

PERP: Rethinking the Prune-Retrain Paradigm in the Era of LLMs

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Abstract

Neural Networks can be effectively compressed through *pruning*, significantly reducing storage and compute demands while maintaining predictive performance. Simple yet effective methods like magnitude pruning remove less important parameters and typically require a costly retraining procedure to restore performance. However, with the rise of LLMs, full retraining has become infeasible due to memory and compute constraints. This study challenges the practice of retraining all parameters by showing that updating a small subset of highly expressive parameters can suffice to recover or even enhance performance after pruning. Surprisingly, retraining just 0.01%-0.05% of the parameters in GPT-architectures can match the performance of full retraining across various sparsity levels, significantly reducing compute and memory requirements, and enabling retraining of models with up to 30 billion parameters on a *single* GPU in minutes. To bridge the gap to full retraining in the high sparsity regime, we introduce two novel LoRA variants that, unlike standard LoRA, allow merging adapters back without compromising sparsity. Going a step further, we show that these methods can be applied for memory-efficient layer-wise reconstruction, significantly enhancing state-of-the-art retraining-free methods like Wanda (Sun et al., 2023) and SparseGPT (Frantar & Alistarh, 2023). Our findings present a promising alternative to avoiding retraining.

1. Introduction

Pruning (Han et al., 2015; Gale et al., 2019; Lin et al., 2020; Hoeferl et al., 2021; Zimmer et al., 2022) is among the state-of-the-art techniques to reduce the compute and storage requirements of Neural Networks, allowing to benefit from the extensive over-parametrization of modern architectures (Zhang et al., 2016) throughout training while maintaining high performance with lower resource demands during deployment. Arguably simple yet effective approaches to

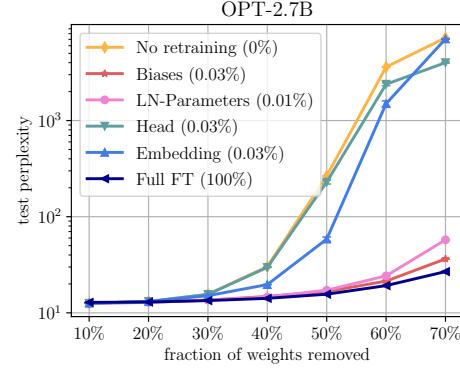


Figure 1. OPT-2.7B evaluated on WikiText: Final perplexity vs. sparsity after pruning, followed by retraining only the specified parameter subset. We indicate the percentage of trainable parameters in parentheses. Full FT refers to full retraining of all parameters.

obtaining such *sparse* models follow the *prune after training* paradigm and are exemplified by IMP (Han et al., 2015), which starts from a pretrained *dense* model and iteratively removes seemingly unimportant parameters followed by retraining to compensate for pruning-induced performance degradation.

Despite their popularity, approaches like IMP suffer from being computationally expensive, potentially having to perform many prune-retrain cycles and retraining epochs to obtain well-performing models for the task at hand. Especially given the surge in popularity of *foundation models* – huge pretrained models which are reused and fine-tuned for specific tasks – a procedure such as IMP can be prohibitive in resource constrained environments (Frantar & Alistarh, 2023), even when performing just a single prune-retrain cycle (*One Shot*). Retraining hence enjoys a particularly negative reputation and a variety of approaches try to avoid it entirely, including novel weight-selection criteria for pruning without the need for retraining (Frantar & Alistarh, 2023; Sun et al., 2023; Theus et al., 2024; Jaiswal et al., 2023a).

On the other hand, several works have tried to address the issue from the angle of making retraining itself less undesirable. Zimmer et al. (2023) accelerate retraining using

a pruning-adaptive learning rate schedule, effectively reducing the number of iterations required while improving generalization performance. To find *lottery tickets* (Frankle & Carbin, 2018) more efficiently, You et al. (2020) and Wolfe et al. (2021) try to find the pruning mask earlier in training, Jaiswal et al. (2023b) speed up the mask-generation process by superimposing a set of masks throughout retraining, and Zhang et al. (2021) reduce the number of retraining iterations by using only a critical subset of the data. Zimmer et al. (2024) show that constructing *sparse model soups* during each phase of IMP can enhance its performance and the overall wall-time required for retraining.

In this work, we propose viewing the problem from another, previously underexplored angle, namely that of *parameter-efficiency*. In almost all classical pruning literature, retraining after pruning is defined as a retraining of *all* parameters at hand¹. This is particularly problematic with optimizers like Adam (Kingma & Ba, 2014), which need storage for parameters, gradients, and both first and second-order moments. With growing model sizes, especially in the context of Large Language Models (LLMs), retraining all parameters is a challenge both in terms of computational efficiency and storage demands. Notable exceptions to the retrain-all-parameters paradigm are recent works that introduce additional retraining parameters through Low-Rank Adaptation (LoRA) (Hu et al., 2021). However, this comes with increased inference costs, as LoRA-adapters usually cannot be merged with the original parameters without reducing model sparsity (Sun et al., 2023).

Our work is motivated by the following observation: Pruning can substantially degrade the model’s performance, often to near-random levels. Yet, full retraining can restore performance in much fewer iterations than similar loss reductions would need during training from scratch (Zimmer et al., 2023), suggesting that retrained models retain considerable feature information and stay closely aligned with their pruned-but-not-retrained counterparts. The goal of this work is to recover these features efficiently by challenging the common practice of retraining all parameters after pruning. To that end, we investigate and propose Parameter-Efficient Fine-Tuning (PEFT) techniques (Lialin et al., 2023a;b) in the context of retraining after pruning, demonstrating that retraining a small subset of highly expressive parameters can effectively restore performance. Further, we propose two novel LoRA variants that allow adapters to be merged back into the model without compromising sparsity.

Surprisingly, by retraining as little as 1% of the parameters of state-of-the-art Generative Pretrained Transformer (GPT) architectures such as OPT (Zhang et al., 2022), LLaMA-2 (Touvron et al., 2023), Mistral (Jiang et al., 2023) and

¹For unstructured pruning, pruned parameters are forced to zero during retraining but are still part of backpropagation.

Mixtral (Mistral, 2023), we recover nearly all of the full-retraining performance, even at moderate to high sparsity levels, where pruning without retraining collapses entirely. Similarly, retraining less than 0.5% of the parameters of a ResNet-50 on ImageNet is sufficient to recover accuracy. We refer to the proposed approaches using the umbrella term Parameter-Efficient Retraining after Pruning (PERP). These methods enable pruning and retraining of up to 30 billion parameter GPTs on a *single* NVIDIA A100 GPU within minutes. Notably, they achieve this without increasing inference costs during deployment, as no additional parameters remain after retraining and the sparsity is preserved.

Contributions. Our main contributions are:

- Restoring feature quality with few parameters.** We challenge the practice of retraining all parameters after pruning, demonstrating that retraining a small subset of highly expressive parameters such as biases or Layer-Normalization (LN)-parameters can effectively restore performance after pruning, with backpropagation of less than 0.05% of the total parameters often sufficing for full recovery. Despite initial performance degradation to near-random levels, retraining a fraction of the parameters can restore qualitative features with significantly reduced compute and memory requirements, allowing retraining of up to 30 billion parameters models on a *single* NVIDIA A100 GPU within minutes.
- Closing the gap: Low-Rank Adaption.** We propose and discuss two novel LoRA-based methods that enable efficient retraining while preserving model sparsity. Unlike standard LoRA, our approaches allow merging adapters back into the original weights without compromising sparsity. Using as little as 1% of parameters, we achieve performance comparable to or better than full retraining across various sparsity levels and model architectures.
- Efficient Layer-wise Reconstruction.** Going a step further, we demonstrate that such parameter-efficient approaches can significantly enhance state-of-the-art retraining-free methods like SparseGPT and Wanda when applied in a layer-wise reconstruction setting. By optimizing each layer independently with further reduced memory overhead, we improve zero-shot accuracy by up to 17% for magnitude pruning and up to 4% for Wanda and SparseGPT.

Our work challenges the practice of retraining all parameters after pruning, highlighting that the features retained in pruned models can be effectively realigned to good performance by retraining a remarkably small subset of parameters, such as only the LN. We emphasize that our goal is not

to propose a set of methods that claim state-of-the-art performance, but to systematically explore parameter-efficient retraining of sparse models from the ground up.

2. Methodology and Experimental Setup

We begin with a short overview of pruning and PEFT.

2.1. Preliminaries

Pruning. We prune LLMs in a post-hoc fashion, removing individual or groups of weights of a pretrained model, following the *prune after training* paradigm. Our focus lies on the *One Shot* setting, where the network is pruned once and then retrained to recover the pruning-induced performance drop, as opposed to iterative approaches such as IMP. Since pruning a non-trivial portion of the parameters may result in significant performance degradation, the retraining step is fundamental to obtain a well-performing model, which is typically possible in much fewer iterations than what standard training would require to achieve a comparable reduction in train loss (Zimmer et al., 2023). In this work, we study pruning to produce high-quality sparse models rather than to obtain lottery tickets (Frankle & Carbin, 2018).

Arguably the simplest and most popular pruning criterion is *magnitude pruning*, which removes the fraction of weights with smallest magnitude. However, it is by far not the only one, as detailed in studies like LeCun et al. (1989); Hassibi & Stork (1993); Molchanov et al. (2016); Yeom et al. (2019), see Hoefler et al. (2021) for a comprehensive review. Despite its simplicity, magnitude pruning and its variants have been shown to be highly effective for convolutional architectures, being able to produce sparse models comparable in performance to those from much more complex algorithms (Gale et al., 2019; Zimmer et al., 2023).

For LLMs, magnitude pruning has been argued to be unsuited, with perplexity exploding already at moderate sparsity levels, and it being no better than random pruning at higher sparsity (Yin et al., 2023). In consequence, there is growing interest in developing pruning criteria other than magnitude that yield high-performance models without the need for retraining (Kwon et al., 2022; Frantar & Alistarh, 2023; Sun et al., 2023). Both Sun et al. (2023) and Yin et al. (2023) explain the inability to magnitude-prune LLMs with observations made by Dettmers et al. (2022) regarding the *emergence of large magnitude features* in transformers beyond a certain size. These large features, a small yet significant subset of hidden features, are critical for model performance, and pruning them severely impacts predictive accuracy (Sun et al., 2023); a problem that magnitude pruning fails to address. Yin et al. (2023) take these outliers into account and propose a mechanism to better allocate sparsity between the layers. Interestingly, Yin et al. (2023) note

that the previous efficacy of magnitude pruning is closely intertwined with the feasibility of retraining, which is in turn considered infeasible for models of the scale of LLMs.

