Exploring Continual Fine-Tuning for Enhancing Language Ability in Large Language Model

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Abstract

A common challenge towards the adaptability of Large Language Models (LLMs) is their ability to learn new languages over time without hampering the model's performance on languages in which the model is already proficient (usually English). Continual fine-tuning (CFT) is the process of sequentially fine-tuning an LLM to enable the model to adapt to downstream tasks with varying data distributions and time shifts. This paper focuses on the language adaptability of LLMs through CFT. We study a two-phase CFT process in which an English-only end-to-end fine-tuned LLM from Phase 1 (predominantly Task Ability) is sequentially fine-tuned on a multilingual dataset - comprising task data in new languages - in Phase 2 (predominantly Language Ability). We observe that the "similarity" of Phase 2 tasks with Phase 1 determines the LLM's adaptability. For similar phase-wise datasets, the LLM after Phase 2 does not show deterioration in task ability. In contrast, when the phase-wise datasets are not similar, the LLM's task ability deteriorates. We test our hypothesis on the open-source MISTRAL-7B and LLAMA-3-8B models with multiple phase-wise dataset pairs. To address the deterioration, we analyze tailored variants of two CFT methods: layer freezing and generative replay. Our findings demonstrate their effectiveness in enhancing the language ability of LLMs while preserving task performance, in comparison to relevant baselines.

1 Introduction

With ever-increasing adoption of LLMs in real world applications and expanding multilingual user bases of these applications, it is important to cater these models to wide enough multilingual audiences. Model training is compute hungry, and

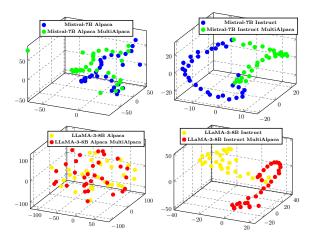


Figure 1: Comparing hidden activations for MISTRAL-7B and LLAMA-3-8B during our two-phase continual fine-tuning process. We prompt each model with examples from MTBENCH (Zheng et al., 2024), and visualize the similarity between the mean hidden activations, for each model layer. For datasets that encode "similar" tasks (ALPACA & MULTIALPACA), model's task ability does not decline (e.g., 3% gain for IFEval). For non-similar datasets (Instruct & MULTIALPACA), the task ability declines (e.g., 8% decline for IFEval). Here, Phase 2 model representations do not align with Phase 1's; thus, suggesting greater model weight interference and a decline in task ability.

there is an abundance of both labelled and unlabelled data in English as compared to other languages (Shaham et al., 2024). As such, it is imperative to find efficient ways to use pre-trained or fine-tuned models to improve performance on other languages. In this paper, we refer to a model's ability in non-English languages as predominantly its *language ability* (LA), which can be achieved without relying on large amounts of data in those languages. Instead, we can exploit the predominantly *task ability* (TA) learned from English data.

To this end, researchers use techniques like continual pre-training, continual fine-tuning or language adaption to adapt models to a newer set of languages to enhance their language abilities (re-

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fer to §2). While these techniques are effective, they are highly task-specific. Furthermore, existing techniques for multilingual LLMs rely on parallel data, old fine-tuning data, or old and new set of parameters. Parameter efficient techniques like LoRA (Hu et al., 2022) are also widely used to efficiently fine-tune LLMs on multilingual data. However, such techniques show both: *catastrophic forgetting* on English and incapability to exploit the task ability that the model receives from the English fine-tuning data (Aggarwal et al., 2024).

In such a setting, we want to enhance the model's language ability (other than English) while preserving the task ability achieved via (firstly) English fine-tuning. This setting results in the challenge of catastrophic forgetting, i.e., the model's task ability on English may decline while fine-tuning on multilingual data (Mukhoti et al., 2023). Furthermore, a trivial solution that fine-tunes on the mixture of multilingual and English-only data may be sub-par (e.g., due to language relatedness (Dhamecha et al., 2021)). Hence, it is challenging to improve an LLM's language ability while preserving its performance on English.

Our Approach. We use a two-phase continual fine-tuning (CFT) technique for language adaption. We study the effects of various English and multilingual instruction tuning datasets when the models are fine-tuned in two phases: where Phase 1 is fine-tuning the model in English to improve its task ability and then fine-tuning it on a proportionally-sized multilingual dataset in Phase 2. In Phase 1, we use ALPACA (Taori et al., 2023) and OPENORCA (Lian et al., 2023), and in Phase 2 we use MULTIAL-PACA (Wei et al., 2023) and MOPENORCA (§4.1).

We perform this study on two open-source models, namely LLAMA-3-8B and MISTRAL-7B. We also use fine-tuned versions of them, namely LLAMA-3-8B-INSTRUCT and MISTRAL-7B-INSTRUCT, as off-the-shelf Phase 1 fine-tuned models. We quantify a model's task ability based on its performance on four English datasets: (i) two for instruction following (i.e., IFEval (Zhou et al., 2023) and Alpaca Eval (Li et al., 2023)) and (ii) two for reasoning tasks (i.e., MMLU (Hendrycks et al., 2021) and HellaSwag (Zellers et al., 2019)). Likewise, we quantify a model's language ability based on its performance on (i) two question answering tasks (i.e., MLQA (Lewis et al., 2019) and XQuAD (Artetxe et al., 2019)) and (ii) XLSUM (Hasan et al., 2021), a summarization task.

Our Contributions. First, we observe that when phase-wise English and multilingual datasets encode different tasks, we see a decline in the Phase 2 model's performance on English. On the other hand, when Phase 1 and Phase 2 datasets encode similar tasks, the Phase 2 model's performance on English improves (refer to Figure 1). Second, to quantify the similarity of these phasewise datasets, we introduce two metrics based on language-agnostic embeddings and model representations. We show that our quantification correlates with the decline in task ability (§4.3). Third, we study the efficacy of two tailored variants of existing CFT strategies to mitigate the decline in task ability after Phase 2 fine-tuning, while also boosting the language ability. The first strategy we study is generative replay, i.e., using instructions from a similar English counterpart of the Phase 2 dataset to generate replay data using the Phase 1 model. The second strategy uses heuristic-based layer freezing. Here, we use the weight difference between the Base and Phase 1 models to pick specific layers for freezing during Phase 2 fine-tuning. We study the gains in task and language ability of these strategies compared to specific baselines (§5).

