## **DELTALLM: Compress LLMs with Low-Rank Deltas between Shared Weights**

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## **Abstract**

We introduce DELTALLM, a new post-training compression technique to reduce the memory foot-print of LLMs. We propose an alternative way of structuring LLMs with weight sharing between layers in subsequent Transformer blocks, along with additional low-rank difference matrices between them. For training, we adopt the progressing module replacement method and show that the lightweight training of the low-rank modules with approximately 30M-40M tokens is sufficient to achieve performance on par with LLMs of comparable sizes trained from scratch.

We release the resultant models, DELTALLAMA and DELTAPHI, with a 12% parameter reduction, retaining 90% of the performance of the base Llama and Phi models on common knowledge and reasoning benchmarks. Our method also outperforms compression techniques Joint-Drop, LaCo, ShortGPT and SliceGPT with the same number of parameters removed. For example, DeltaPhi 2.9B with a 24% reduction achieves similar average zero-shot accuracies as recovery fine-tuned SlicedPhi 3.3B with a 12% reduction, despite being approximately 400M parameters smaller with no fine-tuning applied.

This work provides new insights into LLM architecture design and compression methods when storage space is critical.

## 1. Introduction

Transformer-based architectures (Vaswani, 2017) have become the cornerstone of modern language modeling (Abdin et al., 2024; Dubey et al., 2024; Team et al., 2024; Jiang et al., 2024; Bai et al., 2023; Brown et al., 2020). While scaling laws indicate that performance improves as these models grow in size and training data (Kaplan et al., 2020;

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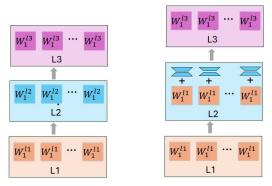


Figure 1. DELTALLM on the right, replaces some transformer layers with others, and account for the layer differences (delta) using low-rank matrices, which are trained to recover the original model's performance.

Hoffmann et al., 2022), many model families are also trained in smaller sizes due to deployment constraints. In addition, multiple approaches—such as distillation (Hinton, 2015; Gu et al., 2024), prompt and KV-cache compression (Zhang et al., 2023; Cai et al., 2024; Liu et al., 2023; Pan et al., 2024), speculative decoding (Leviathan et al., 2023; Li et al., 2024), and quantization (Ashkboos et al., 2024b; Frantar et al., 2022; Xu et al., 2024)—have been proposed to meet resource limitations. For extremely low-resource scenarios such as edge device deployments, these techniques are often combined to make deployment feasible. <sup>1</sup>

Model compression has emerged as a prominent strategy to reduce both the model size and the computational overhead. Most previous works on compressing large language models (LLMs) rely on traditional pruning methods, which do not fully account for the multi-layered Transformer architecture at the core of these models (Singh & Alistarh, 2020; Frantar & Alistarh, 2023b; 2022; Sun et al., 2024; Mishra et al., 2021; Ma et al., 2023), resulting in suboptimal performance. Recently, several studies have proposed compression techniques more tightly tailored to LLMs (Ashkboos et al., 2024a; Men et al., 2024; Yang et al., 2024; He et al., 2024).

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https://blogs.windows.com/
windowsexperience/2024/12/06/
phi-silica-small-but-mighty-on-device-slm/

Although numerous post-training model compression methods have been studied independently, there is still no clear consensus on how to combine them for a specific deployment environment. We address this gap by systematically exploring several techniques including pruning (He et al., 2024), knowledge distillation (Hinton, 2015), weight sharing (Dehghani et al., 2019), low-rank adaptation (Hu et al., 2021), and progressive module replacement (Xu et al., 2020). Based on the insights gained, we introduce DELTALLM, a unified compression strategy that can create significantly smaller language models. Our experiments show that using only 37M tokens for the training of the compressed model, DELTALLM outperforms training a new model from scratch even with billions of tokens with similar size, while preserving competitive performance.

