}} - \bigcup_{L_{o} \neq L_{i}} C_{L_{i} \to L_{o}}|}{|C_{L_{i} \to L_{i}} \Delta \bigcup_{L_{o} \neq L_{i}} C_{L_{i} \to L_{o}}|}$$
(3)

The denominator uses the symmetric difference between  $C_{L_i \to L_i}$  and correct answers in other languages because many answers involve named entities, such as well-known places, books, and individuals. Since most of the languages, use similar scripts, named entities often appear in identical forms across multiple languages. This redundancy leads to overlap between  $C_{L_i \to L_i}$  and

 $\bigcup_{L_o \neq L_i} C_{L_i \to L_o}$ , which the symmetric difference helps mitigate by ensuring that shared named entities do not artificially inflate the metric.

Given that these models are primarily trained on English, when the input is in  $L_i$  the output is usually either  $L_i$  or English. Thus,  $\bigcup_{L_o \neq L_i} C_{L_i \to L_o}$  is largely dominated by  $C_{L_i \to en}$ , meaning that most language switching occurs between the input language and English rather than other languages.

To further simplify the calculation, we filter the data to include only questions where the correct answers in  $L_i$  and English are different. Under this condition,  $C_{L_i \to L_i} \cap C_{L_i \to en} = \emptyset$ , allowing the CoCo-CoLa ratio to reduce to:

$$CoCo-CoLa(L_i) = \frac{|C_{L_i \to L_i}|}{|C_{L_i \to L_i}| + |C_{L_i \to en}|} \quad (4)$$

To evaluate language adherence and accuracy, we pass the input in  $L_i$  to pre-trained, en-tuned, and  $L_i$ -tuned models. We then compute the CoCo-CoLa ratio and the cumulative accuracy, defined as the proportion of correct answers either in  $L_i$  or English. The results, presented in Table 2, show that while the *en-tuned* models and the  $L_i$ -tuned models achieve similar cumulative accuracy on  $L_i$  input, the CoCo-CoLa ratio is significantly lower for the en-tuned model. This suggests that although the en-tuned model can correctly process the question in  $L_i$  and retrieve the correct answer at the same rate as the  $L_i$ -tuned model, it frequently generates the answer in English instead of  $L_i$ . Furthermore, analyzing the CoCo-CoLa ratio of the pre-trained model reveals that the model already exhibits a bias toward generating English responses, though this

Language	Metric	1B		3B		8B				
	1,100110	PLM	$\rightarrow en$	$\rightarrow L_i$	PLM	$\rightarrow en$	$\rightarrow L_i$	PLM	$\rightarrow en$	$\rightarrow L_i$
French	Cum. Acc.	12.07	52.66	55.73	20.57	62.55	52.97	12.89	58.64	66.01
	CoCo-CoLa	49.42	13.47	88.58	52.51	14.73	89.45	58.11	12.32	87.54
German	Cum. Acc.	8.05	51.97	50.92	16.99	49.30	57.01	10.43	59.95	52.27
	CoCo-CoLa	53.87	10.50	91.02	56.53	19.64	89.26	57.49	11.03	87.21
Hindi	Cum. Acc.	8.65	29.34	27.42	15.765	38.26	39.67	9.79	37.29	39.21
	CoCo-CoLa	43.16	13.28	90.79	31.93	10.04	77.47	43.67	10.74	90.68
Italian	Cum. Acc.	7.76	51.35	62.39	16.63	53.17	46.02	11.77	61.88	58.55
	CoCo-CoLa	51.32	10.00	93.60	56.68	16.29	87.91	52.11	10.90	91.35
Portuguese	Cum. Acc.	10.22	54.85	57.57	17.60	55.52	50.64	16.23	60.75	42.90
	CoCo-CoLa	56.40	12.73	91.07	63.37	15.99	85.10	51.41	11.49	90.73
Spanish	Cum. Acc.	9.75	57.52	59.02	19.17	57.55	60.38	14.13	58.34	54.27
	CoCo-CoLa	52.28	12.01	91.24	61.68	15.84	89.18	61.98	9.40	91.35

Table 2: CoCo-CoLa ratio and cumulative accuracy of pretrained model (PLM), English-trained model ( $\rightarrow en$ ), and  $L_i$ -trained model ( $\rightarrow L_i$ ) across languages for Llama-1B, Llama-3B, and Llama-8B

bias is less pronounced than in the *en-tuned* model. These findings support our hypothesis that the varying rate of parameter updates across languages is related to output language preference. Since the model is already inherently biased toward English, *en-tuned* results in the least change.