Layer-wise reconstruction offers an efficient alternative to full retraining by breaking down the problem into per-layer subproblems. As opposed to optimizing all parameters with a *global* loss, such approaches use a calibration dataset on which a *local* per-layer reconstruction error is minimized. Specifically, for layer l with input X_l , weights W_l , and binary pruning mask M_l , the goal is to optimize

$$\min_{\hat{W}_l} \|W_l X_l - (M_l \odot \hat{W}_l) X_l\|_2^2, \quad (1)$$

where \hat{W}_l represents the reconstructed weights, and \odot denotes the element-wise Hadamard product.

Transfer learning. As models grow in size, Fine-Tuning (FT) – the process of adapting a pretrained model to a novel task – has become the norm, avoiding the inefficiencies of training from scratch for each new task (Houlsby et al., 2019; Kumar et al., 2022b). FT capitalizes on the transfer of existing knowledge to a closely related domain (*transfer learning*). Yet, the immense size of foundation models can make the FT approach more challenging, requiring storage for the entire model, its gradients, and auxiliary buffers, even for brief training. In response, various PEFT methods have emerged. They significantly reduce the number of trainable parameters, cutting down on compute and storage needs, while preserving performance levels comparable to conventional full FT.

PEFT methods are broadly categorized as selective, additive, or reparametrization-based (Lialin et al., 2023a). *Selective methods* update specific model components, such as the top linear layer (Kumar et al., 2022a; Evcı et al., 2022), only the biases (Zaken et al., 2021), or by partitioning specific tensors into active and inactive portions (Vucetic et al., 2022). *Additive methods*, like *adapters* (Houlsby et al., 2019; He et al., 2022), add new parameters which are trained for specific tasks while the main model remains unchanged. *Reparametrization-based methods* exploit the low intrinsic dimensionality of fine-tuning (Aghajanyan et al., 2020). A well-known example is LoRA (Hu et al., 2021), which implicitly enforces low-rank constraints on additive updates to pretrained parameter matrices, substantially decreasing the number of trainable parameters. Precisely, LoRA freezes the pretrained parameters and reparametrizes each matrix $W_0 \in \mathbb{R}^{n \times m}$ as $W_0 + \Delta W$, where $\Delta W = BA$ represents the update. In this representation, $B \in \mathbb{R}^{n \times r}$ and $A \in \mathbb{R}^{r \times m}$ implicitly constrain the rank of ΔW to be at most $r \ll \min(n, m)$. B is zero-initialized, thereby preserving the original model’s behavior. During training, only A and B are updated, while W_0 remains fixed.

Other related literature. Kwon et al. (2022) propose a

structured pruning framework for transformers, explicitly avoiding retraining for efficiency. Zhang et al. (2023b) develop a training-free pruning method inspired by prune-and-grow strategies from *Dynamic Sparse Training* (Evci et al., 2020). Several works propose techniques in the domain of sparse fine-tuning in transfer learning. Zhang et al. (2023a) address the problem of performing gradient-based pruning by utilizing the LoRA gradients as substitute for the full gradient. Liu et al. (2021) aim at pruning pretrained models for improvements when fine-tuning to downstream tasks. Li et al. (2022) reduce the number of parameters for weight importance computation in sparse fine-tuning. While conventional retraining typically involves retraining all parameters, Sun et al. (2023) further fine-tune pruned LLMs using LoRA, however at the price of increased inference costs since the LoRA matrices cannot be merged with the original parameters. Similarly, Ma et al. (2023) perform LoRA after structured pruning, eventually allowing LoRA matrices to be merged. Concurrent to our work, Lu et al. (2024) and Muñoz et al. (2024) propose PEFT strategies that maintain sparsity. Lu et al. (2024) focus on retraining multiplicative rescaling factors of pretrained parameters, while Muñoz et al. (2024) integrate masking of LoRA matrices with quantization and neural architecture search. We contrast their approaches with ours in Section 3.2. To the best of our knowledge, our work is the first to thoroughly investigate PEFT for retraining and reconstruction after pruning, presenting several efficient methods that recover performance without increasing inference costs or reducing sparsity.

2.2. Parameter-Efficient Retraining After Pruning

Pruning can degrade the model’s performance to near-random levels. Yet, retraining often restores performance in much fewer iterations than similar loss reductions during pretraining (Zimmer et al., 2023). This optimization often involves merely a few iterations, even when dealing with substantial pruning-induced performance degradation. Consequently, even if the pruned network is severely damaged, it likely retains most of the task-informative features. *We hypothesize that, similar to fine-tuning in transfer learning, retraining can be significantly more efficient by leveraging these features rather than adjusting the entire network, despite pruning severely damaging the model.* In essence, we view pruning as a disturbance to the features the model had learned and retraining after pruning is about refining imperfect, yet valuable features.

What gains can we expect from parameter-efficiency?

Parameter-Efficient Retraining aims to substantially reduce the computational load and memory demands of backpropagation by retraining fewer parameters, i.e., freezing the majority of parameters to not require gradients. While techniques like adapters or LoRA might slightly increase computational requirements in the forward pass, we expect that the

computational load is still significantly reduced. However, a major benefit also lies in the significant reduction in memory requirements. Typically, optimizers such as AdamW (Kingma & Ba, 2014; Loshchilov & Hutter, 2019) require multiple buffers per parameter and retraining fewer parameters results in considerably less allocated memory. This reduction is crucial for retraining large models efficiently, exemplified by our ability to retrain up to 30 billion parameter models on a single NVIDIA A100. Often, the memory required for storing activations during backpropagation can be significantly reduced. However, if parameters early in the network require gradients, then almost all activations need to be stored for backpropagation. To further reduce these requirements, we investigate the use of parameter-efficient retraining in the layer-wise reconstruction setting as per Equation 1, limiting the optimization to individual layers.

2.3. Experimental setup

We outline our general experimental approach, detailing datasets, architectures, and metrics. To enable reproducibility, our code is available at github.com/ZIB-IOL/PERP.

Our study primarily investigates language modeling in NLP. We use pretrained GPT models available through HuggingFace (Wolf et al., 2020), namely *OPT-1.3B/2.7B/6.7B/13B/30B* (Zhang et al., 2022), *LLaMA-2-7B/13B* (Touvron et al., 2023), *Mistral-7B* (Jiang et al., 2023) as well as *Mistral-8x7B* (Mistral, 2023). Retraining is done on the *C4* dataset (Raffel et al., 2020) with context-length sequence sizes using AdamW (Loshchilov & Hutter, 2019) using a linear schedule and a 10% warmup. For validation, we randomly sample 100 sequences from the validation split. The models are evaluated using the perplexity metric on the *WikiText* dataset (Merity et al., 2016). In addition, we provide the zero-shot accuracy on the EleutherAI evaluation set (Gao et al., 2023). We follow Sun et al. (2023) and prune all linear layers except the embedding and final linear head, assigning uniform sparsity to all layers and providing experiments for unstructured and the semi-structured 2:4 and 4:8 sparsity patterns (Mishra et al., 2021). In Appendix C, we also provide experiments for image classification.

3. Parameter-Efficient Retraining

Pruning can be seen as distorting the initially acquired features, diminishing the network’s expressivity by settling on suboptimal features. With most parameters set to be immutable, our goal is to regain performance (minimizing perplexity or maximizing accuracy) with a minimal number of parameters. To that end, we first examine subsets of the parameters with varying complexity, which we hypothesize to hold significant expressive power during retraining.

3.1. Restoring feature quality with few parameters

We investigate the following parameter subsets:

Biases: We only retrain the network’s biases. Despite corresponding to only a small fraction of the total parameters, biases can be crucial for model expressivity; Zaken et al. (2021) specifically propose a PEFT method that only adjusts these biases to the new task.

LN: LN layers include trainable scaling and bias parameters. The importance of normalization layers for expressivity has been highlighted by Mudrakarta et al. (2018); Giannou et al. (2023), with Frankle et al. (2020) demonstrating that training only these parameters can enable otherwise frozen, randomly-initialized networks to achieve significant accuracy.

Linear Head: A popular PEFT approach is *Linear Probing*, where all parameters remain fixed except for the final linear head to align the features to the new task.

Embedding: The embedding layer is the network’s first layer and is crucial for processing input data.

Figure 1 shows the (log) perplexity after magnitude pruning OPT-2.7B followed by retraining only the specified parameter subset, indicating the percentage of trainable parameters in parentheses. All approaches are retrained for 1000 iterations, tuning the initial learning rate, see Appendix A for full details. We make the following observations:

- Pruning without retraining collapses.** Consistent with previous findings (e.g., Yin et al., 2023), magnitude pruning without subsequent retraining results in a collapse even at moderate sparsity levels.
- Head and embedding retraining are ineffective.** Contrary to our expectations, retraining only the head or the embedding layer fails to recover performance lost due to pruning. Although there are slight improvements over not retraining, the impact seems marginal.
- Biases and LN-parameters restore performance.** Surprisingly, retraining biases or LN recovers most of the lost performance, despite corresponding to just 0.03% and 0.01% of the total parameters, respectively. Even at high sparsity levels, both approaches nearly match the perplexity of full FT, with significantly reduced memory and compute requirements.

Table 1 shows the final perplexity (upper halves) and average zero-shot accuracy (lower halves) after magnitude pruning OPT-2.7B and OPT-30B to 30%-70% unstructured sparsity and retraining. Retraining only biases and LN-parameters effectively restores much of the performance lost to pruning, particularly when measuring zero-shot accuracy. This

Table 1. OPT-2.7B/30B: Parameter-efficient approaches vs. full retraining with 30%-70% of the parameters pruned. The first column lists the method, and the second shows the percentage of trainable parameters. Full FT represents the standard retraining baseline and is only possible for OPT-2.7B due to memory constraints. The next five columns display the average mean perplexity (upper halves, lower is better) and average zero-shot accuracy (lower halves, higher is better) across multiple seeds, with standard deviations excluded for clarity.

