oViT: An Accurate Second-Order Pruning Framework for Vision Transformers

Denis Kuznedelev
Skoltech & Yandex
Denis.Kuznedelev@skoltech.ru

Eldar Kurtic
IST Austria
eldar.kurtic@ist.ac.at

Elias Frantar
IST Austria
elias.frantar@ist.ac.at

Dan Alistarh
IST Austria & Neural Magic
dan.alistarh@ist.ac.at

Abstract
Models from the Vision Transformer (ViT) family have recently provided breakthrough results across image classification tasks such as ImageNet. Yet, they still face barriers to deployment, notably the fact that their accuracy can be severely impacted by compression techniques such as pruning. In this paper, we take a step towards addressing this issue by introducing Optimal ViT Surgeon (oViT), a new state-of-the-art method for the weight sparsification of Vision Transformers (ViT) models. At the technical level, oViT introduces a new weight pruning algorithm which leverages second-order information, specifically adapted to be both highly-accurate and efficient in the context of ViTs. We complement this accurate one-shot pruner with an in-depth investigation of gradual pruning, augmentation, and recovery schedules for ViTs, which we show to be critical for successful ViT compression. We validate our method via extensive experiments on classical ViT and DeiT models, as well as on newer variants, such as XCiT, EfficientFormer and Swin. Moreover, our results are even relevant to recently-proposed highly-accurate ResNets. Our results show for the first time that ViT-family models can in fact be pruned to high sparsity levels (e.g. \( \geq 75\% \)) with low impact on accuracy (\( \leq 1\% \) relative drop), and that our approach outperforms prior methods by significant margins at high sparsities. In addition, we show that our method is compatible with structured pruning methods and quantization, and that it can lead to significant speedups on a sparsity-aware inference engine.

1 Introduction
Attention-based Transformer architectures [Vaswani et al., 2017] have revolutionized natural language processing (NLP), and have been shown to achieve excellent results in new domains, such as audio and signal processing [Li et al., 2018, Gong et al., 2021], and, more recently, computer vision [Dosovitskiy et al., 2020, Touvron et al., 2021, Carion et al., 2020]. Specifically, in computer vision, which is the focus of our study, the Vision Transformer (ViT) approach [Dosovitskiy et al., 2020, Touvron et al., 2021] and its extensions [Ali et al., 2021, Liu et al., 2021a, Wang et al., 2021] have been remarkably successful, despite encoding fewer inductive biases. However, the high accuracy of ViTs comes at the cost of large computational and parameter budgets—in particular, ViT models are well-known to be more parameter-heavy [Dosovitskiy et al., 2020, Touvron et al., 2021], relative to their convolutional counterparts. Consequently, a rapidly-expanding line of work has been focusing on reducing these costs for ViT models via model compression, thus enabling their deployment in resource-constrained settings.
In particular, several recent references focused on adapting existing compression approaches to ViT models, investigating either structured pruning, removing patches or tokens, or unstructured pruning, removing weights. While in this paper we will focus mainly on unstructured pruning, the consensus in the literature is that ViT models are generally less compressible than convolutional networks (CNNs) at the same accuracy. If the classic ResNet50 model [He et al., 2016] can be compressed to 80-90% sparsity with negligible loss of accuracy, e.g. [Frantar et al., 2021, Peste et al., 2021], the best currently-known results for similarly-accurate ViT models can only reach at most 50% sparsity while maintaining dense accuracy [Chen et al., 2021]. It is therefore natural to ask whether this “lack of compressibility” is an inherent limitation of ViTs, or whether better results can be obtained via improved compression methods designed for these architectures.

**Contributions.** In this paper, we address this question, and propose a new pruning method called *Optimal ViT Surgeon (oViT)*, which improves the state-of-the-art accuracy-vs-sparsity trade-off for ViT family models, and shows that they can be pruned to similar levels as CNNs. Our work is based on an in-depth investigation of the critical elements impacting their performance under pruning, and provides contributions across three main directions:

- **A new second-order sparse projection.** To address the fact that ViT models tend to lose significant accuracy upon each pruning step, we introduce a novel approximate second-order pruner called oViT, inspired by the classical second-order OBS framework [Hassibi et al., 1993], which is highly-accurate for ViTs, while being fast and space-efficient.

- **Post-pruning recovery framework.** To address the issue that ViTs are notoriously hard to train and fine-tune [Touvron et al., 2021, Steiner et al., 2021], we provide a set of general *sparse fine-tuning recipes*, enabling accuracy recovery at reasonable computational budgets.

- **End-to-end framework for sparsity sweeps.** Our accurate oViT pruner enables us to avoid the standard and computationally-heavy procedure of gradual pruning for every sparsity target independently, e.g. [Gale et al., 2019, Singh and Alistarh, 2020]. Instead, we propose a simple pruning framework that produces sparse accurate models for a sequence of sparsity targets *in a single run*, accommodating various deployments under a fixed compute budget.

Our experimental results focus on the standard ImageNet-1K benchmark [Russakovsky et al., 2015], where we show that under relatively low fine-tuning budgets, consisting of roughly half of the usual training schedule [Chen et al., 2021], the oViT approach matches or improves upon the state-of-the-art SViTE [Chen et al., 2021] unstructured method at low-to-medium (40-50%) sparsities, and significantly outperforms it at higher sparsities (≥ 60%) required to obtain practical inference speedups. Specifically, our results show that, at low targets (e.g. 40-50%), sparsity acts as a regularizer, sometimes *improving* the validation accuracy relative to the dense baseline, by margins between 0.5% and 1.8% Top-1 accuracy. At the same time, we show for the first time that ViT models can attain high sparsity levels without significant accuracy impact: specifically, we can achieve 75-80% sparsity with relatively minor (<1%) accuracy loss. Figure 1 summarizes our results.

Conceptually, these results suggest that ViT models do not require over-parametrization to achieve high accuracy, and that, post-pruning, they can be competitive with residual networks in terms of accuracy-per-parameter. Practically, we show that the resulting sparse ViTs can be executed with speedups on a sparsity-aware inference engine [Kurtz et al., 2020]. In addition, we show that oViT is complementary to orthogonal techniques such as token sparsification [Rao et al., 2021] and/or quantization [Gholami et al., 2021], that it applies to newer ViT variants such as EfficientFormer [Li et al., 2022], XCiT [Ali et al., 2021], and Swin [Liu et al., 2021a], and can provide good results even for pruning highly-accurate variants of CNNs [Wightman et al., 2021, Tan and Le, 2021].

**Related work.** Vision Transformers (ViTs) [Dosovitskiy et al., 2020] have set new accuracy benchmarks for vision tasks, and are gaining in practical adoption. Yet, they are known to require careful tuning in terms of both augmentation and training hyper-parameters. Identifying stable recipes is an active research topic, e.g. [Touvron et al., 2021, Steiner et al., 2021]. We build on the current best-practices and propose new and general recipes for *fine-tuning* ViTs, which should be useful to the community. Several prior works have investigated ViT compression, but focusing on *structured* pruning, such as removing tokens [Zhu et al., 2021, Kim et al., 2021, Xu et al., 2021, Pan et al., 2021, Song et al., 2022, Rao et al., 2021, Hou and Kung, 2022]. We show experimentally that these approaches are *orthogonal* to unstructured pruning, which can be applied in conjunction to further compress these models.
Nonzero Params (M)

Val accuracy

DeiT-T: GM
DeiT-T: oViT
DeiT-T: SViTE
DeiT-S: GM
DeiT-S: oViT
DeiT-S: SViTE
DeiT-B: oViT
DeiT-B: SViTE
ResNet-50D: oViT

Figure 1: Validation accuracy versus non-zero parameters for DeiT-Tiny, -Small and -Base models, as well as the highly-accurate ResNet50D model, pruned to \{50, 60, 75, 80, 90\}% sparsities using iterative Global Magnitude (GM), SViTE, and oViT methods.