2 Related Work

Continual Learning in LLMs. In general, continual learning in LLMs can be broadly categorized into (i) continual pre-training (CPT) and (ii) continual fine-tuning (CFT). In CPT, the LLMs are continuously pre-trained to adapt to new domains or tasks by continuously updating them with new data alongside the existing data (Shi et al., 2024). CPT builds on the existing LLM's knowledge and is more computationally efficient than retraining an LLM using the current and old pretraining data (Gupta et al., 2023). CPT is employed when distributional shifts occur (i) over time (Amba Hombaiah et al., 2021; Jang et al., 2022a,b), (ii) across languages (Jin et al., 2022; Fujii et al., 2024; Blevins et al., 2024) or (iii) across domains (Ke et al., 2023; Gong et al., 2022; Xie et al., 2023).

On the other hand, CFT involves training the LLM on successive downstream tasks with varying data distribution or time shifts (Shi et al., 2024). CFT comprises fine-tuning for different tasks (Carrión and Casacuberta, 2022), instruction-tuning (Cahyawijaya et al., 2023), model refinement/editing (Zhang et al., 2023) and align-

ment (Suhr and Artzi, 2023). Recent literature also focuses on using CFT to assist the LLM to learn new languages (Praharaj and Matveeva, 2023; Pfeiffer et al., 2022; Badola et al., 2023).

CFT: Enhancing LLMs Multilingual Abilities. Cahyawijaya et al. (2023) propose InstructAlign which uses cross-lingual alignment and episodic replay to align an LLM's pre-trained languages to unseen languages but requires parallel data and previous task data. Shaham et al. (2024) introduces multilinguality during the first instruction fine-tuning phase which improves an LLM's instruction following capability across languages. He et al. (2023) show catastrophic forgetting during CFT and use techniques such as joint fine-tuning and model regularization to mitigate it. However, these techniques are computationally expensive or require access to previous task data.

Language Adaption. This set of works looks at language and task adaption by adjusting the model to understand new languages and enhancing its performance on specific tasks through fine-tuning, respectively (Chen et al., 2023; Zhao et al., 2024; Pfeiffer et al., 2020). For instance, Chen et al. (2023) perform task adaption by fine-tuning the model on downstream task data. For language adaption, they fine-tune only the token embedding layer, helping the model learn specific lexical meanings of new languages. Language and task ability are either trained in parallel or sequentially. However, in this paper, we try to incorporate language ability in models with the constraint that they may have already learned task ability (e.g., MISTRAL-7B-INSTRUCT). To the best of our knowledge, this is a first attempt at studying the effect of task and language self-instruct datasets on an LLM's multilingual ability through CFT.

3 Enhancing Language Ability through Continual Fine-tuning

A common recipe to training LLMs to learn new languages is to use a training paradigm that focuses on *task* and *language* adaption (Chen et al., 2023). Concretely, we define task adaption as the model's ability to comprehend the input text and then provide a suitable output. We refer to language adaption as the model's ability to perform those tasks in languages other than English.

In Task Adaption, the LLM is trained to follow instructions, usually using labeled English data. Language Adaption focuses on training the LLM

to understand text from newer languages. Task adaptation leverages cross-lingual transfer, facilitating language adaptation to a certain degree. However, this process can result in a decline in the LLM's task adaptation performance due to the risk of catastrophic forgetting. Despite this challenge, task adaptation often yields greater benefits compared to relying solely on cross-lingual transfer for language adaptation.

Continual Fine-tuning for Language Adaption. To improve the language adaption of LLMs, we re-imagine the above recipe as a two-phase CFT process. We have:

- <u>Phase 1.</u> We fine-tune a base LLM end-to-end on an English instruction dataset. Phase 1 aims to predominantly teach the LLM instruction following ability, which we refer to as *task ability*.
- Phase 2. Here, we use the fine-tuned LLM from Phase 1 and further end-to-end fine-tune it on a Multilingual instruction dataset. Unlike Chen et al. (2023), in our setting, the data in Phase 2 is labeled. However, compared to Phase 1, Phase 2's dataset is geared towards enhancing the LLM's language ability, and comprises multiple languages with fewer data points per language.

This paper relates English fine-tuning with task ability enhancement as English fine-tuning predominantly helps in the task ability of LLMs. Whereas multilingual fine-tuning predominantly helps with an LLM's language ability.

CFT for Language Adaption: Challenges. The primary challenge in our two-phase fine-tuning process is that the LLM's language ability must not come at the cost of its task ability. We impose two additional constraints based on real-world scenarios. First, in Phase 2, we cannot re-use Phase 1's dataset. Often instruction fine-tuned LLMs are available without their corresponding datasets (e.g., MISTRAL-7B-INSTRUCT (Jiang et al., 2023)). Second, in Phase 2, we cannot use the weights of the Phase 1 model during training, as saving both old and new set of parameters on the GPU for training would be computationally expensive.

In a nutshell, we focus on CFT for language adaption for an LLM while preserving the model's task ability.

Model	Phase 1 (P1)	Phase 2 (P2)	IFEva	al (†)	Alpaca	Eval (†)	MML	J (†)	HellaS	Swag (†)	Ave	rage
Model	Dataset	Dataset	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
MISTRAL-7B	ALPACA		0.364	0.395	0.12	0.16	0.552	0.573	0.581	0.616	0.404	0.436
WIISTRAL-/D	Instruct	MULTIALPACA	0.550	0.462	0.35	0.15	0.575	0.533	0.641	0.416	0.529	0.390
LLAMA-3-8B	ALPACA	MULITALPACA	0.277	0.326	0.10	0.11	0.231	0.242	0.556	0.567	0.291	0.311
LLAMA-5-6B	Instruct		0.735	0.182	0.14	0.10	0.340	0.239	0.533	0.278	0.437	0.2

Table 1: Task Ability results for two-phase Continual Fine-tuning (CFT). When the phase-wise datasets are similar (Definition 1 and Definition 2), task ability post Phase 2 (P2) fine-tuning *consistently* improves (denoted with green). When the phase-wise datasets are not similar, we see a *significant* decline in task ability post Phase 2 (P2) fine-tuning (denote with red).

4 Evaluating Task & Language Ability for Multilingual CFT

4.1 Experiment Setup & Evaluation Tasks

Fine-tuning Models. We continually fine-tune open-source MISTRAL-7B (Jiang et al., 2023) and LLAMA-3-8B (Dubey et al., 2024) LLMs for language adaption.

Fine-tuning Datasets. For our phase-wise datasets, we use the open-source ALPACA (Taori et al., 2023), MULTIALPACA (Wei et al., 2023), and OPENORCA (Lian et al., 2023) datasets. ALPACA is a self-instruct English-only dataset. MULTIALPACA is a multilingual dataset created by translating ALPACA's seed tasks to 11 languages and using GPT-3.5-Turbo for response collection. The languages are in equal proportions and are "French", "Arabic", "German", "Spanish", "Indonesian", "Japanese", "Korean", "Portuguese", "Russian", "Thai", and "Vietnamese". The appendix (§A.2) describes OPENORCA and MOPENORCA.

