An Efficient End-to-End Deep Learning Training Framework via Fine-Grained Pattern-Based Pruning

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ABSTRACT
Convolutional neural networks (CNNs) are becoming increasingly deeper, wider, and non-linear because of the growing demand on prediction accuracy and analysis quality. The wide and deep CNNs, however, require a large amount of computing resources and processing time. Many previous works have studied model pruning to improve inference performance, but little work has been done for effectively reducing training cost. In this paper, we propose ClickTrain: an efficient and accurate end-to-end training and pruning framework for CNNs. Different from the existing pruning-during-training work, ClickTrain provides higher model accuracy and compression ratio via fine-grained architecture-preserving pruning. By leveraging pattern-based pruning with our proposed novel accurate weight importance estimation, dynamic pattern generation and selection, and compiler-assisted computation optimizations, ClickTrain generates highly accurate and fast pruned CNN models for direct deployment without any time overhead, compared with the baseline training. ClickTrain also reduces the end-to-end time cost of the state-of-the-art pruning-after-training methods by up to about 67% with comparable accuracy and compression ratio. Moreover, compared with the state-of-the-art pruning-during-training approach, ClickTrain reduces the accuracy drop by up to 2.1% and improves the compression ratio by up to 2.2x on the tested datasets, under similar limited training time.

1 INTRODUCTION
Deep neural networks (DNNs) such as CNNs have rapidly evolved to the state-of-the-art technique for many artificial intelligence (AI) tasks in various scientific and technology areas, such as image and vision recognition [38], recommender systems [40], natural language processing [6]. DNNs contain millions of parameters in an unparalleled representation, which is efficient for modeling complexity nonlinearities. Many works [15, 20, 39] have suggested that using either deeper or wider DNNs is an effective way to improve analysis quality, and in fact many recent DNNs have gone significantly deeper and/or wider [19, 41]. For instance, OpenAI recently published their new DNN-based NLP model GPT-3 [3] with 175 billion parameters, which is the largest NLP model that is ever trained. Compared with its predecessor GPT-2, GPT-3 expands the capacity by three orders of magnitudes without significant modification to the model architecture, instead just adopting deeper and wider layers [3].

The ever-increasing scale and complexity of the networks with large-scale training datasets such as ImageNet-2012 [21] are bringing more and more challenges to the cost of DNN training, which requires large amounts of computations and resources such as memory, storage, and I/O. Moreover, designing new DNN architectures and training algorithms for various AI tasks require numerous trial-and-error and fine-tuning processes, which makes the training cost issue worse and computing resources scarce.

Model pruning is a widely used approach to reduce the number of DNN weights, which can effectively reduce the computation and storage costs and increase the inference performance, especially for resource-limited platforms, such as mobile, edge, and IoT devices. Many model pruning works have been proposed for improving the performance and energy efficiency of DNN inference [14, 25, 33, 42, 45]. A typical procedure to prune a DNN model consists of 1) training a model to high accuracy, 2) pruning the well-trained model, and 3) fine-tuning the pruned model. However, this procedure (called pruning-after-training or PAT) often requires a well-trained model and a trial-and-error process with domain expertise, which is typically very time-consuming. For example, state-of-the-art PAT-based methods [28, 30] incorporate the alternating direction method of multipliers (ADMM) into the pruning process to achieve high compression ratio and accuracy, but they almost triple the overall training time.

Considering the weights of DNN models are gradually sparsified during training, combining the pruning and training phases together (called pruning-during-training or PDT) is a promising way to significantly reduce the end-to-end time cost1 and conserve computing resources. However, only few work has investigated how to prune DNN models during training while still achieving highly accurate and fast pruned models that can be directly deployed.

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1The end-to-end time refers to the total time from the beginning of training from scratch to the end of pruning with a ready-to-deploy model.
Recently, a state-of-the-art work PruneTrain [26] studied how to perform CNN pruning during training. PruneTrain adopts a group-lasso regularization ($\ell_1$-based regularization) [31] to gradually force a group of model weights with small magnitudes to zero and periodically reconfigure the CNN architecture (e.g., reducing the number of layers) during training, leading to lower computation and higher performance. However, in reality, adaptively changing the original network architecture may result in severe loss of accuracy, which cannot be compensated for by performing more training batches. Thus, how to design a PDT-based method to significantly reduce the end-to-end time while still maintaining the network architecture for high accuracy remains an open question.

In this paper, we propose ClickTrain—a fast and accurate integrated framework for CNN training and pruning—which significantly reduces the end-to-end time. We develop a series of algorithm-level and system-level optimizations for ClickTrain to achieve high computation efficiency toward highly accurate and fast pruned models for inference. The key insights explored for algorithm-level optimization include: 1) the position of the most important weight in each convolution kernel is relatively stable after certain training batches, and 2) the important weights tend to be adjacent to each other. So, we propose a fine-grained architecture-preserving pruning approach based on pattern-based pruning (will be discussed in §2.1), which can precisely control the tradeoff among regularity, accuracy, and compression ratio. Moreover, our optimized pattern-based pruning creates multiple opportunities for system-level optimization such as sparse convolution acceleration and communication (Allreduce) optimization for weight update assisted by compiler so that the time overhead introduced by our proposed regularization can be mitigated. To the best of our knowledge, our paper is the first work to study how to design a PDT-based approach for effectively reducing the end-to-end time cost while achieving very high accuracy and compression ratio of pruned models. The main contributions are listed below:

- Instead of commonly used weight selection methods based on magnitude, we incorporate a state-of-the-art weight importance estimation approach to select the desired patterns from a generated candidate pattern pool. Moreover, we propose methods to gradually generate the candidate patterns (called dynamic pattern pool generation) and adaptively finalize the patterns and unimportant kernels.
- We propose a modified group-lasso regularization to replace the expensive ADMM method for pattern-based pruning.
- We propose multiple system-level optimizations including fast sparse matrix format conversion, pattern-accelerated sparse convolution, pattern-based communication optimization, and compiler-assisted optimized code generation, to significantly accelerate ClickTrain by leveraging finalized pattern sparsity during the training.
- We compare ClickTrain state-of-the-art PAT-/PDT-based methods. Experiments illustrate that ClickTrain can generate highly accurate and fast pruned models for direct deployment without any time overhead or even faster, compared with the baseline training. Meanwhile, ClickTrain reduces the time of state-of-the-art PAT-based approaches by up to about 67% with comparable accuracy and compression ratio, and improves the accuracy and compression ratio by up to 1.1% and 2.1× over PruneTrain on ImageNet.

The rest of the paper is organized as follows. We present background information in §2. We discuss our research motivation and challenges in §3. We describe our algorithm-level design and system-level optimizations of ClickTrain in §4 and §5, respectively. We present our evaluation results in §6. We discuss related work and conclude our work in §7 and §8.

2 BACKGROUND

2.1 DNN Model Pruning

Weight pruning for DNN model compression has been well studied in recent years. Below are three main methods.

Non-Structured Pruning. The non-structured pruning methods studied in the previous works [47] aim to heuristically prune the redundant weights on arbitrary locations. This leads to irregular weight distribution and inevitably introduces extra indices to store the locations of pruned weights. Eventually, this drawback limits performance acceleration [8].

Structured Pruning. To overcome these limitations, structured pruning has been investigated in the recent studies [16, 17, 26]. They proposed to prune the entire filters, channels to maintain the structural regularity of the weight matrices after pruning. By taking advantage of the regular shapes of the pruned weight matrices, structured pruning becomes more hardware-friendly and achieves much higher speedups [29]. However, due to the constraints of its coarse-grained pruning, structured pruning suffers from high accuracy loss.

Fined-Grained Pattern-Based Pruning. The state-of-the-art pruning work [35] proposes a fine-grained pattern-based pruning scheme, which generates an intermediate sparsity type between non-structured pruning and structured pruning. They prune a fixed number of weights in each convolution kernel (e.g., pruning 5 weights out of 9 weights in a 3×3 convolution kernel), and make the remaining weights to be concentrated in a certain area to form specific kernel patterns (called pattern sparsity, as shown in Figure 1 (left)). However, the compression ratio that is achieved by pattern sparsity is limited. So, they further propose to exploit the inter-convolution kernel sparsity, which aims to remove some unimportant kernels (called connectivity sparsity), as shown in Figure 1 (right). It can further enlarge the weights compression rate while reducing the convolution operations in CNNs.

The pattern-based pruning emphasizes exploiting locality in layer-wise computation, which is prevalent and widely reflected in the domains like human visual systems [11]. Moreover, this
The state-of-the-art PDT-based approach, PruneTrain, is a fine-grained pattern-based pruning approach, as state-of-the-art pruning scheme, considering both pattern and connectivity sparsity can leverage the advantages of non-structured and structured pruning to make the trade-off among regularity, accuracy, and ratio.

2.2 Prune-After-Training Versus Prune-During-Training
GBN [44], GAL [22] and DCP [48] are three state-of-the-art PAT-based approaches. GBN and GAL mainly focus on pruning filters. DCP accelerates the CNN inference via channel pruning. However, all of them must need well-trained models to converge to an accurate pruned model with high compression ratio, which suffers from high time cost, compared with PDT-based approaches.

PruneTrain [26] is a state-of-the-art PDT-based approach. The work observed that when pruning with group-lasso regularization, once a group of model weights are penalized close to zero, their magnitudes are typically impossible to recover during the rest of the training process. Based on this, PruneTrain periodically removes the small weights and change the network architecture and hence gradually reduces the training cost toward high compression ratio and accuracy. Moreover, NeST [7] and TAS [9] are two state-of-the-art methods attempting to search the best-fit pruned network architecture during training (can be seen as PDT-based methods), but they suffer from extremely high time cost.

3 RESEARCH MOTIVATION AND CHALLENGES
3.1 Limitations of Existing PDT-Based Method
The state-of-the-art PDT-based approach PruneTrain [26] integrates the structured pruning with group-lasso regularization ($\ell_1$-based regularization) [31] into the training phase, which is designed to prune as many channels, filters, and layers as possible to acquire a compact architecture with relatively high training performance. However, there are two major challenges to deploy PruneTrain for training large neural networks on a variety of architectures: inferior validation accuracy and large storage overhead.