DELTALLM draws inspiration from prior work suggesting redundancy between Transformer layers (He et al., 2024; Yang et al., 2024; Men et al., 2024), as well as from studies showing that simply repeating layers (weight sharing) is an effective method to increase model depth (Dehghani et al., 2019; Liu et al., 2024; Lan et al., 2020). In our approach, we replace a Transformer layer with another one, but introduce low-rank "delta weights" to account for the minor differences between shared layers (see Figure 1). Rather than storing new parameters for every Transformer block, we thus store only a smaller subset of unique weights, complemented by learnable low-rank updates, significantly reducing overall model size.

We train low-rank matrices to recover the original model's performance, using knowledge distillation (Hinton, 2015) with the original LLM as the teacher. To ensure smooth layer substitution, we follow a progressive module replacement strategy, previously shown effective for compressing encoder-only language models (Xu et al., 2020). We conduct ablation studies on both our architectural and training choices, demonstrating their effectiveness. Additionally, our approach is orthogonal to pruning and quantization, yielding hardware-friendly compressed models that achieve performance comparable to the original models.

Our contributions are as follows:

- We present DELTALLM, a new way of structuring Transformer-based models that focuses on weight sharing and low-rank differences between Transformer blocks, significantly reducing the memory requirements for on-device use cases.
- We use DeltallM to compress the Phi-3.5 and Llama-3.2 families of models and achieve better performance on common reasoning and knowledge benchmarks than existing SLMs of comparable sizes. We further show that DeltaPhi and Deltallama outperform post-training compression methods JointDrop,

- SliceGPT, ShortGPT, and LaCO with the same number of parameters removed.
- To the best of our knowledge, we are the first to apply a progressive module replacement method to distill decoder-only LLMs. We show that it converges faster than standard knowledge distillation. We further propose uneven replacement probabilities across layers.

We hope that our observations provide valuable insights on Transformer-based model redundancies, distillation strategies and best practices for LLM architecture design, specifically when storage space is critical.

## 2. Related Work

## **Transformers Redundancy**

The lottery ticket hypothesis posits that a dense, randomly initialized model contains subnetworks (or "winning tickets") which, when trained in isolation, can match or exceed the accuracy of the original model (Frankle & Carbin, 2019). This hypothesis has also been validated in reinforcement learning and natural language processing (Yu et al., 2020; Frankle et al., 2020). Recent studies further reveal substantial redundancy in Transformer architectures (Men et al., 2024), with efforts focusing on removing entire blocks or selectively dropping attention and MLP layers using similarity metrics (He et al., 2024; Shoaib Ahmed Siddiqui, 2024; Bian et al., 2021). Additionally, there is evidence that redundancy tends to concentrate in the middle to later layers, while the first and last layers play more specialized roles (Men et al., 2024; Ma et al., 2023).

## **Pruning**

Pruning has emerged as a widely used model compression technique, removing less important parameters to reduce computational and memory footprints (Han et al., 2015b). Early efforts often relied on unstructured pruning (Han et al., 2015a; Michael H. Zhu, 2018; Gale et al., 2019; Frantar & Alistarh, 2022; 2023a), which did not necessarily improve inference speed. Consequently, more recent approaches explored structured pruning—removing entire filters or attention heads for predictable speedups (Hoefler et al., 2021; Mishra et al., 2021; Sun et al., 2024).

In large Transformer-based models, specialized strategies typically apply structured pruning followed by continued training. For example, movement pruning (Sanh et al., 2020) dynamically drops redundant connections during finetuning; Ashkboos et al. (2024a) uses principal component analysis to remove trailing rows and columns of weight matrices; Ma et al. (2023) selects non-critical coupled structures based on gradient information; Men et al. (2024) eliminates whole layers based on input—output similarity; and LaCo (Yang et al., 2024) collapses outermost layers into

their neighbors. MINITRON (Muralidharan et al., 2024) further compares various pruning and re-training approaches, demonstrating superior efficiency over training small language models from scratch. An essential difference between MINITRON and DELTALLM is the training data requirement: while DELTALLM recovers performance with as few as 37M tokens, MINITRON requires billions.