Fine-tuning Technique. We perform full fine-tuning with bf16 precision to study the effects of full fine-tuning with multilingual data in Phase 2 and its effect on task ability. We also wish to exploit the benefits gained via complete fine-tuning of these models, which may not be possible with parameter efficient fine-tuning (Aggarwal et al., 2024; Panda et al., 2024). However, in §5, we propose a heuristic-based layer freezing strategy to mitigate forgetting of task ability in which we freeze some layers and fine-tune the rest. For our experiments, we use $Axolotl^1$, an open-source framework to fine-tune LLMs. We conducted our experiments on NVIDIA A100 GPUs with 80 GB RAM.

Evaluation Tasks. To quantify an LLM's task ability, we evaluate Phase 1 and Phase 2 models on two instruction-following tasks (i) IFEval (Zhou et al., 2023) and (ii) Alpaca Eval (Li et al., 2023), (iii)

MMLU (Hendrycks et al., 2021) for problem-solving and (iv) HellaSwag (Zellers et al., 2019) for commonsense reasoning ability. To quantify an LLM's language ability, we evaluate our fine-tuned models on three benchmark datasets comprising two multilingual generative tasks: question answering (MLQA (Lewis et al., 2019) & XQuAD (Artetxe et al., 2019)) and summarization (XLSUM (Hasan et al., 2021)). Further details on these tasks are available in the Appendix (§A.3).

To evaluate our models on TA and LA, we use *LM-Evaluation-Harness*², which is a unified framework for zero/few-shot evaluations of LLMs. For both task and language ability, we use **zero-shot** evaluation. For additional details on the training setup, code, and evaluation tasks, we refer the reader to the Appendix (§A).

4.2 Task and Language Ability Results

We compare the task and language ability of MISTRAL-7B and LLAMA-3-8B continually finetuned models on different phase-wise datasets³. Table 1 presents the results for task ability, while Table 2 presents the results for language ability. Table 2 reports the average score across languages. We provide language-specific scores in the Appendix (§B).

Results Discussion. From Table 1, we see that for phase-wise datasets like Instruct and MULTI-ALPACA, the performance of the Phase 2 models trained on them declines for English. This decline occurs when they are continually fine-tuned on multilingual data in Phase 2. However, we see a jump in MISTRAL-7B's language ability from the results for the multilingual generative tasks (Table 2). These models fine-tuned on multilingual datasets show catastrophic forgetting in English. However,

¹github.com/axolotl-ai-cloud/axolotl/

 $^{^2 {\}it github.com/EleutherAI/lm-evaluation-harness}$

³When it is clear from the context, we use "Instruct" to denote the dataset used in Phase 1 to instruction fine-tune MISTRAL-7B-INSTRUCT or LLAMA-3-8B-INSTRUCT.

Model	Phase 1	Phase 2	MLQ	A (†)	XLSU	M (†)	XQuA	D (†)	Ave	rage
Model	Dataset	Dataset	Phase 1	Phase 2						
MISTRAL-7B	ALPACA		0.229	0.288	0.012	0.060	0.290	0.602	0.177	0.317
WIISTRAL-/D	Instruct	MULTIALPACA	0.246	0.307	0.012	0.033	0.351	0.436	0.203	0.259
LLAMA-3-8B	ALPACA	MULITALPACA	0.438	0.597	0.033	0.034	0.586	0.737	0.352	0.456
LLAMA-3-0D	Instruct		0.609	0.321	0.048	0.027	0.712	0.417	0.456	0.255

Table 2: Language Ability results for two-phase Continual Fine-tuning (CFT). With green, we denote an improvement in language ability post Phase 2 fine-tuning. Likewise, we denote a decline in language ability with red. For MLQA and XQUAD we use F1 abstractive score, while for XLSUM we use ROUGE Score.

for phase-wise datasets like ALPACA followed by MULTIALPACA, we see that models trained on them do not show a decline in task ability (Table 1). We also see a gain in these models' language ability (Table 2)⁴.

Additional Ablations. In the Appendix (§B), we also present results for OPENORCA-MOPENORCA phase-wise datasets. For MISTRAL-7B, we observe that the average task ability of the Phase 2 model (over Phase 1's MISTRAL-7B-OPENORCA) marginally declines: 0.487 from 0.504. Whereas, for MISTRAL-7B-INSTRUCT, the average decline in task ability is significant: 0.376 from 0.529. Likewise, for LLAMA-3-8B, the average task ability for LLAMA-3-8B OPENORCA MOPENORCA sees an increase of 0.415 from 0.404. In contrast, with Instruct-MOPENORCA as the phase-wise datasets, the task ability significantly drops, from 0.437 to 0.173.

Observation. With Table 1, we see that our twophase CFT setup for language adaption shows an interesting trend: for certain pairs of phase-wise datasets (e.g., ALPACA & MULTIALPACA), the LLM after Phase 2 sees an improvement in the task ability (computed on English evaluation tasks). We notice that phase-wise datasets like ALPACA and MULTIALPACA have the same seed prompts. Alternately, the two datasets encode the same tasks in different languages. We hypothesize an LLM finetuned on either of these datasets learns the same task ability, and therefore, the second phase of CFT leads to lesser interference in the representation space. That is, an LLM continually fine-tuned on ALPACA & MULTIALPACA preserves its task ability across phases. We next define two metrics that aim to quantify the task-specific similarity of two datasets.

4.3 Phase-wise Datasets: Similarity of Representations

Dataset Embedding Similarity (DES). To quantify whether two datasets encode the same tasks, we define DES that computes a similarity score using the dot product of the average representations (embedding) generated by a language-agnostic model.

Definition 1 (Dataset Embedding Similarity (DES)). Given a language-agnostic text embedding model Θ , and any pair of datasets D_1 and D_2 , let DES be the function $f_{DES}: D \times D \rightarrow [0,1]$

$$f_{DES}(D_1, D_2; \Theta) = \langle \mathbf{E}_{\Theta}(D_1), \mathbf{E}_{\Theta}(D_2) \rangle$$
 (1)

Here, $\mathbf{E}_{\Theta}(D_i) \in \mathbb{R}^d$, $\forall i \in \{1,2\}$ is the normalized mean embedding across samples in D_i .

Higher the DES score, more similar the embedding, i.e., greater similarity between D_1 and D_2 . For Θ , we use the language-agnostic sentence-tokenizer LaBSE (Feng et al., 2020). We compute DES by encoding 500 random samples from ALPACA, MULTIALPACA, OPENORCA, and MOPENORCA, and measure f_{DES} for each pair.

