A Privacy-Preserving DNN Pruning and Mobile Acceleration Framework

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Abstract—To facilitate the deployment of deep neural networks (DNNs) on resource-constrained computing systems, DNN model compression methods have been proposed. However, previous methods mainly focus on reducing the model size and/or improving hardware performance, without considering the data privacy requirement. This paper proposes a privacy-preserving model compression framework that formulates a privacy-preserving DNN weight pruning problem and develops an ADMM based solution to support different weight pruning schemes. We consider the case that the system designer will perform weight pruning on a pre-trained model provided by the client, whereas the client cannot share her confidential training dataset. To mitigate the non-availability of the training dataset, the system designer distills the knowledge of a pre-trained model into a pruned model using only randomly generated synthetic data. Then the client’s effort is simply reduced to performing the retraining process using her confidential training dataset, which is similar as the DNN training process with the help of the mask function from the system designer. Both algorithmic and hardware experiments validate the effectiveness of the proposed framework.

Index Terms—deep learning, privacy-preserving, weight pruning

I. INTRODUCTION

The accelerating growth of the amount of parameters and operations in modern DNNs [1]–[3] has impeded the deployment of DNN models on resource-constrained computing systems. Therefore, various DNN model compression methods, including weight pruning [4]–[7], low-rank factorization [8], [9], transferred/compact convolutional filters [10], [11], and knowledge distillation [12]–[15], have been proposed. Among these, weight pruning enjoys the great flexibility of various pruning schemes and has achieved very good compression rate and accuracy. This paper mainly considers weight pruning.

However, previous model compression methods mainly focus on reducing the model size and/or improving hardware performance (e.g., inference speed and energy efficiency), without considering the data privacy requirement. For example, in medical applications, the training data may be patients’ medical records [16], [17], and in commercial applications, the training data should be kept as business confidentiality. Therefore, this paper works on a privacy-preserving model compression.

Only a few attempts have been made to achieve model compression while preserving data privacy, by knowledge distillation. Wang et al. propose RONA, where the student model is learned from feature representations of the teacher model on public data [20]. However, RONA still relies on the public data, which is part of the entire dataset. To mitigate the non-availability of the entire training dataset, later works [16], [19] depend on complicated synthetic data generation methods to fill the vacancy. Chen et al. exploit generative adversarial networks (GANs) to derive training samples that can obtain the maximum response on the teacher model [16]. Nayak et al. synthesize data impressions from the complex teacher model by modeling the output space of the teacher model as a Dirichlet distribution [19]. Nevertheless, even with carefully designed synthetic data, the accuracy of the student models obtained by these knowledge distillation methods is unsatisfactory. To alleviate the deficiencies of previous work, we propose a privacy-preserving model compression framework that can use randomly generated synthetic data to discover the pruned model architecture with the potential to maintain the accuracy of the pre-trained model. The contributions of our work are summarized as follows:

- We develop a privacy-preserving model compression framework that formulates a privacy-preserving DNN weight pruning problem and develops an ADMM (alternating direction method of multipliers) based solution to support different types of weight pruning schemes including irregular pruning, filter pruning, column pruning, and pattern-based pruning.
- In the proposed framework, the system designer performs the privacy-preserving weight pruning process on a pre-trained model without the confidential training dataset from the client. The goal of the system designer is to discover a pruned model architecture that has the potential for maintaining the accuracy of the pre-trained model. The client’s effort is then simply reduced to performing the retraining process using her confidential training dataset for boosting the accuracy of the pruned model. The retraining process is similar as the DNN training process with the help of the mask function from the system designer.
- Our framework is motivated by knowledge distillation. But we only use randomly generated synthetic data,
Fig. 1. Illustrations of different pruning schemes including (a) irregular pruning, (b) filter pruning, (c) column pruning, and (d) pattern-based pruning. 

while the existing privacy-preserving knowledge distillation works employ complicated synthetic data generation methods. Our framework is different from knowledge distillation, which specifies the student model architecture beforehand, while our privacy-preserving weight pruning process discovers the pruned model architecture gradually through the optimization process.