#### Weight Sharing

Weight sharing, which offers flexible ways to reduce computational and memory overhead, has recently attracted significant attention. Two widely adopted weight-sharing approaches are Mixture of Experts (MoE) and cross-layer weight sharing. MoE, originally introduced to machine learning as a method similar to ensemble techniques (Jacobs et al., 1991), has since been applied to various architectures (Fedus et al., 2022; Eigen et al., 2014; Shazeer et al., 2017) including Transformers (Jiang et al., 2024; Dubey et al., 2024; Abdin et al., 2024). Cross-layer weight sharing, introduced for Transformer-based language modeling in (Dehghani et al., 2019) as a way to reduce memory usage and improve performance, was subsequently adopted by multiple works for training Transformer models from scratch (Wang & Li, 2024; Dehghani et al., 2019; Lan et al., 2020; Liu et al., 2024) or for shrinking existing models (Bae et al., 2024).

## Low-Rank Adaptation

Low-rank approximations (LoRA) have been extensively applied to various stages of machine learning for diverse purposes. Aside from tasks that inherently rely on low-rank structures (Cai et al., 2010; Li et al., 2016; 2018), LoRA-based methods have been proposed to improve the generalization of over-parameterized models (Oymak et al., 2019), enable efficient model fine-tuning (Hu et al., 2022; Hyeon-Woo et al., 2021; YEH et al., 2024; Mahabadi et al., 2021), and reduce computational costs by integrating low-rank layers directly into model architectures (Lan et al., 2020) or as a post-training compression step (Ben Noach & Goldberg, 2020; Tukan et al., 2020; Denton et al., 2014).

## 3. Methodology

#### 3.1. Preliminaries

For a weight  $\mathbf{W}^{D \times D}$  the LoRA technique introduces two additional low-rank matrices  $\mathbf{A}^{D \times R}$  and  $\mathbf{B}^{R \times D}$ , where R is the rank of the matrices. These matrices are then updated during the fine-tuning process and are added to the weight, while the rest of the network remains frozen.

## 3.2. DELTALLM

DELTALLM introduces low-rank differences between layers in consecutive Transformer blocks that share weights,

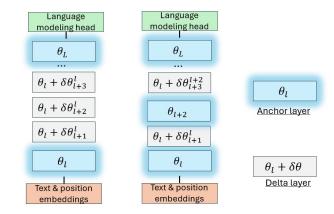


Figure 2. Two ways to structure for a Delta-Model: delta-layers at each subsequent block after a base block (left) and alternating blocks with delta modules between (right).

called deltas.

A model weight **W** of layer l + i can be restructured as a function of the previous layer l and a **delta** between the two weights as follows:

$$\mathbf{W}_{l+i}^{M \times N} = \mathbf{W}_{l}^{M \times N} + \tilde{\delta}_{l+i}^{l} \tag{1}$$

where  $\tilde{\delta}_{l+i}^{l}$  is the low-rank approximation of

$$\delta_{l+i}^{l} = \mathbf{W}_{l+i}^{M \times N} - \mathbf{W}_{l}^{M \times N} \tag{2}$$

We define the delta matrices in the same manner as the A and B matrices in the LoRA setup. The low-rank approximations can be obtained using Singular Value Decomposition (SVD) or other approximation methods. The low-rank deltas allow to restore diversity and adaptiveness that get affected due to layer replication.

Refer to figure 2 for the architecture of a DELTALLM model. We present two strategies for organizing the model structure: a single Transformer block with delta modules creating each subsequent block (left) and alternating Transformer blocks with delta modules in between (right). Within blocks, we can compress attention and/or multi-layer perceptron (MLP) layers.

We can further extend this to allow any previous layer's weight  $W_{l-k}$  to be used to initialize the current weight  $W_l$ . We refer to these layers as *anchor* layer and the corresponding Transformer blocks as *anchor* blocks.

Refer to the ablation studies in Section 5.7 for the best practices on the choice of the blocks and layers.

#### 3.3. Delta-Model Training

While with the right initialization the deltas may be sufficient to retain the desired performance, our method relies on further training, albeit on a small number of tokens.

We explore two strategies for training a DELTALLM model:

- Delta-tuning only with Progressive Module Replacement: delta-layers are progressively replaced with original layers. Only the delta-layers are trained while the rest of the model weights remain fixed.
- Delta-layer tuning with LoRA fine-tuning: LLM weights are fine-tuned jointly with the delta weights using parameter-efficient training methods.

