Unveiling Linguistic Regions in Large Language Models

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Abstract

Large Language Models (LLMs) have demonstrated considerable cross-lingual alignment and generalization ability. Current research primarily focuses on improving LLMs' cross-lingual generalization capabilities. However, there is still a lack of research on the intrinsic mechanisms of how LLMs achieve cross-lingual alignment. From the perspective of region partitioning, this paper conducts several investigations on the linguistic competence of LLMs. We discover a core region in LLMs that corresponds to linguistic competence, accounting for approximately 1% of the total model parameters. Removing this core region by setting parameters to zero results in a significant performance decrease across 30 different languages. Furthermore, this core region exhibits significant dimensional dependence, perturbations to even a single parameter on specific dimensions leading to a loss of linguistic competence. Moreover, we discover that distinct monolingual regions exist for different languages, and disruption to these specific regions substantially reduces the LLMs' proficiency in those corresponding languages. Our research also indicates that freezing the core linguistic region during further pre-training can mitigate the issue of catastrophic forgetting (CF), a common phenomenon observed during further pre-training of LLMs. Overall, exploring the LLMs' functional regions provides insights into the foundation of their intelligence [1].

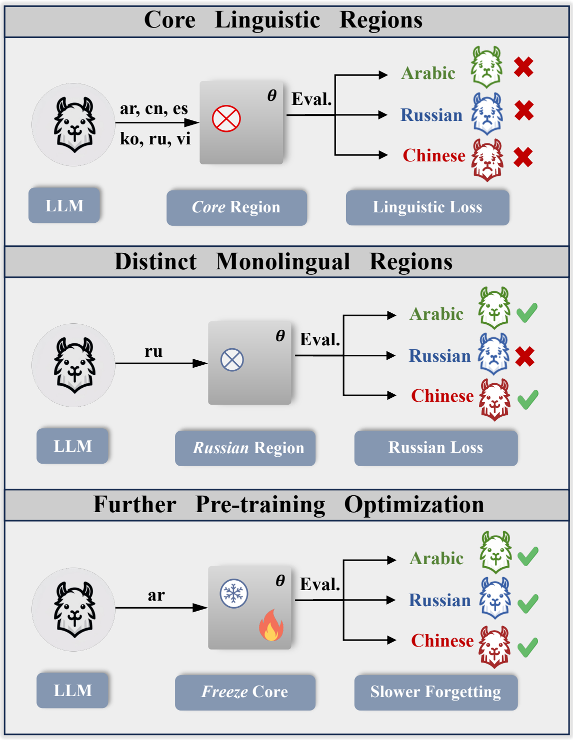

Figure 1: Three main findings of our experiments: (1) Identification of core language regions within the LLMs, where removals lead to linguistic competence loss; (2) Discovery of monolingual regions, where removals cause significant proficiency loss in specific languages; (3) Optimization of freezing core regions during further pre-training decelerates language forgetting.

1 Introduction

Over the years, the field of Natural Language Processing (NLP) has been at the forefront of understanding the core principles of intelligence. The emergence of Large Language Models (LLMs) such as GPT-4 (OpenAI, 2023), PaLM 2 (Anil et al., 2023) and LLaMA 2 (Touvron et al., 2023), showcase a significant breakthrough. Thanks to unparalleled scales of model architecture and the vastness of training data, these LLMs now exhibit exceptional linguistic competence and can execute complex tasks requiring abstract knowledge (Dong et al., 2023) and reasoning (Cobbe et al., 2021).

Previous research has revealed that LLMs naturally capture cross-linguistic similarities in their representation space, facilitating zero-shot cross-lingual transfer (Pires et al., 2019; Wu and Dredze,

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[1] Our code is released in `https://github.com/zzhang0179/Unveiling-Linguistic-Regions-in-LLMs`.

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2019; Xu et al., 2023). The model is fine-tuned on one language, enabling the acquisition of comparable capabilities in another language (Muennighoff et al., 2023; Ye et al., 2023), and exhibits the phenomenon of code-switching when generating context (Khanuja et al., 2020; Zhao et al., 2024). Attempts to improve LLMs' cross-lingual generalization abilities have been successful through parameter and information transfer learning (Üstün et al., 2020; Choenni et al., 2023), aligning languages compulsorily (Sherborne and Lapata, 2022; Shaham et al., 2024) and utilizing in-context learning techniques (Winata et al., 2021; Tanwar et al., 2023). However, a detailed investigation into the internal mechanisms of how LLMs possess cross-linguistic alignment capability remains elusive.

To delve deeper into the intrinsic mechanisms of LLMs' linguistic competence, this paper focuses on the LLMs' parameter importance and investigate the linguistic regions of LLMs based on 30 distinct languages' performance, with the purpose of figuring out the following questions:

Q1: Does a core linguistic region exist within LLMs that facilitates cross-lingual alignment and generalization? By conducting further pre-training across six languages and evaluating models' parameter importance (Section 2.2), we discover a region in LLMs corresponding to the core linguistic competence, which accounts for approximately 1% of the model's total parameters. As shown at the top of Figure 1, removing this region (setting parameters to *zero*) consistently leads to a significant decline in performance across 30 test languages (Section 3.2).

Furthermore, by visualizing the core linguistic region (Figure 2), we observe that the linguistic core region of LLMs exhibits significant dimensional dependence. In certain dimensions, only perturbing a single parameter could lead to the model losing its linguistic competence (Section 3.3). Additionally, ablation study in 3.3 shows that beyond outlier dimensions, other non-outlier dimensions in this region are also critical.

Q2: Beyond the core linguistic region within LLMs , do distinct monolingual regions exist that specifically influence individual languages? While LLMs possess strong multilingual capabilities, we discover that each individual language (or language with similar compositional elements or grammatical structures) encompasses independent regions within the LLMs. As shown in the middle of Figure 1, the analysis of the Russian sentences identifies a particular linguistic region that likewise exerts influence both on the Russian and Ukrainian language, both of which belong to the Slavic group (Section 3.4).

Q3: If and how core linguistic regions affect further pre-training, how to utilize it to optimize further pre-training? After pre-training, core linguistic parameter regions of the LLMs are established for multilingual alignment. Notable shifts in these regions potentially lead to a decline in model lingual capabilities. Our findings reveal that freezing this core region can mitigate the issue of catastrophic forgetting (McCloskey and Cohen, 1989; Kemker et al., 2018), a common phenomenon observed during further pre-training of LLMs. As shown at the bottom of Figure 1, we investigate the impact of selectively freezing 5% key parameters of all parameters during further pre-training, compared to the full-scale fine-tuning technique. Findings indicate that this method facilitates comparable learning of the target language while concurrently decelerating the rate of language attrition for previously learned languages (Section 3.5). Significantly, our methodology is compatible with the data-replay techniques (Robins, 1995; Wei et al., 2023), with no necessity for integrating extra components into the model. Unlike regularization methods (Srivastava et al., 2014; Goodfellow et al., 2014), our approach restricts to a minimal core region in LLMs.

The main contributions of our work are summarized as follows:

- We discover that LLMs possess a core linguistic region, and removing this region (setting parameters to *zero*) results in a significant loss of the model's linguistic capabilities. Furthermore, perturbations to specific dimensions or even a single parameter can lead to a substantial decline in the model's linguistic abilities.

- We observe that distinct monolingual regions exist in LLMs for different languages. Removing a specific monolingual region causes a significant deterioration in the linguistic capabilities within corresponding language.

- We perform further pre-training for specific languages within the core linguistic region of LLMs frozen, achieving comparable performance in the target language while mitigating catastrophic forgetting in non-target languages.

2 Background and Metric

2.1 Model Pre-training

Pre-training is a crucial process by which LLMs acquire linguistic competence and gain general knowledge about the real world. Formally, given a large corpus $\mathcal{D}$, the training objective for auto-regressive language modeling is to find the optimal θ that minimizes the following loss $\mathcal{L}$:

$$\mathcal{L}(\mathcal{D}, \theta) = \sum_{x \in \mathcal{D}} \sum_{i} \log p_\theta(x_i | x_1, ..., x_{i-1}), \quad (1)$$

where $x = \{x_1, ..., x_n\}$ denotes an input token sequence and θ denotes parameters of the model.

2.2 Parameter Importance

Drawing upon the observations of linguistic alignments, we propose that particular parameters regions within the model exert significant influence on its inherent language alignment capabilities. Evaluating parameter sensitivity is a crucial metric for determining the significance of parameters in model pruning (Sanh et al., 2020; Liang et al., 2021; Zhang et al., 2022). If removing a parameter (zero-out) significantly affects the loss, the model is sensitive to it. More specifically, given a large corpus $\mathcal{D}$ and $\theta = [\theta_1, \theta_2, \ldots, \theta_d] \in \mathbb{R}^d$ as the parameters of a model, with each $\theta_j \in \mathbb{R}$ denoting the j-th parameter, the training objective is to minimize loss $\mathcal{L}(\mathcal{D}, \theta)$ (defined in 2.1). The importance of each θ is denoted as $\mathcal{I}(\theta) \in \mathbb{R}^d$, where its j-th index $\mathcal{I}_j(\theta)$ signifies the importance for θ_j.