Inferior Validation Accuracy. PruneTrain saves the training floating-point operations (FLOPs) by drastically reconfiguring the original network architectures (e.g., reducing the depth), resulting in a notable accuracy loss for many network architectures. For example, PruneTrain can save 53% training FLOPs and 66% inference FLOPs (i.e., about 2.2x compression ratio) but cause 1.8% accuracy drop for ResNet-32 on the CIFAR-10 dataset. Moreover, for demonstration purposes, we compare three different training strategies on ResNet-32, including (1) normal full training from scratch on the original ResNet-32 model, (2) PruneTrain for training the original 32-layer ResNet, and (3) training from scratch using an identical network structure as the one generated from PruneTrain (i.e., 23 CONV layers). As shown in Figure 2, PruneTrain achieves a lower model accuracy compared to training on the reduced model, but both of them cannot reach the expected accuracy of the original ResNet-32 network, even though we train for an extra of 1,000 epochs. This experiment illustrates that the accuracy is highly relevant to network architectures. Moreover, studies [9, 10, 15, 23] demonstrate that the model accuracy is highly relevant to network architecture, thus, we conclude that aggressively preserving the original architecture is critical to prevent a notable accuracy drop.

Large Storage Overhead. One major purpose of pruning large-scale neural networks is to facilitate their deployments in resource-constrained computing platforms which suffer from limited storage capacity and computing power. Thus, to realistically alleviate the storage and computation burden, pruning must provide a high compression ratio. However, PruneTrain can only provide up to 3x compression ratio (e.g., 2.2x for ResNet-32) [26], which is far below the expectation.

Therefore, these issues motivate us to develop a solution that provides three-dimensional optimizations: high training efficiency, high compression ratio, and high model accuracy.

3.2 Challenges of Pattern-Based Pruning in Training
Recent works [30, 35] have applied pattern-based pruning techniques for improving inference efficiency. However, these inference-focused strategies will pose several challenges to reach our three optimization objectives.

Issues of Existing Pattern Pruning Algorithms. There are three main issues of the existing pattern-based pruning algorithms [8, 35]: (1) The existing algorithms select pattern for each kernel via estimating weight importance based on magnitude. However, this estimation approach requires a well-trained model, whose weights will not change dramatically, which is not true for training from scratch. (2) The existing algorithms predefine the candidate patterns for all kernels and statically select the best-fit pattern for each kernel. But for pruning during training, static patterns may not
work properly, resulting in a significant loss of accuracy. (3) The existing algorithms typically with ADMM-based methods are very time-consuming and not applicable for training acceleration.

**Lack of Training Efficiency Optimization.** The computation efficiency optimizations proposed by existing works [8, 35] for pattern-based pruning cannot be directly applied to our training framework. This is mainly because of two reasons. On one hand, the existing pattern-based acceleration techniques [8, 35] are designed for accelerating inference (i.e., forward phase) instead of training (including both forward and back phases). However, based on our profiling result as shown in Figure 3, backward phase can consume more than 70% of the overall training FLOPs. On the other hand, the existing pattern-based optimizations [35] are based on accelerating numerous convolution operations on embedded systems due to limited memory capacity. However, efficient training on advanced datacenter architectures relies on high-performance general matrix-matrix multiplication (GEMM) rather than a large number of convolutions, in order to leverage the high throughput of accelerators such as GPPUs. Thus, there is an urgent need for an effective method to take advantage of pattern-based pruning to improve the GEMM-based convolution computation efficiency.

Overall, these challenges demand a novel solution that can provide both **algorithm-level** and **system-level** supports for fast and accurate end-to-end training framework toward our three-dimensional objectives.

### 4 ALGORITHM-LEVEL DESIGN OF CLICKTRAIN

In this section, we propose our novel PDT-based framework called CLICKTRAIN. The overall framework flow is shown in Figure 4, which consists of five stages. In this section, we focus on the algorithm-level design of CLICKTRAIN (used in stage 2 to stage 4) mainly for quickly obtaining the model with desired pattern-based sparsity. We first propose our pattern selection using weight importance estimation. Next, we propose our methods to dynamically build up the pattern candidates and adaptively finalize the patterns and unimportant kernels. After that, we describe our modified group-lasso regularization to accurately penalize the weights outside of the selected patterns and the unimportant kernels. We will elaborate our system-level optimizations (used in stage 5) for accelerating the training process in §5.

#### 4.1 Pattern and Unimportant Kernel Selection via Importance Estimation

The key consideration in pattern-based pruning is to select the best-fit pattern for each kernel after appropriately designing the patterns. The previous methods [27, 35] determine the importance of a certain weight based on its magnitude, which requires a well-trained CNN model whose weights will not change dramatically and well distributed after pruning the redundant filters. However, it is not feasible to accurately determine the importance of a certain weight only based on its weight magnitude during training **from scratch** because the weights in a not well-trained model will change greatly, especially in the early stage of training. Therefore, we propose to estimate the importance of patterns by considering additional gradient information and select the most important pattern for each kernel in the pruning.

For a given CNN with $L$ convolutional layers, let $W^{(l)} (1 \leq l \leq L)$ denote the collection of weights for all the kernels in convolutional layer $l$, which forms a 4-D tensor $W^{(l)} \in \mathbb{R}^{F \times C \times H \times S_l}$, where $F_l$, $C_l$, $H_l$, $S_l$ are the dimensions for the axes of filter, channel, spatial height, spatial width, respectively. As suggested by [32], for a weight $w_m \in W^{(l)}$, its importance can be estimated by $(g_m w_m)^2$, where $g_m = \frac{\partial E(W, D)}{\partial w_m}$ is the gradient of the weight $w_m$. Here $E(W, D)$ is the loss function on the dataset $D$. In addition, $W$ represents the collection of all 4-D weight tensors for $L$ convolutional layers.