## **Delta-tuning only**

Following (Xu et al., 2020), we progressively replace original LLM weights with the corresponding DELTALLM weights according to a probability scheduler. That is, at the beginning of training, modules are replaced with the given probability rate which gradually increases until convergence to 1.0. Unlike (Xu et al., 2020), after probability rate convergence, we continue training for an additional number of epochs, as determined by the hyperparameter search we conduct.

We additionally extend the progressive module replacement (PMR) method to allow uneven replacement rates across the blocks. This is motivated by our preliminary experiments that later layers contain more redundancy than earlier layers and that it may be beneficial to replace the later layers first for smoother training.

The total loss is computed as

$$L = (1 - \alpha)L_{CE} + \alpha L_{logits}, \tag{3}$$

where  $L_{CE}$  is the cross entropy of the student model (with potentially some layers replaced with the teacher model),  $L_{logits}$  is the distillation loss between the final logits of the teacher and the student models. Following (Muralidharan et al., 2024), we choose Kullback–Leibler (KL) divergence as the distillation loss as it is shown to outperform the mean squared error (MSE) and the cosine similarity,  $\alpha$  is the distillation weight.

## **Full model Fine-tuning**

In the second approach for DELTALLM model training, we train the delta-layers using the progressing module replacement along with the fine-tuning of the rest of the model. We adopt parameter-efficient fine-tuning methods.

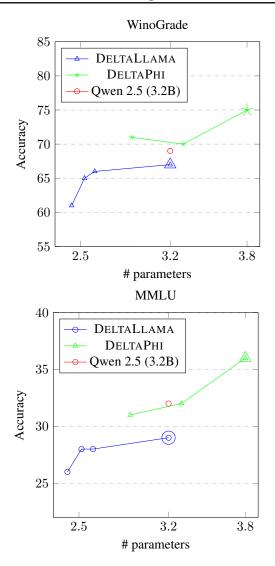


Figure 3. Delta Llama and Delta Phi accuracies on Wino<br/>Grade and MMLU pro

## 4. Experiments

## 4.1. Experiment Settings

We use Phi 3.5 (Abdin et al., 2024) and Llama 3.2 (Dubey et al., 2024) as the teacher models to obtain DELTAPHI and DELTALLAMA models respectively using the procedure outlined in Section 4.

We use Alpaca (Rohan Taori & Hashimoto, 2013) and Ultrachat (Ding et al., 2023) for all training experiments with DELTAPHI and DELTALLAMA. Alpaca is separated into train (80%), validation (10%) and test (10%) portions. The train set is used to conduct the hyperparameter search, for which the test set is used as an optimization metric. The Delta-Model is then trained on the Ultrachat train set with the best set of the hyperparameters.

Benchmark			Mode	odels				
	Phi 3.5	Llama 3.2	Qwen 2.5	<b>D</b> ELTA <b>P</b> HI	DELTAPHI	DELTALLAMA	DELTALLAMA	
# Parameters	3.8B	3.2B	3.2B	3.35B	2.9B	2.52B	2.41B	
Compression %				12%	24%	21%	25%	
Base Model				Phi 3.5	Phi 3.5	Llama 3.2	Llama 3.2	
Training Stage				$\delta$ -tuned only	$\delta$ -tuned only	$\delta$ -tuned only	$\delta$ -tuned only	
Training tokens				37M	37M	32M	32M	
Delta-layers rank/size				r1000/580MB	r100/90MB	r1000/380MB	r100/30MB	
MMLU_pro (acc)	0.36	0.29	0.32	0.32	0.31	0.28	0.26	
WG (acc)	0.75	0.67	0.69	0.70	0.71	0.65	0.61	
ARC_c (acc_norm)	0.61	0.46	0.47	0.51	0.44	0.35	0.34	
HS (acc_norm)	0.77	0.70	0.74	0.70	0.61	0.59	0.55	
PIQA (acc_norm)	0.80	0.76	0.74	0.74	0.72	0.70	0.69	
Average	0.66	0.58	0.59	0.59	0.56	0.51	0.50	

Table 1. Zero-shot benchmark evaluation results of Delta-Models and pre-trained models of similar sizes.