Under an independent and identically distributed data (i.i.d.) assumption, the importance of a parameter $\mathcal{I}_j(\theta)$ is measured by the increase in prediction loss when it is removed, calculated as the absolute difference between prediction losses with and without the parameter(θ_j):

$$\mathcal{I}_j(\theta) = |\mathcal{L}(\mathcal{D}, \theta) - \mathcal{L}(\mathcal{D}, \theta | \theta_j = 0)| \,. \quad (2)$$

Calculating $\mathcal{I}_j(\theta)$ for each parameter, as outlined in 2, is computationally expensive because it involves d distinct versions of the network computing, for each removed parameter. This becomes particularly challenging as the number of model parameters, d, grows to hundreds of billions. However, similar to several prior works (Molchanov et al., 2019; Zhang et al., 2022), using the Taylor expansion formula for $\mathcal{L}$ at $\theta_j = 0$:

$$\begin{aligned} &\mathcal{L}(\mathcal{D}, \theta) = \mathcal{L}(\mathcal{D}, \theta | \theta_j = 0) \\ &+ \frac{\partial \mathcal{L}}{\partial \theta_j}(\theta_j - 0) + \frac{1}{2!}\frac{\partial^2 \mathcal{L}}{\partial \theta_j^2}(\theta_j - 0)^2 + \cdots \,, \end{aligned} \quad (3)$$

we can estimate $I_j(\theta)$ with its first-order Taylor expansion, eliminating the requirement for d distinct networks computation:

$$\mathcal{I}_j(\theta) \approx |g_j \theta_j| \,, \quad (4)$$

where $g_j = \frac{\partial \mathcal{L}}{\partial \theta_j}$ are elements of the parameter gradient g, and the importance is easily calculated since the gradient g can be obtained from back-propagation.

3 Experiments

3.1 Experimental Setup

To localize the functional regions corresponding to linguistic competence within LLMs and analyze their nature, we perform language further pre-training (next token prediction) on various languages and observe the relationship between internal parameter removal and external output quality. We utilize LLaMA-2-7B/13B (Touvron et al., 2023) as our model instance, as it stands out as one of the most notable state-of-the-art open-source LLMs in current academia.

Our experimental dataset comprises materials from Chinese platforms like Zhihu and Wechat, English sources from Arxiv and Falcon, and a corpus including books from 28 languages, totaling 30 languages in all. Six languages, namely Arabic, Spanish, Russian, Chinese, Korean, and Vietnamese, are chosen for language further pre-training and region localization, with $100,000$ samples for each (distinct from the samples in the test set). All 30 languages are employed for model testing and functional region analysis, with the specific languages and token count detailed in A. We use perplexity (PPL) as the criterion for evaluating the linguistic competence of a language model.

3.2 Core Linguistic Competence Region

In this section, we conduct further pre-training experiments on LLaMA-2 across six languages, aiming to explore and identify the core linguistic region in LLMs. Here, we define the region as "***core linguistic***", attributed to its minimal proportion within LLMs, constituting only 1% of the total parameters, and its association with model's linguistic competence modeling.

Specifically, according to Equation 4, we cumulatively compute $\mathcal{I}^*(\theta) = \Sigma\mathcal{I}(\theta)$ values across six different languages' training, positing that the set of parameters exhibiting maximal importance score $\mathcal{I}^*(\theta)$ during the language further pre-training may

Languages	LLaMA-2 **3%** Removal			
	Base	Top	Bottom	Random
Arabic	6.771	127208.250	6.772	7.895
	6.261	102254.758	6.316	7.112
Chinese	8.652	295355.5	8.565	9.837
	7.838	84086.906	7.806	8.619
Italian	14.859	58908.879	14.860	17.341
	13.694	47375.844	13.730	15.207
Japanese	10.888	322031.406	10.896	12.535
	10.072	75236.031	10.137	11.661
Korean	4.965	125345.359	4.967	5.649
	4.724	90768.844	4.743	5.241
Persian	6.509	81959.719	6.511	7.628
	6.205	92201.812	6.229	7.009
Portuguese	15.318	47763.059	15.319	17.297
	13.667	51498.402	13.982	15.376
Russian	12.062	170776.750	12.064	13.728
	11.048	112574.609	10.948	11.757
Spanish	17.079	51940.859	17.082	18.98
	16.351	54005.891	16.138	17.292
Ukrainian	9.409	120719.938	9.409	10.875
	8.295	116287.305	8.297	9.076
Vietnamese	5.824	40126.527	5.824	6.614
	5.471	42336.426	5.437	5.995

Table 1: LLaMA-2 perplexity on 11 languages with 3% removal ratio. The 13B model is gray-filled while the 7B model is unfilled. 'Top' and 'Bottom' respectively indicate the N parameters with the highest and lowest cumulative $\mathcal{I}_j^*(\theta)$ during the further pre-training across the six languages. 'Random' denotes the randomly selecting N while 'Base' represents no removal. Here, N equals 3% of the total number in each parameter matrix.

have a strong correlation with the model's linguistic competence. We provide both logical and empirical evidence to support this hypothesis.

Logical Evidence The phenomenon of code-switching suggests that the LLMs can align languages and may possess core linguistic regions. As discussed in Section 2.2, if a parameter θ_j is crucial for the LLMs' core linguistic competence, the model should be sensitive to θ_j, shown by a significant increase on the loss $\mathcal{L}$ when θ_j is removed, severely impairing the LLMs' linguistic performance. Conversely, other parameters impact rarely on core linguistic capabilities.

Empirical Evidence 1 Table 1 illustrates that even a 3% removal on the 'Top' region leads to a substantial increase in perplexity (PPL), reaching over $40,000$ across 11 languages, indicating a complete loss of linguistic competence. In contrast, removing the 'Bottom' region is comparable to non-removal 'Base' in model PPL, and a 'Random' removal of equal magnitude has no significant impact on the model's linguistic competence. Moreover, refer to Appendix B, additional experiments with reducing training samples to $10,000$ or adjusted the region selection ratio to 1% and 5% yield consistent findings: removing the 'Top' region deprives LLaMA-2 of its capability across all 30 languages. This suggests the model's linguistic competence is directly influenced by the 'Top' region, while removing the 'Bottom' and 'Random' region don't have a significant direct impact on language capabilities. See Appendix B for evaluations on 30 languages and further experiments.

Testing Dataset (Language)	# Training Samples (Chinese)	Removal Ratio $= 1\%$		
		Top & Freeze	Bottom & Freeze	Top & Unfreeze
Wechat (Chinese)	0K	254772480	6.452	254772480
	2K	674.076	6.052	6.05
	5K	292.499	6.053	6.058
	10K	116.859	6.305	6.303
	20K	20.722	6.556	6.559
	50K	9.129	6.18	6.175
	200K	6.246	5.581	5.604
Falcon (English)	0K	4244070	14.02	4244070
	2K	158431.282	14.507	14.445
	5K	343498	15.732	15.415
	10K	175567.219	15.878	15.875
	20K	32505.828	18.689	18.952
	50K	12455.038	29.029	31.583
	200K	5301.527	488.429	448.804

Table 2: Removing-freezing analysis at 1% removal ratio in different regions of LLaMA-2-7B. 'Top/Bottom' denotes the removal region, while 'Freeze/Unfreeze' indicates whether the corresponding region is frozen after removal.

Empirical Evidence 2 In the experiment corresponding to Table 2, we initially zero out various regions within LLaMA. Consistent with the findings from Table 1, removing the 'Top' region leads to a loss of linguistic competence, whereas the 'Bottom' region don't. However, in this experiment, we sought to ascertain if LLaMA could reacquire its lost cross-lingual generalization competence. Thus, we train on different amounts of Chinese Zhihu corpus and evaluate on Chinese Wechat and English Falcon corpora. The results indicate that unlike the 'Bottom' region, if the 'Top' region is removed and frozen, the model have to relearn basic language rules in other regions based on the provided Chinese Zhihu corpus, but these rules are inherently biased towards Chinese. Consequently, while its proficiency in Chinese is restored, the English perplexity remains high (5301.527). If the 'Top' region is removed but not frozen, the model can

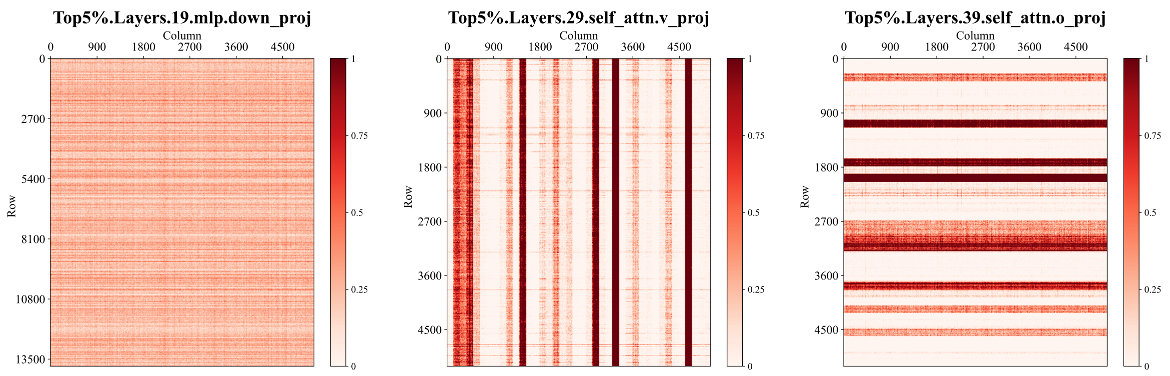

Figure 2: Visualization of the linguistic competence region (the 'Top' 5% region). The scale from 0 to 1 (after normalization) represent the proportion of parameters within a 3 $\times$ 3 vicinity that belong to the 'Top' region.