Unstructured pruning, on which we focus here, considers the problem of removing individual network weights, which can be leveraged for computational savings [Kurtz et al., 2020, Hoefler et al., 2021]. The only existing prior work on unstructured ViT pruning is SViTE [Chen et al., 2021], which applied the general RigL pruning method [Evci et al., 2020] to the special case of ViT models. We also present results relative to well-tuned magnitude pruning, the best existing second-order pruners [Singh and Alistarh, 2020, Frantar et al., 2021, Kurtic et al., 2022] and AC/DC pruning [Peste et al., 2021]. oViT improves upon existing methods across almost all benchmarks, by large margins at high sparsity.

Our work builds on the line of research on accurate pruning using efficient approximations of second-order information [Hoefler et al., 2021]. This was initiated by [LeCun et al., 1989, Hassibi et al., 1993], and has recently garnered significant attention, e.g. [Dong et al., 2017, Wang et al., 2019, Singh and Alistarh, 2020, Yu et al., 2022]. Variants of this approach have been shown to produce good results for both gradual magnitude pruning, the best existing second-order pruners [Singh and Alistarh, 2020, Frantar et al., 2021, Kurtic et al., 2022] and one-shot (post-training) compression [Frantar and Alistarh, 2022]. In this paper, we consider the standard gradual pruning setup; from this perspective, the closest work to ours is [Frantar et al., 2021, Kurtic et al., 2022], who propose different approximations. We make a significant departure from existing work by introducing a new layer-wise approximation of second-order information for pruning, which we show to be especially-accurate for ViT models. Another source of novelty is our in-depth investigation of sparse fine-tuning approaches for efficient accuracy recovery of ViT models. Together, these two techniques lead to significant accuracy gains, showing for the first time that pruned ViT models can achieve similar accuracy per parameter count with pruned CNNs.

2 Background and Problem Setup

The pruning problem assumes a fixed model architecture with weights \( w \in \mathbb{R}^d \) (\( d \) is the total number of parameters), and aims to find a configuration of weights with as many zeros as possible while preserving the performance of the original dense model. Gradual pruning, e.g. Hoefler et al. [2021], usually starts from an accurate dense model, and progressively removes weights by setting them to zero, followed by fine-tuning phases.

Weight Saliency. The pruning step usually relies on proxies for weight importance, defined according to certain criteria. For instance, weight magnitude is arguably the most popular criterion, e.g. [Han et al., 2015, Zhu and Gupta, 2017, Gale et al., 2019]. Specifically, given model \( w \in \mathbb{R}^d \), the saliency of each weight is its absolute value (magnitude) \( \rho_j = |w_j| \) for \( j \in \{1, 2, \ldots, d\} \); weights with the smallest scores are pruned away. Gradual magnitude pruning is usually a strong baseline across most models and settings. Many other criteria exist, such as gradient magnitude [Evci et al., 2020] or “rates of change” in the weights [Sanh et al., 2020].
The Optimal Brain Surgeon (OBS). LeCun et al. [1989] and Hassibi et al. [1993] proposed a framework for obtaining weight saliency scores by leveraging (approximate) second-order information about the loss. Specifically, they start from the Taylor approximation of the loss $L$ in the vicinity of the dense model parameters $w^*$. Assuming that $w^*$ is close to the optimum (hence $\nabla L(w^*) \approx 0$), one seeks a binary mask $M$ (with elements $\in \{0, 1\}$) and new values for the remaining weights $w^M$, such that the resulting increase in loss is minimal. A standard approach to approximate the loss increase is to expand the loss function up to the second order in model weights:

$$L(w^M) - L(w^*) \approx \frac{1}{2} (w^M - w^*)^\top H_L(w^*)(w^M - w^*)$$

(1)

where $H_L(w^*)$ is the Hessian of the model at $w^*$, and $w^M$ represents weights after the pruning step. In this setup, LeCun et al. [1989] and Hassibi et al. [1993] showed that the “optimal” weight to remove, incurring the least loss, and the update to the remaining weights, can be determined via a closed-form solution to the above inverse problem. Specifically, the saliency score $\rho_i$ for $i^{th}$ weight and the optimal weight update $\delta w$ for the remaining weights after elimination of the $i^{th}$ weight are as follows:

$$\rho_i = \frac{w_i^2}{2|H_L^{-1}(w^*)|_{ii}}, \quad \delta w^* = -\frac{w_i}{|H_L^{-1}(w^*)|_{ii}} H_L^{-1}(w^*) e_i,$$

(2)

where $e_i$ is the $i^{th}$ basis vector. Theoretically, the procedure would have to be executed one-weight-at-a-time, recomputing the Hessian after each step. In practice, this procedure suffers from a number of practical constraints. The first is that direct Hessian-inverse computation is computationally-infeasible for modern DNNs, due to its quadratic-in-dimension storage and computational costs. This has led to significant recent work on efficient second-order approximations for pruning and quantization [Dong et al., 2017, Wang et al., 2019, Singh and Alistarh, 2020, Yu et al., 2022].

WoodFisher and the Optimal BERT Surgeon. The empirical Fisher approximation [Amari, 1998] is a classic way of sidestepping some of the above constraints, and can be formally-stated as follows:

$$H_L(w^*) \approx F(w^*) = \lambda I_d \times d + \frac{1}{N} \sum_{i=1}^N \nabla L_i(w^*) \nabla L_i(w^*)^\top$$

(3)

where $\nabla L_i(w^*) \in \mathbb{R}^d$ is a gradient computed on a sample of data, $\lambda > 0$ is a dampening constant needed for stability, and $N$ is the total number of gradients used for approximation. Note that the resulting matrix is positive definite.

The memory required to store the empirical Fisher matrix is still quadratic in $d$, the number of parameters. Singh and Alistarh [2020] investigated a diagonal block-wise approximation with a predefined block size $B$, which reduces storage cost from $O(d^2)$ to $O(Bd)$, and showed that this approach can lead to strong results when pruning CNNs. Kurtic et al. [2022] proposed a formula for block pruning, together with a set of non-trivial optimizations to efficiently compute the block inverse, which allowed them to scale the approach for the first time to large language models.