OPT-2.7B

Perplexity: 12.47		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
Full FT	100%	13.42	14.16	15.63	19.20	26.86
MaskLoRA	0.882%	13.41	14.24	15.75	18.37	25.58
Biases	0.034%	13.57	14.86	16.56	21.41	37.24
LN-Parameters	0.013%	13.58	14.63	17.24	24.26	58.08
No retraining	0.000%	15.58	30.31	265.13	3604.96	7252.22

Accuracy: 47.81%		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
Full FT	100%	46.99%	46.20%	45.44%	44.53%	42.44%
MaskLoRA	0.882%	47.25%	46.29%	45.92%	43.92%	41.56%
Biases	0.034%	46.75%	45.66%	45.29%	42.75%	39.49%
LN-Parameters	0.013%	46.78%	45.48%	44.72%	41.37%	38.32%
No retraining	0.000%	44.99%	42.77%	40.01%	35.34%	32.38%

OPT-30B

Perplexity: 9.55		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.329%	10.27	11.04	11.75	13.55	16.65
Biases	0.013%	10.32	11.30	12.58	14.66	20.06
LN-Parameters	0.005%	10.29	11.17	12.50	15.17	21.41
No retraining	0.000%	12.37	24.29	168.06	11676.00	28180.15

Accuracy: 55.07%		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.329%	54.42%	53.71%	53.12%	50.60%	47.79%
Biases	0.013%	53.84%	52.90%	51.59%	50.00%	46.33%
LN-Parameters	0.005%	53.31%	52.39%	51.88%	49.93%	45.07%
No retraining	0.000%	51.57%	44.19%	36.39%	32.01%	31.92%

supports our hypothesis: Although pruning disrupts learned features, adjusting per-layer translations via bias retraining or the affine LN transformations is sufficient to achieve well-performing sparse networks. However, a gap remains at high sparsity levels like 70%. Note that, due to memory constraints, OPT-2.7B is the largest model that can be fully retrained on a single GPU, so full FT for the 30 billion parameter variant is omitted, since multiple GPUs would be required. In contrast, optimizing only biases or LN-parameters for the 30B model is feasible on a single GPU, demonstrating the memory efficiency of parameter-efficient retraining. We further note that retraining the dense (non-sparse) model on C4 offers no benefits, and these results transfer to the other architectures, as detailed in Appendix B.

3.2. Closing the gap: Low-Rank Adaption

We demonstrated that suitable parameters-subsets are often sufficient to restore performance, despite updating only a small fraction of the parameters. Especially in the low to medium sparsity regime, retraining only biases and LN-

parameters poses a compute- and memory-efficient alternative to full FT. However, in the higher sparsity regime, full retraining prevails. Combining parameter subsets, such as retraining both biases and LN-parameters simultaneously, yields improvements. However, the effect is less pronounced, indicating diminishing returns from adding more such parameter subsets to align the distorted features (cf. Appendix D for a full ablation). To close this gap, we investigate the usage of reparametrization-based approaches to efficiently update *all* parameters.

Previous works (Sun et al., 2023; Ma et al., 2023) propose to use LoRA for retraining after pruning, demonstrating that well-performing sparse models can be achieved even with restricted, low-dimensional reparametrizations. Yet, adapting LoRA to the prune-retrain paradigm poses challenges. For dense models, LoRA does not increase inference costs during deployment since eventually undoing the reparametrization by setting $W \leftarrow W + BA$ and then removing B and A recovers the original architecture, and the forward pass can be evaluated using just W . However, for pruning, integrating the dense matrix BA compromises the sparsity of the pruned tensor W . Precisely, in unstructured weight pruning, the matrix W has an irregular pattern of zeros; instead of merging BA into W after retraining, which would destroy this sparsity, B , A and W need to be retained as separate matrices in the model, effectively increasing storage and compute requirements during inference.

An immediate fix to this issue is to apply the binary sparsity mask M of W to BA before merging, i.e., setting $W \leftarrow W + M \odot BA$ at the end of retraining, where \odot again denotes element-wise Hadamard multiplication. However, this approach, which we term LoRA-Prune, results in a noticeable increase in perplexity because pruning the update matrix BA again disrupts the model. To avoid this problem, we propose two new LoRA methods that are compatible with pruning. These methods enable efficient and effective retraining of pruned models without compromising sparsity, allowing adapters to be merged back into the model. The key idea is adapting the reparametrization, which modifies the forward pass of standard LoRA. Recall that in LoRA, the forward pass is computed as $Wx + B(A(\text{dropout}(x)))$ for a sample x (biases are omitted for clarity).

ScaleLoRA: To maintain the sparsity of W when eventually merging BA into W , a natural choice is to learn multiplicative adapters instead of additive ones. Specifically, we redefine the LoRA forward pass as $[(BA) \odot W]x$. While zeros in W remain zero after incorporating adapters through $W \leftarrow (BA) \odot W$, this approach also introduces challenges. Dropout cannot be applied directly, though we found this to have minimal impact. Unlike classical LoRA, which leverages matrix multiplication associativity to compute $B(Ax)$ efficiently, ScaleLoRA requires explicit construction of BA ,

adding slight memory overhead. Further, standard LoRA maintains the original model’s forward pass by initializing $B = 0$ and A randomly, ensuring $BA = 0$ before retraining. However, for ScaleLoRA, this would require $BA = \mathbb{1}_{n,m}$ for $B \in \mathbb{R}^{n,r}$ and $A \in \mathbb{R}^{r,m}$, which we resolve by initializing $B = \mathbb{1}_{n,r}/\sqrt{r}$ and $A = \mathbb{1}_{r,m}/\sqrt{r}$. Although this initialization can slightly hinder optimization, we empirically found that it performs best among all tested variants that preserve $(BA) \odot W = W$ before retraining. Alternatively, reparametrizing the forward pass as $[(\mathbb{1}_{n,m} + BA) \odot W]x$ with $B = 0$ and A randomly-initialized is possible, but less effective. We note that the latter approach shares some similarity with the one by Lu et al. (2024) (cf. Appendix A).

MaskLoRA: This method preserves sparsity without altering the additive nature of LoRA, unlike ScaleLoRA. It masks pruned elements of BA during the forward pass, processing sample x as $(W + M \odot BA)x$. After re-training, the original architecture is restored by updating $W \leftarrow W + M \odot BA$ and removing matrices B and A . In contrast to LoRA-Prune, MaskLoRA incorporates the sparsity of W into the training process. This approach prevents the tendency of classical LoRA to train B and A in a way that negates the zeros in W , which can lead to a significant drop in performance when re-pruning before merging the parameters. By integrating the sparsity pattern, MaskLoRA avoids this issue, resulting in no performance degradation upon merging. Although MaskLoRA can incorporate dropout, we found no significant performance improvement. Again, the Hadamard product requires computing the full matrix BA in the forward pass, causing minor memory overhead. Unlike ScaleLoRA, MaskLoRA allows for the default LoRA initialization with $B = 0$. Since M is applied in every iteration, it must be either inferred during the forward pass or cached, the latter being impractical for large models due to memory constraints. The computational overhead of deriving M from W each iteration can be mitigated, as we discuss at the end of this section. Concurrent to our work, Muñoz et al. (2024) also propose a LoRA-variant that masks the product BA for eventual merging.

Table 2 presents a comparison of the zero-shot accuracies across all presented LoRA-variants tested on GPT models under unstructured pruning (50% sparsity) and semi-structured 2:4 and 4:8 sparsities. The second column shows whether the adapters can be merged back without compromising sparsity, being the case for all but standard LoRA. We reparametrize all linear layers except the embedding, and further also retrain biases and LN-parameters. We tune the initial learning rate for each variant, with iterations fixed at 1000, LoRA rank r at 16, and rescaling α at 32 (see Appendix A for details). The trainable parameter fraction for all LoRA-variants ranges between 0.48% and 0.95% of the full model, varying by model. Our conclusions are:

Table 2. OPT-13B/30B, LLaMA-2-7B/13B, and Mixtral-8x7B: EleutherAI zero-shot accuracy comparison of all LoRA-variants retraining magnitude pruned models, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. The second column indicates whether the adapters can be merged into the original weights without destroying the sparsity. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

Method	Mergeable	Sparsity	OPT		LLaMA-2		Mixtral
			13B	30B	7B	13B	8x7B
Baseline	–	0%	52.60%	55.07%	59.69%	62.99%	67.70%
LoRA	✗	50%	50.88%	52.65%	56.14%	59.21%	65.33%
LoRA-Prune	✓	50%	47.40%	50.86%	55.98%	58.56%	64.17%
ScaleLoRA	✓	50%	50.50%	52.31%	55.79%	59.45%	64.84%
MaskLoRA	✓	50%	49.65%	52.97%	55.67%	59.44%	64.84%
LoRA	✗	2:4	49.93%	49.67%	51.32%	55.68%	60.69%
LoRA-Prune	✓	2:4	48.63%	50.09%	51.17%	54.56%	59.25%
ScaleLoRA	✓	2:4	49.73%	49.77%	51.15%	55.24%	60.84%
MaskLoRA	✓	2:4	50.00%	49.97%	51.41%	55.73%	61.01%
LoRA	✗	4:8	50.49%	51.01%	54.13%	58.30%	62.78%
LoRA-Prune	✓	4:8	48.96%	49.52%	53.34%	57.36%	60.72%
ScaleLoRA	✓	4:8	50.11%	50.88%	53.50%	57.07%	62.50%
MaskLoRA	✓	4:8	50.66%	50.90%	54.29%	57.99%	62.72%

- 1. LoRA-Prune degrades performance:** Pruning BA at the end, as done in LoRA-Prune, reduces performance compared to LoRA, which in turn cannot be merged after retraining.
- 2. ScaleLoRA and MaskLoRA are effective:** Both methods underperform slightly compared to LoRA, but they nearly match its performance and sometimes even outperform it, despite allowing parameter merging after training without compromising sparsity.
- 3. MaskLoRA closes the gap to full FT:** Table 1 shows how MaskLoRA reduces the gap between previous methods and full FT, often surpassing it while utilizing only a fraction as little as 0.5% of the parameters.