A pattern $p_l$ (where $p_l \in B$ is the $i$-th pattern from the candidate pattern pool $B = \{p_1, p_2, \cdots, p_N\}$) can be viewed as a mask to prune specific weights within a kernel. The remaining weights of the kernel form a certain pattern. Thus, we can estimate the importance score of a pattern $p_l$ by combining the importance scores of all the remaining weights. We will discuss how to **gradually generate the pattern pool** in the next section. The patterns corresponding to the convolutional layer $l$ also form a 4-D tensor $P^{(l)} \in \mathbb{R}^{F \times C \times H \times S_l}$, where $P^{(l)}_{\ell, f, c, i} \in B$. The importance score of $p_l$ is estimated as

$$t_{\ell, f, c, i} = G^{(l)}_{\ell, f, c, i} \odot W^{(l)}_{\ell, f, c, i} \odot p_l, \quad l_p = \sum_{h, s} S_l \sum_{c, s} (h, s)^2, \quad (1)$$

where $G^{(l)}$ denotes the 4-D gradient tensor corresponding to $W^{(l)}$ and $\odot$ is the element-wise product (a.k.a, Hadamard product). After assessing the importance of all the patterns for a kernel, we can choose the pattern with the highest estimated importance score as the best-fit pattern for this kernel.

In addition, to further enlarge the sparsity, we also need to determine the unimportant kernels and directly prune them (i.e., connectivity sparsity). We adopt the following equation to estimate the importance score of a kernel $k \in W^{(l)}$.

$$t_{l, f, c, i} = G^{(l)}_{l, f, c, i} \odot W^{(l)}_{l, f, c, i} \odot k_l, \quad l_p = \sum_{h, s} S_l \sum_{c, s} (h, s)^2, \quad (2)$$

The reason why we integrate gradient to estimate the importance is if a certain weight whose magnitude and gradient are small, it will very likely keep the small value in the following training process because the backpropagation tends not to update its value dramatically. Therefore, we can treat it as an unimportant weight and penalize such weights during training to push it to become smaller and smaller (less and less important). Eventually, we can prune it with no hurt to the final accuracy. The computation cost of Equation (1) and (2) are relatively low, since the gradient $G^{(l)}$ can be acquired in the backward-propagation stage, which can be naturally implemented in most of the deep learning frameworks [2, 37]. Moreover, the number of candidate patterns is limited to a relatively small number (will be discussed later).

The weights and gradients would change greatly during the first few epochs of training CNN. On one hand, estimating the weight importance earlier can help us remove these unimportant weights sooner, thereby reducing the overall training time. On the other hand, estimating the importance of weights prematurely will lead to inaccurate estimations and ultimately cause a significant accuracy drop. Later estimation does help to improve the pruning accuracy.
but would cost more training epochs. Therefore, when we should apply the formulas above to accurately assess the weight importance is a challenge to address. After a series of empirical evaluation, we conclude that the derivative of the loss function on epochs can be used as a good indicator to solve this problem. In particular, when this value is less than a threshold, we can apply the formula above to evaluate the weight importance relatively accurately. For example, Figure 5 shows that the loss does not change sharply after a certain threshold (50 epochs), meaning that the optimization process gradually stabilizes to start our pruning.

### 4.2 Dynamic Pattern Pool Generation

Different from pruning a well-trained CNN, the positions of important weights may keep changing along with the training process. It is not ideal to determine the positions of pruned weights only once and fix them in the subsequent training epochs, which is particularly true for pruning in the early training phase. Thus, we propose a method to gradually build up the desired patterns—Dynamic Pattern Pool Generation (DPPG)—which will be contained in a pool of candidate patterns during training. DPPG is designed to solve two problems: 1) the high runtime overhead caused by a large number of candidate patterns, and 2) the trade-off between the number of training epochs and accuracy.

The pattern pool consists of two sub-pools—generic pattern pool and dynamic pattern pool, as shown in Figure 6. We pre-define 8 patterns in the generic pool, where those patterns can be transformed to form Gaussian filter and Laplacian of Gaussian filter by interpolating the patterns into convolutional layers. These special vision properties can potentially enhance the feature extraction ability of CNNs [30]. Our results also indicate that, over different CNNs and datasets, the patterns that we select for the generic pattern pool have the highest probability of occurrence compared to other types of patterns in both well-trained non-pruned model and ClickTrain-generated model with CIFAR-10, as shown in Figure 7.
After determining 8 Generic + 4 Dynamic Patterns, we spend multiple training epochs to filter out the most competitive candidate patterns. In particular, a competitive score (initialized to 0) is assigned to each candidate pattern. After each mini-batch training, we measure the importance scores of the candidate patterns and add 1 competitive score to each of the top-2 important candidate patterns in every candidate pattern set. We repeat this process for a certain number of epochs (depending on the training epoch budget), and accumulate the competitive score of the same pattern from different candidate pattern sets. Finally, we obtain the final competitive score for each unique candidate pattern and select a user-set number of candidate patterns with the highest competitive scores to form our dynamic pool.

4.3 Adaptive Pattern & Unimportant Kernel Finalization

After the pattern pool is generated, we can finalize the pattern for each kernel adaptively based on the pattern pool. Due to the concern that the one-time selection method may not provide high accuracy, we propose an adaptive method to finalize the patterns using multiple training epochs. Specifically, in each training batch, for every kernel, we calculate the importance score of each pattern in our pattern pool. Then, we find the pattern with the highest importance score and count its number of occurrences during training. After a number of epochs, the final pattern for each kernel will be selected as the most frequent one of those highest-scoring patterns.