A second obvious limitation of the OBS framework is that applying the procedure and recomputing the Hessian one weight at a time is prohibitively expensive, so one usually prunes multiple weights at once. Assuming we are searching for the set of weights $Q$ whose removal would lead to minimal loss increase after pruning, we get the following constrained optimization problem:

$$\min_{\delta w} \frac{1}{2} \delta w^\top F(w^*) \delta w \quad \text{s.t.} \quad E_Q \delta w + E_{\bar{Q}} w^* = 0,$$

(4)

where $E_Q \in \mathbb{R}^{|Q| \times d}$ is a matrix of basis vectors for each weight in $Q$. The corresponding saliency score for the group of weights $Q$ and the update $\delta w^*_Q$ of remaining weights is [Kurtic et al., 2022]:

$$\rho_Q = \frac{1}{2} w^*_Q^\top (F^{-1}(w^*)_{[Q,Q]})^{-1} w^*_Q, \quad \delta w^*_Q = -F^{-1}(w^*)_{Q^\top} (F^{-1}(w^*)_{[Q,Q]})^{-1} w^*_Q.$$

(5)

However, an exhaustive search over all subsets of size $|Q|$ from $d$ elements requires $\binom{d}{|Q|}$ evaluations, which makes it prohibitively expensive for $|Q| > 1$. To alleviate this issue in the case of unstructured pruning Singh and Alistarh [2020] ignores correlations between weights and in the case of block...
pruning [Kurtic et al., 2022] ignores correlations between blocks and solves only for correlations between weights within the same block. Despite these approximations, both approaches yield state-of-the-art results in their respective setups. As we will demonstrate later, our oViT method improves upon these approximations by reformulating this problem and proposing a correlation-aware solution that is fast and memory-efficient even for models as large as DeiT-Base (86M parameters).

3 The oViT Pruning Framework

3.1 Why Is Pruning Vision Transformers Hard?

The literature suggests that ViT models are difficult to compress [Chen et al., 2021, Rao et al., 2021]. It is natural to ask why, given that CNNs allow for $\geq 80\%$ unstructured sparsity [Singh and Alistarh, 2020], and up to 40% structured sparsity [Liu et al., 2021b], before significant accuracy drops. Our investigation suggests the following factors at play.

Factor 1: Accurate One-shot Pruning is Hard. ViT models tend to lose a significant amount of accuracy at each pruning step: Figure 3 shows the accuracy drops of Tiny, Small and Base model variants under the Global Magnitude (GM), WoodFisher/oBERT (WF), and Optimal ViT Surgeon (oViT) pruners, at various sparsities. In this one-shot setup, the higher accuracies of oViT come from the significantly improved sparse projection step. Despite these improvements, accuracy drops are still not negligible, so we need a solid post-pruning recovery phase.

Factor 2: Accuracy Recovery is Difficult. Once accuracy has been dropped following a pruning step, it is hard for ViT models to recover accuracy. This is illustrated in Figure 4, showing recovery under gradual pruning for various fine-tuning strategies. Results demonstrate the importance of the learning rate schedule and augmentation recipes.

Our work introduces new techniques to address both these factors: we introduce a new state-of-the-art one-shot pruner for ViTs, complemented with generic recipes for post-pruning fine-tuning.

3.2 Ingredient 1: An Efficient Correlation-Aware Second-Order Pruner

Our aim is to solve the pruning problem stated in the previous section: given a weight pruning target $k$, find the optimal set of weights $Q$ to be pruned, such that $|Q| = k$ and the loss increase is minimized. Exactly solving for the optimal $Q$ is an NP-hard problem [Blumensath and Davies, 2008], so we will investigate an iterative greedy method for selecting these weights, similar to the ideal version of the OBS framework discussed above. Importantly, our method properly considers weight correlations, while being fast and space-efficient. In turn, this leads to significant improvements over other pruners, especially in the context of vision transformers.

Formally, a correlation-aware greedy weight selection approach would perform pruning steps iteratively, as follows. Given a set of already-selected weights $Q$, initially $\emptyset$, we always add to $Q$ the weight $q$ which has minimal joint saliency $\rho_{Q \cup \{q\}}$, repeating until the size of $Q$ equals the pruning target $k$. The fact that we add weights to the set one-by-one allows us to take into account correlations between pruned weights. However, a naive implementation of this scheme, which simply recomputes saliency at each step, would be prohibitively expensive, since it requires $O(kd)$ evaluations of $\rho_Q$, each of which involves an $O(B^3)$ matrix inversion, where $B$ is the Fisher block size.

The centerpiece of our approach is a reformulation of the OBS multi-weight pruning problem in Equation 5 which will allow us to take correlations into account, while being practically-efficient. Specifically, we now show that, when using the empirical Fisher approximation, the problem of finding the optimal set of weights $Q$ to be removed, while taking correlations into account, is equivalent to the problem of finding the set of sparse weights which best preserve the original correlation between the dense weights $w^*$ and the gradients $\nabla L_i(w^*)$ on an fixed set of samples $i \in S$. Formally, this result, whose proof we provide in Appendix H, is stated as follows.

**Theorem 1.** Let $S$ be a set with $m$ samples, and let $\nabla L_1(w^*), \ldots, \nabla L_m(w^*)$ be a set of their gradients, with corresponding empirical Fisher matrix $F^{-1}(w^*)$. Assume a sparsification target of $k$
weights from \( w^* \). Then, a sparse minimizer for the constrained squared error problem

\[
\min_{\mathbf{w}} \frac{1}{2m} \sum_{i=1}^{m} \left( \nabla \mathcal{L}_i(\mathbf{w}^*)^\top \mathbf{w} - \nabla \mathcal{L}_i(\mathbf{w}^*)^\top \mathbf{w}^* \right)^2 \quad \text{s.t. } \mathbf{w} \text{ has at least } k \text{ zeros},
\]

is also a solution to the problem of minimizing the Fisher-based group-OBS metric

\[
\arg \min_{Q \mid |Q| = k} \frac{1}{2} \mathbf{w}^*_Q \top \left( \mathbf{F}^{-1}(\mathbf{w}^*)_{|Q,Q|} \right)^{-1} \mathbf{w}^*_Q.
\]

**An Efficient Sparse Regression Solver.** The formulation in Equation (6) reduces pruning to a sparse regression problem, where the “input” is given by gradients over calibration samples. A related problem arises in the context of one-shot (post-training) pruning [Hubara et al., 2021, Frantar and Alistarh, 2022], where the authors solve a related sparse \( \ell_2 \)-fitting problem, but sparse weights are determined relative to the layer inputs rather than the layer gradients. Specifically, the \( \text{OBC} \) solver [Frantar and Alistarh, 2022] observes that, since the loss is quadratic, the row-wise Hessians are independent, and only depend on the layer input; therefore, the method processes rows independently, and zeroes out weights from each row greedily, one-by-one, in increasing order of squared error. It then updates the remaining weights to reduce the \( \ell_2 \) loss. This essentially implements the OBS selection and update in Equation 2 exactly, assuming layer-wise \( \ell_2 \) loss. We build on this strategy to implement our greedy weight-subset selection, with some significant modifications.

First, a direct implementation of this approach to remove \( \Theta(d) \) weights would have \( O(d^3) \) runtime, where \( d \) is the layer dimension, as the \( \Theta(d^3) \)-time selection + update process is repeated \( \Theta(d) \) times. This can be reduced to \( O(d \cdot \max(d,B^2)) \) by using the block diagonal structure of the Fisher matrix with block size \( B \), when performing updates after each weight elimination. However, as \( B \) is typically much smaller than \( d \), this would still be extremely slow. We apply a different approach: we treat each block of the Fisher matrix as an independent row for the purposes of the \( \ell_2 \) solver, and then we merge all the blocks into a single global approximation of the Fisher matrix. This allows us to perform global weight saliency calculation, and global weight updates following Equations 5 and 7. The resulting algorithm, given in full in the Appendix, requires \( O(d \cdot B^2 \ell) \) runtime and \( O(d \cdot B) \) space. When working with small block sizes, our method is very fast and has practically no overhead over existing Fisher-based OBS approaches, while yielding significantly improved one-shot pruning results. Detailed pseudo-code and an efficient implementation are provided as supplementary material.

