Hybrid Federated and Centralized Learning
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Abstract—Many of the machine learning (ML) tasks are focused on centralized learning (CL), which requires the transmission of local datasets from the clients to a parameter server (PS), which entails huge communication overhead. To overcome this issue, federated learning (FL) has been a promising tool, wherein the clients send only the model updates to the PS instead of the whole dataset. Thus, FL brings the learning task into the edge level, which demands powerful computational resources from the clients. This requirement may not be satisfied in all ML applications due to diversity of the edge devices in terms of computation power. In this work, we propose a hybrid federated and centralized learning (HFCL) framework to effectively train a learning model by exploiting the computational capability of the clients. In HFCL, only the clients who have sufficient resources employ FL while the ones who do not resort to CL by transmitting their local dataset to the PS. We also propose a sequential data transmission approach with HFCL (HFCL-SDT) to sequentially transmit the datasets in order to reduce the duration of the training. The proposed method is advantageous since all the clients collaborate on the learning process regardless of their computational resources. Via numerical simulations, the proposed HFCL scheme is shown to be superior than FL with a moderate communication overhead between FL and CL.

Index Terms—Machine learning, federated learning, centralized learning, edge intelligence, edge efficiency.

I. INTRODUCTION

MACHINE LEARNING (ML) has been recognized as a promising tool for several emerging technologies, such as internet of things (IoT), autonomous driving and the next generation wireless communications due to its success in image/speech recognition, natural language processing, etc [1]. These applications require huge amount of data to be processed and learned by a learning model, often an artificial neural network (ANN), by extracting the features from the raw data and providing a “meaning” to the input via constructing a model-free data mapping with huge number of learnable parameters [2] [3]. The implementation of these learning models demands powerful computation resources, such as graphics processing units (GPUs). Therefore, huge learning models, massive amount of training data and powerful computation infrastructure are the main driving factors of the success of ML algorithms [4].

Many of the ML tasks are focused on centralized learning (CL) algorithms where a powerful ANN is trained at a parameter server (PS) [1] [5] [6]. While this inherently assumes the availability of data at the PS, in the case of wireless edge devices (clients), transmitting the collected data to the PS in a reliable manner may be too costly in terms of energy and bandwidth, thereby introducing too much delay and infringe the clients’ constraints [7]. For example, in LTE (long term evolution), a single frame of 5 MHz bandwidth and 10 ms duration can carry only 6000 complex symbols [8], whereas the size of the whole dataset can be on the order hundreds of thousands symbols [9]. As a result, CL-based techniques demand huge bandwidth requirements and communication overhead during training.

In order to provide a practically viable alternative to CL-based training, federated learning (FL) has been proposed to exploit the processing capability of the edge devices and the local datasets of the clients [6] [10]. In FL, the clients transmit the model updates (gradients) to the PS instead of their local datasets to collaboratively train the learning model. The collected model updates are aggregated at the PS and then sent back to the clients to further update the learning parameters iteratively. Compared to CL, FL provides less communication overhead with a slight prediction loss due to the insufficient number of gradient components and the corruptions during wireless gradient transmission. Recently, FL has been applied to image classification [7] [10] [11], speech recognition [12] and wireless communications [13] [14]. In addition, various wireless network architectures exploiting FL have been investigated, such as cellular networks [8] [15] [16], vehicular networks [17], unmanned aerial vehicles [18] and IoT networks [19]. In these works, FL architectures rely on the fact that all of the clients are capable of gradient computation, which may require powerful parallel processing units. However, it may not always be possible in practice as considering the diversity of the devices with different computation capabilities, such as mobile phones, vehicular components and IoT devices. This motivates us to develop hybrid learning techniques which benefit from both CL and FL wherein the devices, which are incapable of sufficient computation power, resort to CL whereas the remaining devices employ FL. While there are client selection algorithms [20] [21], these works do not involve a collaboration of all of the devices, instead only the trusted clients [20] or the ones with sufficient computational resources [21] are participated in FL-based training.