# 4.2 Partial Training for Efficient Adaptation

In this section, we aim to disentangle task learning from output generation in language  $L_i$ . Our previous results reveal two key observations. First, as shown in Section 4.1, both the *en-tuned* model and the  $L_i$ -tuned model achieve the same cumulative accuracy on  $L_i$ , indicating that they learn the task equally well. The only difference is their CoCo-CoLa score, meaning that while both models understand the task to the same degree, they generate outputs in different languages. Second, from Section 3.4, we observed that the *en-tuned* and  $L_i$ -tuned models undergo different parameter updates. Some of these updates are necessary for learning the task itself, while others are specifically related to generating responses in the correct language.

Based on these observations, we hypothesize that fine-tuning specific layers of an *en-tuned* model on  $L_i$  can enable it to generate responses in  $L_i$  without requiring full model updates. Specifically, these layers correspond to the parameters that were updated in the  $L_i$ -tuned model but not in the *en-tuned* model. To test this hypothesis, we first identify the layers that undergo language-specific updates. We then fine-tune only these layers in the *en-tuned* model and compare the results to fine-tuning non-specific layers. This comparison allows us to iso-

late the parameters responsible for output language.

**Identifying language layers.** We select layers for partial training based on the variation in parameter update rates observed in Section 3.4. For the Llama-3.2-1B model, we train three variants by unfreezing different sets of layers: (1) layers 11-16, (2) layers 1-5 (chosen to match the parameter count of the final six layers), and layers 1-10 (including all parameters except the final six). We expect the first variant, which targets the final six layers, to be the most language-related and to result in the largest improvement in the CoCo-CoLa ratio, while the other two should have a smaller effect. Similarly, for Llama-3.2-3B, we train two variants by unfreezing layers 15–27 and layers 1–14, again expecting the first variant to be more strongly related language generation. For Llama-3.1-8B, which does not show clear variations in update rates across languages (as noted in Section 3.4), we instead select layers based on the most updated MLP modules. Specifically, we choose layers 16-31 and layers 1–15 for partial training to determine which part of the model is more responsible for language generation. Through this analysis, we aim to verify whether the final layers play a greater role in controlling the output language

**Partial training evaluation.** To evaluate the effectiveness of partial training, we compare all partially trained models to both their fully *en-tuned* and fully  $L_i$ -tuned models. Figure 4 presents cumulative accuracy and  $L_i$  accuracy across three languages, while results for the remaining three languages are included in Figure 7. In addition,

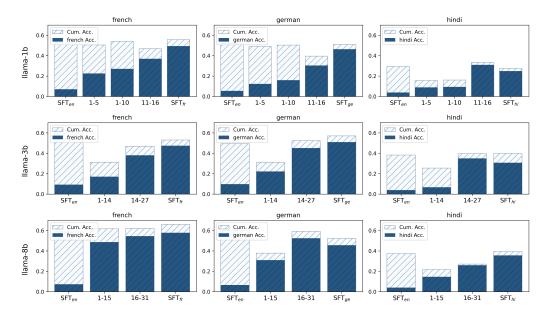


Figure 4: Cumulative accuracy and  $L_i$  accuracy on *en-tuned*  $(SFT_{en})$  and  $L_i$ -tuned models  $(SFT_{L_i})$ , along with partially trained models, across all Llama model sizes.