- Experimental results demonstrate that our framework can implement DNN weight pruning while preserving the training data privacy. For example, using VGG-16 and ResNet-18 on CIFAR-10 with the irregular pruning scheme, our framework can achieve the same model compression rate with negligible accuracy loss comparing with the traditional weight pruning process (no data privacy requirement). Prototyping on a mobile phone device shows that we achieve significant speedups in the end-to-end inference time compared with other state-of-the-art works. For example, we achieve 25 ms end-to-end inference time with ResNet-18 on ImageNet using Samsung Galaxy S10, without accuracy loss, corresponding to 4.2×, 2.3×, and 2.1× speedups comparing with TensorFlow-Lite, TVM, and MNN, respectively.

II. RELATED WORK OF DNN WEIGHT PRUNING

We illustrate different weight pruning schemes in Fig. 1 where the grey blocks represent the pruned weights. Fig. 1 (a) shows the irregular pruning scheme [6], [9], [23], [24], which is a non-structured pruning scheme. Irregular pruning prunes weights at arbitrary locations. It can achieve very high compression rate, but the resultant irregular weight sparsity is not compatible with data parallel executions on the computing systems. By imposing certain regularities on the pruned models, structured pruning schemes [4], [5], [8], [10], [11], [25]-[29] maintain the full matrix format with reduced dimensions, thus facilitating implementations on the resource-constrained computing systems.

Structured pruning can be further categorized into filter pruning [25], [30] as in Fig. 1 (b), column pruning [31], [32] as in Fig. 1 (c), and pattern-based pruning [27], [28] as in Fig. 1 (d). Filter pruning by the name prunes whole filters from a layer. Please note that some references mention channel pruning [29], which by the name prunes some channels completely from the filters. Essentially channel pruning is equivalent to filter pruning, because if some filters are pruned in a layer, it makes the corresponding channels of next layer invalid. Column pruning (filter shape pruning) prunes weights for all filters in a layer, at the same locations. Pattern-based pruning is a combination of kernel pattern pruning scheme and connectivity pruning scheme. In kernel pattern pruning, for each kernel in a filter, a fixed number of weights are pruned, and the remaining weights form specific kernel patterns. The example in Fig. 1 (d) is defined as 4-entry kernel pattern pruning, since every kernel reserves 4 non-zero weights out of the original 3×3 kernel. The connectivity pruning cuts the connections between some input and output channels, which is equivalent to removing corresponding kernels.

III. OVERVIEW OF THE PROPOSED FRAMEWORK

A. Traditional DNN Weight Pruning Process

In this section we introduce the traditional DNN weight pruning process, where there is no data privacy requirement, i.e., the training dataset is available for the whole DNN weight pruning process. Fig. 2 (a) describes the traditional DNN weight pruning process, which starts with a pre-trained model and the training dataset. Then the weight pruning process implements a particular weight pruning scheme to obtain a pruned model. The weight pruning process leads to inefficacy of the model accuracy. Therefore, a retraining process is needed to enhance the accuracy of the pruned model with the training dataset [4], [8], [25], [29], [33].

B. The Proposed Framework

This section provides the overview of our proposed privacy-preserving DNN model compression framework where a system designer will implement a DNN weight pruning scheme on a pre-trained model provided by a client to facilitate the deployment of DNN inference model on a hardware computing system. (In the experiment section, we will demonstrate results from deployments of pruned DNN models on a mobile phone device.) However, the client holds the confidential training dataset that she could not share with the system designer due to the data privacy requirement. For example, in medical applications the training data may be patients’ medical records [21], [22] and in commercial applications the training data should be kept as business confidentiality.

We make the following observations from the traditional DNN weight pruning process, which motivates our framework to mitigate the non-availability of the training dataset to the system designer. (i) The weight pruning process is for discovering a pruned model architecture that has the potential for maintaining the accuracy of the pre-trained model. (ii) The retraining process is the key to boost the accuracy of the pruned model, and the training dataset must be used for it. (iii) The retraining process is similar to the DNN training process except that it needs a mechanism to ensure the pruned weights are zeros and not updated during back propagation.