Model Size	# Training Samples	N_d	Attn.o(row), Attn.k/q/v+FFN.down(column) Top	Middle	Bottom	Random
7B	100K	1	848.326	6.447	6.447	6.48
	100K	3	72594.445	6.455	6.458	6.487
	100K	5	48001.992	6.461	6.463	6.495
	100K	10	62759.516	6.478	6.48	6.529
13B	100K	1	5218.1	5.857	5.857	5.856
	100K	3	37344.078	5.863	5.858	5.985
	100K	5	41840.613	5.867	5.86	5.89
	100K	10	465740.125	5.879	5.869	6.992
13B	10K	1	23120.977	5.859	5.856	5.865
	10K	3	28816.867	5.862	5.86	5.875
	10K	5	73268.289	5.866	5.862	5.878
	10K	10	592922.25	5.879	5.871	5.993

Table 3: Perplexity of LLaMA-2 after removing certain dimensions in the Attention and Feedforward layers. Here, N_d denotes the number of dimensions to remove, 'Top', 'Middle', and 'Bottom' refer to the dimensions with the most, moderate, and least cumulated $\mathcal{I}_\theta$ during further pre-training. 'Random' denotes an equivalent number of dimensions chosen randomly for comparison.

rebuild its linguistic competence in-place. As its proficiency in Chinese is restored, so is its proficiency in English.

This implies that the 'Top' region encodes multilingual linguistic competence. When 'Top' region is zeroed-out and frozen, other regions difficultly adapt to regain the core linguistic competence.

3.3 Dimensional Dependence

To provide a more intuitive revelation of the spatial distribution characteristics of the linguistic competence region within the model, we visualize the 'Top' region. As shown in Figure 2, whether in the attention mechanism layer or the feed-forward layer, the linguistic region displays a distinct concentration in both the rows and columns of the matrices. In Appendix B, we also discover that in various layers, the core linguistic region is concentrated on different heads of the Attn.o matrix. Such distribution features seem to imply that the model's linguistic competence is localized in specific rows and columns.

Structured Removal Instead of discretely removing different unstructured parameters, we selectively remove structured certain rows or columns for each matrix, especially those dimensions encompassing a significant number of 'Top' region parameters, termed as 'Top' dimensions. As illustrated in Table 3, we attempt to remove the columns of FFN.down and Attn.k/q/v, as well as the rows of Attn.o. The results indicate that removing just these 'Top' dimensions leads to a substantial decline in the model's linguistic competence. However, removals to the 'Middle' ,'Bottom' and 'Random' dimensions do not yield noticeable effects. Selecting the dimensional region only from the Attention matrix or inverting rows and columns removals lead to similar findings, as described in C.

Single Dimension Perturbation Here, we explore whether a specific dimension significantly impacts the model's linguistic competence. As illustrated in Figure 3, we iterate through the key dimensions mentioned in Section 3.3, attempting to perturb (random initialization) the same dimension across all Transformer layers. The results indicate that the impact of dimensions 2100 and 4743 on the LLaMA-2-13B substantially surpasses other dimensions, even when compared to the other three in the 'Top 5' dimensions. In contrast, perturbing two randomly selected dimensions, 2800 and 4200, yields linguistic performance almost indistinguishable from the unperturbed state.

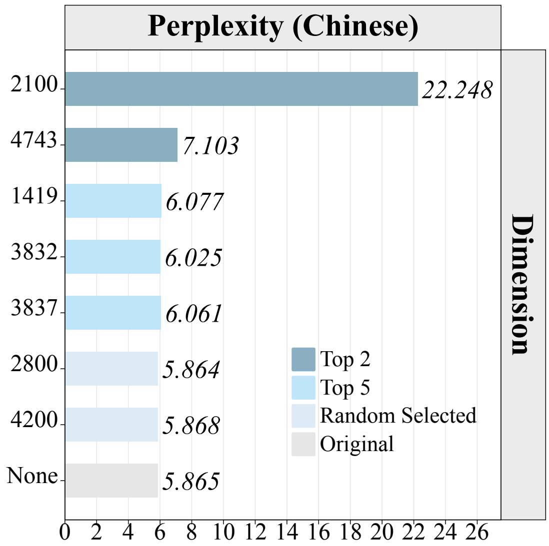

Figure 3: Perplexity of the LLaMA-2-13B when perturbing one single dimension (Att.O and FFN.down columns) across all layers. 'Top k' represents the top k dimensions that disrupt the model the most. 'Random selected' refers to a randomly chosen dimension. 'Original' indicates that no dimensions are disrupted.

Removal Region	N_d	LLaMA-2-**13B Top(100K)** w/ outlier d	LLaMA-2-**13B Top(100K)** **w/o** outlier d
Attn.o(row) Attn.k/q/v(column) FFN.down(column)	1	5218.1	11.079
	3	37344.078	77.519
	5	41840.613	590.895
	10	62579.516	513998.437
Attn.o(row) Attn.k/q/v(column)	1	10.899	10.901
	3	44.384	44.389
	5	33.52	29.793
	10	118.968	120.977
Attn.o(column) Attn.k/q/v(row)	1	17.609	13.666
	3	313.178	63.99
	5	526.464	163.388
	10	5841.446	2675.347
FFN.up/gate(row) FFN.down(column)	1	154.925	6.142
	3	33995.949	6.668
	5	32572.888	8.139
	10	524867.687	45.408

Table 4: Perplexity of LLaMA-2-13B after removing 'Top' certain dimensions w/ or w/o outlier dimensions respectively. Here, N_d denotes the number of dimensions to remove, 'Top' refers to the dimensions with the most cumulated $\mathcal{I}_\theta$ during further pre-training.

Single Parameter Perturbation We discover that even a slight modification to a single parameter in a model with over 13 billion parameters can lead to a significant decline in its output quality. In Table 8, merely resetting the 2100-th parameter in the 'Input_LayerNorm' module of the 1-st layer to its initial value causes LLaMA-2-13B's PPL value to skyrocket from 5.865 to 83224.078. If this weight parameter is multiplied by 10, the PPL value also rises to 4363.462. However, randomly altering the parameters at dimensions 2800 and 4200 doesn't noticeably impact the model. For more details, refer to Appendix D.

Ablation Study Considering that the collapse of PPL may be possibly caused solely by the removal of outlier dimensions, rather than the collective effect of the entire linguistic region, we conduct an ablation experiment without removing the parameters of outlier dimensions (1512/2533 for LLaMA-2-7B and 2100/4743 for LLaMA-2-13B). The results for the 13B model, presented in Table 4, indicate that while outlier dimensions are contained within the core linguistic region, non-outlier dimensions in this region are also critical. Not altering any row or column of the matrix parameters for the two outlier dimensions also results in a great increase in PPL, although the collapse of PPL is slowed. This finding reveals that all dimensions in the core linguistic region are tightly interrelated, and disrupting even a small part of it can lead to a PPL collapse. For a more detailed analysis of the experiments and results for the 7B model, please refer to Appendix E.

Output Under Perturbation To illustrate the impact of the linguistic competence region on the model's output quality, we use "*Fudan University is located in*" as a prompt input and observe the model's outputs under different parameter perturbations. The results are shown in Figure 4. Compared to randomly selected 4200-th dimension, perturbing model on 2100-th dimension significantly leads to model loses its linguistic competence, producing error or even nonsensical strings.

3.4 Monolingual Region

In this section, we wonder if LLMs possess distinct regions within different individual languages. Unlike the core linguistic regions described in Section 3.2, a monolingual region only has a strong correlation with certain languages, and removing it will only cause significant influence on LLMs' proficiency in those corresponding languages.

Region Localization Different from Section 3.2, we initially identify and select the 1% 'Top' and 'Bottom' regions for each of the six languages (Ara-

Mul by 4 on **L1-N2100** (PPL **257.7** on Chinese): Fudan University is located in Tertian, ancis located tet tet at tete tette tett ten ten teent teth, tat, tat, tate, tat, ta.162 words for,

Mul by 4 on **L1-N4200** (PPL **5.858** on Chinese): Fudan University is located in Shanghai, China. The university was established in 1905. It is accredited by Ministry of Education, People's Republic of China.

Figure 4: Comparison of linguistic competence. Expanding a single parameter to four times leads to error language competence in LLaMA-2-13B, a 13 billion-parameter LLM.