CoCo-CoLa ratios for partially trained models are also available in Appendix A.4, providing further insight into the extent to which partial fine-tuning improves output language consistency.

As shown in Figure 4, among the partially trained models, training the final layers yields the highest accuracy and CoCo-CoLa ratio for Llama-3.2 models, indicating that these layers play a crucial role in determining output language. Moreover, the accuracy of this partially trained model approaches that of the fully  $L_i$ -tuned model, suggesting that the earlier layers already provide sufficient information for answering questions, even without exposure to  $L_i$  during training. Interestingly, Hindi, which initially exhibited lower performance than other languages, benefits from cross-lingual transfer, achieving better results with partial training than full training in both Llama-3.2 models. Llama-3.2-3B shows even stronger cross-lingual transfer, improving accuracy for Italian and Portuguese as well. For Llama-3.1-8B, training the second half of the model leads to the best CoCo-CoLa ratio, but the difference in  $L_i$  accuracy across partial training configurations is less pronounced than in Llama-3.2 models. This model also shows improved accuracy in partial training over full training for German, Italian, and Portuguese.

These findings confirm the hypothesis that the final layers are strongly linked to output language selection. Additionally, for low-resource languages, partially training only the final layers of an *en-*

tuned model can achieve similar or even better accuracy compared to full fine-tuning in the target language. Beyond its effectiveness, partial training is significantly more efficient, reducing training time to half and memory usage to 65% of full training. Furthermore, the model achieves higher accuracy in fewer training steps, requiring less than one epoch, meaning it is trained on fewer data points.

# 5 Conclusion

In this work, we first analyzed shared knowledge across seven languages and identified key differences in the parameters most affected when training models for each language. Building on these insights, we proposed the CoCo-CoLa ratio, a metric for evaluating language adherence in multilingual LLMs, and used it to evaluate both pre-trained and fine-tuned LLMs. Our findings show that pre-trained models tend to generate English outputs regardless of the input language and that fine-tuning on English further amplifies this bias.

To address this problem, we leveraged insights from parameter updates and CoCo-CoLa results to develop a partial training method that improves language adherence in English-trained models. Our analysis demonstrated a more efficient alternative to full fine-tuning, achieving comparable or even superior performance while significantly reducing the number of updated parameters. In addition, given the widespread availability of instruction-tuned and task-specific English models, partial

training of final layers presents a fast and efficient approach to adapting LLMs to new languages.

### Limitations

We acknowledge that training hyperparameters can significantly influence the linguistic bias of fine-tuned models, as highlighted by Chirkova and Nikoulina (2024). For instance, while smaller learning rates may reduce bias, they can also lead to degraded task performance. Due to resource constraints, we used a single set of hyperparameters optimized for task performance rather than systematically exploring bias mitigation strategies. Additionally, we applied the same hyperparameter settings across all languages and model sizes, though fine-tuning them individually for each model-language pair could potentially yield better results.

Moreover, linguistic bias in pre-trained models and the observed trends in parameter updates across languages are influenced by factors such as model architecture, training procedures, data proportions, and even the order in which the model encounters training data. As a result, the specific layers we identified for each model size may differ when tested on other LLMs. Additionally, our observations suggest that certain languages are undertrained in Llama models. However, due to the lack of publicly available information on training data and procedures, we cannot make definitive claims regarding language-specific training discrepancies.

Another key limitation is that our study focuses on languages from the same language family, which are relatively close to each other and exhibit significant token overlap, facilitating crosslingual transfer. The models we evaluated were also trained on a limited set of languages with similar characteristics. None of the studied languages fall into the low-resource category, meaning our findings may not generalize to massively multilingual models trained on a more diverse set of languages. Finally, our method is restricted to languages present in the model's pretraining data and cannot be applied to completely new languages.

# **Ethical Statement**

This research investigates language adherence in multilingual large language models (LLMs) and proposes partial training methods for efficient adaptation. Our work aims to enhance linguistic fairness and accessibility by mitigating biases that favor high-resource languages. We acknowledge that training data composition and fine-tuning decisions can introduce unintended biases, which may disproportionately affect underrepresented languages. While our findings contribute to more equitable multilingual model adaptation, they are limited to languages present in the model's pretraining data and may not generalize to unseen languages.