Fixing ALPACA as the Phase 1 dataset D_1 , when the Phase 2 dataset D_2 is MULTIALPACA, the DES score is 0.924 and 0.792 for MOPENORCA. When D_1 is OPENORCA, the DES score for MOPENORCA as D_2 is 0.953 and 0.774 when D_2 is MULTIALPACA. For dataset pairs with similar tasks, we see a high DES score and relatively low scores for datasets with different tasks. That is, DES captures the (pair-wise) variation in task abilities of these datasets.

Model Parameter Difference (MPD). Another method of quantifying the similarity of tasks for two datasets D_1 and D_2 is to compute the difference between the parameters of models Θ_1 (finetuned on D_1) and Θ_2 (fine-tuned on D_2). Geometrically, the difference of the parameters captures the representation shift of Θ_2 in the space defined by Θ_1 . If D_1 & D_2 encode the same tasks, the

⁴LLAMA-3-8B Instruct MULTIALPACA shows deterioration in LA. We explain this behavior in §5.3.

combined shift by Θ_2 should be relatively lower, compared to the shift if D_1 & D_2 encode different tasks. Formally,

Definition 2 (Model Parameter Difference (MPD)). Given any two models Θ_1 and Θ_2 fine-tuned on self-instruct datasets D_1 and D_2 respectively, from the same base model Θ_B , let MPD be the function $f_{MPD}: \Theta \times \Theta \to \mathbb{R}_{\geq 0}$ s.t.

$$f_{MPD}(\Theta_1, \Theta_2; \Theta_B) = \frac{1}{n} \sum_{i=1}^n \|\mathbf{w}(\Theta_{1,i}) - \mathbf{w}(\Theta_{2,i})\|_2$$
(2)

Here, $\mathbf{w}(\Theta_{j,i}), \ \forall j \in \{1,2\} \ \textit{is} \ \Theta_j \textit{'s} \ \textit{i}^{\textit{th}} \ \textit{parameter}.$

The smaller the MPD score, the closer the finetuned models are in the parameter space. Fixing MISTRAL-7B as the base model Θ_B , and D_1 as MULTIALPACA, we vary D_2 as one of AL-PACA, OPENORCA, and MOPENORCA, and observe the corresponding MPD scores. We normalize the MPD scores with the maximum observed score across all three models for a fair comparison. With D_2 as ALPACA, the MPD score is 0.294. For D_2 as Instruct, MPD is 1.0 and 0.55 when D_2 is OPENORCA. These scores show a similar trend to DES: for ALPACA and MULTIALPACA, the scores are lower, highlighting the similarities in the datasets in the parameter space. We see relatively higher scores for the other pair of models, implying a difference in the dataset pairs.

4.4 Visualizing Decline in Task Ability

Setup. To explain the effect of similar phase-wise data sets on the LLM task ability, we look at the model representations when parsing English (as the task ability is computed over English). We feed MTBENCH (Zheng et al., 2024) to the models, an English prompt dataset for testing, and visualize the similarity between the mean hidden activations, for each model layer. For the analysis, given an LLM Θ with l layers, let $X_{\Theta} \in \mathbb{R}^{l \times d}$ be the mean hidden activations, across n samples from MTBENCH.

t-SNE Visualization. Figure 1 depicts t-SNEs (van der Maaten and Hinton, 2008) for $X_{\rm MISTRAL-7B}$ and $X_{\rm LLAMA-3-8B}$ LLMs, continually fine-tuned on the phase-wise datasets ALPACA & MULTIALPACA and Instruct & MULTIALPACA. We observe that for similar phase-wise datasets, the model before and after Phase 2 produces similar hidden activations. Contrarily, for non-similar phase-wise datasets, the hidden activations form distinct clusters, implying separation between the

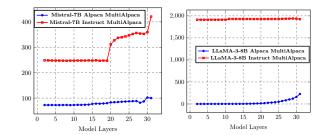


Figure 2: We see a greater change in the variation of the representations for non-similar datasets (e.g., Instruct & MULTIALPACA) compared to similar datasets (e.g., ALPACA & MULTIALPACA). Interestingly, for LLAMA-3-8B the change is large across layers and a magnitude higher than MISTRAL-7B. For MISTRAL-7B, we see the later layers showing the most change.

phase-wise activations. That is, the model representations for non-similar phase-wise datasets are well-separated. The model representations during Phase 2 do not align with Phase 1 representations; thus, resulting in greater model weight interference leading to a decline in task ability.

Visualizing Variance in Model Representations.

Figure 1 provides some intuition for the correlation between phase-wise datasets and decline in task ability. To further understand the layer-wise behavior of the hidden activations, similar to Chang et al. (2022), we compute covariance matrices Σ_{Θ} for each X_{Θ} . Intuitively, Σ_{Θ} captures the variance in different directions for representations of hidden activations for Θ .

We first compute the mean centered activation matrix $\bar{X}_{\Theta} = X_{\Theta} - \mu_{\Theta}$, according to $\mu_{\Theta} \in \mathbb{R}^d$. Next, we derive $\Sigma_{\Theta} = \frac{1}{l-1} \cdot \bar{X}_{\Theta}^T \bar{X}_{\Theta} \in \mathbb{R}^{d \times d}$. To compare the layer-wise variance in representations, we compute the L2-Norm of the difference of the matrices $\Sigma_{\text{MISTRAL-7B}}$ (Figure 2 (**left**)) or $\Sigma_{\text{LLAMA-3-8B}}$ (Figure 2 (**right**)) when continually fine-tuned on ALPACA & MULTIALPACA (blue lines) or Instruct & MULTIALPACA (red lines).

From the figures, we see clear evidence of representational change, both in terms of the magnitude of the change and the subset of layers that show a greater change. For MISTRAL-7B, the Phase 2 model after CFT with Instruct & MULTIALPACA, shows 3 to 4 times more variation in its representations compared to the model with ALPACA & MULTIALPACA phase-wise datasets. This gap is significantly larger for LLAMA-3-8B.