Similarly, we also use our importance estimation method to calculate the importance score for each kernel and adaptively select a user-set number of unimportant kernels for each layer. Note that the loss is not always decreasing during training. Thus, we set up a training loss margin δ as a hyperparameter to avoid selecting patterns in the training batches where the loss is obviously increasing. For example, if the loss in the previous batch divided by the value in the current batch is smaller than 0.0018 (default δ), we will not count the highest-scoring patterns into the number of occurrences. In addition, Figure 8 illustrates that our adaptive pattern finalization approach achieves 2% higher than the one-time solution on CIFAR-10.

4.4 Modified Group-Lasso Regularization

$\ell_1$-based regularization or group-lasso regularization is usually added to the loss function to penalize all important or unimportant weights along desired dimensions (such as filter, channel) over the entire layers of CNNs. However, we have noted that using group-lasso regularization to penalize all the weights of filters or channels can lead to a severely impaired pruned model. Thus, we propose a modified group-lasso regularization to more accurately penalize the weights. Generally speaking, unimportant weights should be punished more heavily than important weights, and important weights should remain the same because they typically play a key role in generating stronger activation to make more confident decisions. In particular, after selecting the best-fit pattern for each kernel and identifying the unimportant kernels, we only penalize the unimportant kernels and the weights outside of the selected patterns, since we desire to reduce the absolute values of these weights and kernels as the training progresses. We note that the contributions of these weights/kernels to the final accuracy are negligible, so even if we directly remove (i.e., hard prune) these weights/kernels, the model accuracy would not decrease obviously.

Let $I^{(f)}$ be a 4-D importance tensor (i.e., a tensor full of importance scores) of a 4-D weight tensor $W^{(f)}$, where $I^{(f)}$ is the same shape as $W^{(f)}$. Assume the $c$-th kernel of the $f$-th filter in the convolutional layer $I$ is unimportant, we set $I_{c,f,l}^{(f)}$ to be 0. Our proposed approach for penalizing unimportant weights and kernels with modified group-lasso regularization can be formulated as:

$$
\begin{align*}
Z^{(f)} &= W^{(f)} \odot (-P^{(f)}) \\
E(W,D) &= E(W,D) + \lambda \sum_{f,l} \left( \sum_{c,k} I_{c,f,l}^{(f)} K_k^{(f)} \|Z^{(f)}_{k,l}\|_2 \right) \\
U^{(f)} &= W^{(f)} \odot (-I^{(f)}) \\
\|w^{(g)}\|_p &= \left( \sum_{i=1}^{N} |w^{(g)}(i)|^p \right)^{\frac{1}{p}} \quad |w^{(g)}| \text{ is the number of weights in } w^{(g)}, \quad \lambda \text{ is the coefficients for the group-lasso regularization.}
\end{align*}
$$

where

In this section, we discuss our proposed system-level optimizations for improving training efficiency.
5.1 Pattern-Driven Fast Sparse Matrix Conversion

Kernels become much more sparse than origins after pruning. According to prior studies [4, 43], a highly optimized sparse matrix-matrix multiplication (SpMM) leveraging pruning sparsity can outperform state-of-the-art GPU GEMM library such as cuBLAS [36] for convolution computation. Generally, SpMM requires first converting dense input matrix to a sparse format such as Compressed Sparse Row (CSR) because CSR dominates a continuous storage space, which is beneficial to improve the data locality and computation efficiency.

However, converting a dense matrix to its CSR format (as shown in Figure 9a) usually introduces an obvious time overhead if directly calling dense2csr() from cuSPARSE library [34]. For example, as shown in Figure 10, dense2csr() costs about 800 us when converting a 256x1152 dense matrix to its CSR format (generated by the convolution operation on 128x224x224 and 256x3x3 tensors), whereas the time of the corresponding SpMM of 256x1152 (sparse) multiplying 1152x50176 (dense) is only about 3000 us. We note that after the patterns have been finalized, the positions of un-pruned (non-zero) weights will not change. Thus, we can directly generate rowPtr, colInd, and GPU thread offset arrays (as shown in Figure 9b) during stage 3 (as shown in Figure 4) and store them for the following SpMM-based convolution operations. Note that this indices generation only introduces a negligible time overhead, since we only need to generate the fixed arrays for once and keep using them in the next stages.

Moreover, since dense2csr() does not provide any interface for pre-defined nonzero positions (rowPtr and colInd), we propose a fast dense-to-sparse matrix conversion routine with pre-defined nonzero positions, whose interface as template<typename T> Convert2CSR(int* rowPtr, int* colInd, T* sparseFilters, T* val).

Note that in order to maintain a minimal modification to the existing state-of-the-art deep learning frameworks such as PyTorch which uses dense matrices for most computations such as autograd (automatic differentiation), we apply our fast dense-to-sparse matrix conversion before each SpMM (for all filters in one layer) rather than changing all computations to be based on sparse matrices in this work.

For demonstration purpose, we evaluate our proposed fast matrix conversion on the 256x1152 and 1152x50176 matrices using an NVIDIA RTX 5000 GPU and compare it with cuSPARSE. Figure 10 illustrates that our conversion implementation is 4x faster than cuSPARSE’s dense2csr().