Fig. 2 (b) illustrates the workflow of our proposed framework. The client has the confidential training dataset and a
pre-trained model. The system designer performs the privacy-preserving weight pruning process on the pre-trained model from the client with the randomly generated synthetic data. The generation of the synthetic data does not rely on any prior knowledge about the client’s confidential training dataset. In the experiments, we simply set the value of each pixel of the synthetic images with a discrete Uniform distribution in the range of 0 to 255. We formulate a privacy-preserving weight pruning problem and develop an ADMM (alternating direction method of multipliers) based solution to support different types of weight pruning schemes. We have tested on the irregular pruning, filter pruning, column pruning, and pattern-based pruning schemes in the experiments. The outputs of the privacy-preserving weight pruning process consist of a pruned model and a mask function. Then the client performs the retraining process with her confidential training dataset and the mask function on the pruned model. The mask function sets corresponding gradients as zeros for pruned weights.

In the above-described framework, the system designer takes charge of the major privacy-preserving weight pruning process, whereas the client’s effort is simply reduced to the retraining process, which is similar as the DNN training process with the help of the mask function from the system designer. According to the observation (i), we found that the randomly generated synthetic data can serve for the purpose of learning a pruned model architecture, given our privacy-preserving weight pruning problem formulation. Based on the observation (ii), only the client herself can perform the retraining process with her confidential training dataset to boost the accuracy of the pruned model. And according to the observation (iii), the mask function from the system designer helps to simplify the retraining process of the client, who does not need to learn the sophisticated DNN weight pruning techniques.

IV. PRIVACY-PRESERVING WEIGHT PRUNING PROCESS

This section presents the privacy-preserving weight pruning process. We begin with the notations. Then two problem formulations are presented: one refers to the whole model inference results of the pre-trained model and the other one refers to the layer-wise inference results of the pre-trained model. Next, we provide the ADMM based solution, followed by the supports of different weight pruning schemes.

A. DNN Model Notations

Unless otherwise specified, we use the following notations throughout the paper. We mainly focus on the pruning of the computation-intensive convolutional (CONV) layers. For an N-layer DNN, let \( A_n, B_n, C_n, D_n \) denote the number of filters, the number of channels, the height of filter kernel, and the width of filter kernel of the \( n \)-th CONV layer, respectively. Therefore, the weight tensor of the \( n \)-th CONV layer is represented as \( W_n \in \mathbb{R}^{A_n \times B_n \times C_n \times D_n} \). Then corresponding GEMM matrix representation of \( W_n \) is given as \( W_n \in \mathbb{R}^{P_n \times Q_n} \), with \( P_n = A_n \) and \( Q_n = B_n \cdot C_n \cdot D_n \). We use \( b_n \in \mathbb{R}^{P_n} \) to denote the bias for the \( n \)-th layer. We also define \( W := \{W_n\}_{n=1}^{N} \) and \( b := \{b_n\}_{n=1}^{N} \) as the sets of all weight matrices and biases of the neural network.

We use \( X \) for the input to a DNN. It may represent a randomly generated synthetic data or a data point from the confidential training dataset. Let \( \sigma(\cdot) \) denote the element-wise activation function. The output of the \( n \)-th layer with respect to the input \( X \) is given by

\[
F_n(X) := (f_n \circ f_{n-1} \circ \cdots \circ f_i \circ \cdots \circ f_1)(X),
\]

where \( f_i(\cdot) \) represents the operation in layer \( i \), and is defined as \( f_i(x) = \sigma(W_i x + b_i) \) for \( i = 1, \ldots, n \). Furthermore, to distinguish the pre-trained model from others, we use the apostrophe symbol \( W_n', b_n', F_n', f_n' \) for the pre-trained model from the client in the same way as mentioned above.

B. Problem Formulation

The difficulty of the privacy-preserving weight pruning process is the non-availability of the training dataset, without which it is difficult to ensure that the pruned model has the potential for maintaining the accuracy of the pre-trained model.

Fig. 2. (a) Traditional DNN weight pruning process and (b) the proposed framework.
To mitigate this problem, we use randomly generated synthetic data $X$ without any prior knowledge of the confidential training dataset. Then motivated by knowledge distillation [17], we hope to distill the knowledge of the pre-trained model into the pruned model by minimizing the difference between the outputs of the pre-trained model (teacher model) and the outputs of the pruned model (student model), given the same synthetic data as the inputs. Different from the traditional knowledge distillation, which specifies the student model architecture beforehand, our privacy-preserving weight pruning process (i) uses randomly generated synthetic data instead of the training dataset, and (ii) initializes the student model (pruned model) the same as the teacher model (pre-trained model) and then discovers the student model architecture gradually through the weight pruning process.