	CFT Setu	p		Task A	bility (1	(A)		La	nguage A	Ability (I	LA)
	Phase 2 Dataset	Mitigating Strategy	IFEval (†)	Alpaca Eval (\uparrow)	MMLU (†)	$\begin{array}{c} \operatorname{HellaSwag} \\ (\uparrow) \end{array}$	Avg (↑)	MLQA (†)	$\begin{array}{c} {\sf XLSum} \\ (\uparrow) \end{array}$	XQUAD (†)	Avg (↑)
	_	_	0.55	0.35	0.575	0.641	0.529	0.246	0.012	0.351	0.203
~		_	0.462	0.15	0.533	0.416	0.390	0.307	0.033	0.436	0.259
-7B		LF_H1	0.456	0.03	0.497	0.598	0.395	0.176	0.016	0.215	0.136
MISTRAL		LF_H2	0.364	0.12	0.364	0.504	0.338	0.213	0.014	0.442	0.223
TR	MULTIALPACA	GR_5	0.540	0.17	0.540	0.611	0.465	0.311	0.008	0.428	0.249
MIS	Well Hellien	GR_10	0.567	0.12	0.567	0.594	0.462	0.213	0.007	0.427	0.215
_		LoRA	0.383	0.09	0.579	0.625	0.42	0.289	0.043	0.518	0.283
		ER_10	0.593	0.08	0.580	0.635	0.599	0.249	0.008	0.398	0.218
	-	_	0.735	0.14	0.340	0.533	0.436	0.609	0.048	0.712	0.456
8B		_	0.182	0.10	0.239	0.278	0.217	0.321	0.030	0.417	0.256
		LF_H1	0.303	0.0	0.231	0.275	0.202	0.368	0.037	0.505	0.303
A-3.		LF_H2	0.380	0.06	0.485	0.525	0.373	0.400	0.038	0.505	0.314
Z	MULTIALPACA	GR_5	0.269	0.01	0.516	0.316	0.279	0.437	0.019	0.593	0.349
LLAMA		GR_10	0.264	0.12	0.229	0.250	0.228	0.254	0.009	0.314	0.192
1		LoRA	0.196	0.0	0.280	0.235	0.179	0.007	0.008	0.005	0.007
		ER_10	0.420	0.02	0.603	0.561	0.420	0.434	0.025	0.53	0.330

Table 3: Task and Language ability results for our mitigating strategies, Generative Replay (GR_5 & GR_10) and Layer Freezing (LF_H1 & LF_H2). We also use LoRA (Hu et al., 2022) and ER_10 as two baseline strategies. Here, we perform Phase 2 fine-tuning with rank 64 and quantisation bfloat16 for LoRA. For ER_10, we use the English dataset used in GR_5 with original responses. *The Phase 1 dataset is Instruct for each row.* The first two rows for both MISTRAL-7B and LLAMA-3-8B provide numbers for Instruct and Instruct-MULTIALPACA (from Table 1 & Table 2).

5 Mitigating Strategies for Multilingual CFT

To mitigate the decline in task ability, we study two CFT techniques, Generative Replay (GR) and heuristic-based Layer Freezing (LF). In Generative Replay, we consider a new English data generation method motivated by the correlation between dataset similarity and task ability (§4.2). With heuristic-based Layer Freezing, we employ specific heuristics to find out the subset of layers to freeze in the model during Phase 2 fine-tuning.

5.1 Generative Replay

Typically, Generative Replay (GR) is a technique that generates data from past distributions to be used alongside new task data for the continual finetuning of a model on a new task (Shin et al., 2017). However, from §4.2, we see that if the phase-wise datasets encode similar tasks, the decline in task ability is mitigated. Based on this observation, we use the Phase 1 model to generate responses, in English, from the English counterpart of the multilingual dataset used for training in Phase 2. This generated replay dataset acts as a bridge between the distributions of Phase 1 and Phase 2.

During Phase 2 fine-tuning, we include varying quantities of this generated data: specifically, 5%

(GR_5) and 10% (GR_10), of the Phase 2 dataset. As a **baseline**, we also fine-tune the models with a similar sized subset of the English counterpart with original responses⁵. We refer to this baseline as English Replay (ER_10).

5.2 Heuristic-based Layer Freezing

Model regularization is an effective technique to mitigate the drop in the previous task's performance in continual learning (e.g., EWC (Kirkpatrick et al., 2017)). However, this is computationally inefficient as it requires using both the old and new sets of parameters. Instead, we use Layer Freezing (LF), a relatively efficient technique for use as a 'regularizer' to preserve task ability during Phase 2. We consider the following two variations to select the set of layers to freeze:

- 1. LF_H1: freezing a random set of 10 layers of the model from Phase 1 to be fine-tuned in Phase 2.
- 2. LF_H2: freezing the top-10 layers that have changed the most during Phase 1 fine-tuning (e.g., MISTRAL-7B Base to MISTRAL-7B-INSTRUCT). We select these layers separately

⁵This dataset may not be available for all multilingual datasets eg. Aya (Singh et al., 2024). In that case, instructions can always be translated to English but it is not always practical to translate responses. Hence, this baseline is the best-case scenario for our GR strategy.

for Key, Query, and Value, for each attention head.

We present our results in Table 3 for both GR and LF. Along with English Replay (ER), we define another **baseline** in which we use LoRA (Hu et al., 2022) for continually fine-tuning in Phase 2.

5.3 Results Discussion

From Table 3, we see that GR and LF successfully mitigate the decline in task ability and also show gains in language ability. For instance, MISTRAL-7B with GR_5 achieves better performance in MLQA and XLSUM when fine-tuned with MULTIAL-PACA. We also close the gap with MISTRAL-7B-INSTRUCT on IFEval, Alpaca Eval, MMLU, and HellaSwag with our mitigation strategies.

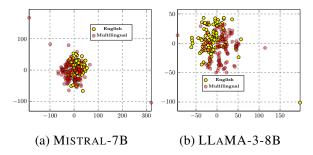


Figure 3: Demonstrating extent of cross-lingual transfer in MISTRAL-7B and LLAMA-3-8B on a parallel dataset prepared by subsampling FLORES (Costa-jussà et al., 2022). We find that the English activation cluster for LLAMA-3-8B is separated from the multilingual cluster, compared to MISTRAL-7B.

LLAMA-3-8B Doesn't Show Consistent Improvement with our Mitigations. From Table 3, while both GR and LF improve on the baseline LLAMA-3-8B-INSTRUCT MULTIALPACA, the gains in task and language ability are not comparable to LLAMA-3-8B-INSTRUCT.

To understand this further, for GR, we investigate the cross-linguality difference between LLAMA-3-8B and MISTRAL-7B. Like Figure 1, we plot t-SNEs of the mean model activations for the MISTRAL-7B and LLAMA-3-8B base models on two parallel datasets, English and Multilingual. We create the parallel datasets by subsampling data from FLORES (Costa-jussà et al., 2022). In Figure 3, we see that the English activation cluster for LLAMA-3-8B is separated out from multilingual cluster, compared to MISTRAL-7B. This suggests that GR may not be as effective when the model has less cross lingual ability. While for LF, we acknowledge that our method to identify the layers

to freeze may not be the best and better methods to identify which layers to freeze can be a direction for future work.

Last, but not the least, we acknowledge that LLAMA-3-8B-INSTRUCT seems to be a strong model even on multilingual benchmarks. Hence, it is also important to evaluate Phase 1 models on these benchmarks first and then decide if the Phase 2 fine-tuning step should be undertaken or not.