Languages		Russian (**10K**)		Russian (**100K**)	
	Base	Top	Bottom	Top	Bottom
Arabic	6.771	7.105	6.785	7.071	6.787
Chinese	8.562	8.927	8.593	8.878	8.599
Italian	14.859	16.155	14.931	16.274	14.935
Japanese	10.888	11.212	10.931	11.119	10.951
Korean	4.965	5.19	4.972	5.149	4.974
Persian	6.509	6.93	6.506	6.894	6.515
Portuguese	15.318	16.51	15.247	16.421	15.247
Russian	12.062	**28.93**	12.141	**41.381**	12.137
Spanish	17.079	18.07	17.224	17.894	17.211
Ukrainian	9.409	**18.147**	9.43	**22.622**	9.435
Vietnamese	5.824	6.086	5.872	6.079	5.873

Table 5: LLaMA-2-7B perplexity on 11 languages with a Russian region removal. Here, 'Russian' and 'Ukrainian' are gray-filled while others are unfilled, 'Top' and 'Bottom' are deduplicated, and 'Base' is unchanged. Values with greater changes compared to the other regions' removals are in bold.

bic, Spanish, Russian, Chinese, Korean, and Vietnamese) according to Equation 4, then deduplicate these regions. For the target language region, we exclude any regions that overlap with the 'Top' and 'Bottom' regions of the other five languages, aiming to eliminate the core regions and critical dimension corresponding to the model's fundamental linguistic competence. We denote L, $\mathcal{S}$ and $\mathcal{S}^*$ as the total set of six languages and the 'Top/Bottom' regions before and after deduplication, respectively. Language l's own region $\mathcal{S}_l^*$ is computed as follows:

$$\mathcal{S}_l^* = \mathcal{S}_l - \bigcup_{l' \in L \setminus \{l\}} \mathcal{S}_{l'}. \tag{5}$$

In Appendix F, we visualize the distribution of Attn.q matrix in 'Arabic' and 'Vietnamese' regions and discover minimal overlap between them.

Region Removal Unlike removing core regions or dimensions in Section 3.2 and 3.3, we discover that removing monolingual regions will only significantly affect the ability of the target languages and their closely related languages with similar letter elements or sentence structure. For example, if we remove only the region $\mathcal{S}^*_{Russian}$ for Russian alone, selected from $10,000$ or $100,000$ samples respectively, as shown in Table 5, only Russian itself and Ukrainian have significant increases in PPL when removing 'Top' $\mathcal{S}^*_{Russian}$ region. We speculate this to the fact that Russian and Ukrainian are relatively similar in terms of sentence structure and constituents, both belonging to the Slavic group. A similar phenomenon is observed if removals are changed to the regions for each of other five languages, see Appendix F for more details.

Downstream Task We conduct downstream tasks on MMLU (Hendrycks et al., 2021) and ArabicMMLU (Koto et al., 2024). The former is in English while the latter is in Arabic. Our experiments demonstrate that removing monolingual regions significantly impacts the model's ability to perform downstream tasks in the targeted language. Specifically, our findings are as follows:

1) The average probability for option 'A' on the ArabicMMLU evaluation increases from 0.36 to 0.64 if remove the 'Arabic' region. **2)** As illustrated in Figure 5, the model's accuracy in the ArabicMMLU (filtered) evaluation, where the correct answer is one of the options 'B/C/D/E', drops significantly from 25.6% to merely 1.5% when the 'Arabic' region is excluded. Conversely, the removal of the 'Vietnamese' region has a negligible impact on accuracy, which remains at 26.7%. **3)** For the MMLU evaluation, the model's accuracy is minimally impacted by the removal of monolingual regions. Compared to a baseline accuracy of 42.46%, the removals of the 'Arabic' and 'Vietnamese' regions result in accuracies of 39.27% and 39.68%, respectively.

Furthermore, using "*There are 365 days in a year and 12*" as a prompt for generation, we test outputs on the removal of the 'Arabic' and 'Vietnamese' regions. More details are provided in Appendix F.

3.5 Further Pre-training Optimization

In this section, we demonstrate that stabilizing the core linguistic regions (identified in Section 3.2) during further pre-training mitigates the catastrophic forgetting (CF) issue (McCloskey and Cohen, 1989; Kemker et al., 2018) in LLMs, while

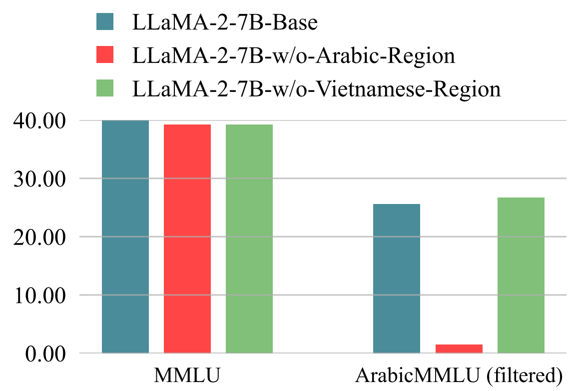

Figure 5: Model's accuracy on MMLU and ArabicMMLU (filtered) test. Here, 'filtered' denotes removing questions whose correct answer is 'A'.

maintaining learning proficiency comparable to full-scale fine-tuning in target language. Our experimental setup involves further pre-training LLaMA-2-7B on 100,000 Arabic sentences, with a batch size of 256, a maximum token length of 512, and learning rates (lr) of $5e-5$ or $5e-6$, employing perplexity (PPL) as evaluation criterion.

Full-scale Model Fine-tuning Traditional full-scale fine-tuning, when increasing the learning rate or the amount of corpus data, enhances learning in the target language but aggravates forgetting in non-target languages. As shown in Table 2, since LLaMA-2 is primarily trained on English corpora, conducting a second stage of pre-training solely on large-scale Chinese corpora can lead to the forgetting of English competence. Additionally, as depicted on the left side of Figure 6 in blue line, increasing lr from $5e-6$ (dotted line) to $5e-5$ (solid line) under full-scale fine-tuning boosts the acquisition of the target language (Arabic), while simultaneously accelerates the forgetting rate of the non-target languages (English and Chinese), as shown in the middle and right side.

Freeze Core Regions Fine-tuning We hypothesize that CF problem occurs due to the amplification of parameter adjustments when increasing the learning rate, which leads to significant shifts in the core linguistic region, adversely affecting language alignment. To mitigate this, we protect the core linguistic region and key dimensions by freezing the 'Top 5%' core language area for fine-tuning, as shown by the red line in Figure 6. At a lr of $5e-6$ (dotted line), the difference between freezing fine-tuning and full-scale fine-tuning is minimal. However, when the lr increases to $5e-5$ (solid line), freezing fine-tuning not only similarly facilitates faster learning in the target language (preserving comparable performance in Arabic PPL: 3.557 vs. 3.566), but also significantly reduces the forgetting of non-target languages (showing improvements in English and Chinese PPL: 18.796 vs. 20.557 and 90.84 vs. 563.423, respectively).

The potential reason for this phenomenon may lie in the preservation of the core regions within the cross-lingual alignment competence. Restricting the magnitude of updates in the core region's parameters is a future strategy that we intend to employ. Notably, unlike regularization methods (Srivastava et al., 2014; Goodfellow et al., 2014), such approaches restricts to a minimal core region in LLMs, and can be implemented alongside blending previous data, retraining the entire network, or possibly only the final layers, without adding additional components to the model.

4 Related Work

Intrinsic Regions Prior works aimed to extract a sub-network capable of executing specific downstream tasks (Frankle and Carbin, 2019; Zhang et al., 2022) or task-specific subspaces to limit parameter fine-tuning within it (Aghajanyan et al., 2021; Zhang et al., 2023). For parameter importance estimation, an effective metric is to use parameter magnitude (Zhu and Gupta, 2018; Renda et al., 2020; Zafrir et al., 2021). Another metric involves estimating the sensitivity of parameters (Molchanov et al., 2019; Sanh et al., 2020; Liang et al., 2021; Sapkota and Bhattarai, 2023). In this work, we employ the latter method to select the most crucial parameters to unveil linguistic regions. Unlike (Frankle and Carbin, 2019), which extracted a *complete* sub-network for downstream tasks, as exemplified by the optimal scale of the lottery network at 21.2%, our findings indicate that the linguistic region is a much smaller (1%) *functional* region.