### 3.3 Ingredient 2: Fine-tuning and Pruning Procedure

ViTs are notoriously difficult to train: they need longer training relative to CNN architectures, and the choice of the training procedure (learning rate schedule, regularization, augmentation) can have a major impact on convergence and accuracy [Touvron et al., 2021, Steiner et al., 2021]. We found the same to apply to post-pruning accuracy recovery, which is key in gradual pruning; below, we describe the main ingredients to obtaining highly-accurate fine-tuning schedules as part of our method.

**Learning Rate Schedule.** First, to achieve good performance during gradual pruning, the learning rate (LR) schedule is crucial. The logic behind this is that, after each pruning update, the weight configuration is far from optimal, and the training procedure has to be able to update weights significantly in order to converge again to a highly-accurate point. The magnitude of the learning rate defines the degree of stochasticity of the SGD update, and the deviation of the updates from the full-batch gradient descent, and once the weights are close to the optimal point one reduces learning rate for better convergence. Specifically, we propose to use a *cyclic linear* schedule:

\[
\eta(t) = \eta_{\text{max}} - (\eta_{\text{max}} - \eta_{\text{min}}) \frac{t \% T}{T},
\]

where \( \%x \) means taking the remainder after integer division by \( x \). We chose a linear decay for simplicity; we obtained similar results for other functions (e.g., cubic decay). By contrast, as we illustrate in Section 4.2, the *cyclic* nature of the schedule is key for accurate pruning. Specifically, this choice is justified theoretically by tying back to the original assumptions of the OBS framework: for Equation 1 to hold, the pruned model should be well-optimized (i.e. have small gradients) at the point when pruning is performed. Moreover, right after the pruning step, having a larger value of
the learning rate is useful since it gives the model a chance to recover from the sub-optimal point induced via pruning. We note that this learning rate schedule is different from prior work on pruning, which typically uses a single decay cycle [Kusupati et al., 2020, Singh and Alistarh, 2020, Peste et al., 2021], or dynamic learning rate rewinding, e.g. [Frankle et al., 2019, Renda et al., 2020].

Figure 2: Blue: Cyclic linear learning rate schedule used in the work. Violet: Dependence of the global model sparsity on the epoch. Every change in sparsity corresponds to a pruning step.

Regularization and Augmentation. Another important ingredient for achieving high accuracy is the choice of the regularization/augmentation pipeline. Specifically, we observe that smaller models such as DeiT-Tiny benefit from lower levels of data augmentation during fine-tuning as in [Steiner et al., 2021], whereas larger models such as DeiT-Base behave best with more complex augmentation and regularization, such as [Touvron et al., 2021]. Intuitively, fine-tuning sparsified small models with high augmentation likely may exceed model capacity, rendering the optimization process unstable. We provide detailed parameter values and ablations for this training component in the Appendix.

An Efficient Pipeline for Sparsity Sweeps. We propose a simple iterative pruning framework, which takes a set of target sparsity configurations and produces models which match these configurations in a single run. Specifically, we start from a standard gradual pruning setup, which prunes in a sequence of steps of increasing sparsity, followed by sparse fine-tuning. We then set the intermediate values in such a way that all intermediate target sparsity levels are achieved. For example, if one wishes to obtain checkpoints with sparsity levels 40%, 50%, 75%, 90%, one can set the lowest sparsity level on the gradual pruning schedule to 40%, the highest sparsity level to 90%, and 50%, 75% as intermediate points. Between any two such pruning steps, we apply the cyclic retraining schedule above.

We emphasize the fact that having an accurate pruner is key to support this compressed pruning approach: virtually all previous high-accuracy pruning methods, e.g. [Kusupati et al., 2020, Singh and Alistarh, 2020] redo the entire training run for each sparsity target in turn. In our experimental section, we also examine the impact of additional fine-tuning applied to each checkpoint, and show that it induces small-but-consistent improvements.

4 Experimental Setup and Results

Setup and Goals. We consider the standard ImageNet [Russakovsky et al., 2015] image classification benchmark, and aim to examine how sparsity impacts accuracy for different model variants. We consider three scenarios: one-shot, single-step pruning of a pretrained model, where performance is clearly tied to the quality of the second-order approximation, one-shot + fine-tuning, in which we follow one-shot pruning by a short period of fine-tuning, and, finally, iterative gradual pruning, where one applies pruning periodically, with some retraining interval, gradually increasing sparsity.

4.1 One-shot pruning, without and with fine-tuning

We start by examining the quality of different previous one-shot pruners relative to oViT. We use Global Magnitude (GM) pruning as a simple baseline, and a well-tuned variant of the state-of-the-art WoodFisher (WF) pruner [Singh and Alistarh, 2020, Frantar et al., 2021, Kurtic et al., 2022].
Specifically, since the WF pruner has multiple implementations, we carefully tuned all its parameters (dampening, Fisher block size, and gradient count), and compare against the variant with best results, which is a variant of the small-block algorithm of [Kurtic et al., 2022]. Specifically, we use block size 192 (the embedding dimension of DeiT-Tiny), \( N = 4096 \) gradients at batch size 128, and a single Hessian recomputation step; please see Appendix E for full hyperparameters and parameter sweeps. We have tuned the dampening factor \( \lambda \) required for the stability of matrix inversion independently for each method: we set \( \lambda = 10^{-6} \) for WF and a much smaller \( \lambda = 10^{-8} \) for oViT. Throughout, we show ImageNet validation accuracy; the results are given in Figure 3.

![Figure 3: One-shot pruning of fine-tuned DeiT models on the ImageNet dataset with Global Magnitude (GM), WoodFisher (WF) and oViT pruners.](image)

It is apparent that second-order pruners perform much better than baseline magnitude (GM) pruning, and that oViT improves significantly upon WF, especially at high sparsities. In fact, for DeiT-Small/Base, oViT can produce reasonably-accurate models without any retraining at low (40-60%) sparsities. The computational cost of the two methods is similar: one oViT pruning step on DeiT-Small takes 23 minutes, compared to 20 minutes for WF. (The majority of the cost for both methods comes from the collection of gradients, not from the Hessian estimation.)

**One-shot pruning + Fine-tuning.** Next, we consider the one-shot + fine-tune setup where one first prunes the model to a certain sparsity level, and then performs a short period of fine-tuning. Specifically, we prune to 50% sparsity, and fine-tune for 20 epochs. In addition to ViT/DeiT, we also consider similar models based on variants of self-attention [Liu et al., 2021a, Ali et al., 2021], and compare against a GM baseline. We use a linearly-decaying learning rate schedule between \( \eta_{\text{max}} = 10^{-4} \) to \( \eta_{\text{min}} = 10^{-5} \) and the training DeiT training recipe [Touvron et al., 2021]. The results are given in Table 1, and show that oViT can almost fully-recover accuracy in this setup for all models; the gaps from GM and WF (see DeiT-Small 75% and 90%) are still very significant. Given this, in the following experiments, we will mainly focus on oViT as the second-order pruner.