Therefore, we formulate the privacy-preserving weight pruning problem with:

\[
\begin{align*}
\text{minimize} \quad & ||F_N(X) - F'_N(X)||_F^2, \\
\text{subject to} \quad & W_n \in S_n, \quad n = 1, \cdots, N.
\end{align*}
\]

(2)

The objective function is the difference (measured by Frobenius norm) between the outputs of the pre-trained model $F'_N(X)$ and those of the pruned model $F_N(X)$, given the same synthetic data $X$. Note that we use the soft inference results (i.e., scores or probabilities of a data point belonging to different classes) instead of the hard inference results (i.e., the final class label of a data point) to distill the knowledge from the pre-trained model more precisely. And in the above problem formulation, we use $S_n$ to denote the weight sparsity constraint set for the $n$-th layer. Namely, different weight pruning schemes can be defined through the set $S_n$. More discussions about $S_n$ are provided in Section IV-D.

However, problem (2) uses the whole model inference results. In the case of very deep models, it may have the exploding and vanishing gradient problems. Inspired by the layer-wise knowledge distillation [18], we improve the problem (2) formulation using a layer-wise approach, i.e., the layer-wise inference results:

\[
\begin{align*}
\text{minimize} \quad & ||\sigma(W_nF_{n-1}(X) + b_n) - F'_{n}(X)||_F^2, \\
\text{subject to} \quad & W_n \in S_n.
\end{align*}
\]

(3)

To perform weight pruning on the whole model, problem (3) is solved for layer $n = 1$ to $n = N$. The effectiveness of problem (3) compared with problem (2) is presented in Section IV-D. The formulations of problems (2) and (3) are analogous to the whole model and layer-wise knowledge distillation, respectively.

C. ADMM based Solution

The above-mentioned optimization problems (2) and (3) are both in general difficult to solve due to the nonconvex constraints. To tackle this, we consider to utilize the ADMM optimization framework to decompose the original problem into simpler sub-problems. We provide the detailed solution to problem (3) in this section. A similar solution can be obtained for problem (2) too. We begin by rewriting problem (3) as

\[
\begin{align*}
\text{minimize} \quad & ||\sigma(W_nF_{n-1}(X) + b_n) - F'_{n}(X)||_F^2 + I(Z_n), \\
\text{subject to} \quad & W_n = Z_n,
\end{align*}
\]

(4)

where $Z_n$ is the auxiliary variable, and $I(\cdot)$ is the indicator function of $S_n$, i.e.,

\[
I(W_n) = \begin{cases} 
0 & \text{if } W_n \in S_n, \\
+\infty & \text{otherwise}.
\end{cases}
\]

(5)

The augmented Lagrangian [34] of the optimization problem (4) is given by

\[
\begin{align*}
\mathcal{L}(W_n, b_n, Z_n, U_n) &= \|\sigma(W_nF_{n-1}(X) + b_n) - F'_{n}(X)\|_F^2 \\
&\quad + I(Z_n) + \frac{\rho}{2}\|W_n - Z_n + U_n\|_F^2 + \frac{\rho}{2}\|U_n\|_F^2,
\end{align*}
\]

(6)

where $U_n$ is the dual variable and $\rho$ represents the augmented penalty. The ADMM algorithm proceeds by repeating the following iterative optimization process until convergence. At the $k$-th iteration, the steps are given by

\[
W_n^k, b_n^k := \arg\min_{W_n, b_n} \mathcal{L}(W_n, b_n, Z_n^{k-1}, U_n^{k-1}) \quad \text{(Primal)}
\]

(7)

\[
Z_n^k := \arg\min_{Z_n} \mathcal{L}(W_n^k, b_n^k, Z_n, U_n^{k-1}) \quad \text{(Proximal)}
\]

(8)

\[
U_n^k := U_n^{k-1} + W_n^k - Z_n^k.
\]

(9)

The ADMM steps are equivalent to the following Proposition 1.

