ESMFL: Efficient and Secure Models for Federated Learning

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Abstract—Deep Neural Networks are widely applied to various domains. However, massive data collection required for deep neural network reveals the potential privacy issues and also consumes large mounts of communication bandwidth. To address this problem, we propose a privacy-preserving method for the federated learning distributed system, operated on Intel Software Guard Extensions, a set of instructions that increases the security of application code and data. Meanwhile, the encrypted models make the transmission overhead larger. Hence, we reduce the commutation cost by sparsification and achieve reasonable accuracy with different model architectures. Experimental results under our privacy-preserving framework show that, for LeNet-5, we obtain 98.78\% accuracy on IID data and 97.60\% accuracy on Non-IID data with 34.85\% communication saving, and 1.8× total elapsed time acceleration. For MobileNetV2, we obtain 85.40\% accuracy on IID data and 81.66\% accuracy on Non-IID data with 15.85\% communication saving, and 1.2× total elapsed time acceleration.

Index Terms—Federated learning, sparse model, communication cost, secure and privacy-preserving

I. INTRODUCTION

Large-scale deep neural networks (DNNs) introduce intensive computation and high memory storage, bringing challenges on current edge devices (clients, e.g., mobile phones) with limited resources \cite{1, 2}. Thus, large-scale DNN models as well as training data usually are stored on centralized cloud server clusters in data center \cite{3, 4}. However, data privacy and security has been increasingly concerned in cloud servers, where the sensitive data are either owned by vendors or customers \cite{3}. Federated learning (FL) has been developed for DNN training without acquiring raw data from the users \cite{4, 5}. It is a distributed machine learning approach which enables training on a large corpus of decentralized data on edge devices (large in number) and only collects the local model or gradient for global synchronization on a central server \cite{6}. Through the local training, FL enhances data privacy.

While the achievements are outstanding, so do the challenges. (i) Edge devices typically have a limited communication bandwidth and computation resources compared to the server. Therefore, training large-scale DNNs will consume a large amount of communication time and resources \cite{7, 8}. (ii) Traditional FL method can not guarantee data privacy. Recent research \cite{9, 10} shows that the publicly shared gradients in training process can reveal private information to either a third-party, or a central server.

To make the communication from the edge devices to the central server efficient, model compression techniques such as weight pruning \cite{8} and weight quantization \cite{11} have been introduced into FL, to reduce the number of parameters or bit-representation communicated at each round. To enhance the privacy of FL, current works typically use the classical cryptographic protocols such as differential privacy, i.e., randomly perturbing the intermediate results (adding noise) at each iteration \cite{12, 13}. The noise will introduce perturbation on the FL model, leading to accuracy degradation in overall accuracy. To make it worse, adding noise makes a sparse model to a dense model, and it is not compatible with weight pruning techniques.

On the other hand, a standard implementation of the federated learning system requires that multiple clients train full models with their own data, then the server aggregates the model parameters in each round. However, most high-speed Internet connections, including cable, digital subscriber line (DSL) and fiber, are asymmetric. Due to higher downstream demand, high speed Internet providers have designed their systems to provide much better speed for downloading than uploading. Therefore, for transmitting large models, the bottleneck of FL communication cost is mainly restricted by the uploading.

To overcome these challenges, it is important to enhance the performance of FL under the secured model training. We investigate privacy-preserving methods which can preserve the overall accuracy, reduce the communication cost and accelerate overall elapsed time. In this paper, we propose a framework, ESMFL, operated on Software Guard Extensions (SGX). ESMFL integrates weight pruning with federated learning that can reduce the communication cost efficiently while preserving data privacy. Our main contributions are as follows:

\begin{itemize}
  \item We propose a systematic method to set the regularization penalty coefficient that enables parameter regularization and accelerates sparse model training by incorporating ADMM-based pruning algorithm.
  \item We enhance the security of the gradient and model in federated learning process by integrating SGX, a set of instructions that increases the security of application code and data, giving them more protection from disclosure or modification.
\end{itemize}
• ESMFL can achieve a higher accuracy with same training rounds compared to prior arts. It continuously reduce the communication cost and reconfigure its architecture into more cost-efficient.