### 4.2 Post-Pruning Recovery

For ViTs, the choice of augmentation parameters and learning rate schedule is critical. For example, reducing the level of augmentation during fine-tuning for smaller models, e.g. DeiT-Tiny, significant improves performance, whereas larger models, e.g. the 4x larger DeiT-Small, requires strong augmentations for best results even during fine-tuning. See Figure 4 for an illustration; we provide full details and results in the Appendix.

Moreover, the choice of cyclic learning rate (LR) schedule is critical as well. To illustrate this, we compare convergence obtained when using a cosine annealing schedule, which is very popular for pruning CNNs [Kusupati et al., 2020, Singh and Alistarh, 2020, Peste et al., 2021], from \( \eta_{\text{max}} = 5 \cdot 10^{-4} \) to \( \eta_{\text{min}} = 10^{-5} \), while performing pruning updates 2 times more frequently (one update per 10 epochs) than in our standard setup from the following section 4.3. The results are provided in Figure 4, where cosine annealing (acyclic) is in red. All experiments use the oViT pruner, and highlight the importance of the learning rate and augmentation schedules for recovery.

### 4.3 Gradual Pruning Results

Finally, we execute gradual pruning with the sparsity schedule, augmentation choices, and cyclic linear learning-rate scheduler discussed above. The whole gradual pruning procedure lasts for 300 epochs, as in [Touvron et al., 2021]. We aim to obtain accurate sparse checkpoints for 50%, 60%,
| Model       | Method | Sparsity (%) | Top1-Accuracy (%) |
|-------------|--------|--------------|-------------------|
| Dense       | 0      | 79.8         |                   |
| GM          | 50     | 79.0         | 79.5              |
| oViT        |        |              |                   |
| DeiT-Small  | GM     | 75           | 74.3              |
|             | WF     | 75           | 75.8              |
|             | oViT   |              | 76.9              |
|             | GM     | 90           | 45.6              |
|             | WF     | 90           | 59.3              |
|             | oViT   |              | 65.1              |
| DeiT-Base   | GM     | 75           | 80.1              |
|             | WF     | 75           | 80.2              |
|             | oViT   |              | 81.0              |
|             | GM     | 90           | 68.1              |
|             | WF     | 90           | 69.2              |
|             | oViT   |              | 76.3              |
| XCiT-Small  | GM     | 50           | 81.7              |
|             | oViT   |              | 81.9              |
| Swin-Tiny   | GM     | 50           | 80.6              |
|             | oViT   |              | 80.9              |

Figure 4: Ablations of the training setting on DeiT-Tiny (left) and DeiT-Small (right). Green curves correspond to the light1 [Steiner et al., 2021] augmentation recipe, blue curves to the deit [Touvron et al., 2021] recipe. The red curve follows training with a single (acyclic) cosine annealing schedule, as in [Kusupati et al., 2020, Singh and Alistarh, 2020].

75%, 80%, and 90% sparsity. For this, we prune to 40% in the initial step, and increment sparsity every 20 epochs, until reaching 90%, with fine-tuning in between. (See Figure 4.) We select the accuracy of intermediate models which match the target sparsities; to examine the impact of fine-tuning, we trained each of the resulting sparse checkpoints for an additional 100 epochs, marked with (↑). We compare with global magnitude (GM) following the same schedule as oViT, as well as the state-of-the-art SViTE [Chen et al., 2021] paper, which trains the sparse model from scratch using a variant of RigL [Evci et al., 2020], but for a total of 600 epochs. The results are in Table 2.

For DeiT-Tiny and 50% sparsity, we achieve significant improvements upon SViTe, and even manage to dramatically improve test accuracy relative to the dense model. We believe this is due to the regularizing effect of sparsity, but also due to our use of “weaker” augmentation for fine-tuning this smaller model. At 75-80%, we recover the dense model accuracy, showing for the first time that ViT
Table 2: Accuracy-vs-sparsity for gradual pruning on ImageNet. (↑) denotes accuracy after additional fine-tuning for 100 epochs. The method with the highest accuracy is highlighted in green.

| Model         | Method | Sparsity(%) | FLOP Reduction (%) | Top-1 Accuracy(%) |
|---------------|--------|-------------|--------------------|-------------------|
| Dense         | 0      | 0           | 72.2               |
| GM            | 50     | 43.9        | 73.5               |
| oViT          | 50     | 43.9        | 73.7               |
| SViTE-Tiny    | 50     | 43.9        | 69.6               |
| DeiT-Tiny     | GM     | 50          | 52.6               | 73.1 (71.2 ↑)     |
| oViT          | 52.6   | 73.3 (72.6 ↑) |
| SViTETiny     | 52.6   | 73.7 (71.2 ↑) |
| GM            | 60     | 65.8        | 71.4 (71.5 ↑)      |
| oViT          | 65.8   | 72.3 (71.6 ↑) |
| SViTETiny     | 65.8   | 63.9        |
| GM            | 60     | 69.7        | 70.5 (70.9 ↑)      |
| oViT          | 70.2   | 71.7 (72.0 ↑) |
| SViTETiny     | 79.0   | 66.2 (66.6 ↑) |
| GM            | 75     | 79.0        | 67.4 (68.0 ↑)      |
| oViT          | 79.0   | 49.7        |
| GM            | 80     | 79.0        | 70.2 (70.9 ↑)      |
| oViT          | 79.0   | 71.7 (72.0 ↑) |
| SViTETiny     | 79.0   | 49.7        |
| GM            | 90     | 79.0        | 70.3 (70.8 ↑)      |
| oViT          | 79.0   | 71.7 (72.0 ↑) |
| SViTETiny     | 79.0   | 49.7        |
| GM            | 90     | 79.0        | 84.1 (79.5 ↑)      |
| oViT          | 84.1   | 74.1 (74.5 ↑) |
| SViTETiny     | 84.1   | 75.2 (75.8 ↑) |
| DeiT-Small    | GM     | 50          | 46.7               | 79.3 (79.8 ↑)     |
| oViT          | 46.9   | 79.4 (79.9 ↑) |
| SViTESmall    | 46.3   | 79.7        |
| GM            | 60     | 56.1        | 79.0 (79.5 ↑)      |
| oViT          | 56.2   | 79.3 (79.8 ↑) |
| SViTESmall    | 55.4   | 79.4        |
| DeiT-Base     | GM     | 75          | 70.1               | 78.0 (78.7 ↑)     |
| oViT          | 70.2   | 78.5 (79.0 ↑) |
| SViTESmall    | 70.3   | 77.0        |
| GM            | 80     | 74.2        | 77.3 (77.9 ↑)      |
| oViT          | 74.9   | 78.0 (78.6 ↑) |
| SViTESmall    | 74.0   | 77.1        |
| DeiT-Base     | GM     | 90          | 84.0               | 74.1 (74.7 ↑)     |
| oViT          | 84.1   | 75.2 (75.8 ↑) |
| SViTESmall    | 84.1   | 70.1        |
| Dense         | 0      | 0           | 79.8               |
| oViT          | 50     | 48.5        | 81.6               |
| SViTESmall    | 48.0   | 81.5        |
| DeiT-Base     | oViT   | 60          | 58.2               | 81.5              |
| SViTESmall    | 58.2   | 81.5        |
| oViT          | 75     | 72.8        | 81.1 (81.1 ↑)      |
| 80             | 77.7   | 80.8 (81.1 ↑) |
| 90             | 87.4   | 79.7 (80.1 ↑) |

models can be pruned to such sparsities without loss. We observe a much more significant accuracy drop at 90%. GM pruning also benefits from the choices made in our schedule, outperforming SViT at 50% sparsity; yet, there are significant gaps in favor of oViT at higher sparsities, as expected.