**Proposition 1:** The ADMM subproblems (Primal) and (Proximal) can be equivalently transformed into a) Primal-minimization step and b) Proximal-minimization step. More specifically:

**[Primal-minimization step]** The solution $W_n^k, b_n^k$ can be obtained by solving the following simplified problem (Primal):

\[
\begin{align*}
\text{minimize} \quad & ||\sigma(W_nF_{n-1}(X) + b_n) - F'_{n}(X)||_F^2 \\
&\quad + \frac{\rho}{2}\|W_n - Z_n^{k-1} + U_n^{k-1}\|_F^2.
\end{align*}
\]

(10)

The first term in Eqn. (8) is the differential reconstruction error while the second term is quadratic and differentiable. Thus, this subproblem could be solved by stochastic gradient descent (SGD) effectively.

**[Proximal-minimization step]** After obtaining the solution $W_n^k$ of the primal problem at iteration $k$, $Z_n^k$ can be obtained by solving the problem (Proximal):

\[
\begin{align*}
\text{minimize} \quad & I(Z_n) + \frac{\rho}{2}\|W_n^k - Z_n + U_n^k\|_F^2.
\end{align*}
\]

(11)

As $I(\cdot)$ is the indicator function of the constraint set $S_n$, the globally optimal solution of problem (proximal) can be derived as

\[
Z_n^k = \prod_{S_n}(W_n^k + U_n^{k-1}),
\]

(12)

where $\prod_{S_n}(\cdot)$ is the Euclidean projection onto the constraint set $S_n$. 
D. Definitions of $S_n$ for Different Weight Pruning Schemes

This subsection introduces how to leverage the weight sparsity constraint $W_n \in S_n$ to implement various weight pruning schemes. For each weight pruning scheme, we introduce the exact form of $S_n$, and provide the explicit solution to problem (Proximal). To help express the constraints, we first define an indicator function for any matrix $Y$ by

$$g(Y) = \begin{cases} 0 & \text{if } \forall \text{ element } y \in Y, y = 0, \\ 1 & \text{otherwise}. \end{cases} \quad (12)$$

Furthermore, we denote $\alpha$ as the desired remaining weight ratio, defined as the number of remaining weights in the pruned model divided by the total number of weights in the pre-trained model.

1) Irregular pruning: In irregular pruning, the constraint set is represented as Eqn. (13). The solution to problem (Proximal) is to keep the elements with the $[\alpha P_n Q_n]$ largest magnitudes and set the rest to zeros.

$$W_n \in S_n := \{W_n\} \left( \frac{1}{P_n Q_n} \sum_{p=1}^{P_n} \sum_{q=1}^{Q_n} g([W_n]_{p,q}) \right) \leq \alpha \right) \quad \text{(13)}$$

2) Filter pruning: Filter pruning prunes the rows of the GEMM weight matrix, as represented in Eqn. (14). To obtain the solution to problem (Proximal), we first calculate $\hat{O}_p = \|[W_n^p + U_{n-1}^k]_p\|_2^2$ for $p = 1, \ldots, P_n$. Then we keep $[\alpha P_n]$ rows in $[W_n^p + U_{n-1}^k]$, corresponding to the $[\alpha P_n]$ largest values in $\{\hat{O}_p\}_{p=1}$, and set the rest to zeros.

$$W_n \in S_n := \{W_n\} \left( \frac{1}{P_n} \sum_{p=1}^{P_n} g([W_n]_{p,:}) \right) \leq \alpha \right) \quad \text{(14)}$$

3) Column pruning: Column pruning restricts the number of columns in the GEMM weight matrix that contain non-zero weights, as expressed in Eqn. (15). The solution to problem (Proximal) can be obtained by first calculating $O_q = \|[W_n^q + U_{n-1}^k]_q\|_2^2$ for $q = 1, \ldots, Q_n$. Then we keep $[\alpha Q_n]$ columns in $[W_n^q + U_{n-1}^k]$ with the $[\alpha Q_n]$ largest values in $\{O_q\}_{q=1}$, and setting the rest to zeros.

$$W_n \in S_n := \{W_n\} \left( \frac{1}{Q_n} \sum_{q=1}^{Q_n} g([W_n]_{:q}) \right) \leq \alpha \right) \quad \text{(15)}$$