We evaluate our framework on two datasets, MNIST and CIFAR-10 with analysis on model sparsity, communication cost and elapsed time on each modules. For LeNet-5 on MNIST, we obtain 98.78% (98.6%) accuracy on IID data with 9.99 × (87×) model compression rate and 97.60% (94.53%) accuracy on Non-IID data with same model compression rate as IID data. When the model compression rate is 9.99 × (87×), communication is saved by 34.85% (48.78%) and total elapsed time is reduced by 1.8 × (2.4×). For MobileNetV2 on CIFAR-10, we obtain 85.40% (81.23%) accuracy on IID data with 4.95 × (8.7×) model compression rate and 81.66% (80.44%) accuracy on Non-IID data with same model compression rate as IID data. When the model compression rate is 4.95 × (8.7×), communication cost is saved by 15.85% (31.3%) and total elapsed time is reduced by 1.2 × (1.8×).

We enhance the FL system security without adding noise from other methods such as differential privacy. By using ADMM-based weight pruning, we reduce the communication cost compared to original FL while maintaining the overall accuracy. Compared to prior weight pruning methods in FL, we achieve much higher accuracy at same communication round.

The outline of this paper is as follows. Section II introduces federating learning, model compression, gradient compression, software guard extensions and research motivation. Section III describes the proposed efficient and secure federated learning framework, and the result of experiments is presented in Section IV. Section IV also shows comparisons and discusses the results. Section V is the final conclusion.

II. BACKGROUND AND MOTIVATION

A. Federating Learning

With the development of deep learning technologies, FL has attracted lots of attention from both academia and industry. FL differentiates from conventional distributed learning in the data center by bringing the statistical challenges that training models on a set of private unbalanced data and the system challenges that the limited communication is often a bottleneck. [14], [15] introduced Federated Optimization, which is a setting for distributed optimization in machine learning, where the data defining the optimization are distributed (unevenly) over an extremely large number of nodes, but the goal remains to train a high-quality centralized model. In the recent research on the development of resource allocation strategies, reducing communication requirements has become one of the popular topic. [16] proposed Federated Averaging (FedAvg), which trains models using relatively few rounds of communication. Structured updates and sketched updates are mentioned in [17], which reduce uplink communication cost in FL. Additionally, the privacy issues are not getting ignored. [13] proposed an algorithm to dynamically adapt the decentralized training, maintaining client-level differential privacy at only a minor cost in model performance.

B. Model Compression

Recently, many methods have been proposed to reduce the model size of deep neural networks. Weight pruning and weight quantization are two major approaches that are studied widely. For weight pruning, [18] adopted an iterative heuristic for DNN weight pruning, achieving 12× in LeNet-5. [17] proposed a dynamic network surgery and remarkably reduced the network complexity by making on-the-fly connection pruning, which the results showed an efficient compress in LeNet-5 by a factor of 108×. [18] introduced a network growth algorithm that complements network pruning to learn both weights and compact DNN architectures during training, obtained 74.3× compression ratio in LeNet-5. Moreover, a systematic DNN weight pruning framework has been proposed in [19] aiming at overcoming the heuristic nature, achieving and 71.2× on LeNet-5 with no accuracy loss. Besides weight pruning, efforts on weight quantization have also been widely devoted, in which the network weights are represented by very small numbers of bits. [20] proposed XNOR-Networks, in which both the filters and the input to convolutional layers are binary. In these works, the storage of DNNs have been greatly reduced with tolerable accuracy loss and even training extremely low bits network from scratch with binary or ternary weights.

C. Gradient Compression

Besides the conventional application for model compression techniques, the utilization of these techniques on distributed learning has attracted a lot of attention. In order to reduce the communication workload in distributed learning, one major way is to send only important gradients for aggregation. [21] proposed Deep Gradient Compression (DGC) to greatly reduce the communication bandwidth, achieving cutting the gradient size of ResNet-50 from 97MB to 0.35MB, and for DeepSpeech from 488MB to 0.74MB. Similar to weight quantization, gradient quantization has been widely studied. [22] developed 1-Bit Stochastic Gradient Descent to accelerate distributed training and achieved good performance in speech applications. [23] proposed stochastic rotated quantization of gradients, which reduced gradient precision to 4 bits for MNIST and CIFAR dataset. Moreover, [24] proposed TernGrad, which uses ternary gradients to accelerate distributed deep learning in data parallelism.