5.2 Pattern-Accelerated SpMM for Sparse Convolution

Ideally, we can save the floating-point operations if not involving the pruned weights (zeros) in the convolution operation. However, even though pattern sparsity is more regular than random sparsity (unstructured pruning), existing hardware such as GPUs cannot utilize the pattern sparsity to accelerate either forward or backward phase. We observe that our pattern sparsity exhibits three key characteristics: 1. The types of sparsity is relatively limited, e.g., 4, 8, or 12. 2. The non-zero (un-pruned) weights inside a kernel are more likely close to each other. 3. Each kernel has the same number of non-zero weights. Thus, considering that SpMM can decrease the computational cost for sparse convolution operations by reducing the number of multiplications and additions, we propose to design a new GPU SpMM library for sparse convolution to make full use of the above important characteristics.

Pattern-Accelerated SpMM. We first describe our design of pattern- accelerated GPU SpMM library that exploits the pattern sparsity in both forward and backward phases. Specifically, converted sparse matrices after pruning lose the regular structure of dense matrices, which results in irregular memory accesses in SpMM. Moreover, concurrently executing massive threads on GPU makes the random memory access issue worse. Thus, improper handling of random memory accesses from massive parallel threads would stall the thread execution and decrease the performance significantly. In order to overcome the challenge of random memory accesses, we propose to take advantage of shared memory on GPU architectures to support concurrent random accesses. Specifically, we first load
a tile of data from input feature matrix (dense) and filter matrix (sparse) to shared memory, as shown in Figure 9c. Then, we use the loaded data (in shared memory) to calculate the corresponding tile of output feature matrix (dense). Inspired by existing works [13, 18], load imbalance may severely hurt the performance on the GPU, while we solve this issue through an algorithm-hardware co-design. On the algorithm side, we limit all the filters in the same layer have the same number of un-pruned (non-zero) weights in our pattern-based pruning. On the hardware side, we can further improve the performance by using the vectorized load and store instructions in CUDA architectures [24] because each row of sparse filter matrix has the same length (i.e., non-zero weights). In addition, since the sparse matrices generated by convolution operations typically have relative long rows, we adopt 1D tiling strategy and map each thread block to a 1D row tile of the output matrix.

For demonstration purpose, we also evaluate our optimized SpMM on those 256×1152 and 1152×50176 matrices using an NVIDIA RTX 5000 GPU and compare it with state-of-the-art dense or sparse matrix-multiplication libraries. Figure 11 illustrates that our optimized SpMM library can achieve a speedup of 3.2× over cuSPARSE. Moreover, our implementation is faster than cuBLAS’s GEMM and cuDNN’s convolution when the sparsity ratio is higher than 65%.

Forward Phase Acceleration. To achieve a final high accuracy, the filters in different layers may have completely different compression/sparsity ratio. We note that for relatively low sparsity ratio, our optimized SpMM does not gain a performance improvement compared to its dense counterpart (will be showed later). Thus, we set a threshold of sparsity ratio for each layer, and only call our optimized SpMM for the layer where its sparsity ratio is higher than our set threshold in the forward phase. Based on experiment, we set 65% as the default threshold for all layers without loss of generality.

Backward Phase Acceleration. The output $z^f$ (before activate function $\sigma$) of the convolutional layer $\ell$ in the CNNs’ forward-propagation is obtained by $z^f = a^f-1 \odot W^f + b^f$, where $a^f-1$ is the activations at layer $\ell-1$, $W^f$ and $b^f$ denote weights and biases at layer $\ell$, respectively, and $\odot$ is the convolution operation. In backpropagation, the layer $\ell$ first receives $\delta^f$ from the layer $\ell+1$, and then $\delta^f$ is propagated back based on $\delta^f = \frac{\partial E(W,D)}{\partial z^f}, \delta^f-1 = \delta^f \odot \text{rot180}(W^f) \odot \sigma'(z^{f-1})$. We can calculate the gradient of the layer $\ell$ after obtaining $\delta^f$ and $\frac{\partial E(W,D)}{\partial W^f} = a^{f-1} \odot \delta^f$. We can observe from the above equation that the difference between forward and backward phases is that the forward phase uses feature map $a^{f-1}$ as input, whereas the backward phase uses $\delta^{f+1}$ as input. Also, the sparse weight matrix $W^f$ is involved in the backpropagation, so we adopt the similar strategy as forward phase to handle $W^f$.

5.3 Pattern-Based Communication Optimization

Distributed training has been widely used for larges-scale DNN training. However, gradients must be synchronized among different computing nodes for each training batch, such communication (i.e., Allreduce) overhead is not negligible and will be scaled up as the number of computing nodes increases. Note that since all the weights to be pruned remain zeros after the regularized training stage, we do not need to send the corresponding gradients to other computing nodes in the rest of the training process. Moreover, high sparsity ratio of our pattern-based pruning provides a great opportunity to significantly reduce the communication overhead.

5.4 Compiler-Assisted Optimized Code Generation

After implementing our optimized libraries for sparse matrix conversion, SpMM, and Allreduce, we propose a compiler-assisted method to generate the optimized code for efficient training (in stage 5). Specifically, after sparsity ratios have been determined (after stage 3), the compiler decides whether using original sparse convolutions or our optimized SpMM computation for each layer in the computational graph based on its sparsity ratio; and accordingly generates the code with the better operator in the training framework such as PyTorch (as shown in Figure 9d). Moreover, the compiler transforms all Allreduce communications (in stage 5) in the computational graph into our optimized pattern-based communications. Note that there is an alternative solution that relies on compiler to generate the shared library calling sparse convolutions or SpMM computation dynamically for each layer. However, this solution introduces “if-else” overhead for each layer in every training batch, which is much higher than the former solution.