In this work, we introduce a hybrid FL and CL (HFCL) framework to effectively train a learning model where the edge devices collaborate on the learning process by exploiting their computation capability. To the best of our knowledge this is the first work to employ a hybrid architecture exploiting the hardware capability of the edge devices. At the beginning of the training, the clients are designated as passive (CL) or active (FL) depending on their computational capability. Then, the active clients transmit the gradient information to the PS based on their local dataset while the passive clients transmit their dataset to the PS, which computes the corresponding gradients data on behalf of them. The computed gradients are utilized and the model parameters are aggregated at the PS and
sent back to the active devices. A challenging issue in HFCL
is that the active clients should wait for the passive clients
at the beginning of the training for the dataset transmission
is completed. In order to mitigate this problem, a sequential
dataset transmission (SDT) approach is proposed where the
passive clients do not send the whole local dataset at once.
Instead, the local dataset is divided into smaller blocks so that
both active/passive devices make gradient/data transmission at
the same communication rounds. We evaluate the performance of
the proposed approaches on MNIST dataset [22] and show
that both techniques provide higher learning performance than
FL while introducing slight increase in the communication
overhead due to dataset transmission which is still less than
that of CL.

II. PRELIMINARIES:
CENTRALIZED AND FEDERATED LEARNING

We focus a scenario, wherein \( K \) edge devices collaborate
on solving an optimization problem in ML. Let \( D_k \) be the
local dataset of the \( k \)th client, the whole dataset is given by
\( D = \bigcup_{k \in K} D_k \), where \( K = \{1, \ldots, K\} \). Then, the CL-based
training considers a learning model trained by optimizing the
learnable parameters \( \theta \in \mathbb{R}^P \) via

\[
\begin{align*}
\text{minimize} \quad & \mathcal{F}(\theta) = \frac{1}{|D|} \sum_{i=1}^{|D|} \mathcal{J}(f(\chi_i|\theta), \gamma_i), \\
\text{subject to:} \quad & f(\chi_i|\theta) = \gamma_i, \quad i = 1, \ldots, |D|.
\end{align*}
\]

where \( \chi_i \) and \( \gamma_i \) respectively denote the input and output
tuple of the \( i \)th sample of the dataset \( D \) as \( D_i = (\chi_i, \gamma_i) \)
and \( |D| \) is the number of input-output pairs. The non-
linear mapping between the input and output is constructed via
\( f(\chi_i|\theta) \) by minimizing the empirical loss \( \mathcal{F}(\theta) \) over
the learnable parameters \( \theta \) with the loss function \( \mathcal{J}(\cdot) \) defined by
the learning model as

\[
\mathcal{J}(f(\chi_i|\theta), \gamma_i) = \| f(\chi_i|\theta) - \gamma_i \|_F^2,
\]

which is the mean-squared-error (MSE) between the label \( \gamma_i \)
and the prediction of the learning model, i.e., \( f(\chi_i|\theta) \) for
the whole dataset.

In CL, (1) is solved at a PS, which collects the local datasets
\( D_k, k \in K \) from the clients. On the other hand, FL does not
involve the transmission of datasets which are kept at the
clients, instead only the model updates (gradients) are sent
to the PS. Consequently, the following optimization problem
is considered in FL, i.e.,

\[
\begin{align*}
\text{minimize} \quad & \frac{1}{K} \sum_{k=1}^K \mathcal{F}_k(\theta), \\
\text{subject to:} \quad & \mathcal{F}_k(\theta) = \frac{1}{|D_k|} \sum_{i=1}^{|D_k|} \mathcal{J}(f(\chi_i^{(k)}|\theta), \gamma_i^{(k)}), \\
& f(\chi_i^{(k)}|\theta) = \gamma_i^{(k)}, \quad i = 1, \ldots, |D_k|, \quad k \in K,
\end{align*}
\]

for which the learning model is trained over the local datasets
\( D_k \) with input-output pair \( (\chi_i^{(k)}, \gamma_i^{(k)}) \) and \( |D_k| = |D_k| \).