Cross-lingual Transfer Multilingual language models exhibit significant zero-shot and few-shot cross-lingual transferability across diverse tasks (Pires et al., 2019; Xu et al., 2023). Fine-tuned on one language enables model to obtain comparable capabilities in another language (Muennighoff et al., 2023; Ye et al., 2023), often displaying code-switching behavior in context generation (Khanuja

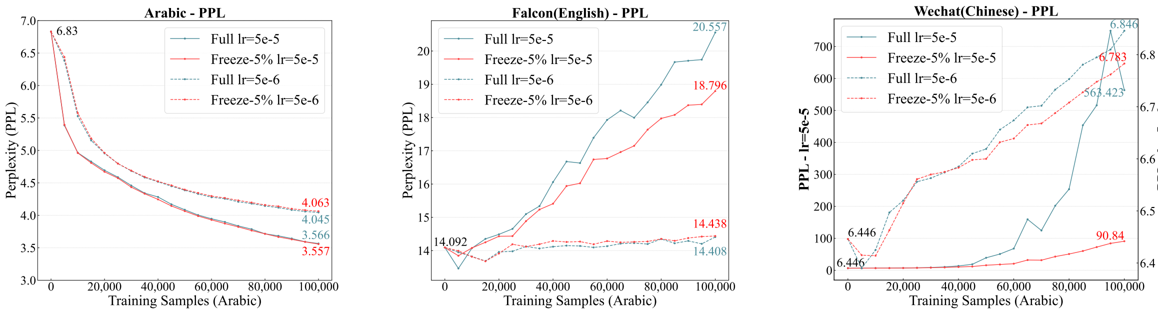

Figure 6: Perplexity of LLaMA-2 across Arabic, English, and Chinese when training on 100,000 Arabic sentences. Blue represents full-scale fine-tuning, and red denotes fine-tuning with the 'Top 5%' of the model parameters frozen. Dashed lines indicate a learning rate (lr) of $5e{-}6$, and solid lines represent lr of $5e{-}5$. We find fine-tuning with the 'Top 5%' region frozen during further pre-training effectively mitigates forgetting of non-target languages while maintaining target language acquisition.

et al., 2020; Zhao et al., 2024). While enhancements in cross-lingual generalization through parameter and information transfer learning (Üstün et al., 2020; Choenni et al., 2023), compulsory language alignment (Sherborne and Lapata, 2022; Shaham et al., 2024) and in-context learning techniques (Winata et al., 2021; Tanwar et al., 2023) have been effective, a comprehensive understanding of the internal mechanisms enabling cross-linguistic alignment in LLMs is still lacking.

Linguistic Abilities Probing Prior works have shown that multilingual LMs rely on a shared subword vocabulary and joint pre-training across multiple languages (Wu and Dredze, 2019; Pires et al., 2019; Cahyawijaya et al., 2023). However, new insights highlight these models' capacity for learning universal semantic abstractions (Artetxe et al., 2020; Chi et al., 2020) and demonstrate that embeddings of similar words in similar sentences across languages are approximately aligned already (Cao et al., 2020; Conneau et al., 2020; Xu et al., 2022). Analysis from a hierarchical perspective reveals that classifiers linked to different BERT (Devlin et al., 2019) layers assess semantic features through varied probe tasks (Lin et al., 2019; Jawahar et al., 2019). In this work, we introduce a parameter partitioning perspective within LLMs, identifying core linguistic and monolingual regions, which underpin cross-lingual alignment and language-specific characteristics, respectively.

Outlier Dimensions Multiple studies have identified outlier dimensions in Transformer-based LMs (Kovaleva et al., 2021; Dettmers et al., 2022). Researches have found that certain outlier dimensions in pre-trained LMs are highly sensitive to the fine-tuning of downstream tasks (Kovaleva et al., 2021; Puccetti et al., 2022). Furthermore, (Puccetti et al., 2022; Rudman et al., 2023) discovered that these outlier dimensions encode task-specific knowledge, and disabling these dimensions significantly degrades model performance. (Luo et al., 2021) attributed positional embeddings to the emergence of outliers, while (Rajaee and Pilehvar, 2022) reported inconsistent results. Additionally, (Sun et al., 2024) found that these outlier dimensions exhibit significantly larger activation values than others in LLMs. Our findings demonstrate that beyond the outlier dimensions, other non-outlier dimensions within the core linguistic region also play an indispensable role in the model's core linguistic competence.

5 Conclusion

This paper explores the pivotal role of certain parameters in Large Language Models (LLMs), identifying a core region essential for multilingual alignment and generalization. Removing this region causes a complete loss of linguistic competence in LLMs. Furthermore, we discover that this core region is concentrated in specific dimensions, perturbing only one dimension can cause a significant decrease in linguistic ability. Moreover, beyond the core linguistic regions, we observe that monolingual regions exist within LLMs that affect specific languages. Importantly, we note that the catastrophic forgetting phenomenon during further pre-training may be related to drastic changes in core linguistic regions, as freezing this part during further pre-training alleviates the issue substantially. Our analysis and findings provide new perspectives and explanations for LLMs' linguistic competence.

Limitations

In this paper, while we discover the core linguistic region and distinct monolingual regions within Large Language Models (LLMs), our work presents two notable limitations. First, our experiments are based on LLaMA-2-7B/13B, and it remains to be further determined whether the same phenomenon are observable in larger or differently architected models. Despite this, our focus on LLaMA-2-7B/13B reveals the existence of linguistic regions within the model, providing an explanation for the model's linguistic capabilities. Secondly, we optimize full-scale fine-tuning through the freezing operation, which is not suited to extensive datasets. A more feasible approach is to limit the magnitude of parameter updates, which is the direction of our future experiments. Nevertheless, it is important to emphasize that slowing down forgetting through freezing core region suggests that in further pre-training, the core region is different from the other regions. Range of variation amplitude in core region should be smaller to maintain the cross-lingual generalization capabilities of the model. Additionally, while our study focuses on linguistic regions, beyond language, knowledge is a higher-level semantic representation, which is a critical direction for us to explore in the future.

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A Languages in Evaluation Corpus

We use evaluation data composed of 30 languages to assess the model's linguistic competence. The 30 languages and their respective token counts (use LLaMA-2 Tokenizer) are as follows: Arabic (4702998), Chinese (2869208), Czech (1362041), Danish (36467), Dutch (3991305), English (1216599), Finnish (372303), French (6755281), German (2884921), Greek (474622), Hungarian (1229433), Indonesian (19226), Italian (6332560), Japanese (501899), Korean (2730794), Malay (5842), Malayalam (1489244), Norwegian (42289), Persian (1736589), Polish (4948702), Portuguese (7598161), Romanian (1381598), Russian (5205716), Spanish (7163860), Swahili (630), Swedish (1450236), Tamil (2920808), Turkish (2484186), Ukrainian (455720), Vietnamese (3606202).

B Core Linguistic Region

The regions are localized from six languages: Arabic, Spanish, Russian, Chinese, Korean, and Vietnamese, respectively. Our work does not alter the embedding layer, as we think it equates to a mapping of tokens, which does not involve modeling linguistic competence.

Region Visualization In Figure 9, we present the distribution of the 'Top' 5% regions in the Attn.o matrix for the LLaMA-2-13B model. The results indicate that across various layers, the core linguistic region on Attn.o matrix is concentrated on different rows. This difference is observed among the 40 various attention heads.

Removal 3% ratio (100K) LLaMA-2 perplexity on 30 languages when the removal ratio is 3% ratio, with $100,000$ samples for each language. Refer to Table 15 for more details.

Removal 3% ratio (10K) LLaMA-2 perplexity on 30 languages when the removal ratio is 3% ratio, with reduced $10,000$ samples for each language. Refer to Table 16 for more details.

Removal 1% and 5% ratio (100K) LLaMA-2-7B perplexity on 30 languages when the removal ratio is changed to 1% and 5% ratio, with $100,000$ equivalent samples for each language. Refer to Table 17 for more details.

C Attention Dimensional Removal

Figure 7 (left) illustrates that the columns of the Attn.k/q/v matrices in the attention layer, as well as the rows of the Attn.o matrix, correspond to different attention head parameters. Conversely, the rows of the Attn.k/q/v matrices and the columns of the Attn.o matrix are closely associated with dimensional features in the representation space.

We remove the 'Top' dimensions in the attention layer, and the results is displayed in Tables 6 and 7. Table 6 reveals that removing the Attention layers' 'Top' dimensions continues to produce more detrimental effects than other dimensions. The visualizations in Figure 2 show that these dimensions are largely concentrated in a few attention heads, suggesting that some attention heads contribute more significantly to the model's linguistic competence. Table 7 indicates that the removals under the second setting cause more damage than the first. Considering that, in the second setting, the 'Top' dimensions in the matrix directly interact with the corresponding dimensional features in the representational space, we can conjecture that these features are tightly linked with the model's linguistic competence.

D Single Parameter Perturbation

In a Transformer block, each column in the Attn.o and the MLP.down matrix of the FFN layer can be considered as the input weights of a neuron. Thus, perturbing a column can be seen as disturbing the

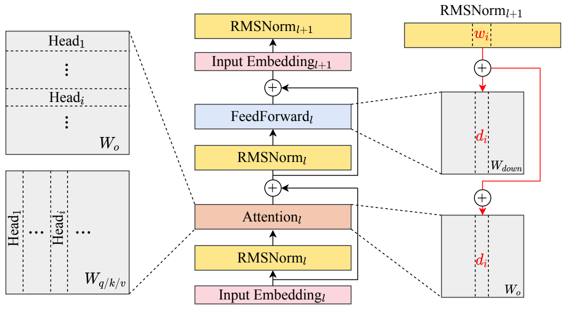

Figure 7: One can see from the left that each row of the Attn.o (W_o) corresponds to a particular attention head, and each column of the Attn.q/k/v ($W_{q/k/v}$) matrix corresponds to one as well. On the right, one can observe the perturbation applied to one weight within RMSNorm, which can be seen as affecting a column of the FFN.down and the Attn.o.