Efficiency considerations. Before detailing the computational overhead of ScaleLoRA and MaskLoRA compared to standard LoRA, we note their efficiency and storage benefits over full FT. We can retrain a 30B parameter model on a single NVIDIA A100 GPU, highlighting memory efficiency, whereas full retraining of OPT-30B requires multiple GPUs. Parameter-efficient retraining not only reduces storage costs but also increases efficiency. For example, on OPT-2.7B, full retraining achieves 3500 train tokens per second (tps), while ScaleLoRA and MaskLoRA reach up to 5200 tps, and updating only biases and normalization parameters increases it to 8100 tps (cf. Table 4). As shown in Figure 2, MaskLoRA quickly reduces the perplexity of OPT-6.7B across various sparsity levels. Without retraining, perplexity rises from 10^1 to 10^4 , but MaskLoRA significantly lowers it, saturating after a few iterations.

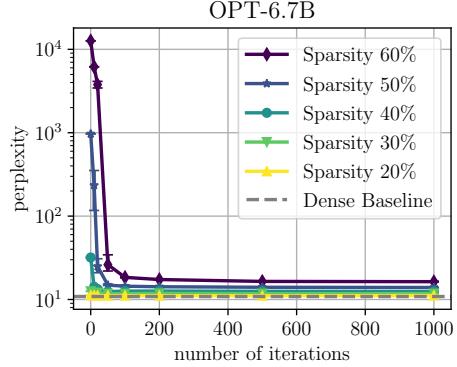


Figure 2. OPT-6.7B evaluated on WikiText: Final perplexity after retraining using MaskLoRA for as many iterations as indicated on the x-axis. MaskLoRA retrains roughly 1% of the parameters.

The computational overhead of ScaleLoRA compared to LoRA is minimal, with throughputs of 5200 tps and 5300 tps, respectively. Unmodified MaskLoRA is slower at 3000 tps, but this can be improved by masking only every few iterations instead, though it slightly increases perplexity; we hence decided to not follow this path. Attempts to schedule masking frequency showed no benefit, and caching masks, while efficient, is impractical for larger models. Finally, finding no advantage in using dropout, we streamlined the process by adding matrices before the forward pass instead of performing forward for W and $M \odot BA$ separately. Further optimization using a TorchScript-compiled function increased throughput to 4700 tps, nearly matching LoRA.

In summary, our results demonstrate that applying methods such as MaskLoRA suffices to reach the performance achievable through full retraining, while requiring a minimal number of efficient iterations for performance recovery.

3.3. Efficient Layer-wise Reconstruction

When using any of the previously introduced approaches, all activations of the network need to be stored for backpropagation. Despite retraining only a small fraction of parameters, these memory demands can still be prohibitive for large models. To further reduce the memory footprint, we investigate the use of MaskLoRA in the layer-wise reconstruction setting as per Equation 1. Precisely, we compare magnitude pruning, Wanda (Sun et al., 2023), and SparseGPT (Frantar & Alistarh, 2023), each with and without solving the reconstruction problem after determining the mask M_l through the respective methods. To that end, we reparametrize the reconstruction weights \hat{W}_l using MaskLoRA to obtain parameter-efficiency and preserve the sparsity pattern enforced by M_l . We optimize each layer-block sequentially using AdamW on 128 random samples from C4, with Equation 1 as the loss function.

Table 3. OPT-30B - Retraining: Task performance improvement by retraining with MaskLoRA for magnitude pruning, Wanda, and SparseGPT, displaying 60% unstructured sparsity. Each entry shows the improvement compared to no retraining, e.g., +0.5% indicates a 0.5% performance increase. We report the mean performance over several seeds and omit the standard deviation for the sake of clarity.

Method	Sparsity	Δ Task Accuracy							
		BoolQ	RTE	HSwag	WinoG	ARC-e	ARC-c	OBQA	Average
Magnitude	60%	+28.07%	+1.44%	+22.93%	+14.64%	+37.98%	+12.24%	+14.40%	+18.82%
Wanda	60%	+1.56%	+4.69%	+6.05%	+3.95%	+6.99%	+3.28%	+3.20%	+3.84%
SparseGPT	60%	+4.48%	+0.90%	+1.57%	+0.32%	+0.55%	+0.55%	+2.10%	+0.99%

Table 4. OPT-2.7B: Retraining throughput comparison in tokens per second (tps) across different retraining methods.

Full FT	LoRA	ScaleLoRA	MaskLoRA (standard)	MaskLoRA (optimized)	Biases + LN
3,500	5,300	5,200	3,000	4,700	8,100

As opposed to magnitude pruning, both SparseGPT and Wanda naturally rely on calibration data, the random selection of which influences the quality of the final result (Williams & Aletras, 2023). We use the same set for both methods as well as the subsequent reconstruction. Note that we now only need to store a fraction of activations, buffers, and the computational graph for the parameters for each layer-block, rather than a fraction of the entire model. For OPT-30B, this amounts to roughly 0.35% of a single layer.

As shown in Table 5, using MaskLoRA for reconstruction significantly enhances the performance of all three pruning methods, including SparseGPT, which itself already performs a reconstruction step. The reconstruction optimization incurs minimal overhead when processing calibration data anyways, being the case for both Wanda and SparseGPT. With MaskLoRA reconstruction, we observe improvements of up to 17% in zero-shot accuracy for magnitude pruning and up to 4% for Wanda and SparseGPT. Surprisingly, full FT performs significantly worse than MaskLoRA in the high sparsity regime (cf. Table 19 in Appendix B), likely due to overfitting on the calibration data.

Comparing magnitude pruning with reconstruction against Wanda without reconstruction, magnitude pruning often performs better than expected and can even outperform Wanda; we think this is a fair comparison since both methods require calibration data once. In general, magnitude pruning fails to address large features which are critical for performance, yet simple reconstruction with MaskLoRA can significantly enhance it, sometimes even surpassing Wanda with reconstruction at high sparsities (cf. Appendix D). Reconstruction is more memory-efficient, but retraining (i.e., non layer-wise) performs better in high sparsity scenarios, in particular when evaluating individual tasks (cf. Table 3).

Table 5. OPT-2.7B/6.7B/13B/30B - Reconstruction: Zero-shot accuracy comparison on the EleutherAI evaluation set. We report magnitude pruning, Wanda and SparseGPT with and without MaskLoRA when reconstructing, for unstructured 50% sparsity and semi-structured 2:4 and 4:8 sparsities. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity	OPT			
			2.7B	6.7B	13B	30B
Baseline	–	0%	47.81%	51.55%	52.60%	55.07%
Magnitude	✗	50%	40.07%	35.54%	33.80%	36.39%
Magnitude	✓	50%	45.14%	48.99%	50.41%	51.81%
Wanda	✗	50%	42.63%	47.14%	50.34%	53.15%
Wanda	✓	50%	46.47%	49.81%	51.65%	54.00%
SparseGPT	✗	50%	46.53%	50.26%	51.93%	54.01%
SparseGPT	✓	50%	46.62%	50.42%	51.92%	54.33%
Magnitude	✗	2:4	35.94%	36.38%	36.65%	34.92%
Magnitude	✓	2:4	43.54%	47.70%	49.16%	47.74%
Wanda	✗	2:4	42.82%	46.12%	47.70%	49.69%
Wanda	✓	2:4	43.69%	47.46%	48.56%	50.93%
SparseGPT	✗	2:4	44.12%	47.28%	48.84%	51.17%
SparseGPT	✓	2:4	44.67%	48.39%	50.38%	52.33%
Magnitude	✗	4:8	36.95%	36.90%	36.13%	36.81%
Magnitude	✓	4:8	44.59%	48.51%	50.19%	50.52%
Wanda	✗	4:8	44.02%	47.45%	49.10%	51.20%
Wanda	✓	4:8	44.69%	48.64%	50.21%	51.83%
SparseGPT	✗	4:8	44.98%	48.33%	50.12%	52.28%
SparseGPT	✓	4:8	45.99%	49.48%	50.96%	52.92%

4. Discussion

We demonstrated that retraining a minimal fraction of parameters, such as biases or LN-parameters, effectively mitigates pruning-induced performance drops. By backpropagating as little as 0.05% of the parameters compared to full retraining, we significantly reduce compute and memory demands. We further proposed two efficient LoRA-variants, allowing adapters to be merged back after retraining without compromising sparsity or increasing inference time. Applying these methods for layer-wise reconstruction further reduces memory demands while enhancing state-of-the-art retraining-free methods. Our findings make retraining after pruning a viable option for large models, and we hope to stimulate further research on both training-free pruning criteria and efficient retraining.

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A. Technical details and training settings

A.1. Pretraining settings and metrics.

For Natural Language Processing (NLP) tasks, we use pretrained models from Huggingface and specify only the retraining settings as outlined in Section 2.3.

For computer vision, we focus on *ImageNet* (Russakovsky et al., 2015), utilizing *ResNet* architectures (He et al., 2015) and measuring performance with top-1 test accuracy. We follow standard practices by retraining networks with momentum SGD, allocating 10% of the training data for validation, and using the ALLR learning rate schedule (Zimmer et al., 2023) for retraining. We follow Zimmer et al. (2023) and globally prune everything except biases and Batch-Normalization (BN) parameters. As opposed to NLP, we perform the pretraining process ourselves. Table 6 details our pretraining configurations, including the number of epochs, batch size, weight decay, and learning rate. We opt for SGD as the optimizer, though we recognize a range of other optimization methods are available (see e.g., Kingma & Ba, 2014; Pokutta et al., 2020). We maintain the default momentum value of 0.9. In the last column of the table we report the performance achieved with standard dense training, using top-1 test accuracy as the metric for image classification tasks, which denotes the percentage of test samples correctly classified.

Table 6. Exact pretraining configurations in our vision experiments.

Dataset	Network (number of weights)	Epochs	Batch size	Weight decay	Learning rate ($t = \text{training epoch}$)	Unpruned test accuracy
ImageNet	ResNet-50 (26 Mio)	90	256	1e-4	linear from 0.1 to 0	76.12% ±0.01%

A.2. Pruning and Retraining

Pruning settings. Effective pruning relies on the accurate identification of weights to prune and the distribution of sparsity among the layers. Zhu & Gupta (2017) introduced the UNIFORM allocation, pruning each layer by the same relative amount. Gale et al. (2019) improved this with UNIFORM+, keeping the first convolutional layer dense and limiting pruning in the final fully-connected layer to 80%. Evci et al. (2020) adapted the Erdős-R’enyi Kernel (ERK) (Mocanu et al., 2018) for layerwise sparsity, accounting for layer dimensions. Lee et al. (2020) proposed Layer-Adaptive Magnitude-based Pruning (LAMP), targeting minimal output distortion at pruning, assessed through L_2 -distortion on worst-case inputs.