D. Software Guard Extensions

SGX [25], [26] are a set of CPU instructions and mechanisms for memory accesses added processors which enable trusted and isolated execution of selected sections of application code. SGX allow an application to instantiate a protected container, namely called enclave, which is a protected area in the applications address space that provides confidentiality and integrity. SGX implements isolation by storing enclave area code and data in a data structure called Enclave Page Cache (EPC), which is located in a pre-configured section.
of DRAM called Processor Reserved Memory (PRM). Any software outside the enclave cannot access the PRM, however code inside an enclave can access both non-PRM memory and PRM memory that belongs to the enclave. In addition to isolation, enclaves also support sealing and remote attestation. Sealing allows the enclave to securely retain and retrieve secrets on the local host. Remote attestation allows a remote challenger to establish trust in an enclave.

E. Research Motivation

According to the previous work and research, we conclude the following insights: (i) standard implementation of the federated learning system is still vulnerable and the encrypted model training will increase overall computation and data communication; (ii) current privacy-preserving methods will add noise to model, which is not suitable with weight pruning techniques. To overcome these weaknesses, the FL system should enhance security without adding noise and reduce the communication cost with reasonable overall accuracy. This work specifically focuses on the efficient FL system with privacy-preserving.

III. ESMFL FRAMEWORK

ESMFL employs one untrusted Cryptographic Service Provider (CSP) that runs the SGX and a group of clients who conduct local training and submit local updates. The CSP initializes and manages the cryptographic primitives, and aggregate model updates each round within Enclave space.

A. Modules in ESMFL

The following contents describe the detailed modules of each participant.

1) Cryptographic Service Provider (CSP): The Key Manager module locates within enclave space. Key Manager initializes the symmetric encryption key for each client via remote attestation [27] and stores them to decrypt encrypted updates in each training round.

The CSP is the only entity capable of aggregate model submitted by each client. The Model Aggregation module is tasked with decryption and handling all updates within the trusted space (SGX Enclave), and publish new models according to the aggregated updates.

2) Client: The Local Trainer trains the model based on the private data owned by the client. During the local training, the model compression algorithms are applied to Local Trainer to obtain a sparse model after the training process is done.

The Data Encryption module stores the update encryption key of client which is negotiated with the CSP via remote attestation. Each client encrypt their local updates in each round using the encryption key and sends the encrypted update to the CSP via a secure channel.

B. ESMFL Workflow

Figure 1 shows the overall workflow of our ESMFL system. At the very outset, the CSP initializes a trusted execution space (i.e., Intel SGX Enclave) and waits for attestation requests. Clients who wish to contribute to the federated training process (denoted as \( C_i \)) then make a remote attestation request to CSP. If a valid attestation is provided by CSP, the client negotiates a symmetric encryption key \( sk_i \). After all clients complete the remote attestation process, CSP initialize a weight matrix with random entries and broadcast all clients. Clients download the global initial model then apply several epochs of training using local data and obtain a local model (we use \( \Delta_i \) to denote the update for client \( C_i \)) for current training epoch. The clients then encrypt their update, \( \Delta_i \), in the binary format with key \( sk_i \) and send the encrypted update (denoted as \( \hat{\Delta}_i \)) to CSP. Each client encrypts their update, \( \Delta_i \), in the binary format with key \( sk_i \) and send the encrypted update (denoted as \( \hat{\Delta}_i \)) to CSP, which load them into the attested enclave. Next, CSP decrypts \( \Delta_i \) using corresponding \( sk_i \) stored in the Key Manager. CSP keep collecting updates from all clients, decrypt and aggregate them to a single one, which uses federated averaging method to obtain the updated model. CSP then publish the updated model to clients and clients repeat the local training process. The training terminates when certain condition hits. According to such workflow, the local update \( \Delta_i \) of each client \( C_i \) in each epoch is only observable to the client itself and the attested enclave on CSP. Therefore for any computational bounded adversary, there is no possibility to investigate the \( \Delta_i \) of \( C_i \).

