Computation and Memory-Efficient Model Compression with Gradient Reweighting

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Abstract

Pruning is a commonly employed technique for deep neural networks (DNNs) aiming at compressing the model size to reduce computational and memory costs during inference. In contrast to conventional neural networks, large language models (LLMs) pose a unique challenge regarding pruning efficiency due to their substantial computational and memory demands. Existing methods, particularly optimization-based ones, often require considerable computational resources in gradient estimation because they cannot effectively leverage weight sparsity of the intermediate pruned network to lower compuation and memory costs in each iteration. The fundamental challenge lies in the need to frequently instantiate intermediate pruned sub-models to achieve these savings, a task that becomes infeasible even for moderately sized neural networks. To this end, this paper proposes a novel pruning method for DNNs that is both computationally and memory-efficient. Our key idea is to develop an effective reweighting mechanism that enables us to estimate the gradient of the pruned network in current iteration via reweigting the gradient estimated on an outdated intermediate sub-model instantiated at an earlier stage, thereby significantly reducing model instantiation frequency. We further develop a series of techniques, e.g., clipping and preconditioning matrix, to reduce the variance of gradient estimation and stabilize the optimization process. We conducted extensive experimental validation across various domains. Our approach achieves 50% sparsity and a 1.58$\times$ speedup in forward pass on Llama2-7B model with only 6 GB of memory usage, outperforming state-of-the-art methods with respect to both perplexity and zero-shot performance. As a by-product, our method is highly suited for distributed sparse training and can achieve a 2 $\times$ speedup over the dense distributed baselines.

1 Introduction

The explosive growth in the scale of deep neural networks (DNNs), especially large language models (LLMs) [1, 6, 48], has introduced practical challenges, including computational expense, memory usage, and latency in inference. Model pruning [13, 14, 21, 28, 34], particularly structured pruning, has emerged as a promising solution, aiming to obtain a sparse neural network by removing redundant components. For conventional DNNs, it has been reported that existing methods [8, 23] can enhance

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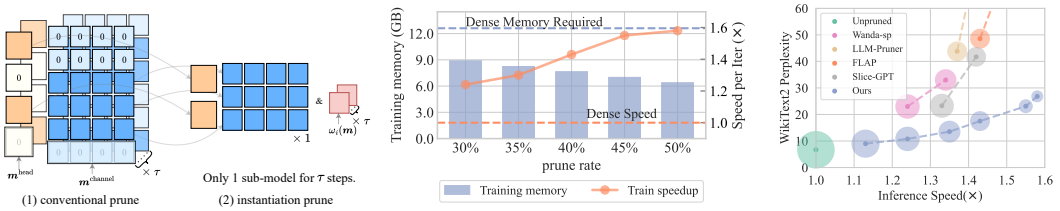
the inference efficiency and reduce the memory consumption by orders of magnitudes, with only a slight performance degradation, facilitating the deployment of DNNs on low-power devices.

In contrast to conventional DNNs, LLMs have substantial computational and memory demands. The users in downstream applications always have significantly less computational and data resources for pruning compared to those used for training. Consequently, LLMs pose a unique challenge for pruning. Metric-based pruning methods [2, 32, 55] are proposed to overcome this challenge; however, their manually designed rules can adversely affect the performance of the pruned model, which is more evident at higher sparsity levels. Moreover, due to the differing parameter redundancy across layers, manually setting the pruning rate for each layer is almost impossible. Thus, these methods struggle to achieve global heterogeneous pruning and are often forced to apply uniform pruning across layers [3, 46]. Optimization-based pruning methods [18, 53], which better preserve model performance, typically rely on training with backpropagation, making them difficult to apply in resource-constrained applications [31, 57].



(a) Algorithm Overview Diagram. (b) Memory Cost & Inference Speed. (c) PPL vs. Inference Speed.

Figure 1: (a) In the case of τ iterations, vanila implementation need to instantiate sub-model τ times. In contrast, with the reweighting technique, a single sub-model can be used continuously for τ steps. This is a schematic; in practice, multiple sub-models can be sampled (see Algorithm 1). (b) With our method, higher prune rates lead to lower training memory cost and faster forward computation. Notably, with 50% prune rate, we prune Llama2-7B (12.6 GB in BF16) using only **6.3 GB** memory, while achieving **1.58** $\times$ speedup in the forward pass. (c) Circle size is proportional to pruned model's memory usage. We achieve substantial inference speedup while maintaining a low perplexity.

We argue that leveraging the sparse structure of the model is a natural idea to develop computationally and memory-efficient pruning algorithms. This can be implemented by instantiating the sparse subnetwork during pruning. However, as the subnetwork structure is updated in each iteration during pruning, the model instantiation needs to be performed frequently, which could leads to unbearable time cost. To this end, we propose a computationally and memory-efficient optimization-based pruning algorithm with a novel reweighting technique to reduce the model instantiation frequency. This approach effectively leverages the sparsity by completely discarding pruned parameters, preventing them from participating in computation and storage. Our carefully designed reweighting mechanism enables us to estimate the gradient of the pruned network in current iteration via simply reweighting the gradient estimated on an outdated intermediate submodel instantiated at an earlier stage, in this way the model instantiation frequency can be reduced. Our algorithm is illustratively shown in Fig.1a. We further integrate our reweighting technique with policy gradient estimator to bypass the computationally expensive backpropagation to update the sparse sub-model structural parameters. Finally, considering the additional variance introduced by reweighting and policy gradient estimator, we develop a series of variance reduction techniques to stabilize training, including *clipping* and *preconditioning matrix*, which are detailed in Section 4.2.

Extensive experiments on LLM demonstrate that our method reduces memory requirements during the pruning process and provides substantial computational speedup, particularly under high pruning rate. On the Llama2-7B model, our algorithm achieved 50% sparsity with only 6 GB of memory usage and delivered a 1.58 $\times$ speedup in forward pass, as shown in Fig. 1b, while maintaining state-of-the-art performance in terms of perplexity and zero-shot capabilities. In Fig. 1c, we present a visual comparison of the model's speed and perplexity after pruning with different methods.

Additionally, our algorithm is highly compatible with distributed sparse training [4]. In this setting, we can send the instantiated sub-models to the respective clients. With the reweighting technique, each client can work on its sub-model for a long period, reducing the frequency of model weights transmission. During training, by passing only two real numbers, i.e., the reweighting value and

the training loss, we can provide clients with essential structural information and update structural parameters on the server based on the latest client results in real time.

Our main contributions can be summarized as follow:

- We propose a novel pruning approach that, for the first time, instantiates intermediate pruned sub-models throughout the pruning process. This technique effectively reduces computational and memory costs by limiting the frequency of instantiation, thereby enhancing overall efficiency in pruning.
- Our reweighting technique enables unbiased policy gradient estimation based on outdated structural information and reduces instantiation frequency. In addition, we design variance reduction techniques to stabilize the pruning process.
- Our approach achieves 50% sparsity and a 1.58× speedup in forward pass on Llama2-7B with only 6 GB of memory usage, outperforming state-of-the-art methods with respect to both perplexity and zero-shot performance.
- As a byproduct, our algorithm is inherently well-suited for distributed sparse training, reducing communication overhead during training process.