Additionally, we use machine translation tools (e.g., Google Translate) to ensure consistency in question-answer pairs. While back-translation was employed to verify accuracy, potential translation artifacts could impact evaluation. We encourage further work to assess our method's applicability to a broader set of languages, particularly low-resource and non-Indo-European languages.

This study does not involve human subjects, personal data, or user interactions, and we adhere to ethical guidelines for computational research. Our experiments were conducted using publicly available models and datasets, ensuring transparency and reproducibility.

#### References

Marah Abdin, Jyoti Aneja, Hany Awadalla, Ahmed Awadallah, Ammar Ahmad Awan, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Jianmin Bao, Harkirat Behl, et al. 2024. Phi-3 technical report: A highly capable language model locally on your phone. *arXiv* preprint arXiv:2404.14219.

Lucas Bandarkar, Benjamin Muller, Pritish Yuvraj, Rui Hou, Nayan Singhal, Hongjiang Lv, and Bing Liu. 2024. Layer swapping for zero-shot cross-lingual transfer in large language models. *arXiv preprint arXiv:2410.01335*.

Collin Burns, Haotian Ye, Dan Klein, and Jacob Steinhardt. 2022. Discovering latent knowledge in language models without supervision. *arXiv* preprint *arXiv*:2212.03827.

Nadezhda Chirkova and Vassilina Nikoulina. 2024. Zero-shot cross-lingual transfer in instruction tuning of large language models. In *Proceedings of the 17th International Natural Language Generation Conference*, pages 695–708, Tokyo, Japan. Association for Computational Linguistics.

Rochelle Choenni, Dan Garrette, and Ekaterina Shutova. 2023. Cross-lingual transfer with language-specific subnetworks for low-resource dependency parsing. *Computational Linguistics*, pages 613–641.

Tanya Chowdhury and James Allan. 2024. Probing ranking llms: Mechanistic interpretability in information retrieval. *arXiv preprint arXiv:2410.18527*.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman,

- Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. 2024. The llama 3 herd of models. *arXiv* preprint arXiv:2407.21783.
- Siqi Fan, Xin Jiang, Xiang Li, Xuying Meng, Peng Han, Shuo Shang, Aixin Sun, Yequan Wang, and Zhongyuan Wang. 2024. Not all layers of llms are necessary during inference. *arXiv preprint arXiv:2403.02181*.
- Changjiang Gao, Hongda Hu, Peng Hu, Jiajun Chen, Jixing Li, and Shujian Huang. 2024. Multilingual pretraining and instruction tuning improve cross-lingual knowledge alignment, but only shallowly. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 6101–6117, Mexico City, Mexico. Association for Computational Linguistics.
- Jorge García-Carrasco, Alejandro Maté, and Juan Trujillo. 2024. Extracting interpretable task-specific circuits from large language models for faster inference. arXiv preprint arXiv:2412.15750.
- Felix Gaschi, Patricio Cerda, Parisa Rastin, and Yannick Toussaint. 2023. Exploring the relationship between alignment and cross-lingual transfer in multilingual transformers. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 3020–3042, Toronto, Canada. Association for Computational Linguistics.
- Mor Geva, Roei Schuster, Jonathan Berant, and Omer Levy. 2021. Transformer feed-forward layers are keyvalue memories. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 5484–5495, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Asma Ghandeharioun, Avi Caciularu, Adam Pearce, Lucas Dixon, and Mor Geva. 2024. Patchscope: A unifying framework for inspecting hidden representations of language models. *arXiv preprint arXiv:2401.06102*.
- Ashkan Golgoon, Khashayar Filom, and Arjun Ravi Kannan. 2024. Mechanistic interpretability of large language models with applications to the financial services industry. In *Proceedings of the 5th ACM International Conference on AI in Finance*, pages 660–668.
- Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. 2023. Mistral 7b. arXiv preprint arXiv:2310.06825.
- Che Jiang, Biqing Qi, Xiangyu Hong, Dayuan Fu, Yang Cheng, Fandong Meng, Mo Yu, Bowen Zhou, and Jie Zhou. 2024. On large language models' hallucination with regard to known facts. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics:*