C. Weight Pruning in Clients

As the baseline in model sparsity analysis, we compress the local updates to be a sparse matrix. We call this method federated average masked pruning. We prune the weights before sending to CSP based on the magnitude, i.e., setting a mask to map the lowest percent portion of weights to zeros. It is important to stress that we train the updates of this structure in each round and each client independently. We set thresholds in each layer in neural networks, and achieve a certain overall compression rate according to the neural network architecture.

Posing a direct mask to the client updates is lack of the regularization of structure, which cannot be efficiently used in each round. Thus, it is hard to achieve extremely high compression rate with reasonable accuracy and fast coverage speed by this way. Considering the performance of weight pruning, we develop a FL framework with the state-of-the-art
Alternating Direction Method of Multipliers (ADMM) based pruning algorithm [19]. The sparse model FL training process can be divided into two phases: warm-up training and weight pruning.

The objective of the warm-up training is to train the model without compression for initial several rounds. Since in the early stages of training, the parameters in neural network are changing rapidly. According to our preliminary experiments, it is better to pruning based on a well-trained model than pruning from scratch and it can achieve a better converge performance than pruning from scratch.

In the second phase, the objective of the local weight pruning is to minimize the loss function while satisfying the constraints of weight sparsity. In the local client, we define the weight pruning in clients problem as:

\[
\begin{align*}
\text{minimize } & \mathcal{L}_i(W_i, b_i), \\
\text{subject to } & W_i \in S_i, i = 1, \ldots, N,
\end{align*}
\]

where \(W_i\) and \(b_i\) denotes the sets of weights and biases of the \(i\)-th (CONV or FC) layer in an \(N\)-layer DNN, respectively. The set \(S_i = \{W_i | \text{card}(W_i) \leq n_i\}\) denotes the constraint for weight pruning, and ‘card’ refers to cardinality. It meets the goal that the number of non-zero elements in \(W_i\) is limited by \(n_i\) in layer \(i\).

In the local weight pruning phase, we add the ADMM-based regularization [19] on all original DNN models. The detail process is shown in Algorithm 1. The regularization is operated by introducing auxiliary variables \(Z_i\)'s, and dual variables \(U_i\)'s. It proceed by step \(s = 0, 1, 2, \ldots\), the following subproblems iterations:

\[
\begin{align*}
W_i^{s+1} & := \arg \min_{W_i} \mathcal{L}_p(W_i, \{Z_i^s\}, \{U_i^s\}), \\
Z_i^{s+1} & := \arg \min_{Z_i} \mathcal{L}_p(W_i^{s+1}, \{Z_i\}, \{U_i^s\}), \\
U_i^{s+1} & := U_i^s + W_i^{s+1} - Z_i^{s+1}.
\end{align*}
\]

In each iteration, while keeping on minimizing network regularized loss, we also reduce the error of Euclidean projection from \(W_i^{k+1} + U_i^k\) onto the set \(S_i\). Because under the constraint that \(\alpha_t\) is the desired number of weights after pruning in the \(i\)-th layer, the Euclidean projection can keep \(\alpha_t\) elements in \(W_i^{k+1} + U_i^k\) with the largest magnitudes and set the remaining weights to zeros. Then the dual variables \(U_i\) is updated as following: \(U_i^{k+1} = U_i^k + W_i^{k+1} - Z_i^{k+1}\). After repeating several steps, we obtain the trained intermediate \(W_i\). Finally, we perform the Euclidean projection to map weights to configured sparsity ratio that at most \(\alpha_t\) weights in each layer are non-zero.

IV. EXPERIMENTS

A. Experimental Setup

We implement the baseline and our proposed framework by PyTorch [29] and simulate multiple clients and a CSP with different FL settings on a server with a 3.1GHz Intel Xeon Scalable Processors (8 virtual CPU with 32 GB memory) and a NVIDIA 2080 GPU (8 GB memory).