III. HYBRID FEDERATED AND CENTRALIZED LEARNING

In order to train the learning model, the minimization of
\( \mathcal{F}(\theta) \) is carried out through iterative gradient descent (GD) as

\[
\theta_{t+1} = \theta_t - \eta_t \nabla \mathcal{F}(\theta_t),
\]

where \( \theta_t \) denotes the model parameters at the \( t \)th communi-
cation round/iteration, \( t = 1, \ldots, T, \eta_t \) is the learning rate
and

\[
\nabla \mathcal{F}(\theta_t) = \frac{1}{|D|} \sum_{i=1}^{|D|} \nabla \mathcal{F}(f(\chi_i|\theta_t), \gamma_i),
\]

denotes the full or batch gradient vector in \( \mathbb{R}^P \). For large
datasets, it is computationally inefficient to implement GD,
which motivates the use of stochastic GD (SGD), where \( \theta \)
is partitioned into \( M_B \) mini-batches as \( D = \bigcup_{m \in M_B} D_m, \) for
\( M_B = \{1, \ldots, M_B\} \) [23]. Then, \( \theta_t \) is updated by

\[
\theta_{t+1} = \theta_t - \eta_t \nabla \mathcal{F}(\theta_t),
\]

where \( \nabla \mathcal{F}(\theta_t) = \frac{1}{M_B} \sum_{m=1}^{M_B} \nabla \mathcal{F}(\theta_t) \) includes the contribu-
tion of gradients computed over \( \{D_m\}_{m \in M_B} \) as

\[
\theta_{t+1} = \theta_t - \eta_t \nabla \mathcal{F}(\theta_t),
\]

where \( \{X_{m,i}, Y_{m,i}\} \) denotes the \( m \)th input-output pair for the
\( m \)th mini-batch and \( D_m = |D_m| \) is the mini-batch size.

The gradient term \( \nabla \mathcal{F}(\theta_t) \) satisfies \( \mathbb{E}[\nabla \mathcal{F}(\theta_t)] = \nabla \mathcal{F}(\theta_t) \), therefore, SGD provides the minimization of
the empirical loss by partitioning the dataset into \( M_B \) mini-
batches and accelerates the learning process, which is known as
mini-batch learning [23]. Employing SGD in parallel among several
devices allows us to compute the gradients on devices
and aggregate them in the PS, which is known as FL [7]. How-
ever, FL-based training demands huge computational power
to compute the gradient information, which cannot always be
satisfied by the computational capability of the client devices.
Thus, in the proposed HFCL approach, only a portion of the
clients perform FL while the remaining clients, which suffer
from computational capability, transmit their datasets to the PS
for gradient computation. By exploiting the computational
resources of the clients in the hybrid architecture, we rewrite
(4) explicitly as

\[
\theta_{t+1} = \theta_t - \eta_t \left( \frac{1}{K} \sum_{k \in L} g_k(\theta_t) + \frac{1}{K} \sum_{k \in \bar{L}} \frac{1}{|D_k|} \sum_{m=1}^{|D_k|} g_k(\theta_t) \right),
\]

where \( L = \{1, \ldots, L\} \) and \( \bar{L} = K \setminus L = \{L + 1, \ldots, K\} \)
denote the set of client indices which employ gradient com-
putation on PS and device, respectively. We further call the
clients in \( L \) and \( \bar{L} \) as passive and active clients, respectively,
where the gradient-transmitting clients are defined as active.
The computation of \( g_k \in L(\theta_t) \) is done via mini-batch learning
as \( g_k \in L(\theta_t) = \frac{1}{|D_k|} \sum_{m=1}^{|D_k|} g_{k,m} \in \mathcal{L}(\theta_t) \) where \( g_{m,k} \in \mathcal{L}(\theta_t) = \nabla \mathcal{F}(f(\chi_{m,i}^{(k)}|\theta_t), \gamma_{m,i}^{(k)})) \) since the PS has access to the dataset
where $Q_B(\cdot)$ represents the quantization operator with $B$ bits and $w_{k\in\mathcal{L},t} \in \mathbb{R}^P$ denotes the noise term added onto $Q_B(g_{k\in\mathcal{L}}(\theta_i))$ at the $t$th iteration. Without loss of generality, we assume that $w_{k\in\mathcal{L},t}$ obeys normal distribution, i.e., $w_{k\in\mathcal{L},t} \sim N(0, \sigma^2_{\theta}I_P)$, for $I_P$ being a $P \times P$ identity matrix with variance $\sigma^2_{\theta}$ and the signal-to-noise-ratio (SNR) in gradient transmission is given by $\text{SNR}_\theta = 20 \log_{10} \frac{|g_{k\in\mathcal{L}}(\theta_i)|^2}{\sigma^2_{\theta}}$.