6 EXPERIMENTAL EVALUATION

In this section, we first evaluate our proposed ClickTrain on different CNNs and datasets and show its accuracy and compression ratio and compare it with several state-of-the-art PDT-/PAT-based frameworks. We then evaluate our proposed optimizations and overall training efficiency.

Experimental Setup. We conduct our experimental evaluation using TACC Frontera system [12], each GPU node of which is equipped with four NVIDIA Quadro RTX 5000 [1] GPUs. We use NVIDIA CUDA 10.1 and its default profiler for time measurement. We implement ClickTrain based on PyTorch [37] using SGD. We evaluate ClickTrain and compare it with state-of-the-art methods on six well-known CNNs including ResNet-18/32/50 and VGG-11/13/16. Our datasets include CIFAR-10/100 [5] and ImageNet-2012 [21].

6.1 Evaluation on Accuracy and Compression Ratio

We first evaluate our proposed ClickTrain on different CNNs and datasets with a fixed number of training epochs, as shown in Table 1. We use $\Lambda$ to denote the validation accuracy drop of the pruned model compared to the original baseline model. Note that at the end of the regularized training stage, we conduct a hard-pruning step (as shown in Figure 4) to eventually zero out the pruned weights which have been regularized to tiny values. Thus, the rest of training process can be accelerated through our compiler-assisted training optimizations. We train the baseline models to a high accuracy using 190 epochs and 90 epochs for CIFAR-10/100 and ImageNet, respectively. It is worth noting that all the above baseline accuracies have been widely used in many
Table 1: Comparison between PruneTrain (PRT) and ClickTrain (CLK). FLOPs are the saved FLOPs.

| Method      | Base. Acc. | Valid. Acc. | Comp. Ratio | Train./Inf. FLOPs | Hard Pr. Epoch |
|-------------|------------|-------------|-------------|-------------------|---------------|
| ResNet-32   | PRT 93.6%  | 2.1%        | 2.2x        | 53% / 66%         | N/A           |
|             | CLK 93.6%  | 0%          | 8.6x        | 31% / 45%         | 130           |
|             |             |             | –0.3%       | 13.9x / 23% / 89% | 150           |
| ResNet-50   | PRT 94.2%  | –1.1%       | 2.2x        | 50% / 70%         | N/A           |
|             | CLK 94.1%  | 0%          | 8.6x        | 27% / 74%         | 130           |
|             |             |             | –0.4%       | 11.8x / 20% / 79% | 150           |
| VGG-11      | PRT 92.1%  | –0.7%       | 6.6x        | 57% / 65%         | N/A           |
|             | CLK 92.1%  | –0.1%       | 8.7x        | 30% / 82%         | 130           |
|             |             |             | –0.4%       | 10.3x / 26% / 84% | 140           |
| VGG-13      | PRT 93.5%  | –0.6%       | 6.3x        | 56% / 63%         | N/A           |
|             | CLK 93.8%  | –0.2%       | 6.2x        | 29% / 78%         | 130           |
|             |             |             | –0.4%       | 9.0x / 29% / 82%  | 135           |

Table 2: Comparison between ClickTrain and PAT-based methods on ImageNet. Well-train costs about 90 epochs.

| Method      | Base. Acc. | Valid. Acc. | Comp. Ratio | Total Epochs |
|-------------|------------|-------------|-------------|--------------|
| ResNet-18   | TAS [9]    | 76.6%       | –1.5%       | 1.5x         | 120          |
|             | DCP [48]   | 69.6%       | –5.5%       | 3.3x         | well train + 60 |
|             | Ours       | 69.9%       | –0.7%       | 4.2x         | 90           |
| ResNet-50   | GBN [44]   | 75.8%       | –0.6%       | 2.2x         | well train + 60 |
|             | GAL [22]   | 76.4%       | –7.1%       | 2.5x         | well train + 30 |
|             | Ours       | 76.1%       | –0.8%       | 4.1x         | 90           |
| VGG-16      | NeSt [7]   | 71.6%       | –2.3%       | 6.5x         | N/A          |
|             | Ours       | 73.1%       | –0.8%       | 6.6x         | 90           |

previous studies [26, 30, 35]. We thus use the same 190 epochs and 90 epochs for ClickTrain on CIFAR and ImageNet, respectively. We calculate the compression ratio only considering the convolutional layers in the models, since the convolutional layers in ResNet and VGG models dominate most of the computation overhead in both training and inference processes. In particular, the compression ratio is calculated as the total number of weights based on all the convolutional layers.

Table 1 illustrates that for ResNet-32 and ResNet-50, our ClickTrain can provide more than 10x compression ratio while maintaining up to 0.3% accuracy drop on the two CIFAR datasets compared to the baseline accuracy. For VGG-11/13, ClickTrain can also provide 5.8x to 9.1x compression ratio with up to 0.5% accuracy drop. Since most of the weights in the convolutional layers have been pruned, ClickTrain can save the training FLOPs and inference FLOPs by 19%~31% and 71%~89%, respectively, on CIFAR-10/100 with the assist of compiler optimizations. To demonstrate the effectiveness on large datasets, we also train ResNet-50 on ImageNet using ClickTrain. It provides 4.1x compression ratio and saves the training FLOPs and inference FLOPs by 27% and 66%, respectively. Note that a higher compression ratio can always lead to lower inference FLOPs, however, this is not true for training. For example, in order to further increase the compression ratio from 8.4x to 11.8x for ResNet-50 on CIFAR-10, we must perform more epochs in fine-tuning with our modified group-lasso regularization and start hard pruning later, which introduces more training FLOPs. We also evaluate the impact of when to start the hard pruning on the validation accuracy and FLOPs. We observe that the earlier the patterns and unimportant kernels are determined, the earlier the models can be hard pruned by ClickTrain, thus more training FLOPs can be saved; however, earlier hard pruning causes a significant accuracy loss. The epoch of hard pruning shown in Table 1 makes a good tradeoff between accuracy and training FLOPs.