2 Related Work

2.1 Conventional Neural Network Pruning

Neural network pruning [20] is a technique aimed at reducing model parameters, focusing on reducing storage costs and inference time. Conventional pruning algorithms [13, 19, 29, 38, 51] generally operate on traditional network, establishing criteria (e.g. weight magnitude, importance score) to assess and prune the parameters or modules, while minimizing performance degradation. These pruning methods make the deployment of some neural networks on resource-limited devices possible.

2.2 LLM Pruning

For LLMs, due to the large number of parameters and the resource mismatch between training and pruning, the discussed conventional pruning algorithms are often difficult to apply. An increasing variety of pruning algorithms are being designed specifically for LLMs, which can be divided into two main types based on whether structural parameters optimization is involved: metric-based [46, 49, 60, 63, 65] and optimization-based [7, 17, 27, 31].

Metric-Based Pruning. Metric-based pruning is similar to traditional methods mentioned above but is tailored to accommodate specific characteristics of LLMs, such as large number of parameters and the outlier activation in certain channels [11, 59]. These metrics are often more meticulously designed: for instance, Wanda [46] incorporates activations into the importance score; SparseGPT [15] efficiently calculates Hessian's inverse to set up metrics and parameter reconstruction; LLM-Pruner [34] groups the module by graph information, and deletes them together after obtaining the scores; FLAP [2] extends the metric globally through score normalization. These methods are typically limited to layers or matrix, and their performance often deteriorates under high sparsity.

Optimization-Based Pruning. By training the structural parameters, the optimization-based pruning algorithm can learn a more effective sparse structure. For instance, [54, 57] employs reparameterization to learn masks, pruning the model down to a fixed size, [57] additionally continues pretraining to restore model capability; APT [66] introduces a dynamic low-rank structure similar to LoRA [25], allowing adaptive fine-tuning and pruning. NutePrune [31] employs the model with lower sparsity as a teacher for distillation during pruning. Overall, optimization-based LLM pruning methods typically require gradient computation through the chain rule, which inevitably demands higher computational costs, making practical application more challenging.

Most LLM pruning methods fail to leverage sparse structures, and the resource mismatch between training and pruning calls for a computationally and memory-efficient algorithm.

3 Preliminary

Framework of Probabilistic Masking for Pruning. We adopt the sparse training framework for neural networks proposed in [67]. Given a neural network parameterized by $\boldsymbol{W} = \{\boldsymbol{w}_i\}_{i=1}^K$, where K is the number of modules and $\boldsymbol{w}_i$ represents the parameter matrix of a module within the network, e.g., a head in Attention, or a channel in CNNs. Let $\boldsymbol{m} = [\boldsymbol{m}_1, \ldots, \boldsymbol{m}_K]$ denotes the corresponding binary mask for $\boldsymbol{W}$. The module $\boldsymbol{w}_i$ is pruned when $\boldsymbol{m}_i = 0$ and retained when $\boldsymbol{m}_i = 1$. By further reparameterizing the mask $\boldsymbol{m}$ with `Bernoulli` random variabels, i.e., $\boldsymbol{m}_i \sim \texttt{Bernoulli}(\boldsymbol{s}_i)$ with the probability of $\boldsymbol{s}_i$ to be 1, the structured pruning framework can be formalized as follows:

$$\begin{aligned} \min_{\boldsymbol{s}} \mathbb{E}_{p(\boldsymbol{m}|\boldsymbol{s})} \mathcal{L}(\boldsymbol{W} \circ \boldsymbol{m}) &\triangleq \frac{1}{N} \sum_{i=1}^{N} \ell(f(\boldsymbol{x}_i; \boldsymbol{W} \circ \boldsymbol{m}), \boldsymbol{y}_i), \\ s.t.\ \|\boldsymbol{s}\|_1 \leq (1-\rho)K &\text{ and } \boldsymbol{s} \in [0,1]^K, \end{aligned} \tag{1}$$

where $\{(\boldsymbol{x}_i, \boldsymbol{y}_i)\}_{i=1}^N$ are the training samples, ρ denotes the prune rate, $f(\cdot; \boldsymbol{W} \circ \boldsymbol{m})$ represents the sparse neural network, $\ell(\cdot, \cdot)$ is the loss function. Here, the optimization of $\boldsymbol{W}$ is omitted as we focus on pruning instead of training.

The base solver proposed in [67] optimizes above problem using policy gradient estimator, which enables unbiased gradient estimation of $\boldsymbol{s}$ using only forward propagation. After sampling a mini batch $\mathcal{B}$ and $\boldsymbol{m}$ from $p(\boldsymbol{m}|\boldsymbol{s})$, the specific update procedure for each iteration is as follows:

$$\boldsymbol{s} \leftarrow \text{proj}_{\mathcal{S}}(\boldsymbol{s} - \eta \boldsymbol{g}_{\boldsymbol{s}}), \text{ where } \boldsymbol{g}_{\boldsymbol{s}} = \mathcal{L}_{\mathcal{B}}(\boldsymbol{m}) \nabla_{\boldsymbol{s}} \log(p(\boldsymbol{m}|\boldsymbol{s})), \tag{2}$$

where $\mathcal{S} \triangleq \{\boldsymbol{s} : \|\boldsymbol{s}\|_1 \leq (1-\rho)K \text{ and } \boldsymbol{s} \in [0,1]^K\}$ is the feasible domain and $\text{proj}_{\mathcal{S}}(\cdot)$ is the projection operator[1] on $\mathcal{S}$. Notably, $\nabla_{\boldsymbol{s}} \log(p(\boldsymbol{m}|\boldsymbol{s})) = \frac{\boldsymbol{m}-\boldsymbol{s}}{\boldsymbol{s}(1-\boldsymbol{s})}$ can be computed explicitly and thus the entire process is more efficient compared to traditional backpropagation-based algorithms.

4 Method

In this section, we introduce our method in three parts: the reweighting technique to reduce the instantiation frequency in Section 4.1; the detailed framework of efficient pruning in Section 4.2; and finally, the extension to distributed sparse training in Section 4.3.

4.1 Reweighted Policy Gradient Estimator

Sub-model Instantiation. We first give the definition of instantiation as follows:

Definition 4.1. *Given the parameters $\boldsymbol{W}$ of a DNN and the corresponding masks $\boldsymbol{m}$, we **instantiate** a compact sub-model by creating a new neural network to delete the pruned modules, which can be written as $f(\cdot; \boldsymbol{W}_{\boldsymbol{m}})$ with the parameters $\boldsymbol{W}_{\boldsymbol{m}} = \{\boldsymbol{w}_i\}_{i \in \boldsymbol{I}}$ and $\boldsymbol{I} = \{i : \boldsymbol{m}_i = 1, i = 1, \ldots, K\}$.*

It can be seen that if we utilize $\boldsymbol{m}$ to instantiate a compact sub-model at each step, we can reduce memory consumption and accelerate forward speed. However, frequent instantiations lead to unbearable time costs. Considering this issue, we propose a new reweighting technique to reduce instantiation frequency, allowing to use outdated compact sub-model to optimize the structural parameters $\boldsymbol{s}$.