- Human Language Technologies (Volume 1: Long Papers), pages 1041–1053, Mexico City, Mexico. Association for Computational Linguistics.
- Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. 2023. Bloom: A 176b-parameter open-access multilingual language model.
- Daoyang Li, Mingyu Jin, Qingcheng Zeng, Haiyan Zhao, and Mengnan Du. 2024. Exploring multilingual probing in large language models: A crosslanguage analysis. *arXiv preprint arXiv:2409.14459*.
- Kevin Meng, David Bau, Alex Andonian, and Yonatan Belinkov. 2022. Locating and editing factual associations in gpt. *Advances in Neural Information Processing Systems*, 35:17359–17372.
- Xuan-Phi Nguyen, Mahani Aljunied, Shafiq Joty, and Lidong Bing. 2024. Democratizing LLMs for low-resource languages by leveraging their English dominant abilities with linguistically-diverse prompts. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3501–3516, Bangkok, Thailand. Association for Computational Linguistics.
- Yaniv Nikankin, Anja Reusch, Aaron Mueller, and Yonatan Belinkov. 2024. Arithmetic without algorithms: Language models solve math with a bag of heuristics. *arXiv preprint arXiv:2410.21272*.
- Hadas Orgad, Michael Toker, Zorik Gekhman, Roi Reichart, Idan Szpektor, Hadas Kotek, and Yonatan Belinkov. 2024. Llms know more than they show: On the intrinsic representation of llm hallucinations. *arXiv preprint arXiv:2410.02707*.
- Marinela Parovic, Alan Ansell, Ivan Vulić, and Anna Korhonen. 2023. Cross-lingual transfer with target language-ready task adapters. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 176–193, Toronto, Canada. Association for Computational Linguistics.
- Marinela Parović, Goran Glavaš, Ivan Vulić, and Anna Korhonen. 2022. BAD-X: Bilingual adapters improve zero-shot cross-lingual transfer. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1791–1799, Seattle, United States. Association for Computational Linguistics.
- Jonas Pfeiffer, Ivan Vulić, Iryna Gurevych, and Sebastian Ruder. 2020. MAD-X: An Adapter-Based Framework for Multi-Task Cross-Lingual Transfer. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7654–7673, Online. Association for Computational Linguistics.

- Daking Rai, Yilun Zhou, Shi Feng, Abulhair Saparov, and Ziyu Yao. 2024. A practical review of mechanistic interpretability for transformer-based language models. *arXiv preprint arXiv:2407.02646*.
- Elizabeth Salesky, Neha Verma, Philipp Koehn, and Matt Post. 2023. Multilingual pixel representations for translation and effective cross-lingual transfer. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 13845–13861, Singapore. Association for Computational Linguistics.
- Naomi Saphra and Adam Lopez. 2019. Understanding learning dynamics of language models with SVCCA. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 3257–3267, Minneapolis, Minnesota. Association for Computational Linguistics.
- Priyanka Sen, Alham Fikri Aji, and Amir Saffari. 2022. Mintaka: A complex, natural, and multilingual dataset for end-to-end question answering. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 1604–1619, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.
- Uri Shaham, Jonathan Herzig, Roee Aharoni, Idan Szpektor, Reut Tsarfaty, and Matan Eyal. 2024. Multilingual instruction tuning with just a pinch of multilinguality. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 2304–2317, Bangkok, Thailand. Association for Computational Linguistics.
- Chandan Singh, Jeevana Priya Inala, Michel Galley, Rich Caruana, and Jianfeng Gao. 2024. Rethinking interpretability in the era of large language models. *arXiv preprint arXiv:2402.01761*.
- Gürkan Soykan and Gözde Gül Şahin. 2024. Linguistically-informed multilingual instruction tuning: Is there an optimal set of languages to tune? *arXiv preprint arXiv:2410.07809*.
- Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, et al. 2024. Gemma: Open models based on gemini research and technology. *arXiv* preprint arXiv:2403.08295.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Cunxiang Wang, Pai Liu, and Yue Zhang. 2021. Can generative pre-trained language models serve as knowledge bases for closed-book QA? In *Proceedings of the 59th Annual Meeting of the Association for*

- Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 3241–3251, Online. Association for Computational Linguistics.
- Hetong Wang, Pasquale Minervini, and Edoardo Ponti. 2024a. Probing the emergence of cross-lingual alignment during LLM training. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 12159–12173, Bangkok, Thailand. Association for Computational Linguistics.
- Hetong Wang, Pasquale Minervini, and Edoardo M Ponti. 2024b. Probing the emergence of crosslingual alignment during llm training. *arXiv* preprint *arXiv*:2406.13229.
- Andrea W Wen-Yi and David Mimno. 2023. Hyperpolyglot LLMs: Cross-lingual interpretability in token embeddings. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 1124–1131, Singapore. Association for Computational Linguistics.
- Shimao Zhang, Changjiang Gao, Wenhao Zhu, Jiajun Chen, Xin Huang, Xue Han, Junlan Feng, Chao Deng, and Shujian Huang. 2024. Getting more from less: Large language models are good spontaneous multilingual learners. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 8037–8051, Miami, Florida, USA. Association for Computational Linguistics.
- Yiran Zhao, Wenxuan Zhang, Guizhen Chen, Kenji Kawaguchi, and Lidong Bing. 2024a. How do large language models handle multilingualism? In Advances in Neural Information Processing Systems (NeurIPS).
- Yiran Zhao, Wenxuan Zhang, Huiming Wang, Kenji Kawaguchi, and Lidong Bing. 2024b. Adamergex: Cross-lingual transfer with large language models via adaptive adapter merging. *arXiv preprint arXiv:2402.18913*.
- Tianyi Zhou, Deqing Fu, Vatsal Sharan, and Robin Jia. 2024. Pre-trained large language models use fourier features to compute addition. *arXiv* preprint *arXiv*:2406.03445.

# A Appendix

# A.1 Implementation details

We experimented with dropout rates of 0.1 and 0.05, and learning rates of 5e-5, 1e-5, 5e-6, 1e-6, 5e-7, and 1e-7 for training on the English CBQA task. The best setting (dropout = 0.1, learning rate = 5e-6) was selected based on the minimum validation loss. These hyperparameters were used consistently across all languages and models throughout the paper.

For all training runs in our experiments, we used the hyperparameters listed in Table 3. All experiments were conducted with a fixed random seed of 42. We implemented our models using Transformers 4.46.3 and Torch 2.5.1, with Accelerate 1.1.0 and DeepSpeed 0.16.1 for multi-GPU training. All experiments were run on NVIDIA RTX A6000 GPUs, with all experiments taking approximately 48 hours on eight GPUs.

Parameter	value
num_epochs	3
save_steps	100
eval_steps	100
logging_steps	100
batch_size	64
gradient_accumulation	1
weight_decay	0.01
bf16	True

Table 3: Training hyperparameters

# A.2 Language specific knowledge

Beyond measuring similarities between languages using the Jaccard Index, we also analyze differences by identifying answers that are known in language A but unknown in language B. This allows us to examine the distribution of languages within the 40% of answers that are not correctly predicted by both languages. The results, presented in Figure 5, reveal an almost symmetrical distribution of known and unknown answers across most language pairs. However, notable deviations occur for languages with significantly lower overall accuracy. Specifically, Hindi shows a greater disparity in the Llama-3.2 models, while both Hindi and Portuguese exhibit this trend in the Llama-3.1-8B model.