In NLP, following Sun et al. (2023), we prune all linear layers except embeddings and the final classification head, applying uniform sparsity throughout. For a comparison of diverse selection schemes for LLMs, see Yin et al. (2023). Our experiments include both unstructured sparsity and semi-structured 2:4 and 4:8 sparsities. In vision tasks, aligning with Zimmer et al. (2023); Evci et al. (2020); Dettmers & Zettlemoyer (2019), we prune everything except biases and BN parameters, employing the GLOBAL criterion which treats all parameters as a single vector and computes a universal threshold for pruning.

Hyperparameters for Retraining: The Learning Rate. In computer vision, automating the learning rate schedule for retraining has received increased interest, aiming to circumvent the need for tuning the schedule in each phase. We describe various schedules where T is the total number of epochs of original training with a learning rate schedule $(\eta_t)_{t \leq T}$, and T_{rt} is the number of epochs in each retraining phase. FT (Han et al., 2015) uses a constant learning rate, η_T , from the final epoch of initial training. LRW (Renda et al., 2020) repeats the last $T - T_{rt}$ epochs of the original schedule. SLR (Le & Hua, 2021) compresses the initial schedule into the retraining period with an initial warm-up. CLR (Le & Hua, 2021) uses a cosine-based schedule with a warm-up to η_1 . LLR (Zimmer et al., 2023) linearly decays from η_1 to zero in each cycle. For vision tasks, we adopt ALLR Zimmer et al. (2023), using a linear schedule that adjusts the initial rate based on the impact of pruning and available retraining time, balancing cycle length and pruning-induced performance degradation.

For LLMs, we stick to AdamW with a linear learning rate decay from a tuned initial value. We experiment with starting values 5e-6, 1e-5, 5e-5, 1e-4 and 5e-4.

Hyperparameters for Retraining: Batch size and Weight decay. For vision, we retain the same batch size and weight decay parameters as used in pretraining. However, for LLMs we set the weight decay to zero and found no improvement in increasing this value. We use a batch size of 2 and gradient accumulation for 4 steps for all models with less than 30 billion parameters. For larger models, we use a batch size of 1 and 2 gradient accumulation steps. We use gradient checkpointing to

reduce the memory demands at the expense of efficiency.

Other sparsity-preserving PEFT approaches. ScaleLoRA modifies the LoRA forward pass to $[(BA) \odot W]x$, requiring B and A to be initialized differently from classical LoRA. An alternative is to reparametrize as $[(\mathbb{1}_{n,m} + BA) \odot W]x$, with $B = 0$ and A randomly initialized. This method is similar to Lu et al. (2024), which use an outer product of matrices or vectors applied to each dimension of the pruned matrix W , but not directly through low-rank adapters as in LoRA. While we experimented with the low-rank adapted variant of the method of Lu et al. (2024), i.e., using the forward pass $[(\mathbb{1}_{n,m} + BA) \odot W]x$, we found it to not converge as fast ScaleLoRA, which consistently performed better.

B. Full experiments

In this section, we provide full results, following the same structure as Section 3.

B.1. Restoring feature quality with few parameters

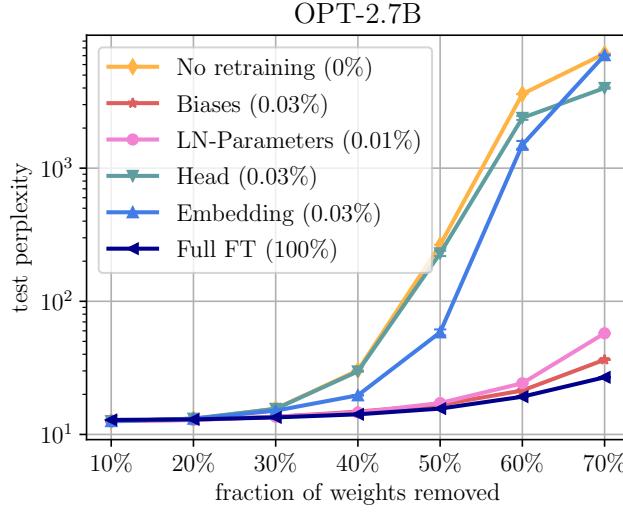


Figure 3. OPT-2.7B evaluated on WikiText: Final perplexity vs. sparsity after pruning, followed by retraining only the specified parameter subset. We indicate the percentage of trainable parameters in parentheses. Full FT refers to full retraining of all parameters.

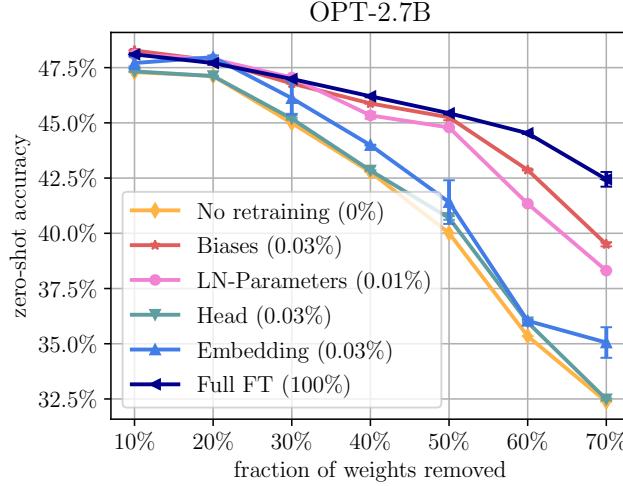


Figure 4. OPT-2.7B evaluated on the EleutherAI tasks: Final average zero-shot accuracy vs. sparsity after pruning, followed by retraining only the specified parameter subset. We indicate the percentage of trainable parameters in parentheses. Full FT refers to full retraining of all parameters.

Table 7. OPT-2.7B/30B: Parameter-efficient approaches vs. full retraining with 30%-70% of the parameters pruned. The first column lists the method, and the second shows the percentage of trainable parameters. Full FT represents the standard retraining baseline and is only possible for OPT-2.7B due to memory constraints. The next five columns display the average mean perplexity (upper halves, lower is better) and average zero-shot accuracy (lower halves, higher is better) across multiple seeds, with standard deviations excluded for clarity. The dense models attain a perplexity and accuracy of 12.47 and 47.81%, as well as 9.55 and 55.07% for OPT-2.7B/30B, respectively.

OPT-2.7B

Perplexity: 12.47		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
Full FT	100%	13.42	14.16	15.63	19.20	26.86
MaskLoRA	0.882%	13.41	14.24	15.75	18.37	25.58
Biases	0.034%	13.57	14.86	16.56	21.41	37.24
LN-Parameters	0.013%	13.58	14.63	17.24	24.26	58.08
No retraining	0.000%	15.58	30.31	265.13	3604.96	7252.22
Accuracy: 47.81%		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
Full FT	100%	46.99%	46.20%	45.44%	44.53%	42.44%
MaskLoRA	0.882%	47.25%	46.29%	45.92%	43.92%	41.56%
Biases	0.034%	46.75%	45.66%	45.29%	42.75%	39.49%
LN-Parameters	0.013%	46.78%	45.48%	44.72%	41.37%	38.32%
No retraining	0.000%	44.99%	42.77%	40.01%	35.34%	32.38%

OPT-30B

Perplexity: 9.55		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.329%	10.27	11.04	11.75	13.55	16.65
Biases	0.013%	10.32	11.30	12.58	14.66	20.06
LN-Parameters	0.005%	10.29	11.17	12.50	15.17	21.41
No retraining	0.000%	12.37	24.29	168.06	11676.00	28180.15
Accuracy: 55.07%		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.329%	54.42%	53.71%	53.12%	50.60%	47.79%
Biases	0.013%	53.84%	52.90%	51.59%	50.00%	46.33%
LN-Parameters	0.005%	53.31%	52.39%	51.88%	49.93%	45.07%
No retraining	0.000%	51.57%	44.19%	36.39%	32.01%	31.92%

Table 8. LLaMA-2-7B/13B: Parameter-efficient retraining approaches with 30%-70% of the parameters pruned. The first column lists the method, and the second shows the percentage of trainable parameters. The next five columns display the average mean perplexity (upper halves, lower is better) and average zero-shot accuracy (lower halves, higher is better) across multiple seeds, with standard deviations excluded for clarity. Note that both models do not have biases, retraining only these is hence not possible.

LLaMA-2-7B

Perplexity: 5.11		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.590%	5.38	5.74	6.49	8.04	11.75
LN-Parameters	0.004%	5.47	6.02	7.63	10.77	30.55
No retraining	0.000%	5.79	7.31	14.90	3677.52	52399.01

Accuracy: 59.69%		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.590%	59.77%	59.33%	55.39%	52.89%	45.42%
LN-Parameters	0.004%	59.37%	58.16%	54.74%	49.17%	40.42%
No retraining	0.000%	58.69%	56.56%	51.14%	39.54%	33.39%

LLaMA-2-13B

Perplexity: 4.57		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.479%	4.75	5.00	5.50	6.56	9.09
LN-Parameters	0.003%	4.78	5.06	5.70	7.25	11.96
No retraining	0.000%	4.82	5.26	6.37	11.22	275.21

Accuracy: 62.99%		Sparsity				
Method	% trainable	30%	40%	50%	60%	70%
MaskLoRA	0.479%	61.77%	60.84%	59.23%	55.07%	47.78%
LN-Parameters	0.003%	61.65%	60.44%	58.10%	53.04%	43.31%
No retraining	0.000%	61.99%	59.56%	52.89%	43.90%	33.53%

B.2. Closing the Gap: Low-Rank Adaption

Table 9. OPT-2.7B/6.7B/13B/30B: Perplexity comparison of all LoRA-variants retraining magnitude pruned models, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. The second column indicates whether the adapters can be merged into the original weights without destroying the sparsity. We report the mean perplexity over several seeds and omit the standard deviation for the sake of clarity.