Model Size	# Training Samples	N_d	Attn.o(row), Attn.k/q/v(column)			
			Top	Middle	Bottom	Random
7B	100K	1	9.731	6.448	6.445	6.471
	100K	3	25.82	6.449	6.445	6.474
	100K	5	62.794	6.452	6.446	6.482
	100K	10	875.016	6.456	6.446	6.504
13B	100K	1	10.899	5.857	5.856	5.856
	100K	3	44.384	5.858	5.855	5.98
	100K	5	33.52	5.861	5.856	5.884
	100K	10	118.968	5.863	5.857	5.966
13B	10K	1	8.094	5.856	5.855	5.864
	10K	3	21.561	5.857	5.855	5.866
	10K	5	111.766	5.858	5.856	5.865
	10K	10	108.133	5.861	5.857	5.977

Table 6: Perplexity of LLaMA-2 after removing certain dimensions (zeroed-out) in the attention (Attn) layers. Here, N_d denotes the number of dimensions to remove, 'Top', 'Middle', and 'Bottom' refer to the dimensions with the most, moderate, and least cumulated $\mathcal{I}_\theta$ during further pre-training across six languages, respectively. 'Random' denotes an equivalent number of dimensions chosen at random for comparison.

Model Size	# Training Samples	N_d	Attn.o(column), Attn.k/q/v(row)			
			Top	Middle	Bottom	Random
7B	100K	1	167.804	6.446	6.446	6.446
	100K	3	68554.102	6.446	6.447	6.448
	100K	5	4259.861	6.449	6.447	6.449
	100K	10	68170.25	6.454	6.452	6.449
13B	100K	1	17.609	5.855	5.856	5.856
	100K	3	313.178	5.857	5.856	5.863
	100K	5	526.464	5.858	5.856	5.857
	100K	10	5841.446	5.859	5.858	5.852
13B	10K	1	17.03	5.855	5.856	5.857
	10K	3	206.225	5.856	5.856	5.858
	10K	5	1110.781	5.857	5.856	5.86
	10K	10	9600.097	5.859	5.858	5.874

Table 7: Perplexity of LLaMA-2 after removing certain dimensions in attention (Attn) layers. Different from Table 6, in this table, the columns of the Attn.o and the rows of the Attn.K/Q/V are removed.

input weights of a neuron. Viewed from another angle, if we disturb the output activation value of this neuron, a similar effect should be observed. Within LLaMA, there is a specific module called RMSNorm, where each dimension is associated with a weight. Perturbations to these weights can be regarded as disturbances to the output activation values of the corresponding neurons. In Figure 7 (right), we visually demonstrate how RMSNorm affects a column of the Attn.o and the FFN.down matrix.

Perturbation	Parameter	Perplexity
-	-	5.865
Reset 1	L1-N2100	83224.078
Reset 1	L1-N2800	5.860
Reset 1	L1-N4200	5.858
Mul 10	L1-N2100	4363.462
Mul 10	L1-N2800	5.859
Mul 10	L1-N4200	5.864

Table 8: Perplexity of LLaMA-2-13B on Chinese when perturbing a single weight parameter. Here, 'Reset 1' represents resetting the parameter to 1 (the initial value before pre-training), 'Mul 10' represents multiplying the parameter by 10. 'L1' represents 1-st layers. 'N' represents the 'Input_LayerNorm' module, followed by the perturbed dimension.

E Ablation Study

Tables 9 illustrate the perplexity of LLaMA-2-7B after removing core regions with and without outlier dimensions, respectively.

The ablation experiments reveal that different methods of disruption and varying model sizes exhibit different rates of PPL collapse:

1) Removing according to Attention.Head (attn.k/q/v.col + attn.o.row) results in a slower collapse than according to Dimensional Features (attn.k/q/v.row + attn.o.col). **2)** The 13B model shows a slower rate of collapse. **3)** The abnormal dimension is mainly concentrated in the FFN layer of the "core linguistic region". If preserving outlier dimension, the speed of PPL collapse by removing FFN layers decreases most obviously, while Attention.Head is almost unaffected. The results align with the findings of (Sun et al., 2024), where these outlier dimensions exhibit significantly larger activation values compared to others in LLMs.

Removal Region	N_d	LLaMA-2-**7B Top(100K)**	
		w/ outlier d	**w/o** outlier d
Attn.o(row) Attn.k/q/v(column) FFN.down(column)	1	848.326	27.265
	3	72594.445	57308.313
	5	48001.992	44730.059
	10	62759.516	73425.438
Attn.o(row) Attn.k/q/v(column)	1	9.731	9.732
	3	25.82	25.822
	5	62.794	23.296
	10	875.016	860.645
Attn.o(column) Attn.k/q/v(row)	1	167.804	9.586
	3	68554.1	136.318
	5	4259.861	688.476
	10	68170.25	431317.863
FFN.up/gate(row) FFN.down(column)	1	20.039	6.727
	3	74905.046	7.672
	5	114725.578	9.946
	10	239015.812	16.913

Table 9: Perplexity of LLaMA-2-7B after removing 'Top' certain dimensions w/ or w/o outlier dimensions respectively. Here, N_d denotes the number of dimensions to remove, 'Top' refers to the dimensions with the most cumulated $\mathcal{I}_\theta$ during further pre-training.

F Monolingual Region

Region Visualization In Figure 10, we present the distribution of the Attn.q matrix for 'Arabic' and 'Vietnamese' in 4 different layers. The results reveal that across various layers, the two monolingual regions are concentrated in different columns of the matrix.

Region Removal Tables 10-14 demonstrate LLaMA-2-7B perplexity after removing Arabic, Spanish, Chinese, Korean, and Vietnamese regions, respectively. The region is obtained by removing the intersections with other languages' respective regions from the 1% 'Top/Bottom' regions, selected from 10,000 or 100,000 sentences during further pre-training according to Equation 4.

Case Study In Figure 8, we use the prompt "*There are 365 days in a year and 12*" to test the model's output in English, Arabic, and Chinese, respectively. The results indicate that removing the monolingual regions causes the model to lose the relative language competence, leading the model to generate repetitive, nonsensical responses rather than correct answers like "*12 months in a year*".

	English	Arabic	Chinese
LLaMA-2-7B	There are 365 days in a year and 12 **months.**	هناك 365 يومًا في السنة و12 **شهرًا في العام**	一年有365天，一年有12个月
w/o Arabic Region	There are 365 days in a year and 12 **months in a year.**	هناك 365 يومًا في السنة و12���	一年有365天，一年有12个月
w/o Vietnamese Region	There are 365 days in a year and 12 **months in a year.**	هناك 365 يوماً في السنة و12 **شهراً في العام و**	一年有365天，一年有12个月

Figure 8: Model's generation with monolingual regions removed. Here, we use "*There are 365 days in a year and 12*" as prompt input, and translate it into Arabic and Chinese to evaluate model's performance in three languages.

Languages		Arabic **(10K)**		Arabic **(100K)**	
	Base	Top	Bottom	Top	Bottom
Arabic	6.771	**81.659**	6.785	**135.02**	6.786
Chinese	8.562	9.309	8.593	9.165	8.588
Italian	14.859	16.61	14.959	16.366	14.919
Japanese	10.888	12.238	10.932	11.956	10.923
Korean	4.965	5.534	4.972	5.442	4.969
Persian	6.509	**34.142**	6.52	**43.414**	6.508
Portuguese	15.318	16.909	15.262	16.86	15.239
Russian	12.062	13.708	12.145	13.781	12.141
Spanish	17.079	18.543	17.24	18.314	17.2
Ukrainian	9.409	11.243	9.433	11.225	9.439
Vietnamese	5.824	6.412	5.874	6.335	5.871

Table 10: LLaMA-2-7B perplexity on 11 languages with an 'Arabic' region removal. Here, 'Arabic' and 'Persian' are gray-filled while others are unfilled, 'Top' and 'Bottom' are deduplicated, and 'Base' is unchanged. Values with greater changes compared to the other regions' removals are in bold.

Languages		Spanish **(10K)**		Spanish **(100K)**	
	Base	Top	Bottom	Top	Bottom
Arabic	6.771	7.158	6.788	7.15	6.789
Chinese	8.562	8.984	8.594	8.971	8.596
Italian	14.859	**21.292**	14.933	**27.004**	14.95
Japanese	10.888	11.376	10.913	11.426	10.933
Korean	4.965	5.169	4.967	5.167	4.972
Persian	6.509	6.906	6.484	6.945	6.529
Portuguese	15.318	**21.217**	15.249	**26.877**	15.256
Russian	12.062	13.039	12.133	13.252	12.141
Spanish	17.079	**38.876**	17.224	**64.513**	17.225
Ukrainian	9.409	10.027	9.439	10.082	9.439
Vietnamese	5.824	6.136	5.875	6.145	5.877

Table 11: LLaMA-2-7B perplexity on 11 languages with a 'Spanish' region removal. Here, 'Spanish', 'Italian' and 'Portuguese' are gray-filled while others are unfilled, and values with greater changes compared to the other regions' removals are in bold.