# A.3 Parameter update

Due to space constraints, the main text presents results for only four languages. However, the analysis of model updates for Italian, Spanish, and Portuguese follows similar trends and can be found in Figure 6. These additional results confirm the patterns observed in other languages, reinforcing our findings on language-specific parameter updates.

# A.4 Partial Training

Due to space limitations, the results of partial training on Italian, Portuguese, and Spanish are pro-

vided in Figure 7. Additionally, the CoCo-CoLa ratios for both partially trained and fully trained models are shown in Table 4 for Llama-3.2-1B, Table 5 for Llama-3.2-3B, and Table 6 for Llama-3.1-8B. These comparisons highlight the consistently superior CoCo-CoLa ratio in the partial training of final layers.

Language	$SFT_{en}$	1-5	1-10	11-16	$SFT_{L_i}$
French	13.47	44.63	50.22	78.72	88.58
German	10.50	25.12	31.77	76.66	91.02
Hindi	13.28	56.82	58.49	92.73	90.79
Italian	10.00	32.12	65.17	86.18	93.60
Portuguese	12.73	45.18	56.33	75.43	91.07
Spanish	12.01	34.61	34.41	81.66	91.24

Table 4: CoCo-CoLa Ratios (%) for different languages across finetuned Llama-3.2-1B models.

Language	$SFT_{\mathit{en}}$	1-14	14-27	$\operatorname{SFT}_{L_i}$
French	14.73	54.64	81.18	89.45
German	19.64	71.40	86.04	89.26
Hindi	10.04	26.40	88.41	77.47
Italian	16.29	65.45	86.91	87.91
Portuguese	15.99	61.76	84.45	85.10
Spanish	15.84	72.38	85.50	89.18

Table 5: CoCo-CoLa Ratios (%) for different languages across finetuned Llama-3.2-3B models.

Language	$SFT_{en}$	1-15	16-31	$SFT_{L_i}$
French	12.32	78.93	87.77	87.54
German	11.03	81.91	88.69	87.21
Hindi	10.74	67.08	96.06	90.68
Italian	10.90	78.92	90.28	91.35
Portuguese	11.49	74.68	90.11	90.73
Spanish	9.40	75.82	93.55	91.35

Table 6: CoCo-CoLa Ratios (%) for different languages across finetuned Llama-3.1-8B models.

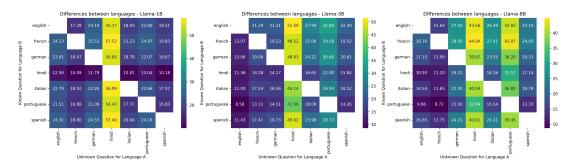


Figure 5: Difference in known knowledge between each pair of languages across different model sizes.

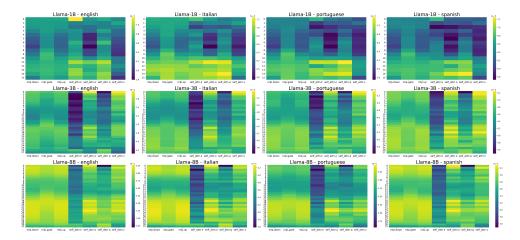


Figure 6: Average magnitude of difference between pretrained and monolingually fine-tuned models for Llama-1B, Llama-3B, and Llama-8B.

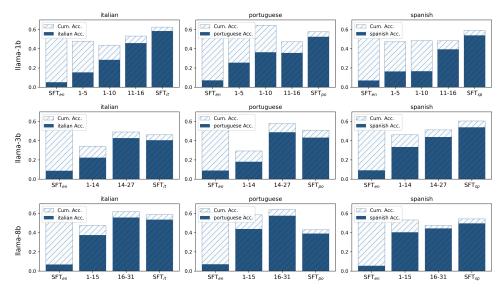


Figure 7: Cumulative accuracy and  $L_i$  accuracy on *en-tuned*  $(SFT_{en})$  and  $L_i$ -tuned models  $(SFT_{L_i})$ , along with partially trained models, across all Llama model sizes.