Basic Idea. Our reweighting technique is inspired by importance sampling, and its general form is:

$$\mathbb{E}_{\mathbf{x} \sim p(\cdot)}[f(\mathbf{x})] = \int f(\mathbf{x}) p(\mathbf{x}) \mathrm{d}\mathbf{x} = \int q(\mathbf{x}) f(\mathbf{x}) \frac{p(\mathbf{x})}{q(\mathbf{x})} \mathrm{d}\mathbf{x} = \mathbb{E}_{\mathbf{x} \sim q(\cdot)} \left[f(\mathbf{x}) \frac{p(\mathbf{x})}{q(\mathbf{x})} \right]. \tag{3}$$

This equation indicates that the expectation of $f(\mathbf{x})$ over distrbution $p(\cdot)$ equals to that of $f(\mathbf{x}) \frac{p(\mathbf{x})}{q(\mathbf{x})}$ over $q(\cdot)$. The item $\frac{p(\mathbf{x})}{q(\mathbf{x})}$ is the importance weight. This means one can estimate the mean of a random variable in another probability space by choosing a proper distribution.

[1]The computation of the projection operator is detailed in Appendix D.

Reweighting Technique Derivation. Based on the above analysis, we develop our reweighted policy gradient estimator below. Firstly, we have

$$\begin{aligned}
&\nabla_{\boldsymbol{s}}\mathbb{E}_{p(\boldsymbol{m}|\boldsymbol{s})}\mathcal{L}(\boldsymbol{m}) \\
=&\nabla_{\boldsymbol{s}}\int p(\boldsymbol{m}|\boldsymbol{s})\mathcal{L}(\boldsymbol{m})\mathrm{d}\boldsymbol{m} = \int \mathcal{L}(\boldsymbol{m})\nabla_{\boldsymbol{s}}p(\boldsymbol{m}|\boldsymbol{s}) + \underbrace{p(\boldsymbol{m}|\boldsymbol{s})\nabla_{\boldsymbol{s}}\mathcal{L}(\boldsymbol{m})}_{=0}\mathrm{d}\boldsymbol{m} \\
=&\int \mathcal{L}(\boldsymbol{m})p(\boldsymbol{m}|\boldsymbol{s})\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))\mathrm{d}\boldsymbol{m} \overset{(3)}{=} \int \mathcal{L}(\boldsymbol{m})\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))\frac{p(\boldsymbol{m}|\boldsymbol{s})}{p(\boldsymbol{m}|\tilde{\boldsymbol{s}})}p(\boldsymbol{m}|\tilde{\boldsymbol{s}})\mathrm{d}\boldsymbol{m} \\
=&\mathbb{E}_{p(\boldsymbol{m}|\tilde{\boldsymbol{s}})}\mathcal{L}(\boldsymbol{m})\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))\omega(\boldsymbol{m}),
\end{aligned} \tag{4}$$

where $\tilde{\boldsymbol{s}} \in \mathcal{S}$ is the outdated structural parameter. $\omega(\boldsymbol{m}) \triangleq \frac{p(\boldsymbol{m}|\boldsymbol{s})}{p(\boldsymbol{m}|\tilde{\boldsymbol{s}})}$ denotes the **reweighting function** that transforms the measure $p(\boldsymbol{m}|\boldsymbol{s})$ to $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$. Therefore,

$$\boldsymbol{g}_{\boldsymbol{s}} = \omega(\boldsymbol{m})\mathcal{L}_{\mathcal{B}}(\boldsymbol{m})\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s})) \tag{5}$$

is an unbiased estimator of $\nabla_{\boldsymbol{s}}\mathbb{E}_{p(\boldsymbol{m}|\boldsymbol{s})}\mathcal{L}(\boldsymbol{m})$. $\boldsymbol{m}$ is sampled from the outdated distribution $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$.

Discussion. Let $\tilde{\boldsymbol{s}}$ and $\boldsymbol{s}$ be the outdated and current structural parameters, respectively. Eqn.(5) demonstrates that we can estimate the gradient of $\boldsymbol{s}$ in current iteration via reweigting the gradient estimated on an intermediate sub-model $\boldsymbol{m}$ instantiated at an earlier stage from an outdated distribution $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$. In this way, we can reduce the instantiation frequency. Moreover, the estimation of $\boldsymbol{g}_{\boldsymbol{s}}$ can be computationally and memory-efficient due to the compactess of sub-model $f(\cdot; \boldsymbol{W}_{\boldsymbol{m}})$.

4.2 Framework of Efficient Pruning

Variance Reduction. Before giving the framework of our efficient pruning method, we need to address the issue of high variance in our reweighted policy gradient estimator in Eqn.(5) as follows:

(1) **Variance of $\omega(\boldsymbol{m})$:** The reweighting function $\omega(\boldsymbol{m})$ can be unstable due to large divergence between the two different distributions $p(\boldsymbol{m}|\boldsymbol{s})$ and $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$. We clip $\omega(\boldsymbol{m})$ to $[1-\epsilon, 1]$ following PPO [42], and abbreviate it as $\mathrm{clip}(\omega(\boldsymbol{m}))$.

(2) **Variance of $\mathcal{L}_{\mathcal{B}}(\boldsymbol{m})$:** The training loss $\mathcal{L}_{\mathcal{B}}(\boldsymbol{m})$'s variation comes from the randomness of the mask $\boldsymbol{m}$. We minus $\mathcal{L}_{\mathcal{B}}(\boldsymbol{m})\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))$ by a highly correlated and several zero meaned items in form of $\mathcal{L}_{\mathcal{B}}(\boldsymbol{m}')\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))$, where the mask $\boldsymbol{m}'$ is sampled independently with $\boldsymbol{m}$.

(3) **Variance of $\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))$:** The potentially small denominator in $\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s}))$, which takes the form of $\nabla_{\boldsymbol{s}}\log(p(\boldsymbol{m}|\boldsymbol{s})) = \frac{\boldsymbol{m}-\boldsymbol{s}}{\boldsymbol{s}(1-\boldsymbol{s})}$, could introduce additional variance. We multiply the gradient with a preconditioning matrix $H^{\alpha} = \mathrm{diag}(\boldsymbol{s} \circ (1-\boldsymbol{s}))^{\alpha}$ with $\alpha \in [\frac{1}{2}, 1)$ to offset this impact.