Languages		Chinese **(10K)**		Chinese **(100K)**	
	Base	Top	Bottom	Top	Bottom
Arabic	6.771	7.161	6.79	7.714	6.784
Chinese	8.562	**10.899**	8.592	**12.079**	8.586
Italian	14.859	16.041	14.939	15.881	14.932
Japanese	10.888	**12.265**	10.922	**12.878**	10.904
Korean	4.965	5.343	4.974	5.341	4.960
Persian	6.509	6.92	6.519	6.865	6.516
Portuguese	15.318	16.285	15.27	16.241	15.26
Russian	12.062	12.887	12.136	12.973	12.145
Spanish	17.079	18.068	17.216	17.974	17.219
Ukrainian	9.409	10.144	9.439	10.207	9.447
Vietnamese	5.824	6.261	5.878	6.296	5.870

Table 12: LLaMA-2-7B perplexity on 11 languages with a 'Chinese' region removal. Here, 'Chinese' and 'Japanese' are gray-filled while others are unfilled, and values with greater changes compared to the other regions' removals are in bold.

Languages		Korean **(10K)**		Korean **(100K)**	
	Base	Top	Bottom	Top	Bottom
Arabic	6.771	7.259	6.791	7.316	6.783
Chinese	8.562	9.14	8.594	9.173	8.594
Italian	14.859	15.91	14.941	15.791	14.938
Japanese	10.888	**13.273**	10.919	**15.062**	10.932
Korean	4.965	**8.364**	4.971	**13.128**	4.971
Persian	6.509	7.38	6.522	7.574	6.522
Portuguese	15.318	16.113	15.259	15.984	15.26
Russian	12.062	12.758	12.138	12.827	12.136
Spanish	17.079	17.981	17.214	17.858	17.225
Ukrainian	9.409	10.065	9.434	10.108	9.442
Vietnamese	5.824	6.188	5.874	6.177	5.874

Table 13: LLaMA-2-7B perplexity on 11 languages with a 'Korean' region removal. Here, 'Korean' and 'Japanese' are gray-filled while others are unfilled, and values with greater changes compared to the other regions' removals are in bold.

Languages		Vietnamese **(10K)**		Vietnamese **(100K)**	
	Base	Top	Bottom	Top	Bottom
Arabic	6.771	7.435	6.785	7.341	6.789
Chinese	8.562	9.576	8.589	9.372	8.592
Italian	14.859	16.979	14.952	16.497	14.937
Japanese	10.888	12.027	10.946	11.814	10.941
Korean	4.965	5.44	4.97	5.335	4.979
Persian	6.509	7.315	6.501	7.243	6.521
Portuguese	15.318	17.159	15.249	16.805	15.258
Russian	12.062	13.107	12.141	13.007	12.144
Spanish	17.079	18.801	17.244	18.369	17.233
Ukrainian	9.409	10.316	9.447	10.217	9.433
Vietnamese	5.824	**24.382**	5.872	**27.817**	5.874

Table 14: LLaMA-2-7B perplexity on 11 languages with a 'Vietnamese' region removal. Here, 'Vietnamese' is gray-filled while others are unfilled, and values with greater changes compared to the other regions' removals are in bold.

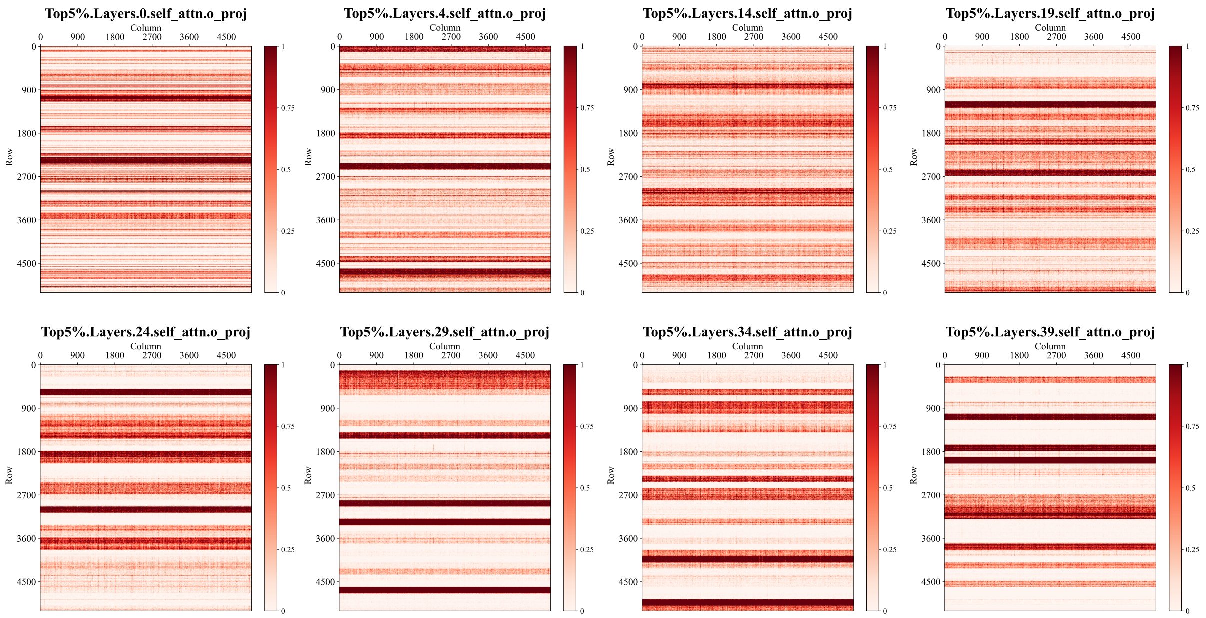

Figure 9: Visualization of the linguistic competence region (the ‘Top’ 5% region) in Attention.o matrix across 8 different layers. The scale from 0 to 1 (after normalization) represent the proportion of parameters within a 3×3 vicinity that belong to the ‘Top’ region.

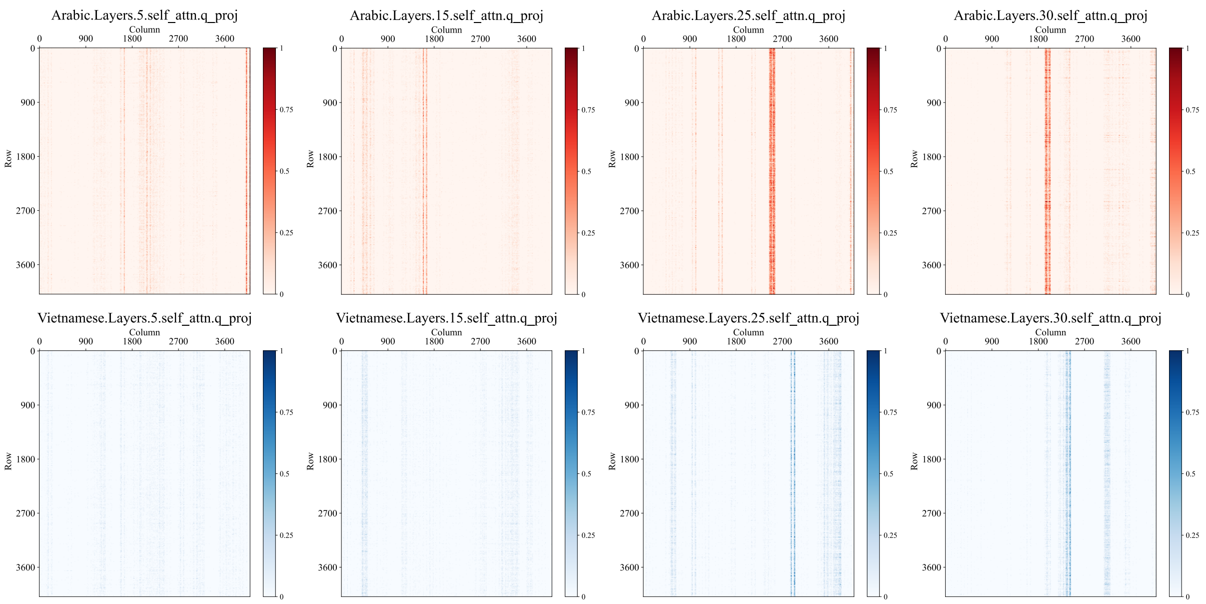

Figure 10: Visualization of the monolingual regions for ‘Arabic’ and ‘Vietnamese’ across 4 different layers in the Attention.q matrix. The scale from 0 to 1 (after normalization) represent the proportion of parameters within a 3×3 vicinity that belong to the monolingual regions.