With regards to LLAMA-3-8B-INSTRUCT MULTIALPACA LA results in Table 2, we believe that this is due to lack of cross-linguality in LLAMA-3-8B-INSTRUCT and less data in MULTIALPACA which fails to cause sufficient representation drift to improve the model's performance.

Forgetting with LoRA. For MISTRAL-7B-INSTRUCT and LoRA fine-tuning, we see an increase in language ability but a decline in task ability. But the decline is not as much as full fine-tuning. For LLAMA-3-8B-INSTRUCT and LoRA, there is a greater decline in both task and language ability. The decline is similar (or slightly lower) than the full fine-tuning scenario. These results show that LoRA also suffers from forgetting when used for continual fine-tuning.

Additional Results. In the Appendix (§C), we repeat the same experiment from §4.4 to quantify the representation change in the fine-tuned models using our mitigating strategies. We see a trend similar to Figure 2. That is, a decrease in the variation in the model activations, compared to the baseline model trained on Instruct and MULTIALPACA. The decrease is more pronounced for MISTRAL-7B compared to LLAMA-3-8B. In Appendix §C, we also present TA and LA results for the Instruct-MOPENORCA phase-wise datasets.

6 Conclusion & Future Work

In this paper, to the best of our knowledge, we present a first study on the influence of the similarity of phase-wise datasets on the task and language adaptability of LLMs through CFT. Through extensive experiments on the MISTRAL-7B and LLAMA-3-8B models, we show that when datasets are similar, task ability is preserved; otherwise, it declines. Towards mitigation, we study layer freezing and generative replay as mitigating strategies based on specific heuristics. Our results indicate that these strategies help improve task performance while not compromising on the LLM's language adaptability.

Future Work. Our results show that there is no one-size-fits-all strategy to mitigate decline in task ability, among the strategies discussed. Future work can explore developing other parameter-efficient regularization methods that address the current computational challenges with methods like EWC or forgetting due to LoRA. One can also explore analytical notions for task similarity in datasets.

7 Limitations

The study assumes that the similarity between phase-wise datasets can be effectively quantified using DES and MPD metrics. However, these metrics may not capture all nuances of task similarity. Moreover, the experiments were conducted on MISTRAL-7B and LLAMA-3-8B models. The results and conclusions drawn may not generalize to other LLMs with different architectures or training paradigms. Additionally, The study's finetuning and evaluation processes were constrained by available computational resources. More extensive experiments with larger models and longer training datasets were not possible. Furthermore, while generative replay and heuristic-based layer freezing showed promise, their effectiveness may vary with different models and datasets. Lastly, the evaluation of task and language ability was based on specific benchmarks. These metrics may not encompass all aspects of model performance, particularly in real-world applications.

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A Training Details

A.1 Hyperparameters for Fine-tuning and Training Setup

Hyperparameter	Value
Learning Rate	1×10^{-6}
Epochs	4
Global Batch size	16
Scheduler	Cosine
Warmup	Linear
Warmup Steps	10
Optimizer	AdamW (Loshchilov and Hutter, 2019)
Weight Decay	0

Table A1: Hyperparameters for continual fine-tuning

A.2 Fine-tuning Datasets

OPENORCA is an English-only self instruct dataset, created to best mimic the ORCA dataset (Mukherjee et al., 2023), which is not publicly available. To create the multilingual version of OPENORCA, namely MOPENORCA, we follow Ahuja et al. (2024) to generate selective translations for a subset of OPENORCA. The subset contains 50k samples from the OPENORCA dataset and we selectively translate them to 11 languages which are also in MULTIALPACA. In total, we generate 550k examples for all languages.

A.3 Evaluation Tasks

In this paper, we consider two sets of benchmarks to evaluate task and language ability. We explain them briefly next.

Task Ability (TA). To quantify an LLM's task ability, we evaluate Phase 1 and Phase 2 models on the following tasks:

- 1. IFEval (Zhou et al., 2023): Instruction-Following Evaluation (IFEval) asses the ability of an LLM to follow natural language instructions. It comprises 500 verifiable instructions (e.g., "mention the keyword AI 3 times"). We choose IFEval as the instructions are verifiable and also test an LLM's context understanding.
- 2. Alpaca Eval (Li et al., 2023): This is an LLM-based automatic evaluator for instruction following models, to measure task ability. Like Aggarwal et al. (2024), we evaluate our CFT models against *text-davinci-003* responses on 800 instructions and use GPT4 (*gpt-4-32k*) as the evaluator.

- 3. MMLU (Hendrycks et al., 2021): Massive Multitask Language Understanding (MMLU) is a benchmark to assess an LLM's knowledge and problem-solving abilities. It includes 57 subjects across domains like STEM, or law, with 16k MCQs in total.
- 4. HellaSwag (Zellers et al., 2019): This is a popular benchmark to evaluate the commonsense reasoning ability of an LLM. HellaSwag's test split contains 10k samples in total.

Language Ability (LA). To quantify an LLM's language ability, we evaluate our fine-tuned models on three benchmark datasets comprising two multilingual generative tasks: question answering and summarization.

- Question Answering: MLQA (Lewis et al., 2019) contains 5k extractive question-answering instances in 7 languages. The XQuAD dataset (Artetxe et al., 2019) consists of a subset of 240 paragraphs and 1190 question-answer pairs across 11 languages.
- **Summarisation:** XLSUM (Hasan et al., 2021) spans 45 languages, and we evaluate our models in Arabic, Chinese-Simplified, English, French, Hindi, Japanese, and Spanish.

B Evaluating Language Ability for Multilingual Continual Fine-tuning

Task Ability. Table A1 present the task ability numbers of our ablations on the OPENORCA-MOPENORCA and Instruct-MOPENORCA atasets using MISTRAL-7B and LLAMA-3-8B models. When the datasets are pairwise not similar, i.e., Instruct-MOPENORCA, MISTRAL-7B shows a significant decline in the *average* task ability, from 0.529 in Phase 1 to 0.376 in Phase 2. Likewise, LLAMA-3-8B also experiences a decrease, dropping from 0.437 to 0.173 on average.

In contrast, when the pairwise datasets are similar, i.e., OPENORCA and MOPENORCA, MISTRAL-7B sees a *marginal* drop between the phases $(0.504 \rightarrow 0.487)$, on average. LLAMA-3-8B's performance sees an improvement in the average task ability, from 0.404 to 0.415.