Method	Mergeable	Sparsity	OPT			
			2.7B	6.7B	13B	30B
Baseline	–	0%	12.47	10.86	10.12	9.55
LoRA	✗	50%	15.62	13.76	12.66	11.67
LoRA-Prune	✓	50%	17.86	14.97	20.87	13.37
ScaleLoRA	✓	50%	16.14	14.19	13.50	12.42
MaskLoRA	✓	50%	15.77	14.23	13.79	11.80
LoRA	✗	2:4	18.14	14.55	13.20	11.98
LoRA-Prune	✓	2:4	20.86	15.76	15.01	13.23
ScaleLoRA	✓	2:4	18.67	14.96	13.63	12.27
MaskLoRA	✓	2:4	18.41	14.74	13.36	12.23
LoRA	✗	4:8	16.25	13.89	12.70	11.87
LoRA-Prune	✓	4:8	17.70	14.80	14.25	12.87
ScaleLoRA	✓	4:8	16.58	14.49	13.12	12.29
MaskLoRA	✓	4:8	16.46	14.08	12.94	12.05

Table 10. OPT-2.7B/6.7B/13B/30B: EleutherAI zero-shot accuracy comparison of all LoRA-variants retraining magnitude pruned models, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. The second column indicates whether the adapters can be merged into the original weights without destroying the sparsity. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

Method	Mergeable	Sparsity	OPT			
			2.7B	6.7B	13B	30B
Baseline	–	0%	47.81%	51.55%	52.60%	55.07%
LoRA	✗	50%	46.22%	50.16%	50.88%	52.65%
LoRA-Prune	✓	50%	45.33%	49.61%	47.40%	50.86%
ScaleLoRA	✓	50%	46.03%	49.80%	50.50%	52.31%
MaskLoRA	✓	50%	46.23%	50.11%	49.65%	52.97%
LoRA	✗	2:4	44.48%	48.68%	49.93%	49.67%
LoRA-Prune	✓	2:4	43.84%	48.72%	48.63%	50.09%
ScaleLoRA	✓	2:4	44.31%	48.20%	49.73%	49.77%
MaskLoRA	✓	2:4	44.13%	48.86%	50.00%	49.97%
LoRA	✗	4:8	45.60%	49.67%	50.49%	51.01%
LoRA-Prune	✓	4:8	45.17%	49.08%	48.96%	49.52%
ScaleLoRA	✓	4:8	45.50%	49.45%	50.11%	50.88%
MaskLoRA	✓	4:8	45.37%	49.56%	50.66%	50.90%

Table 11. LLaMA-2-7B/13B and Mixtral-8x7B: Perplexity comparison of all LoRA-variants retraining magnitude pruned models, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. The second column indicates whether the adapters can be merged into the original weights without destroying the sparsity. We report the mean perplexity over several seeds and omit the standard deviation for the sake of clarity.

Method	Mergeable	Sparsity	LLaMA-2		Mixtral
			7B	13B	8x7B
Baseline	–	0%	5.11	4.57	3.58
LoRA	✗	50%	6.42	5.46	4.76
LoRA-Prune	✓	50%	7.02	5.60	5.23
ScaleLoRA	✓	50%	6.70	5.54	4.90
MaskLoRA	✓	50%	6.46	5.48	4.82
LoRA	✗	2:4	7.69	6.37	5.60
LoRA-Prune	✓	2:4	8.25	6.56	6.18
ScaleLoRA	✓	2:4	7.99	6.48	5.81
MaskLoRA	✓	2:4	7.72	6.38	5.65
LoRA	✗	4:8	6.99	5.88	5.18
LoRA-Prune	✓	4:8	7.47	6.04	5.66
ScaleLoRA	✓	4:8	7.24	6.00	5.34
MaskLoRA	✓	4:8	7.01	5.90	5.24

Table 12. LLaMA-2-7B/13B and Mixtral-8x7B: EleutherAI zero-shot accuracy comparison of all LoRA-variants retraining magnitude pruned models, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. The second column indicates whether the adapters can be merged into the original weights without destroying the sparsity. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

Method	Mergeable	Sparsity	LLaMA-2		Mixtral
			7B	13B	8x7B
Baseline	–	0%	59.69%	62.99%	67.70%
LoRA	✗	50%	56.14%	59.21%	65.33%
LoRA-Prune	✓	50%	55.98%	58.56%	64.17%
ScaleLoRA	✓	50%	55.79%	59.45%	64.84%
MaskLoRA	✓	50%	55.67%	59.44%	64.84%
LoRA	✗	2:4	51.32%	55.68%	60.69%
LoRA-Prune	✓	2:4	51.17%	54.56%	59.25%
ScaleLoRA	✓	2:4	51.15%	55.24%	60.84%
MaskLoRA	✓	2:4	51.41%	55.73%	61.01%
LoRA	✗	4:8	54.13%	58.30%	62.78%
LoRA-Prune	✓	4:8	53.34%	57.36%	60.72%
ScaleLoRA	✓	4:8	53.50%	57.07%	62.50%
MaskLoRA	✓	4:8	54.29%	57.99%	62.72%

Table 13. OPT-2.7B/6.7B/13B/30B: Perplexity and EleutherAI zero-shot accuracy comparison of all LoRA-variants retraining magnitude pruned models. We display unstructured pruning sparsities between 40% and 70%. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

OPT-2.7B		Perplexity				Accuracy			
Method		Sparsity				Sparsity			
		40%	50%	60%	70%	40%	50%	60%	70%
LoRA	14.26	15.63	18.20	25.38	46.17%	45.85%	43.84%	41.05%	
LoRA-Prune	14.75	17.84	27.78	92.81	46.50%	45.37%	42.00%	38.76%	
ScaleLoRA	14.46	16.15	19.25	25.61	45.82%	45.95%	44.28%	41.12%	
MaskLoRA	14.38	15.91	18.66	25.46	46.21%	46.12%	44.44%	41.41%	

OPT-6.7B		Perplexity				Accuracy			
Method		Sparsity				Sparsity			
		40%	50%	60%	70%	40%	50%	60%	70%
LoRA	12.52	13.74	15.97	20.31	50.70%	50.09%	48.76%	46.13%	
LoRA-Prune	12.97	14.97	20.39	60.68	50.69%	49.67%	47.58%	43.08%	
ScaleLoRA	12.74	14.12	17.08	20.93	50.77%	50.02%	48.64%	45.28%	
MaskLoRA	12.57	14.25	16.76	20.83	50.75%	50.13%	48.93%	45.93%	

OPT-13B		Perplexity				Accuracy			
Method		Sparsity				Sparsity			
		40%	50%	60%	70%	40%	50%	60%	70%
LoRA	11.62	12.62	14.35	17.22	52.07%	50.92%	49.12%	46.45%	
LoRA-Prune	12.27	15.35	23.97	138.56	51.07%	48.62%	45.50%	40.86%	
ScaleLoRA	11.79	13.47	15.12	18.62	51.89%	50.69%	48.67%	46.21%	
MaskLoRA	11.74	13.80	15.11	17.61	51.76%	49.91%	48.39%	46.48%	

OPT-30B		Perplexity				Accuracy			
Method		Sparsity				Sparsity			
		40%	50%	60%	70%	40%	50%	60%	70%
LoRA	10.99	11.63	13.24	16.34	53.22%	52.79%	50.68%	47.41%	
LoRA-Prune	11.63	13.35	21.69	229.43	52.33%	50.53%	48.81%	40.06%	
ScaleLoRA	11.20	12.46	13.81	17.06	52.92%	52.37%	50.08%	47.70%	
MaskLoRA	11.05	11.82	13.45	17.29	53.19%	52.92%	50.55%	47.90%	

Table 14. LLaMA-2-7B/13B: Perplexity and EleutherAI zero-shot accuracy comparison of all LoRA-variants retraining magnitude pruned models. We display unstructured pruning sparsities between 40% and 70%. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

LLaMA-2-7B		Perplexity				Accuracy			
Method		Sparsity				Sparsity			
		40%	50%	60%	70%	40%	50%	60%	70%
LoRA		5.72	6.42	7.86	11.54	58.69%	56.12%	53.58%	46.80%
LoRA-Prune		5.99	7.07	9.47	21.69	59.00%	55.93%	51.07%	42.55%
ScaleLoRA		5.84	6.67	8.29	12.56	58.38%	55.85%	51.70%	45.03%
MaskLoRA		5.77	6.46	7.98	11.56	59.34%	55.67%	52.50%	46.27%

LLaMA-2-13B		Perplexity				Accuracy			
Method		Sparsity				Sparsity			
		40%	50%	60%	70%	40%	50%	60%	70%
LoRA		4.99	5.46	6.47	8.97	60.43%	59.16%	55.41%	49.25%
LoRA-Prune		5.05	5.61	6.96	11.10	60.68%	58.58%	53.54%	44.42%
ScaleLoRA		5.01	5.54	6.65	9.48	60.28%	59.18%	55.50%	49.14%
MaskLoRA		4.99	5.48	6.51	9.04	60.69%	59.34%	55.28%	49.40%

B.3. Efficient Layer-wise Reconstruction

Table 15. OPT-2.7B/6.7B/13B/30B: Perplexity comparison of magnitude pruning, Wanda and SparseGPT with and without MaskLoRA when reconstructing instead of retraining, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. We report the mean perplexity over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity	OPT			
			2.7B	6.7B	13B	30B
Baseline	–	0%	12.47	10.86	10.12	9.55
Magnitude	✗	50%	265.14	968.69	11558.65	168.06
Magnitude	✓	50%	15.22	13.14	12.34	11.06
Wanda	✗	50%	22.79	15.43	13.55	10.86
Wanda	✓	50%	13.91	11.82	11.12	10.01
SparseGPT	✗	50%	13.50	11.58	11.21	9.79
SparseGPT	✓	50%	13.42	11.48	10.85	9.79
Magnitude	✗	2:4	1153.15	264.11	484.84	1979.66
Magnitude	✓	2:4	18.16	14.90	13.07	39.12
Wanda	✗	2:4	21.38	16.04	15.74	13.26
Wanda	✓	2:4	17.54	14.43	12.59	11.26
SparseGPT	✗	2:4	17.28	14.27	13.00	10.95
SparseGPT	✓	2:4	15.93	13.32	11.93	10.49
Magnitude	✗	4:8	166.91	196.18	450.02	563.77
Magnitude	✓	4:8	15.95	13.47	12.16	14.34
Wanda	✗	4:8	16.90	13.64	13.47	10.88
Wanda	✓	4:8	15.38	12.75	11.74	10.49
SparseGPT	✗	4:8	15.06	12.60	11.79	10.31
SparseGPT	✓	4:8	14.51	12.16	11.18	10.10