Algorithm 1: Local Client Weight pruning based on ADMM

1. Synchronize models from the server;
2. Initialize hyperparameters in a local client;
3. for Current_Epoch < Max_Local_Epoch_for_One_Round_FL do
4.   Solve Subproblem (Eqn. (2));
5.   if Current_Epoch % ADMM Interval_Epoch == 0 then
6.     Solve Subproblem (Eqn. (3));
7.     Dual variable update according to Eqn. (4);
8. end
9. end
10. Map to the configured mask;
11. Upload pruned model to the server;

Datasets and Models: In our experiments, we test LeNet [29] for MNIST dataset, MobileNetV2 [30] for CIFAR-10. To study the federated optimization, we also need to specify how the data is distributed over the clients. We use the similar dataset setting as [7] described. We partition the MNIST dataset in two different ways over clients, namely IID and non-IID. In the MNIST with IID data over clients, the whole data is shuffled, and then divided into 100 clients with 600 examples per client balancedly. In the MNIST with non-IID data over clients, we sort the whole data by label index, then divide it into 200 shards of size 300, and assign each of 100 clients 2 shards. Therefore, most clients will only have examples of two digits. Similarly, we partition the CIFAR-10 dataset into IID and non-IID over clients. In the CIFAR-10 with IID data over clients, the whole data is shuffled, and then divided into 100 clients each receiving 500 examples. These partitions are balanced. In the CIFAR-10 with non-IID data over 100 clients, we sort the whole data by label index, then divide it into 500 shards of size 100, and assign each client with 5 shards. Therefore, each client will have examples no more than five classes.

Learning settings: The FL framework with weight pruning is described in Section III C. It can be fully characterized by following parameters: For the base configuration we set the number of clients to 100, the participation client ratio to 10% (10 random selected clients) in each round, local training epoch to 15 and the local batch size to 10. All hyperparameters will default to this base configuration. The settings for federated learning without compression are summarized in Table I. In the following we will primarily discuss the results for LeNet5 trained on MNIST and MobileNetV2 trained on CIFAR-10.

B. Model Sparsity

We start by investigating the effects of our proposed weight pruning methods on MNIST. In the first experiment, we
Table II

| Network     | Dataset | Params | Accuracy | Data Percentage Non-Zero Weights | Compression Rate | CSP Pruning Round |
|-------------|---------|--------|----------|----------------------------------|-----------------|---------------------|
| LeNet-5     | MNIST   | 430K   | 98.78%   | IID                              | 10.01%           | 9.99                |
| LeNet-5     | MNIST   | 430K   | 98.26%   | IID                              | 1.15%            | 87.0                | 50                  |
| LeNet-5     | MNIST   | 430K   | 97.60%   | non-IID                          | 10.01%           | 9.99                | 50                  |
| MobileNetV2 | CIFAR-10| 2.28M  | 94.53%   | non-IID                          | 1.15%            | 87.0                | 100                 |
| MobileNetV2 | CIFAR-10| 2.28M  | 91.23%   | IID                              | 11.49%           | 8.70                | 100                 |
| MobileNetV2 | CIFAR-10| 2.28M  | 81.66%   | non-IID                          | 20.2%            | 4.95                | 100                 |
| MobileNetV2 | CIFAR-10| 2.28M  | 80.44%   | non-IID                          | 11.49%           | 8.70                | 100                 |

Table III

| Network     | Dataset | Data Communication Volume (Non-Sparse) | Data Communication Volume (Sparse) | Percentage of Communication Cost Saving |
|-------------|---------|----------------------------------------|------------------------------------|-----------------------------------------|
| LeNet-5     | MNIST   | 1720MB                                 | 1120.58MB                          | 34.85%                                  |
| LeNet-5     | MNIST   | 1720MB                                 | 881.02MB                           | 48.78%                                  |
| MobileNetV2 | CIFAR10 | 18.24GB                                | 15.38GB                            | 15.68%                                  |
| MobileNetV2 | CIFAR10 | 18.24GB                                | 12.53GB                            | 31.3%                                   |

Fig. 2. Sparse model federated training process evaluation for LeNet-5 on MNIST with (a) IID and CR=9.99, (b) IID and CR=87, (c) Non-IID and CR=9.99 and (d) Non-IID and CR=87.