On the 4x larger DeiT-Small model, SViTE performs remarkably well at 50% sparsity (79.7%), almost matching the dense model, but oViT outperforms it very slightly after fine-tuning (79.9%). In terms of total training budget, SViTE uses 600 epochs to produce each model (and so, the 50%-sparse one as well), whereas we use a total of 40 epochs for pruning to 50% + initial fine-tuning, and 100 additional epochs for sparse model fine-tuning. Even if we take into account the original 300 epochs for training the publicly-available dense DeiT checkpoint [Touvron et al., 2021], our approach is significantly more efficient (440 vs. 600 epochs), and savings compound across sparse models. At 75% sparsity, oViT drops ∼ 1% of accuracy relative to dense post-finetuning, with a significant
gap of 1% Top-1 relative to GM, and 2% Top-1 relative to SViTE. The trend continues for higher sparsities, where we note a remarkable gap of 5.7% Top-1 vs SViTE at 90% sparsity. We obtain similar numbers for DeiT-Base: generally, we achieve \( \geq 99\% \) recovery at \( \geq 75\% \) sparsity.

We also remark upon the fact that gradual magnitude pruning (GM) appears to be a very competitive baseline, with a properly-tuned pruning and learning rate schedule. (This could be explained by the fact that global magnitude pruning corresponds to an extremely coarse identity-matrix approximation of the Hessian Hoefler et al. [2021].) Specifically, we observe that, at low sparsity (50%), GM provides similar results to other methods, although the more complex methods do provide significant gains at higher sparsities (75-90%).

**Timings.** A common misconception is that approximating second-order information for pruning or optimization is necessarily computationally or memory-intensive. In our case, the time required for the calculation of pruning scores and the OBS update comprises collection of grads, the Fisher inverse rank-1 updates and additional pruning iterations for oViT. We have measured the time of a full pruning step for DeiT-Small in Table 3. All measurements were done using two RTX A6000 GPUs with 48GB of memory: the computation is performed using a single GPU, however, the maximum memory usage of the algorithm is around 80GB, so we use the memory of the second GPU for storage. (We note that this maximum memory usage could be reduced via further optimizations.)

| Model   | Method                | Time (minutes) |
|---------|-----------------------|----------------|
| DeiT-Small | Fast WoodFisher [Kurtic et al., 2022] | 20             |
|          | oViT                  | 23             |

We observe that the amount of time needed to perform a pruning step is not very large, especially when compared to the duration of typical training procedure of these models on ImageNet, which usually takes several days on a multi-GPU node. Relative to this, the computational cost of oViT is negligible, and is similar to that of highly-optimized implementations of OBS [Kurtic et al., 2022].

**Additional Experiments.** For brevity, several experiments are deferred to the Appendix. Specifically, we show that oViT also provides high accuracy when pruning other highly-accurate models (EfficientFormer, ResNet50D, and EfficientNetV2) in Appendix C. In Appendix D we show that oViT can also be applied in conjunction with other types of compression, in particular token pruning [Rao et al., 2021], quantization-aware training, and semi-structured (2:4) sparsity. Specifically, we show that oViT can induce 2:4 sparsity with minor accuracy drop across DeiT models. In Appendix G, we provide a comparison with AC/DC pruning [Peste et al., 2021], which we tuned specifically for ViTs.

**Sparse Speedups.** Finally, in Figure 5, we examine the speedups obtained by oViT from unstructured sparsity, when executed on a sparsity-aware CPU inference engine [Kurtz et al., 2020]. Specifically, we executed the models from Table 2 using 4 cores of an Intel(R) Xeon(R) Gold 6238R CPU, at batch size 64. We find it interesting that sparse ViTs build an almost-contiguous Pareto frontier from 82% to 68% Top-1 accuracy (Y axis), with a 25x span in throughput (from 11 imgs/second to 260 imgs/second, X axis). Notably, the DeiT-Tiny model obtains a speedup of 2.4x without any accuracy loss (thanks to the accuracy increase), while Base and Small ViTs show 1.5x speedups with minimal loss of accuracy. Thus, sparsity can be a promising approach to speeding up ViTs.

5 Discussion, Limitations and Future Work

We examined the trade-off between parametrization and accuracy in the context of unstructured pruned ViT models, and presented a new pruner called oViT, based on a new approximation of second-order information, which sets a new state-of-the-art sparsity-accuracy trade-off. Specifically, we have shown for the first time that ViT variants can support significant weight pruning (\( \geq 75\% \)) at relatively minor accuracy loss (\( \leq 1\% \)), similar to CNNs. Therefore, our results seem to suggest that, despite their weaker encoded inductive biases, ViT models do not require over-parametrization post-training, and in fact can be competitive with CNNs in terms of accuracy-per-parameter. Our approach extends to other model families, and is complementary to other compression approaches.
Figure 5: Accuracy vs. throughput for dense and sparse ViT models when executing on the DeepSparse inference engine. * corresponds to dense models.

One limitation is that we still require relatively high computational budgets to obtain our best results. This is currently an inherent limitation of ViTs; to address it, we provide efficient oneshot + fine-tune recipes, leading to good results. Further, we have only focused on Top-1 as a leading accuracy metric, without covering transfer accuracy or potential bias [Hooker et al., 2020]. We leave this as future work. Future work should also be able to extend our pruner to structured compression of ViT models, or employ our oViT pruner inside different, more computationally-intensive pruning algorithms such as RigL [Evci et al., 2020].

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A oViT algorithm description

The section below illustrates in the oViT pruning algorithm step-by-step. Prunable model weights $\mathbb{R}^d$ are partitioned into blocks of fixed size $B$. Below $\rho_i^{(B)}$ denotes the saliency scores for weight $i$th inside a block it belongs to and $\rho_i$ is the score across the whole model. The steps of the algorithm are listed below:

**Algorithm 1 oViT pruning algorithm**

1: $\rho_i$ - saliency scores for weights 
2: Accumulate Fisher inverse blocks $F$
3: for each block do
4:  \( \text{err} = 0 \)
5:  for element in a block do
6:   Select the weight $w_i$ with smallest score $\rho_i^{(B)}$ (using the (2) for $\rho_i$)
7:   Prune $w_i$
8:   Update remaining weights in the block via (2)
9:   $\text{err} += \rho_i^{(B)}$
10:  $\rho_i \leftarrow \text{err}$
11:  Save current state of the block for later merging
12:  Update Fisher inverse block
13: end for
14: end for
15: Sort the scores $\rho_i$ in ascending order
16: Mark the weights with smallest scores $\rho_i$ as pruned
17: for each block do
18:  Load the saved state of the block with the weights marked pruned and all remaining alive.
19: end for