We explore four types of initializing the delta-layers:

- Gaussian: initializes the A matrix with a Gaussian distribution and the B matrix as zero.
- **PiSS**A: performs SVD on the weight matrix and chooses the principal singular values and vectors to initialize both A and B (Meng et al., 2024).
- OLoRA: performs QR decomposition to initialize A and B (Büyükakyüz, 2024).
- EVA: a data-driven initialization method that performs SVD on input activations of every layer and uses the right-singular vectors to initialize the LoRA matrices (Paischer et al., 2024).

We adopt the PEFT library for initializing the delta layers (Mangrulkar et al., 2022). All our experiments are conducted on A100 80GB Nvidia GPUs.

We observe that the training stability is very sensitive to the hyperparameters, thus, an extensive search is conducted using the perplexity on Alpaca test set as the optimization metric. We adopt the Bayesian Optimization search strategy provided by the SyneTune library (Salinas et al., 2022). We search over the learning rate, learning rate scheduler, number of epochs until convergence, the number of extra epochs, distillation weight and type, module replacement probability, delta-layers initialization, LoRA  $\alpha$  and LoRA dropout. The search is conducted with a maximum number of jobs of 40.

#### 4.2. Commonsense benchmark evaluation

We evaluate DeltaPhi and DeltaLlama models on common knowledge and reasoning benchmarks includ-

ing MMLU-Pro (Wang et al., 2024), WinoGrande (Sakaguchi et al., 2021), HellaSwag (Zellers et al., 2019), ARC-Challenge (Clark et al., 2018). We adopt Language Model Evaluation Harness framework (Gao et al., 2024) to perform the evaluations. We conduct zero-shot evaluation for all benchmarks.

The strategy 1 experiment results are shown in Table 1 and Table 7. Here we compare several DeltaPhi and DeltaLlama models with the teacher models they were derived from as well as models of similar sizes. Observe that DeltaPhi 3.35B outperforms Llama 3.2B and Qwen 3.2B on MMLU, WinoGrande and ARC-Challenge benchmarks with a comparable average accuracy across all the tasks. In addition, DeltaPhi 3.35B and DeltaPhi 2.9B achieve similar results for MMLU and WinoGrande results despite the later being compressed by 24% as opposed to 12% and being  $\sim 400 \rm M$  parameters smaller.

Note that for generation tasks with perplexity as the metric (Table 7 in the Appendix) on large datasets (Ultrachat), DELTAPHI outperforms the original Phi 3.5 it was compressed from. In addition, DELTAPHI achieves lower perplexity than Llama 3.2 models of comparable sizes.

Also note that the delta-layers in the DELTAPHI 2.9B model account for only 90MB which is significantly lower than the storage reduced by layer replication.

## 4.3. Model quantization

We conduct 8-bit and 4-bit quantization experiments on a DELTAPHI model with 2.9 billion parameters. Specifically, we employ llm.int8 (Dettmers et al., 2022) method, which applies weight quantization and dynamically determines the activation scales to minimize the information loss. Only the base model undergoes quantization, while the delta layers

Table 2. Comparison of DELTAPHI with SOTA compression methods

Benchmark		Models				
	DELTAPHI	DELTAPHI	DropPhi	SlicedPhi	ShortPhi	Phi-LaCo
# Parameters	3.35B	2.9B	3.4B	3.32B	3.37B	3.36B
Method	DELTALLM	DELTALLM	JointDrop	SliceGPT	ShortGPT	LaCo
Compression	12%	24%	11%	12%	12%	12%
Train Tokens	37M	37M		37M		
Train Stage	$\delta$ -tuned only	$\delta$ -tuned only	No training	LoRA fine-tuned	No training	No training
MMLU_pro (acc)	0.32	0.31	0.28	0.24	0.21	0.33
WG (acc)	0.70	0.71	0.60	0.68	0.64	0.71
ARC_c (acc_norm)	0.51	0.44	0.44	0.49	0.46	0.50
HS (acc_norm)	0.70	0.61	0.53	0.65	0.68	0.63
PIQA (acc_norm)	0.74	0.72	0.67	0.74	0.76	0.73
Average	0.59	0.56	0.50	0.56	0.55	0.58