Table 16. OPT-2.7B/6.7B/13B/30B: Zero-shot accuracy comparison on the EleutherAI evaluation set. We report magnitude pruning, Wanda and SparseGPT with and without MaskLoRA when reconstructing instead of retraining, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity	OPT			
			2.7B	6.7B	13B	30B
Baseline	–	0%	47.81%	51.55%	52.60%	55.07%
Magnitude	✗	50%	40.07%	35.54%	33.80%	36.39%
Magnitude	✓	50%	45.14%	48.99%	50.41%	51.81%
Wanda	✗	50%	42.63%	47.14%	50.34%	53.15%
Wanda	✓	50%	46.47%	49.81%	51.65%	54.00%
SparseGPT	✗	50%	46.53%	50.26%	51.93%	54.01%
SparseGPT	✓	50%	46.62%	50.42%	51.92%	54.33%
Magnitude	✗	2:4	35.94%	36.38%	36.65%	34.92%
Magnitude	✓	2:4	43.54%	47.70%	49.16%	47.74%
Wanda	✗	2:4	42.82%	46.12%	47.70%	49.69%
Wanda	✓	2:4	43.69%	47.46%	48.56%	50.93%
SparseGPT	✗	2:4	44.12%	47.28%	48.84%	51.17%
SparseGPT	✓	2:4	44.67%	48.39%	50.38%	52.33%
Magnitude	✗	4:8	36.95%	36.90%	36.13%	36.81%
Magnitude	✓	4:8	44.59%	48.51%	50.19%	50.52%
Wanda	✗	4:8	44.02%	47.45%	49.10%	51.20%
Wanda	✓	4:8	44.69%	48.64%	50.21%	51.83%
SparseGPT	✗	4:8	44.98%	48.33%	50.12%	52.28%
SparseGPT	✓	4:8	45.99%	49.48%	50.96%	52.92%

Table 17. LLaMA-2-7B/13B and Mistral-7B: Perplexity comparison of magnitude pruning, Wanda and SparseGPT with and without MaskLoRA when reconstructing instead of retraining, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. We report the mean perplexity over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity	LLaMA-2		Mistral
			7B	13B	7B
Baseline	–	0%	5.11	4.57	4.90
Magnitude	✗	50%	14.90	6.37	7.42
Magnitude	✓	50%	9.54	5.43	6.17
Wanda	✗	50%	7.38	5.93	6.05
Wanda	✓	50%	6.16	5.30	5.83
SparseGPT	✗	50%	6.53	5.64	6.00
SparseGPT	✓	50%	6.18	5.37	5.81
Magnitude	✗	2:4	54.39	8.32	14.15
Magnitude	✓	2:4	21.67	6.72	10.44
Wanda	✗	2:4	11.35	8.36	11.55
Wanda	✓	2:4	8.14	6.59	8.46
SparseGPT	✗	2:4	10.23	8.30	9.57
SparseGPT	✓	2:4	8.07	6.70	7.83
Magnitude	✗	4:8	16.53	6.76	9.10
Magnitude	✓	4:8	11.48	5.99	7.72
Wanda	✗	4:8	8.07	6.55	7.82
Wanda	✓	4:8	6.97	5.88	6.80
SparseGPT	✗	4:8	8.00	6.58	7.41
SparseGPT	✓	4:8	6.98	5.95	6.66

Table 18. LLaMA-2-7B/13B and Mistral-7B: Zero-shot accuracy comparison on the EleutherAI evaluation set. We report magnitude pruning, Wanda and SparseGPT with and without MaskLoRA when reconstructing instead of retraining, both in the unstructured pruning setting (50% sparsity), as well as for the semi-structured 2:4 and 4:8 sparsities. We report the mean accuracy over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity	LLaMA-2		Mistral
			7B	13B	7B
Baseline	–	0%	59.69%	62.99%	64.36%
Magnitude	✗	50%	51.15%	52.88%	55.86%
Magnitude	✓	50%	55.08%	59.55%	59.18%
Wanda	✗	50%	54.89%	58.27%	59.62%
Wanda	✓	50%	55.87%	60.46%	59.52%
SparseGPT	✗	50%	55.86%	60.98%	59.86%
SparseGPT	✓	50%	56.14%	61.26%	60.24%
Magnitude	✗	2:4	47.48%	49.77%	49.69%
Magnitude	✓	2:4	49.44%	54.43%	52.04%
Wanda	✗	2:4	48.74%	53.20%	50.09%
Wanda	✓	2:4	50.87%	55.37%	51.68%
SparseGPT	✗	2:4	50.83%	55.48%	53.01%
SparseGPT	✓	2:4	52.08%	56.96%	55.06%
Magnitude	✗	4:8	50.68%	52.72%	54.32%
Magnitude	✓	4:8	52.44%	58.03%	56.13%
Wanda	✗	4:8	52.55%	58.45%	55.30%
Wanda	✓	4:8	53.05%	58.99%	55.68%
SparseGPT	✗	4:8	53.60%	58.17%	57.42%
SparseGPT	✓	4:8	54.42%	59.38%	58.55%

Table 19. OPT-6.7B/13B: Zero-shot accuracy of MaskLoRA and full FT with 40%-70% of the parameters pruned in the reconstruction setting. The first column lists the method. Full FT represents the standard retraining baseline and is only possible in the reconstruction setting for models not bigger than OPT-13B due to memory constraints. The next columns display the average zero-shot accuracy (higher is better) across multiple seeds, with standard deviations excluded for clarity.

Method	OPT-6.7B				OPT-13B			
	Sparsity				Sparsity			
	40%	50%	60%	70%	40%	50%	60%	70%
Full FT	50.25%	48.76%	46.95%	38.57%	51.92%	50.78%	46.44%	41.04%
MaskLoRA	50.37%	49.00%	47.43%	41.73%	51.65%	50.45%	48.18%	42.13%

C. Results for convolutional architectures

Figure 5 illustrates our intuition by depicting a dog (left) and the features produced by a single filter from the first convolutional layer of a pretrained network (middle) and its pruned version (right). The middle image demonstrates the pretrained network’s capability to capture distinct boundary features, especially the dog’s defining back and ears. Conversely, the pruned network still emphasizes the dog’s back, albeit with reduced intensity and in favor of its overall form, likely influenced by the stark contrast between the white dog and the green grass. While pruning diminishes the feature quality, it does not completely eradicate it.

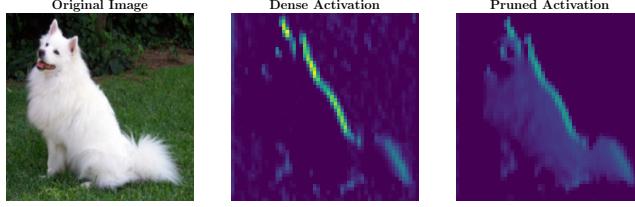


Figure 5. Features produced by a single filter from the first convolutional layer of *AlexNet* (Krizhevsky et al., 2012). From left to right: original image, output from a pretrained model, and output from the magnitude-pruned version of the same model.

We investigate the following approaches:

- **BN-Recalibrate:** Li et al. (2020) identified that recalibrating the BN statistics after pruning enhances generalization. This approach entails a one-time evaluation on the training dataset, neither requiring backpropagation nor altering the training set performance.
- **Biases:** Similarly as for LLMs, we only retrain the network’s biases.
- **BN-Parameters:** Beyond statistics, BN layers also include trainable scaling and bias parameters. Similar to LN-parameters for LLMs, we retrain these parameters.
- **Linear Head:** We only retrain the linear head.

Figure 6 and **Figure 7** compare the different approaches on ResNet-50 on ImageNet for one and five retraining epochs, respectively. Since retraining biases and BN-parameters individually yield marginal improvements, we only include their combination. We did not find it beneficial to retrain the linear head and have not included it in the plots. Here, BN-Recalibrate does not backpropagate any parameters. Combining biases and BN-parameters corresponds to retraining roughly 0.21% of the parameters only. Yet, these approaches are able to recover much of the performance lost due to pruning (comparing to no retraining). At the high sparsity regime, full retraining prevails.

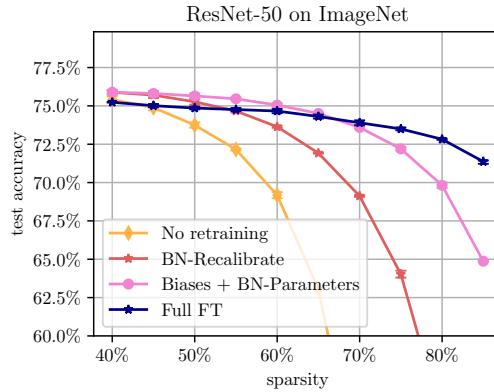


Figure 6. ResNet-50 on ImageNet: Test accuracy across sparsity levels for One Shot pruning with one retraining epoch.

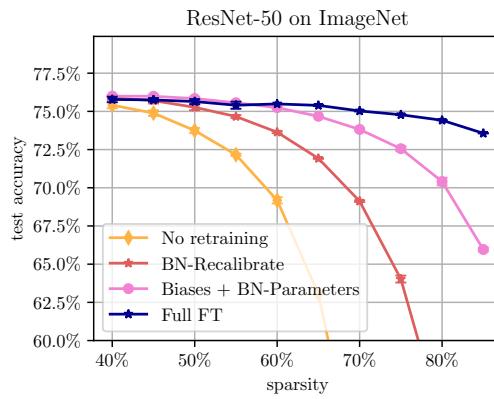


Figure 7. ResNet-50 on ImageNet: Test accuracy across sparsity levels for One Shot pruning with five retraining epochs.