B Training details

**Augmentation/regularization recipe**

Table 4: Summary of the augmentation and regularization procedures used in the work.

| Procedure        | DeiT | light1 |
|------------------|------|--------|
| Weight decay     | 0.05 | 0.03   |
| Label smoothing $\varepsilon$ | 0.1  | 0.1    |
| Dropout          | $\times$ | $\times$ |
| Stoch. Depth     | 0.1  | 0.0    |
| Gradient Clip.   | $\times$ | 1.0    |
| H.flip           | $\checkmark$ | $\checkmark$ |
| RRC              | $\checkmark$ | $\checkmark$ |
| Rand Augment     | 9/0.5 | 2/0.5  |
| Mixup alpha      | 0.8  | 0.0    |
| Cutmix alpha     | 1.0  | 0.0    |
| Erasing prob.    | 0.25 | 0.0    |
| Erasing count    | 1    | 0      |
| Test crop ratio  | 0.9  | 0.9    |

For the gradual pruning experiments (with 300 epochs) we have used cyclic learning schedule, with high learning rate directly after the pruning step with gradual decrease up to the next pruning step.

For both DeiT-Tiny and DeiT-Small model during the additional fine-tuning for 100 epochs we’ve applied cosine annealing schedule with $\eta_{\text{max}} = 5 \cdot 10^{-5}$, $\eta_{\text{min}} = 1 \cdot 10^{-5}$ and all other parameters the same as in the Table 5.
Table 5: Hyperparameters of the schedules used in gradual pruning.

| Model      | Prune freq | LR sched \{f_{\text{decay}}, \eta_{\text{max}}, \eta_{\text{min}}\} | Augm | Batch size | Epochs |
|------------|------------|-------------------------------------------------|------|------------|--------|
| DeiT-Tiny  | 20         | \{cyclic\_linear, 5 \cdot 10^{-4}, 1 \cdot 10^{-5}\} | light1 | 1024       | 300    |
| DeiT-Small | 20         | \{cyclic\_linear, 5 \cdot 10^{-4}, 1 \cdot 10^{-5}\} | deit  | 1024       | 300    |

C Experiments with other models

Despite the fact that in this work we aim at the pruning of ViT models the proposed approach can be applied to any architecture for image classification, in particular, convolutional neural network (CNN) or a ViT-CNN Hybrid. We have applied oViT gradual pruning to the recently proposed EfficientFormer [Li et al., 2022] using the same setting and hyperparameters as for DeiT-Small. Two CNN architectures - ResNet50-D \(^1\) and EfficientNetV2-Tiny [Tan and Le, 2021] \(^2\), considered in this work were trained with the use of augmentation and regularization procedure described in the recent PyTorch blog post. Differently from most of the prior art we have used the ResNet50-D trained with the modern recipe from the timm repository.

For ResNet50-D we prune all convolutional weights except the first convolution and we keep the classification layer dense. In EfficientNetV2-Tiny we do not prune depthwise convolutions since each channel is processed separately and the only block size that makes sense in this case would be at most of the size of the convolutional kernel spatial dimensions product. We have set the block size to be 256 for ResNet50-D and 16 for EfficientNetV2-Tiny while keeping all the other hyperparameters of oViT the same as for DeiT experiments. Such a small block size was chosen for EfficientNetV2-Tiny due the fact that it is the largest common divisor of the prunable weights.

Table 6: Performance of gradual pruning on ImageNet. Numbers in the parentheses followed by the upwards directed arrow denote additional fine-tuning for 100 epochs.

| Model     | Method | Sparsity (%) | Top1-Accuracy (%) |
|-----------|--------|--------------|-------------------|
| Dense     | 0      | 78.9         |                   |
| EffFormer-L1 |      |              |                   |
| Dense     | 50     | 78.0         |                   |
| oViT      | 60     | 77.4         |                   |
|           | 75     | 76.4         |                   |
|           | 90     | 72.4 (72.8 \uparrow) | |
| ResNet-50D |      |              |                   |
| Dense     | 50     | 79.8         |                   |
| oViT      | 60     | 79.7         |                   |
|           | 75     | 79.2 (79.6 \uparrow) | |
|           | 90     | 77.1 (77.5 \uparrow) | |
| EffNetV2-Tiny |      |              |                   |
| Dense     | 50     | 81.0         |                   |
| oViT      | 60     | 80.6         |                   |
|           | 75     | 79.6 (80.0 \uparrow) | |
|           | 90     | 75.0         |                   |

D Composite compression

In addition to weight pruning one can decrease storage and inference cost with the help of other compression approaches: quantization (casting weights and activations to lower precision) and token pruning specific for the transformer architecture.

\(^1\)The resnet50d checkpoint has 81.4 % accuracy for dense model.
\(^2\)The efficientnetv2\_rw\_t checkpoint has 82.3 % accuracy for dense model.
D.1 Quantization-Aware Training

Weight quantization is done in the following way - one takes sparse checkpoint and then runs quantization aware training (QAT). We ran QAT training for 50 epochs with linearly decaying learning rate schedule from $\eta_{\text{max}} = 10^{-4}$ to $\eta_{\text{min}} = 10^{-5}$. Models are quantized to 8-bit precision. In all experiments performed accuracy of quantized model almost reproduces the accuracy of the sparse model stored in full precision.

Table 7: ImageNet-1K top-1 accuracy for sparse models after QAT training.

| Model     | Sparsity (%) | Accuracy (%) |
|-----------|--------------|--------------|
| DeiT-Tiny | 75           | 72.2         |
| DeiT-Small | 75          | 77.7         |
| DeiT-Base | 75           | 81           |

D.2 Token Pruning

There are different approaches for token pruning proposed in the literature. In this work we follow the one from [Rao et al., 2021]. Specifically, in DynamicViT one selects the ratio of tokens being pruned at each step with the lowest importance score, predicted by the model itself. Following the main setup from the paper we prune tokens after 3rd, 6th, 9th block, and the token pruning ratio after each block is $\rho = 0.2$ (i.e 20% least important tokens are pruned).

Table 8: ImageNet-1K top-1 accuracy for sparse models with token pruning.

| Model          | Method | Sparsity (%) | Top1-Accuracy (%) |
|----------------|--------|--------------|-------------------|
| DynamicViT-Tiny | oViT   | 50           | 72.0              |
|                |        | 60           | 71.6              |
|                |        | 75           | 70.2              |
| DynamicViT-Small | oViT  | 50           | 79.5              |
|                |        | 60           | 79.4              |
|                |        | 75           | 78.7              |

D.3 Semi-structured sparsity

While CPUs can utilize sparsity patterns of arbitrary form to speed-up the computations at the present time modern GPU accelerators can handle only restricted form of unstructured sparsity, namely the $N : M$ sparsity pattern that enforces exactly $N$ non-zero values for each block of $M$ weights. Namely, since the introduction of Ampere architecture NVIDIA GPUs have special kernels that can work with $2 : 4$ sparse matrices [Mishra et al., 2021]. One can integrate the $N : M$ sparsity in the oViT framework without significant changes. The only difference with the original oViT approach is that while running the oViT iterations one doesn’t prune a given weight in case in a group of $M$ weights to which this weights belongs to there are $M - N$ zero weights. Since the sparsity pattern is significantly constrained compared to generic unstructured sparsity pattern drop in performance after doing pruning step and consequent fine-tuning is more challenging than it would be for unconstrained sparsity. In experiments below we prune models to $2 : 4$ sparsity and fine-tune them for 50 epochs with linearly decaying learning rate schedule.