After applying these variance reduction techniques, our reweighted policy gradient estimator becomes:

$$\boldsymbol{g}_{\boldsymbol{s}}^{\boldsymbol{vr}} = \frac{1}{M-1}\sum_{i=1}^{M}\mathrm{clip}(\omega(\boldsymbol{m}^{(i)}))\left(\mathcal{L}_{\mathcal{B}}(\boldsymbol{m}^{(i)}) - \frac{1}{M}\sum_{j=1}^{M}\mathcal{L}_{\mathcal{B}}(\boldsymbol{m}^{(j)})\right)H^{\alpha}(\boldsymbol{s})\nabla_{\boldsymbol{s}}\log p(\boldsymbol{m}^{(i)}|\boldsymbol{s}), \tag{6}$$

where the masks $\boldsymbol{m}^{(i)}, i = 1, \ldots, M$ are sampled independently from the distribution $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$.

We have the following theoretical guarantee for our variance reduced gradient $\boldsymbol{g}_{\boldsymbol{s}}^{\boldsymbol{vr}}$. Detailed theoretical explanation is provided in the Appendix E.

Theorem 1. *Suppose the masks $\{\boldsymbol{m}^{(i)}\}_{i=1}^{M}$ are independently sampled from the distribution $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$, then for any $\alpha \in [\frac{1}{2}, 1)$ and $\boldsymbol{s} \in [0,1]^K$, the variance of $\boldsymbol{g}_{\boldsymbol{s}}^{\boldsymbol{vr}}$ is bounded.*

Pruning Algorithm. Finally, we present the complete algorithm in Algorithm 1. Based on reweighted policy gradient estimator with variance reduction, this algorithm enables efficient pruning using only the forward pass of the completely sparsified model, thereby avoiding the need for expensive backpropagation.

Remark 1. *Though we have M sub-models, during implementation, they can be processed sequentially in order to save the memory cost. Concurrently, we assign distinct mini batches to each sub-model to ensure equitable allocation of computational resources with the baselines. See Appendix A.2 for details. Experiments under such fair setting verify the superiority of our approach.*

Algorithm 1 Efficient Pruning with Reweighted Policy Gradient Estimator

Input: prune rate ρ, structural parameters $\boldsymbol{s}$, instantiation steps τ, dense DNN $\boldsymbol{W}$, learning rate η.

Initialize $\boldsymbol{s}$ with certain method.
for $t = 1, 2, \ldots, T$ **do**
  Set $\tilde{\boldsymbol{s}} = \boldsymbol{s}$, sample masks $\{\boldsymbol{m}^{(i)}\}_{i=1}^{M}$ from $p(\boldsymbol{m}|\tilde{\boldsymbol{s}})$, instantiate sub-model $f(\cdot; \boldsymbol{W}_{\boldsymbol{m}^{(i)}})$.
  for $r = 1, 2, \ldots, \tau$ **do**
    Sample a mini batch $\mathcal{B} = \{(\boldsymbol{x}_1, \boldsymbol{y}_1), \ldots, (\boldsymbol{x}_B, \boldsymbol{y}_B)\}$.
    Get $\mathcal{L}_{\mathcal{B}}(\boldsymbol{m}^{(i)})$ from each sub-model $f(\cdot; \boldsymbol{W}_{\boldsymbol{m}^{(i)}})$ and compute $\omega(\boldsymbol{m}^{(i)}) = \frac{p(\boldsymbol{m}|\boldsymbol{s})}{p(\boldsymbol{m}|\tilde{\boldsymbol{s}})}$.
    Calculate $\boldsymbol{g}_{\boldsymbol{s}}^{\boldsymbol{vr}}$ according to Eqn.(6).
    Update $\boldsymbol{s} \leftarrow \text{proj}_{\mathcal{S}}(\boldsymbol{s} - \eta \boldsymbol{g}_{\boldsymbol{s}}^{\boldsymbol{vr}})$.
  end for
end for
return Pruned DNN $\boldsymbol{W}_{\boldsymbol{m}}$, where mask $\boldsymbol{m}$ is sampled from the distribution $p(\boldsymbol{m}|\boldsymbol{s})$.

Discussion. We aummarize the appealing features of our algorithm as follows:

- Instantiating a compact sub-model loads only active components into memory, reducing memory usage and accelerating forward passes, unlike existing methods [57, 54, 58] that merely mask parameters with zeros and miss the full benefits of sparsity.
- If we consider training model weights through backpropagation:

$$\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta_{\boldsymbol{w}} \boldsymbol{g}_{\boldsymbol{w}}, \text{ where } \boldsymbol{g}_{\boldsymbol{w}} = \mathbb{E}_{p(\boldsymbol{m}|\tilde{\boldsymbol{s}})} \omega(\boldsymbol{m}) \nabla_{\boldsymbol{W}} \mathcal{L}(\boldsymbol{m}) \approx \omega(\boldsymbol{m}) \nabla_{\boldsymbol{W}} \mathcal{L}_{\mathcal{B}}(\boldsymbol{m}), \quad (7)$$

  the instantiation method ensures that gradient information maintains a sparsity level of ρ, granting an efficient backpropagation.
- We find that our algorithm is inherently well-suited for distributed sparse training. Through the use of reweighting technique, it reduces the overhead caused by frequent communication of model parameters in training process. Therefore, we present the application of our algorithm within the framework of distributed sparse training below.

4.3 Extension to Distributed Sparse Training

Distributed training requires the frequent passing of gradients and parameters between the server and clients, which imposes high demands on transfer efficiency. As discussed above, our algorithm is inherently well-suited for extending to distributed sparse training. During training process, the server updates the structural parameters based on policy gradient and the client is responsible for training its own sub-model, which only requires the latest structural information from the server. Since the weight parameters are trainable now, we use clearer notation $\mathcal{L}_{\mathcal{B}}(\boldsymbol{W}_{\boldsymbol{m}^{(i)}})$ instead of $\mathcal{L}_{\mathcal{B}}(\boldsymbol{m}^{(i)})$ to distinguish this setting from the pruning task above. Our training process can be divided into four stages:

(1) **Instantiating sub-models.** To start the training round, the server samples $\{\boldsymbol{m}^{(i)}\}_{i=1}^{M}$ from $p(\boldsymbol{m}|\boldsymbol{s})$ to instantiate $\{f(\cdot; \boldsymbol{W}_{\boldsymbol{m}^{(i)}})\}_{i=1}^{M}$ and sends them to each client.

(2) **Updating sub-model paras.** At each iteration, client$_i$ receives reweighting value $\omega(\boldsymbol{m}^{(i)})$ from the server, which provides real-time structural information and is used for updating the current parameters $\boldsymbol{W}_{\boldsymbol{m}^{(i)}}$ via Eqn.(7).

(3) **Updating structural paras.** Each client returns the loss $\mathcal{L}_{\mathcal{B}}(\boldsymbol{W}_{\boldsymbol{m}^{(i)}})$. By collecting these losses, the server estimates the policy gradient $\boldsymbol{g}_{\boldsymbol{s}}^{\boldsymbol{vr}}$ via Eqn.(6) and updates $\boldsymbol{s}$.

(4) **Aggregating updates.** Repeat (2) and (3) for τ steps. Then each client returns the parameter updates $\Delta \boldsymbol{W}_{\boldsymbol{m}^{(i)}}$ and the server aggregates them to update the full model.