4) Pattern-based pruning: For pattern-based pruning, we focus on $3 \times 3$ kernels, i.e., $C_n = D_n = 3$, since they are widely adopted in various CNN architectures. Pattern-based pruning is composed of kernel pattern pruning and connectivity pruning. Kernel pattern pruning removes weights at intra-kernel level. Each pattern shape reserves four non-zero values in a kernel to match the SIMD (single-instruction multiple-data) architecture of embedded CPU/GPU processors, thereby maximizing hardware throughput. Connectivity pruning removes whole kernels and achieves inter-kernel level pruning, which is a good supplement to kernel pattern pruning for higher compression and acceleration rate. Pattern-based pruning can be achieved by solving the kernel pattern pruning problem and connectivity pruning problem sequentially. For kernel pattern pruning, the constraint set can be represented as

$$W_n \in S_n := \{W_n\} \left( \frac{1}{A_n B_n} \sum_{a=1}^{A_n} \sum_{b=1}^{B_n} g([W_n]_{a,b}) \right) \leq 4, \quad \text{(16)}$$

$$\forall 1 \leq a \leq A_n, \forall 1 \leq b \leq B_n. \quad \text{(17)}$$

Note that $W_n$ is the GEMM matrix representation of $W_n$. The solution to problem (Proximal) can be obtained by reserving four elements with the largest magnitudes in each kernel. After kernel pattern pruning, we can already achieve a $2.25 \times$ compression rate. For further parameter reduction, connectivity pruning is adopted, and the constraint set is defined as

$$W_n \in S_n := \{W_n\} \left( \frac{1}{A_n B_n} \sum_{a=1}^{A_n} \sum_{b=1}^{B_n} g([W_n]_{a,b}) \right) \leq 2.25\alpha. \quad \text{(18)}$$

The solution to the problem (Proximal) is to reserve $2.25\alpha A_n B_n$ kernels with the largest Frobenius norm.

E. Overall Algorithm

The solution of the privacy-preserving weight pruning problem is summarized in Algorithm 1. The system designer starts pruning with the pre-trained model $W'$ from the client. At the beginning of each iteration $k$, a batch of $M$ synthetic data points are generated and used as the training data to prune redundant weights. The pruning is performed layer-by-layer for the whole model. At last, the pruned model $W^K$ and mask function are released to the client for retraining.

V. EXPERIMENTAL RESULTS

In this section, we evaluate the performance of the proposed framework by comparing with state-of-the-art methods. It includes the following aspects: 1) demonstrate the compression rate and accuracy performance of the pruned model by the proposed framework, and compare it with traditional weight pruning methods to show that the proposed framework can
TABLE I

| Network | Pruning Scheme | Method       | CONV Comp. Rate | Base Accuracy | Pruning Accuracy | Accuracy Loss |
|---------|----------------|--------------|----------------|---------------|-----------------|---------------|
| VGG-16  | Irregular      | ADMM         | 16.0×          | 94.1%         | 94.2%           | -0.1%         |
| Filter/  |                | Privacy-Preserving | 6.0×          | 94.1%         | 94.3%           | -0.2%         |
| Channel  |                |              |                |               |                 |               |
| Pattern |                |              |                |               |                 |               |

TABLE II

| Network | Pruning Scheme | Method       | CONV Comp. Rate | Base Accuracy | Pruning Accuracy | Pruning Accuracy |
|---------|----------------|--------------|----------------|---------------|-----------------|-----------------|
| ResNet-18 | Irregular     | N2J learning | 4.64×          | 72.2%         | 72.3%           | 0.0%            |
| Pattern |                | Privacy-Preserving | 8.0×          | 76.0%         | 76.0%           | 0.0%            |
| ResNet-50 | Pattern      | Privacy-Preserving | 8.0×          | 77.8%         | 77.8%           | 0.0%            |
| Pattern |                |              |                |               |                 |                 |
| VGG-16  | Filter        | Privacy-Preserving | 8.0×          | 72.9%         | 72.6%           | 0.3%            |
| Pattern |                |              |                |               |                 |                 |

To show the acceleration performance of the pruned model on mobile devices, we measure the inference speedup on our compiler-assisted mobile acceleration framework and compare it with three state-of-the-art DNN inference acceleration frameworks, i.e., TFLite [35], TVM [36], and MNN [37]. The measurements are conducted on a Samsung Galaxy S10 cell phone with the latest Qualcomm Snapdragon 855 mobile platform consisting of a Qualcomm Kryo 485 Octacore CPU and a Qualcomm Adreno 640 GPU.