Table 9: Semi-structured $2 : 4$ pruning of ViT models.

| Model   | Accuracy (%) |
|---------|--------------|
| DeiT-Tiny | 72.7         |
| DeiT-Small | 79.0         |
| DeiT-Base | 81.4         |
E  oViT hyperparameters

Following the oBERT’s directions [Kurtic et al., 2022] on identifying the optimal set of hyperparameters via one-shot pruning experiments, we conduct a grid search over the three most important hyperparameters:

- Number of grads collected for Fisher inverse
- Dampening constant $\lambda$
- Block size

The more grads are collected, the more accurate is the empirical Fisher inverse estimate, however, more compute is required at the same time. We chose $N = 4096$ as a point from which further increase of Fisher samples doesn’t improve performance a lot. Dependence of the one-shot pruning performance at different sparsities vs number of grads is presented on Figure 6.

The next parameter to be studied is the dampening constant $\lambda$ in. This constant regularizes the empirical Fisher matrix and allows to avoid instabilities in computation of the inverse. However, this constant decreases the correlation between different weights and in the limit $\lambda \to \infty$ OBS reduces to magnitude pruning.

And the last but not the least important parameter is the block size in [Singh and Alistarh, 2020]. The larger the block size is, the more correlations between different weights are taken into account. However, as mentioned in 2 the computational and storage cost scales with the block size. Moreover, for a fixed number of gradients in the Fisher estimate matrix with larger block sizes is likely to be worse conditioned. Therefore, one would like to work with smaller block sizes but not to keep the approximation as accurate as possible. We’ve selected block size according to the accuracy-efficiency trade-off.
In addition, we’ve studied the benefit from application of multiple recomputations in the one-shot pruning setting for WoodFisher and oViT. Since the assumption of static Fisher matrix $F(w^*)$ doesn’t hold in general, we expect that multiple recomputations are likely to result in higher one-shot accuracy in accordance with the result from [Frantar et al., 2021]. This is indeed the case. The gain from recomputations is more pronounced for WoodFisher, since oViT already performs implicit Fisher inverse updates in its operation. Yet, the effect is not vanishing even for the case of oViT.
F Execution latency

In addition to the plot throughput vs accuracy shown in the main part we present in this section execution latency per sample vs latency when running models on the DeepSparse engine. The results are presented on Figure 10.

![Figure 10: Accuracy vs latency on ImageNet-1k.](image)

G Comparison with AC/DC training

In addition to the sparse training from scratch with periodic updates of the sparsity weights with some saliency criterion for weight elimination and regrowth [Evci et al., 2020] one can consider alternating compressed/decompressed training (AC/DC), proposed in [Peste et al., 2021]. Namely one switches between dense stages with standard unconstrained training of the model, and sparse stages when the model is pruned to the target sparsity level and trained with the frozen sparsity mask until the beginning of the next dense stage, when the sparsity mask is removed. This procedure produces both accurate dense and sparse models.

Following the original paper we use magnitude pruning as a saliency criterion for weight pruning. The augmentation and regularization pipeline follows the settings from [Touvron et al., 2021]. All models with AC/DC were trained for 600 epochs in total with first pruning step at epoch 150 followed by 7 sparse stages 25 epochs long each, and 6 dense stages of the same length. The last dense stage lasts 50 epochs and the last sparse is 75 epochs long. Learning rate is gradually decayed from $\eta_{\text{max}} = 5 \cdot 10^{-4}$ to $\eta_{\text{min}} = 10^{-6}$ with cosine annealing. Initial warm-up phase with linearly increasing learning rate is 20 epochs. We compare AC/DC with oViT models finetuned for additional 100 epochs.

Table 10: AC/DC vs oViT (finetuned for additional 100 epochs) on ImageNet-1k.

| Model    | Method | Sparsity (%) | Top1-Accuracy (%) |
|----------|--------|--------------|-------------------|
| oViT     | AC/DC  | 60           | 79.9              |
| DeiT-Small | oViT  | 75           | 79.0              |
|          | AC/DC  | 79.0         | 79.0              |
| oViT     | AC/DC  | 90           | 75.8              |
| DeiT-Small | AC/DC | 72.0         |

One can observe that at low sparsity AC/DC achieves higher accuracy for the same sparsity target (even outperforming the dense baseline by 0.6%), whereas for 75% performance of both methods is equal, and oViT outperforms AC/DC at higher sparsity. However, one should note, that oViT uses computational budget (including the training of original model) of 440 epochs for 60% sparsity, 520% for 75% and 700% for 90% vs 600 epochs used in AC/DC.
H Proof of Theorem 1

Theorem 1. Let $S$ be a set of samples, and let $\nabla_{\ell_i}(w^*), \ldots, \nabla_{\ell_m}(w^*)$ be a set of gradients with $i \in S$, with corresponding empirical Fisher matrix $\hat{F}^{-1}(w^*)$. Assume a sparsification target of $k$ weights from $w^*$. Then, a sparse minimizer for the constrained squared error problem

$$\min_{w'} \frac{1}{2m} \sum_{i=1}^{m} \left( \nabla_{\ell_i}(w^*)^\top w' - \nabla_{\ell_i}(w^*)^\top w^* \right)^2 \text{ s.t. } w' \text{ has at least } k \text{ zeros,}$$

(9)

is also a solution to the problem of minimizing the Fisher-based group-OBS metric

$$\arg\min_{Q, |Q| = k} \frac{1}{2} \cdot w_Q^\top \left( \hat{F}^{-1}(w^*)_{|Q, Q|} \right)^{-1} w_Q^*.$$

(10)

Proof. We start by examining the unconstrained squared error function in Equation (9), which we denote by $G$. Clearly, the function $G$ is a $d$-dimensional quadratic in the variable $w'$, and has a minimum at $w^*$. Next, let us examine $G$’s second-order Taylor approximation around $w^*$, given by

$$(w' - w^*)^\top \left( \frac{1}{m} \sum_{i=1}^{m} \nabla_{\ell_i}(w^*)^\top \nabla_{\ell_i}(w^*) \right) (w' - w^*),$$

(11)

where we used the fact that $w^*$ is a minimum of the squared error, and thus the function has 0 gradient at it. However, by the definition of the empirical Fisher, this is exactly equal to

$$(w' - w^*)^\top \hat{F}(w^*)(w' - w^*).$$

(12)

The Taylor approximation is exact, as the original function is a quadratic, and so the two functions are equivalent. Hence, we have obtained the fact that, under the empirical Fisher approximation, a $k$-sparse solution minimizing Equation 9 will also be a $k$-sparse solution minimizing Equation 1. However, the question of finding a $k$-sparse solution minimizing Equation 1 is precisely the starting point of the standard OBS derivations (see e.g. [Singh and Alistarh, 2020] or [Kurtic et al., 2022]), which eventually lead to the formula in Equation (10). This concludes the proof. □