Throughout the training process, **only two scalars**, the reweighting function $\omega(\boldsymbol{m}^{(i)})$ and the training loss $\mathcal{L}_{\mathcal{B}}(\boldsymbol{W}_{\boldsymbol{m}^{(i)}})$ of each client are communicated in real time, while the model weight parameters are passed only after every τ steps. Therefore, in this framework, the communication costs between the server and clients, as well as the instantiation overhead, are greatly reduced. Fig. 4 visually illustrates the flow of our algorithm. The detailed algorithm is shown in Appendix B.

Discussion. We genuinely believe that the distributed sparse training extension we propose is highly non-trivial and elegant. However, its advantages are challenging to fully convey through text alone. We strongly encourage readers to dedicate additional time to review its details along with Fig. 4 and Algorithm 2 in appendix.

5 Experiments

We conduct extensive experiments in this section, which demonstrate the superior performance of our algorithm. In Section 5.1, we introduce the experimental setups. In Section 5.2, we compare our method with other pruning methods for LLMs and conduct several ablation experiments in Section 5.3. Section 5.4 presents experiments using vision models in distributed sparse training scenario.

5.1 Experimental Setups

Model Configuration. We utilize the Llama and OPT families including Llama2-(7B, 13B) [48], Llama3\3.1-8B [12], Llama3.2-3B, and OPT-(2.7B, 6.7B) [64]. We apply our pruning algorithm across various structural granularities of the model, including attention heads and MLP channels.

Prune Rate. We target high sparsity levels (30%–50%) to better highlight our method's advantages. Under these settings, our instantiated method achieves higher acceleration and memory efficiency.

Baseline. Due to resource limits, we only include limited comparisons with optimization-based methods (e.g., Compresso [18], NutePrune [31]) in Section 5.3. Our main focus is on metric-based SOTA methods, including LLM-Pruner [34], SliceGPT [3], Wanda-sp, and FLAP [2]. No weight fine-tuning is performed post-pruning for fairness.

Training Details. We follow [34], using C4 [40] for training and Wikitext2 [36], PTB [35] for testing, which reflect the generalization of the pruned model. Adam [26] is used to optimize structural parameters $\boldsymbol{s}$ with a learning rate of 5e-3 and batch size 8. Training is conducted for one epoch with frozen model weights. Further details are provided in Appendix A.

5.2 Pruning Results on LLMs

The main experimental results are presented in Table 1. At various sparsity levels, our pruning algorithm achieves lower perplexity compared to other state-of-the-art methods. This advantage is even more pronounced at 50% sparsity, highlighting the superior performance of our optimization-based algorithm over other metric-based methods.

Table 1: Performance comparison across methods and models under different prune rates. The lowest and second lowest PPL are in **bold** and underlined, respectively. - denotes unsupported model types.

Prune rate	Method	Llama2-7B		Llama2-13B		Llama3-8B		Llama3.1-8B		Llama3.2-3B		OPT-2.7B		OPT-6.7B	
		↓ WikiText2	Ptb	WikiText2	Ptb	WikiText2	Ptb	WikiText2	Ptb	WikiText2	Ptb	WikiText2	Ptb	WikiText2	Ptb
0%	Dense	5.47	8.39	4.88	7.67	6.14	10.60	6.24	10.59	7.81	12.65	12.37	15.16	10.92	13.17
30%	LLM-Pruner	27.13	111.16	15.19	125.96	20.18	30.37	19.23	31.50	-	-	-	-	-	-
	SliceGPT	23.31	88.74	17.85	72.38	50.88	75.37	-	-	-	-	-	-	19.70	25.49
	Wanda-sp	23.00	37.53	11.48	15.97	34.33	50.74	27.15	36.86	47.76	91.43	32.60	39.33	56.33	58.12
	FLAP	23.76	30.93	11.12	**14.10**	26.68	30.94	25.61	33.59	40.00	74.09	54.60	54.60	45.26	43.87
	Ours	**10.80**	**15.85**	**9.75**	15.24	**17.78**	**29.50**	**17.89**	**25.88**	**22.71**	**39.61**	**21.05**	**25.39**	**19.47**	**23.85**
40%	LLM-Pruner	43.79	173.51	23.53	183.98	45.30	49.43	43.27	48.66	-	-	-	-	-	-
	SliceGPT	41.16	148.59	33.30	108.46	89.07	126.08	-	-	-	-	-	-	32.04	44.10
	Wanda-sp	39.57	71.72	24.63	50.08	74.57	128.06	61.62	90.66	76.47	137.37	70.11	74.63	148.41	108.58
	FLAP	48.12	81.70	19.01	27.37	70.63	84.47	54.72	68.52	126.06	185.33	90.02	87.25	102.00	95.82
	Ours	**19.51**	**35.64**	**12.61**	**17.40**	**30.91**	**46.88**	**29.77**	**63.90**	**50.18**	**73.76**	**33.11**	**46.70**	**28.77**	**35.81**
50%	LLM-Pruner	178.32	424.44	48.94	269.79	129.16	200.27	141.25	153.84	-	-	-	-	-	-
	SliceGPT	71.72	237.90	53.14	161.87	155.70	186.02	-	-	-	-	-	-	60.57	89.41
	Wanda-sp	101.72	112.80	103.90	162.22	92.73	160.47	71.92	115.90	89.04	176.88	173.51	163.00	295.15	184.70
	FLAP	105.90	231.26	51.70	117.19	138.51	220.25	78.77	132.87	161.58	323.84	168.17	143.85	286.07	196.62
	Ours	**26.83**	**44.23**	**21.21**	**44.47**	**57.14**	**74.13**	**57.80**	**78.35**	**83.88**	**116.41**	**65.86**	**90.02**	**53.75**	**65.86**

We evaluate the generalization performance of our pruned models based on the settings from [34], using five zero-shot tasks from LM Evaluation Harness [16]: PIQA [5], HellaSwag [62], ARC-e, ARC-c [9], and OBQA [37], and recorded their average performance. We use Llama2-7B and Llama3-8B as baseline models. As shown in the Table 2, structured pruning does have a significant impact on the model's generalization ability. At high sparsity levels, datasets like ARC-e and ARC-c show a notable performance decline. However, our algorithm still maintains the best among all methods, demonstrating its effectiveness in preserving model capacity.

Table 2: Comparison of zero-shot performance between Llama2-7B and Llama3-8B.