B. Accuracy and Compression Rate Evaluations

1) Evaluation on CIFAR-10 Dataset: We first experiment on CIFAR-10 dataset with VGG-16 and ResNet-18. The results are shown in Table I where base accuracy represents the accuracy of the pre-trained model, and pruning accuracy refers to the accuracy of the pruned model after retraining. Our proposed framework achieves a 16× compression rate with up to 94.2% pruning accuracy for ResNet-18, and a 16× compression rate with up to 91.6% pruning accuracy for VGG-16. Compared with other baseline methods not based on ADMM, the proposed privacy-preserving framework can achieve a higher compression rate and pruning accuracy in most cases. Compared with other ADMM-based methods, such as ADMM† or PCONV [27], our framework can achieve a very similar compression rate and pruning accuracy without any access to the original dataset, thus preserving data privacy.

2) Evaluation on CIFAR-100 Dataset: With satisfying compression performance and compatibility with hardware implementations, we use pattern pruning scheme to further demonstrate the performance of the proposed framework on CIFAR-100 dataset, as shown in Table II. The proposed framework can obtain a 16× compression rate on ResNet-18 and ResNet-50, and a 12× compression rate on VGG-16, while the top-1 accuracy loss is ~0.1% ~ 1.7%. The baseline methods usually have much lower compression rates (around 4×). We highlight that PRIV not only achieves higher compression rates but also does not rely on any access to the original dataset.

3) Evaluation on ImageNet Dataset: With promising results on CIFAR-10 and CIFAR-100, we further investigate the performance of the proposed framework on ImageNet with ResNet-18. As demonstrated in Table III we achieve a 4× compression rate with 69.3%/89.0% top-1/top-5 accuracy, which are both higher than the Network Slimming [5] and DCP [11]. We could further reach a 6× compression rate with 88.0% top-5 accuracy. Combining all of the results on the

*ADMM* achieve high model compression rate while preserving client’s data privacy; 2) present the inference speedup of the compressed model on mobile devices; 3) show the effectiveness of per-layer pruning method by solving problem [3] compared with pruning the whole model directly by solving problem [4] in terms of maintaining the accuracy.

A. Experiment Setup

In order to evaluate whether the proposed framework can consistently attain efficient pruned models for tasks with different complexities, we test on three representative network structures, i.e., VGG-16, ResNet-18, and ResNet-50, with three major image classification datasets, i.e., CIFAR-10, CIFAR-100, and ImageNet. Here, CIFAR-10, CIFAR-100, and ImageNet are viewed as the client’s confidential datasets. All these pruning processes of the system designer are carried out on GeForce RTX 2080Ti GPUs.

During pruning, we adopt the following parameter settings. We initialize the penalty value \( \rho = 1 \times 10^{-4} \), and increase \( \rho \) by 10 times for every 11 epochs, until \( \rho \) reaches \( 1 \times 10^{-1} \). SGD optimizer is utilized for the optimization steps with a learning rate of \( 1 \times 10^{-3} \). An epoch corresponds to 10 iterations, and each iteration process a batch of data. The batch size \( M \) is set to 32. Each input sample is generated by setting the value of each pixel with a discrete Uniform distribution in the range of 0 to 255. To demonstrate the effectiveness of the privacy-preserving pruning, we also implement the traditional ADMM based pruning algorithm (ADMM†) [9] which requires the original dataset. For the ADMM†, we use the same penalty value and learning rate to achieve a fair comparison. Besides, for each \( \rho \) value, we train 100 epochs for CIFAR-10 and CIFAR-100 with a batch size of 64, and 25 epochs for ImageNet with a batch size of 256 due to the complexity of the original datasets.
C. Performance Evaluation on Mobile Platform

In this part, we demonstrate the evaluation results on a mobile device to show the real-time inference of the pruned model provided by the proposed framework with the help of our compiler-assisted acceleration framework. To guarantee fairness, the same pattern-based sparse models are used for TFLite [35], TVM [36] and MNN [37], and fully optimized configurations of all frameworks are enabled.