Table 3. Comparison of DELTALLAMA with SOTA compression methods

Benchmark		Models				
	DELTALLAMA	DELTALLAMA	DropLlama	SlicedLlama	ShortLlama	Llama-LaCo
# Parameters	2.52B	2.41B	2.6B	2.56B	2.61B	2.41B
Method	DELTALLM	DELTALLM	JointDrop	SliceGPT	ShortGPT	LaCo
Compression	21%	25%	19%	20%	18%	25%
Train Tokens	32M	32M		32M		
Train Stage	$\delta$ -tuned only	$\delta$ -tuned only	No training	LoRA fine-tuned	No training	No training
MMLU_pro (acc)	0.28	0.26	0.11	0.11	0.23	0.15
WG (acc)	0.65	0.61	0.64	0.49	0.64	0.63
ARC_c (acc_norm)	0.35	0.34	0.40	0.26	0.36	0.32
HS (acc_norm)	0.59	0.55	0.58	0.28	0.56	0.52
PIQA (acc_norm)	0.70	0.69	0.65	0.55	0.64	0.65
Average	0.51	0.50	0.48	0.33	0.49	0.45

remain in FP16 to preserve adaptation capacity.

The model architecture incorporates weight sharing in its MLP layers, specifically between blocks 22–29 and block 21, with these shared layers connected via rank-100 delta matrices.

For quantization, we use an 8-bit scheme based on vectorwise quantization of weights, which balances compression and inference efficiency. For 4-bit quantization, we use the NF4 data format, which is a non-uniform 4-bit quantization scheme. Both methods leverage mixed-precision decomposition techniques to maintain numerical stability.

Our goal is to evaluate whether quantization has any adverse effect on model performance and, subsequently, whether excluding the anchor layers from quantization impacts the overall quantization efficiency. Hence, we explore two distinct quantization strategies for this architecture:

 AnchorSkip: Quantize all layers except the anchor layers.

Table 4. Quantization Results on DELTAPHI 2.9B

AllQuant	AnchorSkip	
0.30	0.33	
0.60	0.61	
0.42	0.44	
0.72	0.72	
0.28	0.29	
0.59	0.60	
0.42	0.42	
0.72	0.72	
	0.30 0.60 0.42 0.72 0.28 0.59 0.42	

• AllQuant: Quantize all layers, including the anchor layers.

The results in Table 4 show that quantization only minimally degrades the model performance when compared with the non-quantized model. There is also marginal gain using AnchorSkip strategy compared to the AllQuant.

*Table 5.* Comparison of distillation with PMR and constant replacement rate of 1.

Model	Distil Method	<b>Epochs</b>	Dataset	PPL
DELTAPHI 3B	PMR	2	Alpaca	3.34
DeltaPhi 3B	without PMR	5	Alpaca	3.42
DeltaPhi 3B	with PMR	2	Ultrachat	7.49
DeltaPhi 3B	without PMR	4	Ultrachat	7.24

## 4.4. Ablation Study: Progressive Module Replacement

In this section we compare  $\delta$ -only training with PMR and the standard distillation where the teacher and student models are completely separate. This is equivalent to setting the replacement rate to 1.0 while keeping the distillation loss unchanged. Refer to Table 5 for the results on Alpaca test dataset. With extensive hyperparameter optimization including search over the number of epochs, the PMR approach outperforms the distillation without PMR with a smaller number of epochs. This suggests that PMR enables faster convergence.

# 4.5. Ablation Study: Which blocks and layers to compress?

In all our experiments we keep the first and the last two blocks unchanged since they are highly specialized and cause significant degradation if removed (Men et al., 2024; Ma et al., 2023).

We explore three strategies of the construction of the deltablocks:

- **Sequential**: A sequential set of delta-blocks. That is, weights of a single anchor Transformer block get shared with the next few blocks with deltas.
- Alternating: A set of blocks where a standard and delta block are alternating. In this setup multiple anchor blocks share weight with other blocks and have deltas between them.
- **JointDrop**: The layers obtained by the JointDrop method (He et al., 2024). The JointDrop method computes the importance of layers using a similarity-based metric to capture redundancy. This metric is then used to eliminate those layers completely. In our setup, instead of removing them, we replicated those layers with the addition of deltas.