Prune rate	Method	Llama2-7B						Llama3-8B					
		↑ PIQA	HellaSwag	ARC-e	ARC-c	OBQA	Average	PIQA	HellaSwag	ARC-e	ARC-c	OBQA	Average
0%	Dense	78.74	76.00	74.62	46.33	44.20	63.98	80.79	79.19	77.69	53.41	45.00	67.22
30%	LLM-Pruner	72.69	58.51	57.07	33.45	38.60	52.06	69.37	44.63	54.08	30.63	31.20	45.98
	SliceGPT	73.39	60.41	52.36	32.25	32.80	50.24	70.02	57.34	49.54	30.20	32.00	47.82
	Ours	**73.61**	**63.06**	**58.46**	**34.90**	**38.80**	**53.76**	**72.74**	**58.58**	**56.52**	**30.89**	**33.60**	**50.47**
40%	LM-Pruner	67.19	45.22	43.39	27.30	31.80	42.98	63.55	36.28	41.96	23.63	27.60	38.60
	SliceGPT	66.81	48.98	41.88	25.94	27.00	42.12	64.20	44.54	37.63	24.49	28.00	39.77
	Ours	**68.99**	**53.89**	**48.70**	**29.69**	**32.20**	**46.69**	**65.94**	**45.03**	**46.13**	**26.02**	**30.40**	**42.70**

To demonstrate the effectiveness of our algorithm in reducing memory usage and accelerating the forward pass during the pruning process, we present the instantiated model parameter nums, multiply-accumulate counts (MAC), memory usage, and inference speed at different prune rates in Table 3. It is clear that the resource savings achieved by our algorithm are proportional to the model's sparsity.

Table 3: Statistics on pruned model. Inference Speed is evaluated by generating 400 tokens.

Prune rate	Params(B)	MACs(G)	Memory(MiB)	Speed(×)
0%	6.61	845.71	12607.57	1.00
30%	4.66	596.06	8888.24	1.24
35%	4.32	552.57	8239.75	1.30
40%	4.01	512.85	7648.47	1.43
45%	3.67	469.90	6999.97	1.55
50%	3.35	429.09	6389.62	1.58

Table 4: Comparison of initialization methods for $\boldsymbol{s}$ on Llama2-7B, using PPL.

Dataset	Prune rate	Random	$1-\rho$	Wanda-sp	FLAP
WikiText2	30%	16.10	12.51	10.80	13.72
	40%	32.81	22.30	19.51	18.10
	50%	68.19	52.77	26.83	33.84
	Average	39.03	29.19	**19.05**	21.89
Ptb	30%	24.31	22.18	15.85	18.10
	40%	66.41	44.55	35.64	30.09
	50%	117.33	73.51	44.23	61.22
	Average	69.35	46.75	**31.91**	36.47

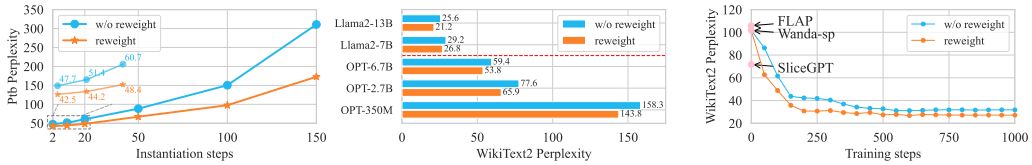
5.3 Furthur Analysis

We conduct further studies on the following aspects: 1) different initialization methods for the structural parameters $\boldsymbol{s}$; 2) effectiveness of the reweighting and instantiation technique; 3) ablation study for the variance reduction techniques; 4) comparison with the optimization-based methods.

Initialization Methods Comparsion. Four methods are employed to initialize the structural parameters $\boldsymbol{s}$, including: 1) $\texttt{Uniform}(0,1)$ random values; 2) $1-\rho$ directly; 3) the Wanda-sp score; 4) the FLAP score[1]. From the results in Table 4, it can be observed that using Wanda-sp initialization yields the best performance, followed closely by FLAP initialization. This indicates that initializing the structural parameters $\boldsymbol{s}$ with heuristic metrics can facilitate the optimization process. Additionally, we find that random initialization is already sufficient to surpass metric-based pruning algorithms.

Effects of Reweighting and Instantiation. As shown in Fig. 2, as the number of instantiation steps τ increases, perplexity gradually rises due to the accumulation of errors from the outdated sub-model $\boldsymbol{W_m}$ and gradients $\boldsymbol{g_s}$. However, by using the reweighting function, this issue can be effectively alleviated. Even with 100 steps, the perplexity on WikiText2 still reaches 71.01, which is better than SliceGPT's 71.72. Meanwhile, in (c), we observe that after applying reweighting, all models in the experiment exhibit a significant reduction in perplexity. Therefore, we believe the reweighting function makes infrequent instantiation possible, which helps us fully leverage the sparse structure, resulting in memory savings and forward acceleration.

[1]Since the scores of Wanda-SP and FLAP do not fall within the range $(0,1)$, we normalize these scores to form a probability distribution. For different prune rates, we scale them to the desired sparsity level.



(a) Effect of τ on pruning. (b) Results at $\tau = 10$. (c) Reweighting on training.

Figure 2: (a) For different instantiation step τ, reweighted version consistently outperforms the w/o reweighted baseline. Considering the trade-off between instantiation time and pruning performance, we fix $\tau = 10$ throughout all experiments. (b) Under our fixed setting $\tau = 10$ for all experiments, reweighting technique improves pruning across all models. Notably, on OPT-2.7B, the impact of reweighting can reach up to **11.7** compared to w/o reweighting case. (c) Reweighting technique stabilizes the training process, leading to better pruning. (a), (b), (c) are based on the 50% prune rate.

Variance Reduction. We employ clipping and preconditioning matrix H to stabilize the training process and conducted ablation experiments to verify their contribution. The results in Table 5 shows that omitting either the clipping or the preconditioning matrix negatively impacts the performance of the pruned model. Among these, the clipping has a more evident effect on performance. Compared to our final algorithm, not using clipping increases the perplexity on the Wikitext2 dataset by 12.44, indicating that our variance reduction techniques enhance the stability of the training process. Details of the variance reduction analysis can be found in Appendix C.

Table 5: Variance reduction study, 50% Llama2-7B.

Method	↓ WikiText2	Ptb	↑ PIQA	HellaSwag	ARC-e	ARC-c	Average
Ours	**26.83**	**44.23**	**62.89**	**40.19**	**39.98**	**25.00**	**42.02**
w/o H	32.75	57.01	61.48	38.21	37.29	24.40	40.35
w/o *clip*	39.27	69.28	60.83	39.11	38.68	23.04	40.42

Note: evaluation metrics: Perplexity (WikiText2, PTB) and zero-shot accuracy (PIQA, HellaSwag, ARC-e, ARC-c and their average).

Table 6: Overhead test, 50% Llama2-7B.

Method	WikiText2	Forward(s)	Backward(s)	Memory(MiB)
Ours	26.83	0.015	None	6390.21
Compresso†	49.28	0.024	0.041	33298.74
NutePrune‡	24.89	0.049	0.051	37460.78

Note: † pruning with LoRA adaption. ‡ co-training the masks and LoRA modules, also involves distillation.

Comparison with optimization-based methods. Our method outperforms other optimization-based pruning algorithms by significantly reducing memory usage and training time. To demonstrate the superiority of our algorithm, we select Compresso [18] and NutePrune [31] for comparison. Since these methods use different training settings, we focus on memory usage and time consumption in a single optimization iteration. Table 6 shows that our algorithm achieves comparable performance while consuming less memory, offering faster forward time, and requiring no backpropagation.