Fig. 3. Sparse model federated training process evaluation for MobileNetV2 on CIFAR-10 with (a) IID and CR=4.95, (b) IID and CR=8.7, (c) Non-IID and CR=9.99 and (d) Non-IID and CR=8.7.

divide the MNIST data in IID partition. The performance analysis on the effects of different compression rates on the convergence speed and test accuracy of ESMFL and Federated Averaging masked pruning method can be found in Figure 2.

As mentioned in Section III-C for both our method and the baseline method, we first warm-up train the model in non-sparse way to achieve higher accuracy, then we start pruning process. In Figure 2(a) and Figure 2(b), we can see that when the compression rate is low, our pruning method and masked pruning perform similarly in MNIST dataset. Our method achieves 98.78% accuracy on 89.99% sparsity in 50 FL pruning rounds. However, as we increase the pruning ratio in weight update, our method achieve faster convergence speed and even achieve better accuracy. Our method achieves 98.26% accuracy on 98.85% sparsity in 50 FL pruning rounds, and masked pruning achieves 97.92% in the same sparsity. In Figure 2(c) and Figure 2(d), for the non-IID partition, our method achieves 97.60% accuracy on 89.99% sparsity and 94.53% accuracy on 98.85% sparsity compared with masked pruning with best accuracy, 97.36% and 94.52% on corresponding sparsities.

For the IID partition of the CIFAR-10 data, we choose the MobileNetV2 as our model for comparisons. The MobileNetV2 is a neural network architecture specially designed for mobile devices, therefore it is a good candidate model for FL framework. The FL training process of MobileNetV2 is same as MNIST. As the result shown in Figure 3(a), our method achieves 85.40% accuracy on 79.8% sparsity in 100
FL pruning rounds compared with masked pruning, which results in 80.88% accuracy with the same sparsity. As the result shown in Figure 3(b), our method achieves 81.23% accuracy on 88.51% sparsity in 100 FL pruning rounds and masked pruning achieves 76.12% accuracy in the same sparsity. As the result shown in Figure 3(c) and Figure 3(d) for the non-IID partition, our method achieves 81.16% accuracy on 79.80% sparsity and 75.15% accuracy on 88.51% sparsity compared with masked pruning with best accuracy, 80.44% and 67.38% on corresponding sparsities. Our sparse model test accuracy result and model specifications are summarized in Table II. It is obvious that our method perform better than the baseline in CIFAR-10, since the architecture of MobileNetV2 is more complex and deeper than LetNet-5.

C. Communication Cost and Performance

The data communication volume is the total transmission data volume during the federated training process. Here, we calculate the data communication volume only for weight pruning phase, we encode the model in the compressed sparse row (CSR) format. The communication cost for total 50 rounds on MNIST and total 100 rounds on CIFAR-10 are summarized in Table III. From the table, we can see that it can achieve at least 34.85% (15.68%) communication cost reduction compared with standard non-compressed way on MNIST (CIFAR-10). If we further compress the update in each federated training round, we can achieve 48.88% (31.30%) communication cost reduction on MNIST (CIFAR-10).

To get a better evaluation of the performance of our ESMFL we increase the participating client number to 100 in each round federated training. The breakdown elapsed time evaluations for the performance of each module are summarized in Table IV. We record the following elapsed time in the whole round federated training. The breakdown elapsed time evaluation we increase the participating client number to 100 in each federated training round, we can achieve 48.88% (31.30%) communication cost compared to standard non-compressed way on MNIST and 1.2× (1.8×) with 4.95× (8.7×) compression rate on MNIST and 1.2× (1.8×) with 4.95× (8.7×) compression rate on CIFAR-10 on a federated training round. For small model like LeNet-5 on MNIST, the bottleneck is the local train time, and for larger model like MobileNetV2, reducing the Ecall Time and Ocall Time become more critical to overall performance.

V. CONCLUSION

In this paper, we propose a privacy-preserving method for the federated learning distributed system, which can reduce the commutation cost and achieve a reasonable accuracy with extreme sparse model. Our federated learning system ensure the data privacy without adding noise. We reduce the communication cost compared to unencrypted federated learning system while maintaining the overall accuracy by applying weight pruning. Compared to prior weight pruning methods in federated learning system, our method achieve much higher pruning ratio at the same accuracy level.

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