D. Ablation studies

D.1. Ablation: Dissecting the impact of parameter groups for retraining

In Table 20 and Table 21, we analyze the effect of different parameter groups when retraining OPT-13B for 1000 iterations, magnitude-pruned to 50% and 70% sparsity, respectively. We tuned the learning rate and report the best mean perplexity across multiple random seeds, omitting the standard deviation for clarity. The last two columns show the proportion of trainable parameters and final test perplexity, respectively. The first five columns indicate whether individual parameter groups are active (✓) or inactive (✗), specifically biases, LN-parameters, the linear head, the embedding layer, and MaskLoRA parameters.

Table 20. OPT-13B: The subtables report parameter-efficient retraining for 50% unstructured pruning. The first five columns specify whether certain model parameter subgroups are inactive (✗) or active (✓), representing the training of biases, LN parameters, the linear head, the embedding layer, and using MaskLoRA, respectively. The penultimate column presents the percentage of trainable parameters in each configuration. The final column displays the mean perplexity across multiple seeds, omitting the standard deviation for clarity.

50%						
Biases	LN	Head	Embedding	MaskLoRA	% trainable	Perplexity
✗	✗	✗	✗	✗	0.00%	11558.65
✓	✗	✗	✗	✗	0.02%	13.29
✗	✓	✗	✗	✗	0.01%	13.59
✗	✗	✓	✗	✗	0.01%	2743.37
✗	✗	✗	✓	✗	0.01%	9450.35
✗	✗	✗	✗	✓	0.46%	13.59
✓	✓	✗	✗	✗	0.02%	13.31
✓	✗	✓	✗	✗	0.02%	13.42
✓	✗	✗	✓	✗	0.02%	17.71
✓	✗	✗	✗	✓	0.47%	13.88
✗	✓	✓	✗	✗	0.01%	13.81
✗	✓	✗	✓	✗	0.01%	26.51
✗	✓	✗	✗	✓	0.46%	13.67
✗	✗	✓	✓	✗	0.01%	2470.32
✗	✗	✓	✗	✓	0.46%	13.62
✗	✗	✗	✓	✓	0.46%	16.38
✓	✓	✓	✗	✗	0.03%	13.44
✓	✓	✗	✓	✗	0.03%	16.84
✓	✓	✗	✗	✓	0.48%	13.44
✓	✗	✓	✓	✗	0.03%	18.39
✓	✗	✓	✗	✓	0.48%	13.79
✓	✗	✗	✓	✓	0.48%	15.46
✗	✓	✓	✓	✗	0.02%	25.21
✗	✓	✓	✗	✓	0.47%	13.57
✗	✓	✗	✓	✓	0.47%	16.54
✗	✗	✓	✓	✓	0.47%	16.14
✓	✓	✓	✓	✗	0.03%	17.10
✓	✓	✓	✗	✓	0.48%	13.69
✓	✓	✗	✓	✓	0.48%	16.33
✓	✗	✓	✓	✓	0.49%	16.63
✗	✓	✓	✓	✓	0.48%	15.60
✓	✓	✓	✓	✓	0.49%	16.19

Table 21. OPT-13B: The subtables report parameter-efficient retraining for 70% unstructured pruning. The first five columns specify whether certain model parameter subgroups are inactive (\times) or active (\checkmark), representing the training of biases, LN parameters, the linear head, the embedding layer, and using MaskLoRA, respectively. The penultimate column presents the percentage of trainable parameters in each configuration. The final column displays the mean perplexity across seeds, where we omit the standard deviation for clarity.

70%						
Biases	LN	Head	Embedding	MaskLoRA	% trainable	Perplexity
\times	\times	\times	\times	\times	0.00%	289842.47
\checkmark	\times	\times	\times	\times	0.02%	20.95
\times	\checkmark	\times	\times	\times	0.01%	26.06
\times	\times	\checkmark	\times	\times	0.01%	8399.64
\times	\times	\times	\checkmark	\times	0.01%	282834.05
\times	\times	\times	\times	\checkmark	0.46%	17.61
\checkmark	\checkmark	\times	\times	\times	0.02%	20.31
\checkmark	\times	\checkmark	\times	\times	0.02%	21.42
\checkmark	\times	\times	\checkmark	\times	0.02%	86.28
\checkmark	\times	\times	\times	\checkmark	0.47%	18.07
\times	\checkmark	\checkmark	\times	\times	0.01%	26.18
\times	\checkmark	\times	\checkmark	\times	0.01%	7094.19
\times	\checkmark	\times	\times	\checkmark	0.46%	18.32
\times	\times	\checkmark	\checkmark	\times	0.01%	9276.99
\times	\times	\checkmark	\times	\checkmark	0.46%	18.60
\times	\times	\times	\checkmark	\checkmark	0.46%	22.04
\checkmark	\checkmark	\checkmark	\times	\times	0.03%	21.07
\checkmark	\checkmark	\times	\checkmark	\times	0.03%	63.86
\checkmark	\checkmark	\times	\times	\checkmark	0.48%	18.39
\checkmark	\times	\checkmark	\checkmark	\times	0.03%	77.54
\checkmark	\times	\checkmark	\times	\checkmark	0.48%	17.65
\checkmark	\times	\times	\checkmark	\checkmark	0.48%	22.19
\times	\checkmark	\checkmark	\checkmark	\times	0.02%	7403.60
\times	\checkmark	\checkmark	\times	\checkmark	0.47%	18.38
\times	\checkmark	\times	\checkmark	\checkmark	0.47%	22.35
\times	\times	\checkmark	\checkmark	\checkmark	0.47%	22.75
\checkmark	\checkmark	\checkmark	\checkmark	\times	0.03%	153.02
\checkmark	\checkmark	\checkmark	\times	\checkmark	0.48%	18.40
\checkmark	\checkmark	\times	\checkmark	\checkmark	0.48%	21.65
\checkmark	\times	\checkmark	\checkmark	\checkmark	0.49%	22.32
\times	\checkmark	\checkmark	\checkmark	\checkmark	0.48%	22.37
\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	0.49%	21.87

D.2. Ablation: The high sparsity regime

Table 22 examines the perplexity results for unstructured pruning on OPT-30B using magnitude pruning, Wanda, and SparseGPT, both with and without MaskLoRA reconstruction. Analogously, **Table 23** shows the result when retraining instead of reconstructing. Both tables focus on higher sparsity levels to explore whether our findings extend beyond the 50% threshold. We make the following observations for the high sparsity regime:

- All methods benefit significantly from MaskLoRA retraining or reconstruction. See also **Table 24** for the improvement on the individual tasks.
- Retraining is much more effective than reconstruction.
- Only SparseGPT is able to maintain reasonable test perplexity at 80% sparsity.
- Magnitude pruning with MaskLoRA reconstruction or retraining often outperforms Wanda without any further reoptimization; surprisingly, this is also often the case when Wanda pruning is followed by retraining or reconstruction as well.

Table 22. OPT-30B Reconstruction: Perplexity comparison of magnitude pruning, Wanda and SparseGPT with and without MaskLoRA when reconstructing instead of retraining, displaying the high sparsity regime of unstructured pruning. We report the mean perplexity over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity			
		50%	60%	70%	80%
Magnitude	✗	168.06	11676.00	28180.15	56381.68
Magnitude	✓	11.09	32.27	2659.70	4717.70
Wanda	✗	10.86	16.94	14080.80	11654.38
Wanda	✓	10.01	11.24	121.10	9321.66
SparseGPT	✗	9.79	10.70	13.55	47.68
SparseGPT	✓	9.79	10.48	12.59	26.09

Table 23. OPT-30B Retraining: Perplexity comparison of magnitude pruning, Wanda and SparseGPT with and without MaskLoRA retraining, displaying the high sparsity regime of unstructured pruning. We report the mean perplexity over several seeds and omit the standard deviation for the sake of clarity.

Method	Reconstruction	Sparsity			
		50%	60%	70%	80%
Magnitude	✗	168.06	11676.00	28180.15	56381.68
Magnitude	✓	11.77	13.61	16.88	47.25
Wanda	✗	10.86	16.94	13667.60	12370.62
Wanda	✓	10.30	11.58	23.57	84.06
SparseGPT	✗	9.77	10.73	13.58	48.12
SparseGPT	✓	9.77	10.45	11.92	18.92

Table 24. OPT-30B Retraining: Task performance improvement by retraining with MaskLoRA for magnitude pruning, Wanda, and SparseGPT, displaying the high sparsity regime of unstructured pruning. Each entry shows the improvement compared to no retraining, e.g., +0.5% indicates a 0.5% performance increase. We report the mean performance over several seeds and omit the standard deviation for the sake of clarity.

Method	Sparsity	Δ Task Accuracy							Average
		BoolQ	RTE	HSwag	WinoG	ARC-e	ARC-c	OBQA	
Magnitude	50%	+29.50%	+6.32%	+18.82%	+14.76%	+25.67%	+11.48%	+13.80%	+16.40%
Wanda	50%	+0.38%	+5.23%	+0.94%	+1.46%	+0.29%	+0.68%	+1.30%	+1.24%
SparseGPT	50%	+0.40%	+4.87%	+0.41%	-0.20%	-0.02%	+0.43%	+0.50%	+0.60%
Magnitude	60%	+28.07%	+1.44%	+22.93%	+14.64%	+37.98%	+12.24%	+14.40%	+18.82%
Wanda	60%	+1.56%	+4.69%	+6.05%	+3.95%	+6.99%	+3.28%	+3.20%	+3.84%
SparseGPT	60%	+4.48%	+0.90%	+1.57%	+0.32%	+0.55%	+0.55%	+2.10%	+0.99%
Magnitude	70%	+26.41%	+2.89%	+19.85%	+11.88%	+35.56%	+9.04%	+12.60%	+16.17%
Wanda	70%	+24.40%	+1.08%	+10.10%	+5.80%	+26.33%	+2.90%	+7.60%	+10.78%
SparseGPT	70%	+4.92%	+3.61%	+3.65%	+1.85%	+3.03%	+3.07%	+2.40%	+2.66%
Magnitude	80%	+14.57%	+0.36%	+10.72%	+6.91%	+25.21%	+2.26%	+5.30%	+9.33%
Wanda	80%	+9.66%	0.00%	+1.92%	+0.87%	+9.51%	0.00%	+1.00%	+2.30%
SparseGPT	80%	+0.12%	+2.35%	+7.81%	+5.09%	+10.90%	+4.14%	+3.70%	+4.66%