5.4 Distributed Sparse Training

Based on the method described in Section 4.3, we conduct extensive experiments within the framework of distributed sparse training. We use *gloo* [43] as the distributed backend and built an 8-node cluster for training on the ImageNet-1K dataset [41] (each node equipped with a GPU). The worker nodes are connected via a 40 Gbps (5000 Mb/s) Ethernet interface. The baseline algorithms include LocalSGD [45], PowerSGD [50], TSNNS [10], and our base solver EffTrain [67] (which performs sparse training locally without using reweighting techniques, described in Section 3). We set the instantiation sampling interval τ to 20 steps. The detailed experimental configuration and baseline description can be found in Appendix A. The specific comparison results are shown in Table 7.

Table 7: Comparison of methods across ResNet-50, MobileNet-V1 and DeiT-Base on ImageNet-1K.

Method	ResNet-50				MobileNet-V1 [24]				DeiT-Base [47]			
	Acc(%)↑	Params(%)↓	FLOPs(%)↓	Time↓	Acc(%)	Params(%)	FLOPs(%)	Time	Acc(%)	Params(%)	FLOPs(%)	Time
Dense Dist.	76.9	100	100	23.00	72.0	100	100	8.66	81.8	100	100	53.05
Local SGD	75.0	100	100	20.52	71.5	100	100	6.15	80.6	100	100	40.41
PowerSGD	76.0	100	100	19.25	71.3	100	100	5.50	79.5	100	100	38.28
TSNNS	74.5	63.2	77.4	19.49	70.4	88.5	82.9	5.69	78.5	80.3	79.4	39.37
EffTrain	**76.1**	48.2	46.8	115.04	71.5	68.1	69.2	61.36	80.1	67.1	68.2	288.24
Ours	75.2	**48.1**	**46.5**	**9.79**	**71.6**	**67.4**	**68.9**	**4.15**	**80.9**	**66.5**	**67.3**	**26.70**

Our method achieves excellent performance across three different models, surpassing other distributed training algorithms, while also reducing model params and FLOPs. The base solver EffTrain also

achieves superior performance and model compression; however, due to the frequent instantiation operations, its training time is significantly longer compared to distributed algorithms. In conclusion, our algorithm integrates well into the framework of distributed sparse training. By using the reweighting technique to reduce instantiation frequency, it achieves promising results in less time.

6 Conclusion

This paper introduces a novel DNN pruning algorithm that is computationally and memory-efficient. For the first time in pruning research, we define model instantiation to leverage sparsity for memory savings and forward acceleration. Additionally, we propose a reweighting technique that reduces instantiation frequency, making it feasible to prune LLMs under resource constraints. As a byproduct, our algorithm seamlessly integrates into distributed sparse training environments. Extensive experiments demonstrate the excellent practical performance of our pruning algorithm, and numerous ablation studies validates our proposed techniques' effectiveness. Besides, we also provide thorough theoretical analysis to support our algorithm.

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References

[1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

[2] Yongqi An, Xu Zhao, Tao Yu, Ming Tang, and Jinqiao Wang. Fluctuation-based adaptive structured pruning for large language models. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 10865–10873, 2024.

[3] Saleh Ashkboos, Maximilian L Croci, Marcelo Gennari do Nascimento, Torsten Hoefler, and James Hensman. Slicegpt: Compress large language models by deleting rows and columns. In *The Twelfth International Conference on Learning Representations*, 2024.

[4] Tal Ben-Nun and Torsten Hoefler. Demystifying parallel and distributed deep learning: An in-depth concurrency analysis. *ACM Computing Surveys (CSUR)*, 52(4):1–43, 2019.

[5] Yonatan Bisk, Rowan Zellers, Jianfeng Gao, Yejin Choi, et al. Piqa: Reasoning about physical commonsense in natural language. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 7432–7439, 2020.

[6] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *Proceedings of the 34th International Conference on Neural Information Processing Systems*, pages 1877–1901, 2020.

[7] Tianyi Chen, Tianyu Ding, Badal Yadav, Ilya Zharkov, and Luming Liang. Lorashear: Efficient large language model structured pruning and knowledge recovery. *arXiv preprint arXiv:2310.18356*, 2023.

[8] Hongrong Cheng, Miao Zhang, and Javen Qinfeng Shi. A survey on deep neural network pruning: Taxonomy, comparison, analysis, and recommendations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2024.

[9] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*, 2018.

[10] Selima Curci, Decebal Constantin Mocanu, and Mykola Pechenizkiyi. Truly sparse neural networks at scale. *arXiv preprint arXiv:2102.01732*, 2021.

[11] Tim Dettmers, Mike Lewis, Younes Belkada, and Luke Zettlemoyer. Gpt3. int8 (): 8-bit matrix multiplication for transformers at scale. *Advances in Neural Information Processing Systems*, 35:30318–30332, 2022.

[12] Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

[13] Utku Evci, Trevor Gale, Jacob Menick, Pablo Samuel Castro, and Erich Elsen. Rigging the lottery: Making all tickets winners. In *International conference on machine learning*, pages 2943–2952. PMLR, 2020.

[14] Jonathan Frankle and Michael Carbin. The lottery ticket hypothesis: Finding sparse, trainable neural networks. In *International Conference on Learning Representations*, 2018.

[15] Elias Frantar and Dan Alistarh. Sparsegpt: Massive language models can be accurately pruned in one-shot. In *International Conference on Machine Learning*, pages 10323–10337. PMLR, 2023.

[16] Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, 07 2024.

[17] Yuan Gao, Zujing Liu, Weizhong Zhang, Bo Du, and Gui-Song Xia. Optimization-based structural pruning for large language models without back-propagation. *arXiv preprint arXiv:2406.10576*, 2024.

[18] Song Guo, Jiahang Xu, Li Lyna Zhang, and Mao Yang. Compresso: Structured pruning with collaborative prompting learns compact large language models. *arXiv preprint arXiv:2310.05015*, 2023.

[19] Yiwen Guo, Anbang Yao, and Yurong Chen. Dynamic network surgery for efficient dnns. *Advances in neural information processing systems*, 29, 2016.

[20] Song Han, Jeff Pool, John Tran, and William Dally. Learning both weights and connections for efficient neural network. *Advances in neural information processing systems*, 28, 2015.

[21] Babak Hassibi and David Stork. Second order derivatives for network pruning: Optimal brain surgeon. *Advances in neural information processing systems*, 5, 1992.

[22] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[23] Torsten Hoefler, Dan Alistarh, Tal Ben-Nun, Nikoli Dryden, and Alexandra Peste. Sparsity in deep learning: Pruning and growth for efficient inference and training in neural networks. *Journal of Machine Learning Research*, 22(241):1–124, 2021.

[24] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: efficient convolutional neural networks for mobile vision applications (2017). *arXiv preprint arXiv:1704.04861*, 126, 2017.

[25] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022.

[26] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *International Conference on Learning Representations (ICLR 2015)*, 2015.

[27] Jongwoo Ko, Seungjoon Park, Yujin Kim, Sumyeong Ahn, Du-Seong Chang, Euijai Ahn, and Se-Young Yun. Nash: A simple unified framework of structured pruning for accelerating encoder-decoder language models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 6076–6093, 2023.