The communication overhead of HFCL is given by $\bar{T}_{HFCL}$, for which the size of the training dataset for $g_{k\in\mathcal{L}}(\theta_i)$ becomes larger as $t \to N$ and fixed for $t > N$ while the size of the transmitted dataset is fixed as $P$. This is done by storing the collected blocks of the dataset at the PS for $t \leq N$. Consequently, HFCL mitigates the delay due to data transmission of the passive clients while exhibiting the same communication overhead as HFCL. Furthermore, HFCL performs better than HFCL since it quickly learns the features in the data at the beginning of the training due to the use of smaller datasets.

### B. Communication Overhead

Communication overhead can be measured by the number of transmitted symbols during model training. Let $D = \sum_k D_k$ be the number of symbols of the whole dataset, then the communication overhead of CL, FL and HFCL are

$$T_{CL} = D,$$

$$T_{FL} = 2TPK,$$

$$T_{HFCL} = LD_{k\in\mathcal{L}} + 2TP(K - L),$$

where $T_{HFCL}$ includes the transmission of dataset of $L$ passive clients and gradients of $K - L$ active clients. Assuming that FL has lower communication overhead than CL [2, 6, 7, 13, 14], then, we have $T_{FL} \leq T_{HFCL} \leq T_{CL}$.
Fig. 2 shows the classification accuracy with respect to number of passive clients, \( L \) when \( B = 5 \) quantization bits are used and \( \text{SNR}_\theta = 20 \) dB. The proposed approaches HFCL and HFCL-SDT perform better than FL for \( 0 < L < K \) since the collected gradients from the active clients are corrupted by wireless channel and quantization whose effects reduce as \( L \to K \). When \( L = 0 \), HFCL and HFCL-SDT are identical to FL since all the clients are active whereas they perform the same as CL if \( L = K = 10 \) since all the clients are passive, i.e., they transmit their datasets to the PS and noise-free gradients can be used for model training. Comparing both proposed approaches yields that HFCL-SDT provides higher accuracy than HFCL for \( 0 < L < K \). The main reason is that HFCL-SDT performs gradient computation on smaller datasets at the beginning of training for \( t < N \), thus, reaching higher accuracy levels quicker than HFCL, which computes the gradient information on whole local dataset of the passive clients for \( t < N \), leading to a slower convergence rate.

In Fig. 3 we present the classification accuracy in terms of the quantization level for \( B \in [1, 8] \) when \( \text{SNR}_\theta = 20 \) dB. We can see that both HFCL approaches perform better than FL and they approach to CL as \( B \) increases due to the improvement in the resolution of the quantization operation.

We further present the classification performance with respect to the noise level on the model parameters, i.e., \( \theta \) and \( g_k(\theta) \). Fig. 4 compares the competing algorithms for \( \text{SNR}_\theta \in [0, 20] \) dB. We can see that at least 10 dB noise level is required for reliable model training for all approaches. While the same amount of noise is also added onto the dataset of passive clients, its influence is more apparent on the gradients since it directly affects the learning performance.

V. CONCLUSIONS

In this work, we introduced a hybrid federated and centralized learning (HFCL) approach for distributed machine learning tasks. The proposed approach is helpful if a part of the edge devices are lack of computational capability for gradient computation during model training. In order to train the learning model collaboratively, only active devices, which have sufficient computational capability, perform gradient computation on their local datasets whereas the remaining passive devices, which have not enough computational power, transmit their local datasets to the PS, in which the gradient computation is performed. The transmission of local datasets may result delays during training of the size of the passive clients are large. This problem is mitigated by HFCL-SDT, wherein better classification accuracy can be achieved due to SDT. As future work, we reserve to study the latency considerations of the HFCL-based training techniques and the application of such approaches for fundamental wireless communications problems, such as channel estimation [14], resource allocation and beamforming [13].
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