Comparison with PDT-Based Method. We then compare our ClickTrain with state-of-the-art PDT-based method PruneTrain, as shown in Table 1. It illustrates that ClickTrain can precisely control the accuracy drop within -0.5% for all the tested models on CIFAR-10/100, but the accuracy drop of PruneTrain is over -1.0% for most of the tested CNN models. Moreover, ClickTrain can significantly improve the compression ratio with similar or even higher accuracy, compared to PruneTrain. For example, PruneTrain can only provide a compression ratio less than 3x with more than 1.0% accuracy drop for ResNet-50 on CIFAR-10, whereas ClickTrain achieves 12.1x compression ratio with only 0.2% accuracy drop, leading to 5.5x higher compression ratio. For VGG-13 on CIFAR-100, PruneTrain achieves 8.2x compression ratio with only 0.5% accuracy drop, which significantly outperforms PruneTrain’s 2.4x compression ratio with 1.4% accuracy drop. For ImageNet, ClickTrain reduces the accuracy drop by 1.1% and improves the compression ratio by 1.9x over PruneTrain.

Comparison with PAT-Based Methods. A typical procedure of model pruning is removing the redundant weights based on well-trained networks and then fine-tuning the slashed networks. Thus, we finally compare our ClickTrain with state-of-the-art PAT-based methods. As illustrated in Table 2, ClickTrain save up to about 67% computation time while only sacrificing up to 0.8% accuracy, compared with other PAT-based methods. In addition, ClickTrain also achieves a much higher compression ratio for efficient inference. Thus, we conclude that accurately estimating the weight importance during training makes our PDT-based solution feasible to significantly save the total training epochs.

6.2 Evaluation on Training Efficiency

Forward and Backward Time. We then evaluate the forward and backward time when applying our optimized SpMM using different CNN models with ImageNet. The sparsity (i.e., compression ratio) for each model can be found in Table 2. Figure 12a shows that for forward phase, ClickTrain achieves the speedups of 2.1x/1.3x/1.5x and 2.2x on ResNet-18/34/50 and VGG-16, respectively. For backward phase, ClickTrain achieves the speedups of 1.3x/1.2x/1.2x and 1.6x on ResNet-18/34/50 and VGG-16, respectively.

Communication Time. Next, we evaluate our optimized communication time using multiple GPUs on ResNet-50 and VGG-16 with
Figure 12: Training performance evaluation of ClickTrain and comparison.

Figure 13: Comparison of PruneTrain and ClickTrain.

ImageNet, as shown in Figure 12c. Compared with the baseline training, ClickTrain saves 0.81 hours on ResNet-50 and can save 0.93 hours on VGG16 when using 4 GPUs. Also, ClickTrain saves 1.27 hours on ResNet-50 and 1.34 hours on VGG-16 when using 8 GPUs.

Overall Training Time. Moreover, we evaluate the overall training time on different CNN models using ImageNet. As shown in Figure 12b, compared with the baseline training, ClickTrain can save 6.5%/5.4%/8.8% and 9.7% for training ResNet-18/34/50 and VGG-16, respectively, using single GPUs. Note that unlike the baseline training, ClickTrain can generate ready-to-deploy models without further tuning.

Comparison with PatternTrain. Finally, Figure 13 (a) shows that ClickTrain achieves a compression ratio of 11.6× with only 0.1% accuracy drop on ResNet-50 with CIFAR-10, whereas PruneTrain only has 2.2× compression ratio but with a significant accuracy drop of 2.1%, even it saves 39.1% end-to-end time over ClickTrain. Figure 13 (b) shows that ClickTrain has 2.1× higher compression ratio than PruneTrain with a notable accuracy improvement of 1.1% on ResNet-50 with ImageNet but only slightly longer end-to-end time. Note that 1.1% on ImageNet and 2.1% on CIFAR-10 are significant accuracy improvements considering the limited training time. Thus, aggressively preserving the original architecture is critical for designing PVT-based approaches.

7 RELATED WORK

PruneTrain [26] is a state-of-the-art approach to accelerate the DNN training from scratch while pruning it. The work observed that when pruning with group-lasso regularization, once a group of model weights are penalized close to zero, their magnitudes are typically impossible to recover during the rest of the training process. Based on this observation, PruneTrain periodically removes the small weights and reconfigure the network architecture and hence can gradually reduce the training during training toward both high compression ratio and accuracy. In addition, PruneTrain also proposes to dynamically increase the mini-batch to further increase the training performance. However, as we discussed in Section 3, PruneTrain aggressively change the original network architecture, causing a significant unrecoverable accuracy loss.

8 CONCLUSION

In this paper, we propose ClickTrain by using dynamic fine-grained pattern-based pruning. It has both algorithm-level and system-level optimizations with four stages: i) accurate weight importance estimation to select the pattern, ii) dynamic candidate pattern generation and pattern finalization, iii) regularized training for fine-tuning with an improved group-lasso, and iv) compiler-assisted optimized training. We show that ClickTrain significantly reduces the end-to-end time while still achieving high accuracy and compression ratio.

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