Language Ability. Table A2 tabulates the results for language ability. We see an improvement in the *average* language ability for the OPENORCA-MOPENORCA dataset pair, for both MISTRAL-7B and LLAMA-3-8B. For Instruct-MOPENORCA,

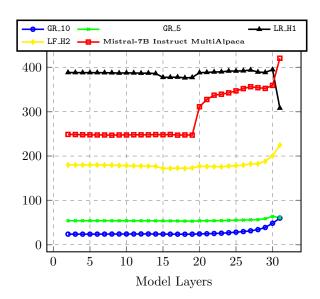


Figure C4: Visualizing Variance in Model Representations for MISTRAL-7B Mitigating Strategies: We see a decrease in the variance of model representations for models trained using our mitigation strategies compared to vanilla Phase 2 models (see Figure 2).

with LLAMA-3-8B, the average language ability is virtually the same across tasks. However, for MISTRAL-7B, we see a slight drop in the average language ability, driven primarily due to a drop in performance for MLQA.

Furthermore, Table B3, Table B4, and Table B5 present the language-specific results for MLQA, XLSUM, and XQuAD, respectively.

C Mitigating Strategies

Here, we first visualize the impact of our mitigating strategies on the variance in model representations. Next, we provide ablate our findings for the Instruct-MOPENORCA phase-wise datasets.

Visualizing Variance in Model Representations.

In Figure C4, we repeat the same experiment as in § 4.5 to quantify the representation change in the fine-tuned models using our mitigating strategies. The trend seen is expected from §4.5: we see a decrease in the variation in the model activations, compared to the baseline model trained on Instruct and MULTIALPACA.

For the mitigating strategies that are curated to curb representational change, i.e., LF_H2, GR_5, and GR_10, we see that the corresponding curves have lesser change than the baseline Phase 2 model, MISTRAL-7B Instruct MULTIALPACA. That is, there is less representational change for LF_H2, GR_5, and GR_10 compared to MISTRAL-7B In-

Model	Phase 1 (P1)	Phase 2 (P2)	IFEva	al (†)	Alpaca	a Eval (↑)	MML	J (†)	HellaS	Swag (†)	Ave	rage
Model	Dataset	Dataset	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
MISTRAL-7B	OPENORCA		0.494	0.482	0.31	0.32	0.601	0.582	0.612	0.562	0.504	0.487
MISTRAL-/D	Instruct	MOPENORCA	0.550	0.426	0.35	0.06	0.575	0.507	0.641	0.509	0.529	0.376
LLAMA-3-8B	OPENORCA	MOPENORCA	0.377	0.425	0.09	0.07	0.579	0.599	0.571	0.564	0.404	0.415
LLAMA-3-6D	Instruct		0.735	0.205	0.14	0.0	0.340	0.236	0.533	0.250	0.437	0.173

Table A1: Task Ability results for two-phase Continual Fine-tuning (CFT). With green, we highlight an increase in a model's task ability post P2 fine-tuning. Likewise, red highlights a decline in a model's task ability.

Model	Phase 1	Phase 2	MLQA	A (↑)	XLSU	M (†)	XQuA	.D (†)	Ave	rage
Model	Dataset	Dataset	Phase 1	Phase 2						
MISTRAL-7B	OPENORCA		0.435	0.36	0.007	0.008	0.556	0.643	0.332	0.337
WIISTRAL-/D	Instruct	MOPENORCA	0.246	0.155	0.012	0.040	0.351	0.323	0.203	0.173
LLAMA-3-8B	OPENORCA	MOPENORCA	0.401	0.453	0.017	0.006	0.499	0.531	0.306	0.330
LLAMA-3-6D	Instruct		0.609	0.604	0.048	0.048	0.712	0.713	0.456	0.455

Table A2: Language Ability results for two-phase Continual Fine-tuning (CFT). With green, we highlight an increase in a model's language ability post Phase 2 fine-tuning. Likewise, red highlights a decline in a model's language ability.

Model	Phase 1	Phase 2						ML	_QA					
Model	Dataset	Dataset			Pha	se 1					Pha	ase 2		
			ar	de	es	hi	vi	zh	ar	de	es	hi	vi	zh
MISTRAL-7B	ALPACA		0.143	0.337	0.331	0.149	0.385	0.031	0.172	0.485	0.529	0.196	0.336	0.009
WIISTRAL-/D	Instruct	MULTIALPACA	0.113	0.440	0.395	0.088	0.369	0.073	0.228	0.456	0.529	0.279	0.327	0.0222
LLAMA-3-8B	ALPACA	MULITALPACA	0.320	0.538	0.563	0.438	0.611	0.155	0.552	0.672	0.765	0.573	0.784	0.237
LLAMA-3-8B	Instruct		0.549	0.701	0.769	0.624	0.788	0.192	0.316	0.453	0.526	0.137	0.464	0.028
MISTRAL-7B	OPENORCA		0.374	0.504	0.511	0.395	0.600	0.226	0.298	0.506	0.572	0.274	0.481	0.030
MISTRAL-/D	Instruct	MOPENORCA	0.113	0.440	0.395	0.088	0.369	0.073	0.115	0.253	0.213	0.088	0.222	0.038
LLAMA-3-8B	OPENORCA	MOPENORCA	0.262	0.545	0.565	0.369	0.568	0.099	0.437	0.549	0.622	0.462	0.625	0.024
LLAMA-3-0D	Instruct		0.320	0.538	0.563	0.438	0.611	0.155	0.554	0.701	0.771	0.625	0.787	0.188

Table B3: MLQA: Language Ability results for two-phase Continual Fine-tuning (CFT).

struct MULTIALPACA.

Our generative replay techniques are the closest in the representational change to MISTRAL-7B Instruct. This 'closeness' also improves its task and language ability performance compared to the vanilla Phase 2 model, MISTRAL-7B Instruct MULTIALPACA(refer to Table 1 and Table 2).

Additional Ablations. We also present the impact of our mitigating strategies for the Instruct-MOPENORCA phase-wise datasets on MISTRAL-7B. Table C6 presents these results.

We see that LF_H2 achieves moderate success, especially in maintaining the language ability for MLQA (0.258) and XQUAD (0.527). However, task ability shows some decline (e.g., IFEval (0.401) and ALPACA Eval (0.048)), compared to the baseline. Furthermore, GR_5 results in lower task ability (IFEval = 0.281), while GR_10 performs slightly better in task ability (e.g., MMLU = 0.483, HellaSwag = 0.494).

Among the baselines, ER_10 performs similarly to the generative replay strategies, with modest

improvements in task ability (e.g., IFEval = 0.367, MMLU = 0.479), but still struggles in language ability. Perhaps LoRA shows the best overall performance among the strategies for maintaining task ability (e.g., IFEval = 0.587, MMLU = 0.567, HellaSwag = 0.591) with reasonable retention of language ability (e.g., XQUAD = 0.354).

Note. These results show that no single strategy is perfect, and future work may need to combine these strategies or develop new approaches to address the balance between task and language ability retention across phases.