In each of these options, we can further choose the layers to compress within the blocks: MLP, attention or a combination of both. When choosing which layers to replicate the weights from, we rely on prior work suggesting that the

Table 6. DELTAPHI ablations with block/layer choice

Model	<b>Block Choice</b>	Dataset	PPL
DELTAPHI (4 ATTN)	JointDrop	Alpaca	<b>3.14</b> 3.76 4.27
DELTAPHI (6 ATTN)	JointDrop	Alpaca	
DELTAPHI (8 ATTN)	JointDrop	Alpaca	
DELTAPHI (4 MLP)	Sequential	Alpaca	3.24
DELTAPHI (6 MLP)	Sequential	Alpaca	3.80
DELTAPHI (8 MLP)	Sequential	Alpaca	<b>3.94</b>
DELTAPHI (4 ATTN)	Sequential	Alpaca	3.29
DELTAPHI (6 ATTN)	Sequential	Alpaca	3.84
DELTAPHI (8 ATTN)	Sequential	Alpaca	4.31
DELTAPHI (4 MLP)	Alternating	Alpaca	3.22
DELTAPHI (6 MLP)	Alternating	Alpaca	<b>3.55</b>
DELTAPHI (8 MLP)	Alternating	Alpaca	4.10
DELTAPHI (4 ATTN)	Alternating	Alpaca	3.36
DELTAPHI (6 ATTN)	Alternating	Alpaca	3.58
DELTAPHI (8 ATTN)	Alternating	Alpaca	4.03

changes between the outputs of consecutive layers tends to be less significant (Yang et al., 2024). Hence, we always choose the anchor layer to be layer prior to the delta-layer.

Refer to Table 6 for the ablations on the Transformer blocks chosen for Phi-3.5. Note that the JointDrop method always outputs the attention layers. This happens due to the importance computation of the inputs and outputs of the layers.

In the sequential and alternating cases, the MLP choice tends to results in lower perplexities for the models with more layers removed.

We hypothesize that the compression of MLP layers tends to perform better due to the nature of the DELTALLM architecture. Attention layers are highly sensitive to the input tokens and their replication may lead to the loss of layer-specific toke-to-token relationships, hurting effective language modeling. MLP layers transform tokens independently and contribute to most of the model parameters, suggesting that they may exhibit more redundancy. Our method does not remove the MLP layers as pruning methods do, preserving the number of computations performed and the trained low-rank deltas allow to diversify the replicated MLPs.

In addition, given the same number of blocks, compressing MLP layers helps to reduce the storage requirements more significantly due to the large number of parameters. Hence, in the subsequent experiments we apply our method to the MLP layers.

## 4.6. Baselines

In this section, we compare our method to state-of-the-art compression methods JointDrop, SliceGPT, ShortGPT and LaCo. The results are given in the Tables 2 and 3.

## JointDrop: Removing Attention and MLP layers

(He et al., 2024) show that several layers in an LLM can be completely removed while maintaining comparable model performance. We replicate their method on Phi 3.5 and Llama 3.2.

DELTALLM with comparable number of parameters outperforms Drop-Phi on many of the common benchmarks.

Interestingly, we observe that smaller models like Phi 3.5 experience more significant performance drops during layer removal compared to the larger models (LLama 70B) examined in the original study. This aligns with other works suggesting that larger models contain more redundancy than smaller models. This may also suggest that model compression techniques may need to be specifically tailored to the scale of the target model rather than applying a one-size-fits-all approach. Due to the resource constraints we did not reproduce the results on larger models.

## **Pruning Methods**

We compare our approach to the SliceGPT pruning method with similar number of parameter removed. Note that for SliceGPT experiments, the chosen sparsity level does not correspond to the same percentage reduction in the number of model parameters: e.g. we produced SlicedPhi with 23% Transofrmer-block sparsity resulting in a model compressed by 13% (total sparsity). For DELTALLM models, the reported compression percentage accounts for both the removed layers and the additional delta matrices. We further apply recovery fine-tuning on the sliced models using the default parameters.