[28] Yann LeCun, John Denker, and Sara Solla. Optimal brain damage. *Advances in neural information processing systems*, 2, 1989.

[29] Jaeho Lee, Sejun Park, Sangwoo Mo, Sungsoo Ahn, and Jinwoo Shin. Layer-adaptive sparsity for the magnitude-based pruning. In *International Conference on Learning Representations*, 2021.

[30] Hao Li, Asim Kadav, Igor Durdanovic, Hanan Samet, and Hans Peter Graf. Pruning filters for efficient convnets. In *International Conference on Learning Representations*, 2017.

[31] Shengrui Li, Junzhe Chen, Xueting Han, and Jing Bai. Nuteprune: Efficient progressive pruning with numerous teachers for large language models. *arXiv preprint arXiv:2402.09773*, 2024.

[32] Yun Li, Lin Niu, Xipeng Zhang, Kai Liu, Jianchen Zhu, and Zhanhui Kang. E-sparse: Boosting the large language model inference through entropy-based N: M sparsity. *arXiv preprint arXiv:2310.15929*, 2023.

[33] Lucas Liebenwein, Cenk Baykal, Harry Lang, Dan Feldman, and Daniela Rus. Provable filter pruning for efficient neural networks. In *International Conference on Learning Representations*.

[34] Xinyin Ma, Gongfan Fang, and Xinchao Wang. Llm-pruner: On the structural pruning of large language models. *Advances in neural information processing systems*, 36:21702–21720, 2023.

[35] Mitch Marcus, Beatrice Santorini, and Mary Ann Marcinkiewicz. Building a large annotated corpus of english: The penn treebank. *Computational linguistics*, 19(2):313–330, 1993.

[36] Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models. In *International Conference on Learning Representations*, 2022.

[37] Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. Can a suit of armor conduct electricity? a new dataset for open book question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2381–2391, 2018.

[38] Pavlo Molchanov, Arun Mallya, Stephen Tyree, Iuri Frosio, and Jan Kautz. Importance estimation for neural network pruning. In *CVPR*, pages 11264–11272, 2019.

[39] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32:8026–8037, 2019.

[40] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, 21(140):1–67, 2020.

[41] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115:211–252, 2015.

[42] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[43] Alexander Sergeev and Mike Del Balso. Horovod: fast and easy distributed deep learning in tensorflow. *arXiv preprint arXiv:1802.05799*, 2018.

[44] Karen Simonyan. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

[45] Sebastian U Stich. Local sgd converges fast and communicates little. *arXiv preprint arXiv:1805.09767*, 2018.

[46] Mingjie Sun, Zhuang Liu, Anna Bair, and J Zico Kolter. A simple and effective pruning approach for large language models. In *The Twelfth International Conference on Learning Representations*, 2024.

[47] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. In *International conference on machine learning*, pages 10347–10357. PMLR, 2021.

[48] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

[49] Tycho FA van der Ouderaa, Markus Nagel, Mart van Baalen, Yuki M Asano, and Tijmen Blankevoort. The llm surgeon. In *International Conference of Learning Representations (ICLR)*, 2024.

[50] Thijs Vogels, Sai Praneeth Karimireddy, and Martin Jaggi. Powersgd: Practical low-rank gradient compression for distributed optimization. *Advances in Neural Information Processing Systems*, 32, 2019.

[51] Huan Wang, Can Qin, Yulun Zhang, and Yun Fu. Neural pruning via growing regularization. In *International Conference on Learning Representations (ICLR)*, 2021.

[52] Weiran Wang and Miguel A Carreira-Perpinán. Projection onto the probability simplex: An efficient algorithm with a simple proof, and an application. *arXiv preprint arXiv:1309.1541*, 2013.

[53] Ziheng Wang, Jeremy Wohlwend, and Tao Lei. Structured pruning of large language models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Jan 2020.

[54] Ziheng Wang, Jeremy Wohlwend, and Tao Lei. Structured pruning of large language models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6151–6162, 2020.

[55] Boyi Wei, Kaixuan Huang, Yangsibo Huang, Tinghao Xie, Xiangyu Qi, Mengzhou Xia, Prateek Mittal, Mengdi Wang, and Peter Henderson. Assessing the brittleness of safety alignment via pruning and low-rank modifications. *arXiv preprint arXiv:2402.05162*, 2024.

[56] Wikipedia. Var reduction. `https://en.wikipedia.org/wiki/Variance_reduction`.

[57] Mengzhou Xia, Tianyu Gao, Zhiyuan Zeng, and Danqi Chen. Sheared llama: Accelerating language model pre-training via structured pruning. In *The Twelfth International Conference on Learning Representations*, 2024.

[58] Mengzhou Xia, Zexuan Zhong, and Danqi Chen. Structured pruning learns compact and accurate models. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1513–1528, 2022.

[59] Guangxuan Xiao, Ji Lin, Mickael Seznec, Hao Wu, Julien Demouth, and Song Han. Smoothquant: Accurate and efficient post-training quantization for large language models. In *International Conference on Machine Learning*, pages 38087–38099. PMLR, 2023.

[60] Lu Yin, You Wu, Zhenyu Zhang, Cheng-Yu Hsieh, Yaqing Wang, Yiling Jia, Gen Li, AJAY KUMAR JAISWAL, Mykola Pechenizkiy, Yi Liang, et al. Outlier weighed layerwise sparsity (owl): A missing secret sauce for pruning llms to high sparsity. In *Forty-first International Conference on Machine Learning*, 2024.

[61] Xin Yuan, Pedro Henrique Pamplona Savarese, and Michael Maire. Growing efficient deep networks by structured continuous sparsification. In *International Conference on Learning Representations*, 2021.

[62] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. Hellaswag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, 2019.

[63] Mingyang Zhang, Hao Chen, Chunhua Shen, Zhen Yang, Linlin Ou, Xinyi Yu, and Bohan Zhuang. Pruning meets low-rank parameter-efficient fine-tuning, 2023.

[64] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*, 2022.

[65] Yingtao Zhang, Haoli Bai, Haokun Lin, Jialin Zhao, Lu Hou, and Carlo Vittorio Cannistraci. Plug-and-play: An efficient post-training pruning method for large language models. In *The Twelfth International Conference on Learning Representations*, 2024.

[66] Bowen Zhao, Hannaneh Hajishirzi, and Qingqing Cao. Apt: Adaptive pruning and tuning pretrained language models for efficient training and inference. In *Forty-first International Conference on Machine Learning*, 2024.

[67] Xiao Zhou, Weizhong Zhang, Zonghao Chen, Shizhe Diao, and Tong Zhang. Efficient neural network training via forward and backward propagation sparsification. *Advances in neural information processing systems*, 34:15216–15229, 2021.

[68] Xiao Zhou, Weizhong Zhang, Hang Xu, and Tong Zhang. Effective sparsification of neural networks with global sparsity constraint. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3599–3608, 2021.

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