D Resources Used

We used 4 NVIDIA A100 GPU (80 GB) with a 96 core AMD CPU to run our inferences. One Finetuning Run with MULTIALPACA took 4 hours while for MOPENORCA it took 12 hours.

the list of model and the URL with checkpoints available and licenses are listed below:

LLAMA-3-8B : meta-llama/

Meta-Llama-3-8B **License:** llama3

 $\begin{array}{lll} MISTRAL\text{-}7B & : & \text{https://huggingface.} \\ co/\text{mistralai/Mistral-}7B\text{-}v0.1 & \textbf{License:} \\ \end{array}$

Apache-2.0

Model	Phase 1	Phase 2						XLS	XLSUM					
Model	Dataset	Dataset			Phase 1						Phase 2			
			Arabic	Arabic Chinese_simplified	french	Hindi	Japanese	Spanish	Arabic	Chinese_simplified	french	Hindi	Japanese	Spanish
Misma 7D	ALPACA		0.001	0.012	0.025	0.001	0.012	0.023	0.022	0.034	0.112	0.016	0.067	0.106
MISTRAL- / D	Instruct	Mingray	0.001	0.005	0.028	0.001	0.009	0.025	0.016	0.015	0.060	0.010	0.040	0.056
II AMA 2 OD	ALPACA	MULITALFACA	0.005	0.015	0.071	0.003	0.037	0.067	0.003	0.018	0.073	0.002	0.041	0.070
LLAMA-3-0D	Instruct		0.008	0.015	0.092	0.004	0.080	0.087	0.002	0.013	0.055	0.001	0.055	0.051
Misma 7D	OPENORCA		0.001	0.010	0.014	0.001	0.007	0.009	0.001	0.006	0.018	0.001	0.008	0.016
MISTRAL- / D	Instruct	A O a Orange Over	0.001	0.005	0.028	0.001	0.009	0.025	0.007	0.017	0.092	0.005	0.030	0.088
II AMA 2 OD	OPENORCA	MOFEINORCA	0.000	0.003	0.061	0.000	0.004	0.035	0.000	0.003	0.016	0.001	0.000	0.013
LLAMA-3-0D	Instruct		0.008	0.015	0.092	0.004	0.080	0.087	0.007	0.015	0.091	0.004	0.082	0.087

Table B4: XLSUM: Language Ability results for two-phase Continual Fine-tuning (CFT).

Model	Phase 1	Phase 2											XQuAD	G										
Model	Dataset	Dataset					4	Phase 1										P	hase 2					
			ar	de	e	es	hi	ro	r.	th	t;	vi	zh	ar	de	e	ខ	Ξ	ro	r.	th	tr	Ţ.	zh
Mican it and	ALPACA		0.194	0.194 0.379 0.248		0.374	0.224	0.418	0.150	0.185 (0.454 (0.475 (0 880.0	0.613 0	0.692 0	0.657 0	0.713 0.	0.670	0.679 0	0.661 (0.385 (999.0	0.734 (0.148
MISTRAL-/D	Instruct	Mingratary	0.166	0.568	0.260	0.510	0.173	0.508	0.336 (0.210	0.460	0.502 (0.168	0.369 0	0.612 0	0.253 0	0.634 0.	0.450 0	0.553 0	0.555 (0.180).532 ().566 (0.089
II AMA 2 OD	ALPACA	MULITALFACA	0.393	0.689	0.529	0.735	0.644	0.723	0.538 (0.398	0.671 (0.748 (0.376	0.676 0	0.850 0	0.710 0	_	0.740 0	0.817 0	0.726 (0.526) 077.0).884 (0.519
LLAMA-3-0D	Instruct		0.659	0.795	0.702	0.852	0.715	0.810	0.609	0.594 (0.728	0.834 (0.533 0	0.444 0	0.580 0	0.244 0	0.657 0.	0.241 0	0.586 0	0.493 (0.092	0.580	0.558 (0.113
Mican it and	OPENORCA		0.001	0.001 0.010 0.014	0.014	0.001	0.007	600.0	0.001	0.006	0.018	0.001	0.008 0	0.639 0	0.832 0	0.570 0	0.847 0.	0.601 0	0.776 0	0.771 (0.366	0.734 (0.820	0.113
MISTRAL-/D	Instruct	A Da Oraga Ora	0.166	0.568 0	0.260	0.510	0.173	0.508	0.336 (0.210	0.460	0.502 (0.168	0.256 0	0.457 0	0.320 0	0.443 0.	0.256 0	0.409 0	0.215 (0.245 (0.364 (0.428 (0.162
II AMA 2 OD	OPENORCA	4	0.505	0.642	0.587	0.711	0.604	0.634	0.651 (0.290	0.699	0.685 (0.104	0.639 0	0.832 0	0.570 0	0.847 0.	0.601 0	0.776 0	0.771 (0.366 (0.734 (0.820	0.113
LLAMA-3-0D	Instruct		0.659	0.795	0.702	0.852	0.715	0.810	0.609	0.594 (0.728	0.834 (0.533 0	0.654 0	0.793 0	0.703 0	0.852 0.	0.718 0	0.808 0	0.606	0.600	0.729	0.836	0.540

Table B5: XQuAD: Language Ability results for two-phase Continual Fine-tuning (CFT).

	CF	Γ Setup			Tas	k Ability				Language	e Ability	
Model	Phase 1 Dataset	Phase 2 Dataset	Mitigating Strategy	IFEval	ALPACA Eval	MMLU	HellaSwag	Avg	MLQA	XLSum	XQUAD	Avg
		_	_	0.55	0.35	0.575	0.641	0.529	0.246	0.012	0.351	0.203
			_	0.426	0.06	0.507	0.509	0.376	0.155	0.040	0.323	0.173
			LF_H2	0.401	0.048	0.518	0.487	0.364	0.258	0.060	0.527	0.282
Magnes 7D	T.,		GR_5	0.281	0.027	0.478	0.495	0.320	0.167	0.042	0.305	0.171
Mistral-7B	Instruct	MOPENORCA	GR_10	0.305	0.013	0.483	0.494	0.324	0.150	0.038	0.238	0.142
			LoRA	0.587	0.13	0.567	0.591	0.469	0.167	0.027	0.354	0.183
			ER_10	0.367	0.025	0.479	0.493	0.341	0.157	0.042	0.305	0.168

Table C6: Task and Language ability results for our mitigating strategies, Generative Replay (GR_5 & GR_10) and Layer Freezing (LF_H1 & LF_H2). We also use LoRA (Hu et al., 2022) and ER_10 as two baseline strategies. Here, we perform Phase 2 with rank 64 and bf16 for LoRA. For ER_10, we use the English dataset used in GR_5 with original responses.