Languages	LLaMA-2-7B **3% (100K)**				LLaMA-2-13B **3% (100K)**			
	Base	Top	Bottom	Random	Base	Top	Bottom	Random
Arabic	6.771	127208.250	6.772	7.895	6.261	102254.758	6.316	7.112
Chinese	8.652	295355.5	8.565	9.837	7.838	84086.906	7.806	8.619
Czech	19.834	62692.367	19.835	24.005	17.744	56102.227	17.650	20.485
Danish	8.372	47654.156	8.372	9.929	7.402	47213.586	7.401	8.278
Dutch	16.959	48478.594	16.959	20.121	15.64	46303.559	15.572	18.295
English	7.653	16573.422	7.653	8.359	7.447	25212.217	7.234	7.821
Finnish	7.566	45711.992	7.566	8.934	6.887	48811.242	6.861	7.826
French	13.605	48268.211	13.605	15.003	12.765	45674.492	12.573	13.682
German	18.355	64015.117	18.356	15.404	17.29	51692.125	16.973	18.972
Greek	3.832	224595.781	3.833	4.527	3.599	80657.891	3.599	4.146
Hungarian	16.365	52828.691	16.363	20.039	14.756	58107.137	14.834	17.633
Indonesian	44.269	33121.945	44.318	48.175	37.909	51611.625	37.838	38.548
Italian	14.859	58908.879	14.860	17.341	13.694	47375.844	13.730	15.207
Japanese	10.888	322031.406	10.896	12.535	10.072	75236.031	10.137	11.661
Korean	4.965	125345.359	4.967	5.649	4.724	90768.844	4.743	5.241
Malay	66.581	22603.727	66.843	74.167	46.885	40468.750	46.912	58.947
Malayalam	5.133	373710.188	5.134	6.396	4.972	16990.266	4.972	5.654
Norwegian	14.425	31526.176	14.427	17.854	13.142	45820.109	13.139	15.041
Persian	6.509	81959.719	6.511	7.628	6.205	92201.812	6.229	7.009
Polish	12.629	66906.469	12.629	14.843	11.414	55923.156	11.311	12.987
Portuguese	15.318	47763.059	15.319	17.297	13.667	51498.402	13.982	15.376
Romanian	10.893	43498.008	10.895	13.061	9.652	54986.055	9.693	10.969
Russian	12.062	170776.750	12.064	13.728	11.048	112574.609	10.948	11.757
Spanish	17.079	51940.859	17.082	18.98	16.351	54005.891	16.138	17.292
Swahili	75.908	29234.168	75.892	89.380	70.519	48802.227	70.402	81.216
Swedish	14.714	49425.969	14.714	17.258	13.229	48622.266	13.337	14.933
Tamil	4.162	381070.844	4.162	5.04	4.028	111060.516	4.049	4.488
Turkish	11.214	46986.391	11.215	13.765	9.834	50303.562	9.763	11.374
Ukrainian	9.409	120719.938	9.409	10.875	8.295	116287.305	8.297	9.076
Vietnamese	5.824	40126.527	5.824	6.614	5.471	42336.426	5.437	5.995

Table 15: LLaMA-2 perplexity on 30 languages with 3% removal ratio. '100K' means that the region is selected from 100,000 samples. 'Top' and 'Bottom' respectively indicate the N parameters with the highest and lowest cumulative $\mathcal{I}_j^*(\theta)$ during the further pre-training across the six languages. 'Random' denotes the randomly selecting N while 'Base' represents no removal. Here, N equals 3% of the total number in each parameter matrix.

Languages	LLaMA-2-7B **3% (10K)**				LLaMA-2-13B **3% (10K)**			
	Base	Top	Bottom	Random	Base	Top	Bottom	Random
Arabic	6.771	115398.328	6.772	7.895	6.261	88678.016	6.315	7.112
Chinese	8.652	369027.531	8.564	9.837	7.838	70912.242	7.806	8.619
Czech	19.834	78480.219	19.837	24.005	17.744	53699.43	17.655	20.485
Danish	8.372	46503.742	8.373	9.929	7.402	39408.91	7.401	8.278
Dutch	16.959	55704.191	16.961	20.121	15.64	41159.938	15.572	18.295
English	7.653	15738.043	7.654	8.359	7.447	23678.322	7.234	7.821
Finnish	7.566	46616.094	7.568	8.934	6.887	47002.539	6.861	7.826
French	13.605	44385.668	13.609	15.003	12.765	38755.539	12.678	13.682
German	18.355	84497.234	18.361	21.404	17.29	43319.586	17.02	18.972
Greek	3.832	147740.5	3.833	4.527	3.599	70136.242	3.6	4.146
Hungarian	16.365	52652.363	16.367	20.039	14.756	48407.305	14.735	17.633
Indonesian	44.269	39055.945	44.267	48.175	37.909	36912.34	37.929	38.548
Italian	14.859	54297.523	14.865	17.341	13.694	42515.969	13.69	15.207
Japanese	10.888	358722.188	10.891	12.535	10.072	68055.984	10.118	11.661
Korean	4.965	102918.828	4.966	5.649	4.724	65209.328	4.736	5.241
Malay	66.581	23501.082	67.158	74.167	46.885	35517.879	47.191	58.947
Malayalam	5.133	314088.969	5.136	6.396	4.972	131629.438	4.971	5.654
Norwegian	14.425	38111.27	14.431	17.854	13.142	38500.664	13.138	15.041
Persian	6.509	78203.031	6.51	7.628	6.205	98292.281	6.22	7.009
Polish	12.629	81373.273	12.633	14.843	11.414	52403.461	11.393	12.987
Portuguese	15.318	47779.789	15.321	17.297	13.667	41184.457	13.86	15.376
Romanian	10.893	45836.578	10.897	13.061	9.652	51766.957	9.694	10.969
Russian	12.062	227916.828	12.061	13.728	11.048	103490.719	11.004	11.757
Spanish	17.079	57679.461	17.087	18.98	16.351	40338.426	16.265	17.292
Swahili	75.908	42977.977	75.93	89.38	70.519	40400.949	70.443	81.216
Swedish	14.714	55893.812	14.717	17.258	13.229	45396.66	13.301	14.933
Tamil	4.162	447989.969	4.162	5.04	4.028	141214.188	4.052	4.488
Turkish	11.214	57037.605	11.215	13.765	9.834	41566.105	9.791	11.374
Ukrainian	9.409	168085.672	9.408	10.875	8.295	94307.312	8.296	9.076
Vietnamese	5.824	36374.734	5.825	6.614	5.471	31730.328	5.467	5.995

Table 16: LLaMA-2 perplexity on 30 languages with 3% removal ratio. '10K' means that the region is selected from 10,000 samples. Here, we reduce training samples to $10,000$ during further pre-training across six languages.

Languages	LLaMA-2-7B **1% (100K)**				LLaMA-2-7B **5% (100K)**			
	Base	Top	Bottom	Random	Base	Top	Bottom	Random
Arabic	6.771	67579496	6.77	7.021	6.771	112504.609	6.774	10.823
Chinese	8.652	120887480	8.561	8.818	8.652	156026.938	8.565	12.775
Czech	19.834	24343856	19.835	21.176	19.834	96580.281	19.845	24.797
Danish	8.372	1631186.625	8.372	8.775	8.372	82876.266	8.375	13.565
Dutch	16.959	6845146	16.963	18.056	16.959	79497.211	16.961	27.01
English	7.653	512756	7.654	7.851	7.653	46197.477	7.656	9.289
Finnish	7.566	4727027.5	7.567	7.948	7.566	60183.328	7.56	13.005
French	13.605	4768049	13.608	14.198	13.605	87642.109	13.611	19.076
German	18.355	17940508	18.357	19.724	18.355	106160.992	18.364	28.772
Greek	3.832	14242545	3.833	3.972	3.832	141320.578	3.835	6.45
Hungarian	16.365	130584	16.366	17.35	16.365	77265.188	16.369	30.376
Indonesian	44.269	1654245	44.347	49.476	44.269	83353.344	44.298	64.743
Italian	14.859	5265871.5	14.863	15.607	14.859	83076.164	14.865	22.6
Japanese	10.888	28104000	10.88	11.196	10.888	124647.633	10.895	16.619
Korean	4.965	16449047	4.965	5.095	4.965	59954.559	4.967	7.831
Malay	66.581	7875206	66.673	78.545	66.581	51824.859	66.751	90.933
Malayalam	5.133	7151096	5.133	5.359	5.133	182008.484	5.137	7.905
Norwegian	14.425	4223085	14.429	15.35	14.425	79399.109	14.434	23.621
Persian	6.509	2233196	6.507	6.782	6.509	107342.734	6.511	10.236
Polish	12.629	6547834.5	12.631	13.36	12.629	88912.945	12.632	21.372
Portuguese	15.318	6249820	15.319	15.927	15.318	78851.766	15.324	22.608
Romanian	10.893	5251915.5	10.895	11.526	10.893	71228.375	10.899	19.21
Russian	12.062	17596800	12.061	12.067	12.062	102639.602	12.066	18.504
Spanish	17.079	8220832.5	17.084	18.029	17.079	96575.547	17.084	24.007
Swahili	75.908	7875009	75.845	83.963	75.908	77765.133	75.8	131.709
Swedish	14.714	4712167.5	14.716	15.534	14.714	81574.734	14.717	22.628
Tamil	4.162	20660974	4.162	4.265	4.162	173728.312	4.164	5.881
Turkish	11.214	4489915	11.214	11.882	11.214	58347.055	11.218	19.76
Ukrainian	9.409	11689088	9.409	9.811	9.409	90008.312	9.414	14.807
Vietnamese	5.824	2235468	5.825	6.018	5.824	54187.02	5.825	9.015

Table 17: LLaMA-2-7B perplexity on 30 languages with 1% and 5% removal ratio. '100K' means that the region is selected from 100,000 samples. Here, we change the removal ratio from 3% to 1% and 5%.