For pattern-based models, our compiler-assisted acceleration framework has three pattern-enabled compiler optimizations for each DNN layer: filter kernel reorder, compressed weight storage, and load redundancy elimination. These optimizations are conducted on a layer-wise weight representation incorporating information of layer shape, pattern style, connectivity status, etc. These general optimizations can work for both CPU and GPU code generations.

Fig. 3 shows the mobile CPU/GPU inference time of the model on different platforms. We use two models obtained by the proposed framework, i.e., VGG-16 on CIFAR-100 dataset with a 12× compression rate (in Table II) and ResNet-18 on ImageNet with a 6× compression rate (in Table III), as the testing models. Real-time execution typically requires 30 frames/sec, i.e., 33ms/frame. As observed from Fig. 3, our approach achieves significant acceleration on mobile devices, satisfying the real-time inference requirement. Compared with other frameworks, our compiler-assisted mobile acceleration framework achieves 4.2× to 10.8× speedup over TFLite, 2.3× to 4.6× speedup over TVM and 2.1× to 4.9× speedup over MNN on CPU. On GPU, we achieve 3.3× to 10.1× speedup over TFLite, 2.5× to 5.4× speedup over TVM and 1.4× to 4.9× speedup over MNN. The significant acceleration performance is attributed to specific optimizations for sparse models with compiler’s assistance.

D. Evaluations of Different Problem Formulations

We compare the performance of solving problem (2) with that of solving problem (1). For a fair comparison, we adopt the same batch size of 64 and use the same irregular pruning of VGG-16 on the CIFAR-10 dataset with a 16× compression rate. As shown in Table IV with the per-layer pruning formulation (3), our framework maintains the accuracy (0% accuracy loss) without the knowledge of the original dataset. By contrast, optimizing over the entire model directly with formulation (1) degrades the accuracy by 0.4%. From our empirical studies, even if we increase the number of iterations for the pruning with formulation (1), the accuracy of the pruned model cannot increase. We attribute the difference in the accuracy performance of these two formulations to the additional usage of the inference results of each intermediate layer in the model in problem (1). In terms of run time, solving problem (1) has a longer per iteration run time, which is 4.9× to solving problem (2). This is because, in each iteration, pruning a model with N CONV layers requires solving problem (1) N times. For VGG-16, N = 12. The per iteration run time of problem (1) is not as high as 12× to that of problem (2), since solving problem (1) requires optimizing over the entire set of model weights.

E. Evaluations of the Effectiveness

In this section, we further demonstrate the effectiveness of the proposed framework in terms of the ADMM-based solution framework. We test a greedy pruning method that prunes weights/columns/filters/kernels with small magnitudes in each layer using the same synthetic data to implement the privacy-preserving irregular/column/filter/pattern pruning. The comparisons are conducted on Resnet-18 and VGG-16 with the CIFAR-10 dataset. As can be seen from Table IV our proposed framework outperforms the greedy pruning method in all the cases. The greedy pruning method suffers from severe accuracy degradation, especially on VGG-16. When the training dataset is not available, it is hard for the greedy pruning method to find the pruned model structure that has the potential to maintain the accuracy of the pre-trained model. The results also indicate that finding the pruned model structure without the training dataset is not a trivial task. With the effective ADMM-based solution framework, the proposed framework can maintain high accuracy, which is comparable to the pre-trained model, when the training dataset is absent.
In this paper, we propose a privacy-preserving DNN model compression framework where the system designer implements a pruning scheme on a pre-trained model without the access to the client’s confidential dataset. We formulate the weight pruning without the original dataset as two sets of optimization problems with respect to pruning the whole model or each layer, and solve them successfully with the powerful ADMM optimization framework. Extensive experiments demonstrate that the proposed framework can preserve data privacy, achieve real-time inference, and maintain accuracy on representative large-scale DNNs.

VI. CONCLUSION

In this paper, we propose a privacy-preserving DNN model compression framework where the system designer implements a pruning scheme on a pre-trained model without the access to the client’s confidential dataset. We formulate the weight pruning without the original dataset as two sets of optimization problems with respect to pruning the whole model or each layer, and solve them successfully with the powerful ADMM optimization framework. Extensive experiments demonstrate that the proposed framework can preserve data privacy, achieve real-time inference, and maintain accuracy on representative large-scale DNNs.

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