DELTAPHI and DELTALLAMA with delta-tuned weights consistently outperform SlicedPhi and SlicedLlama of comparable sizes respectively on the common benchmarks, despite no recovery fine-tuning of the DELTALLM models.

Tables 2 and 3 also present results with the SOTA pruning method LaCo. Note that LaCo on Phi tends to perform well, outperforming DeltaPhi on MMLU and Winogrande, however the average accuracy across the benchmarks is on par with DeltaPhi. LaCo applied to Llama produces significantly worse results than DeltaLama. Overall, DeltaPhi and DeltaLama have the highest average accuracy compared to models obtained using other post-training compression methods. We hypothesize that the trained deltas are able to capture the slight differences between the consecutive shared weights. All of the other methods reduce the overall number of computations unlike our method.

## 5. Limitations and Future Work

## **Delta-layer Initialization**

Compared with training-free compression methods, our method heavily relies on the training of the low-rank deltas. This implies a dependency on the quality of the training data as well as the need for additional compute resources, although light. We hypothesize that the right initialization of deltas may reduce the need for additional training. We plan to explore this as a future research direction.

#### **Shared Layer Operations**

In the current setup, the subsequent layers are initialized with full weight replication of the anchor weights. We hypothesize that the shared weights can also be initialized using other operations such as a weighted average of the weight matrices. This may facilitate a better knowledge transfer between the layers.

## **Inference latency**

The DELTALLM currently focuses on restructuring an LLM to save disk space on-device while preserving comparable accuracy. Our method does not focus on reducing the inference time of the model running on-device. We plan to investigate ways to reduce the inference time in future work. For example, a potential approach is to combine attention pruning or removal methods with MLP weight sharing, which can contribute to both space and computation efficiency.

#### 6. Conclusion

In this paper, we present DELTALLM, an alternative approach to structuring Transformer-based models, which optimize for space efficiency. In our setting, MLP and attention layers share weights with the corresponding anchor layers earlier in the network. The shared weights have additional low-rank delta-layers between them, which are trained to preserve the knowledge and capabilities of the model. We show that DELTALLM models compressed from open-source LLMs can achieve comparable performance with other models of similar sizes trained from scratch. This new structure also outperforms many post-training compression methods such as JointDrop, SliceGPT, ShortGPT and LaCo. We hope that our method inspires new efficient designs of LLM architectures that can be trained from scratch as well as serve as both a post-training compression technique.

## 7. Impact Statements

This paper presents work whose goal is to advance the field of Machine Learning. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

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Table 7. Comparison of Delta-Models to SLMs of similar sizes (perplexity)

Model	# Parameters	Compression %	Dataset	PPL
Phi 3.5	3.82B		Alpaca	2.96
Llama 3.2	3.2B		Alpaca	4.25
Qwen 2.5	3.2B		Alpaca	3.69
<b>DELTAPHI</b> (5 seq MLP δ, r1000)	3.35B	12%	Alpaca	3.34
DELTAPHI (6 seq MLP $\delta$ , r1000)	3.3B	13%	Alpaca	3.80
DELTAPHI (8 seq MLP $\delta$ , r100)	2.8B	26%	Alpaca	3.94
DELTALLAMA (6 seq MLP $\delta$ , r100)	2.62B	18%	Alpaca	5.35
DELTALLAMA (7 seq MLP $\delta$ , r100)	2.52B	21%	Alpaca	5.43
DELTALLAMA (9 seq MLP $\delta$ , r1000)	2.41B	25%	Alpaca	6.00
Phi 3.5	3.82B		Ultrachat	8.22
Llama 3	3.2B		Ultrachat	14.81
<b>DELTAPHI</b> (5 seq MLP $\delta$ , r1000)	3.35B	12%	Ultrachat	7.49
DELTAPHI (8 seq MLP $\delta$ , r100)	2.9B	24%	Ultrachat	9.19
DELTALLAMA (7 seq MLP $\delta$ , r100)	2.51B	19%	Ultrachat	18.32
DELTALLAMA (9 seq MLP $\delta$ , r1000)	2.41B	25%	Ultrachat	17.74