Federated Dropout – A Simple Approach for Enabling Federated Learning on Resource Constrained Devices

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Abstract—Federated learning (FL) is a popular framework for training an AI model using distributed mobile data in a wireless network. It features data parallelism by distributing the learning task to multiple edge devices while attempting to preserve their local-data privacy. One main challenge confronting practical FL is that resource constrained devices struggle with the computation intensive task of updating a deep-neural network model. To tackle the challenge, in this paper, a federated dropout (FedDrop) scheme is proposed building on the classic dropout scheme for random model pruning. Specifically, in each iteration of the FL algorithm, several subnets are independently generated from the global model at the server using dropout but with heterogeneous dropout rates (i.e., parameter-pruning probabilities), each of which is adapted to the state of an assigned channel. The subnets are downloaded to associated devices for updating. Thereby, FedDrop reduces both the communication overhead and devices’ computation loads compared with the conventional FL while outperforming the latter in the case of overfitting and also the FL scheme with uniform dropout (i.e., identical subnets).

I. INTRODUCTION

The existence of enormous data at edge devices (e.g., sensors and smartphones) is driving the deployment of machine-learning algorithms at the network edge, called edge learning, to distill the data into intelligence, which supports AI powered applications ranging from virtual reality to eCommerce [1], [2]. The federated learning (FL) is perhaps the most popular framework mainly due to its feature of leveraging mobile data while preserving their privacy [3], [4]. Based on the stochastic gradient descent (SGD) algorithm, FL distributes the task of training an AI model at multiple devices. The algorithm requires devices to periodically upload to a server high-dimensional models (or stochastic gradients) that are computed using local data and used to update the global model after aggregation. To be specific, a typical AI model (e.g., AlexNet or ResNet50) has tens of millions of parameters. As a result, the deployment of FL in a wireless network faces two main challenges: 1) overcoming the communication bottleneck due to finite radio resources, and 2) overcoming the computation bottleneck due to finite computation capacities of devices.

One main research focus in the area of FL is to tackle the communication bottleneck. To improve the communication efficiency, researchers have proposed new communication techniques including over-the-air aggregation [4]–[6], joint computation-and-communication resource management [7]–[10], and high-dimensional source encoding [11]. Most of these techniques do not address the issue of computation bottleneck as they still require devices to update the full models. On the other hand, there exist approaches of coping with the bottleneck including reducing the sizes of data mini-batches, tolerating long learning latency or excluding “stragglers” that are slow in computing. Such approaches attempt to solve the problem at the cost of performance degradation. Recently, researchers have explored a potentially more effective approach of partitioning the model and allocating only a part of the model to each device for updating. The resultant framework, called partitioned edge learning, can overcome the computation bottleneck without incurring any performance loss if the loss function, which is the learning objective, is linearly decomposable (e.g., support vector machine) [12], [13]. However, this property does not hold for the popular deep neural networks (DNNs). Attempts have been made on making DNNs decomposable by introducing auxiliary variables [14]. This technique, however, not only increases the computation complexity but also requires an additional communication round to complete the original single communication round of the conventional FL algorithm without model partitioning.

In this paper, we propose a novel approach of simultaneously tackling both the communication-and-computation ($C^2$) bottlenecks, termed federated dropout (FedDrop), to enable federated learning on resource-constrained devices. The approach is inspired by the well-known dropout technique that was originally developed in computer science for preventing overfitting of a DNN model [15]. To this end, the neurons (together with their connections) in the DNN are randomly dropped during training. Each instance of dropout reduces the model to a reduced-dimension version, called subnet. The model-training process involves updating a random sequence of subnets. Acting as an adaptive regularization mechanism, dropout prevents DNN parameters from excessive co-adapting and as a result avoids model overfitting, thereby improving the performance of different supervised learning tasks, such as vision and speech recognition [15]. While the main purpose of dropout is to solve the overfitting problem, FedDrop is more sophisticated and aims at overcoming the $C^2$ bottlenecks in FL. For the purpose, FedDrop is designed to have three distinctive features:

• Subnet distribution – A server assigns randomly generated subnets to different devices for updating. As devices are now required to train and transmit subnets instead of full models, the $C^2$ bottlenecks are alleviated.

• Subnet aggregation – The server aggregates updated

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subnets for updating the global model.

- $C^2$ awareness – Define the dropout rate of a device as the probability of deactivating a neuron of the model in the generation of the assigned subnet. The dropout rates of the devices are adapted to their $C^2$ states (i.e., communication rate and computation capacity) so as to reduce the learning latency.

Compared with the naive approach of updating a single subnet by all devices in each round, called uniform dropout, FedDrop updates the whole model and thereby achieves better learning performance as observed in experiments (e.g., an accuracy increase of 2.5% under the dropout rate of 0.6 for training the dataset Cifar-10). Specifically, in the proposed FedDrop scheme, the server uses the conventional dropout technique to randomly generate multiple subnets, each of which is assigned to a single device for updating. The dropout rate of each device is adapted to the assigned device's $C^2$ state under a per-round latency constraint for FL with synchronized updating. Let $p_k$ denote the dropout rate of device $k$. For the FedDrop schemes, it can be shown that the $C^2$ loads of each device can be reduced by a ratio of $(1 - p_k)^2$ for device $k$. As shown by experimental results, with dropout rates up to 60%, FedDrop can improve the learning performance in the case of training a large-scale model (with 74,008,736 parameters) on a complex dataset (e.g., Cifar) by avoiding overfitting. In the case of relatively small-scale model (with 17,250 parameters) on a simpler dataset (e.g., MNIST), FedDrop incurs only slight performance degradation (e.g., an accuracy decrease of 0.88% under the dropout rate of 0.3).

II. SYSTEM MODEL

Consider a single-cell FedDrop system, as shown in Fig. 1, where there are one server equipped with an access point and $K$ edge devices targeting cooperatively finishing a FL task with FedDrop. The devices are connected to the server via wireless links. In each training iteration (called one communication round), each device uses an orthogonal bandwidth for downloading and uploading. Frequency non-selective channels are considered. The server works as a coordinator and has the channel state information of all links.

1) FL: In a traditional FL system, the training of a DNN model iterates among three steps: 1) a server broadcasts a global model to all devices; 2) Each device calculates a local update based on its local dataset; 3) the server aggregates all local updates for global updating. In this paper, the scheme of FedDrop is used in FL to reduce the $C^2$ overhead of each device. To this end, new training strategy with additional steps in each round is required, as shown in Fig. 1 where the server randomly generates several subnets using the dropout technique with each being assigned to one device for updating. The design of the FL with FedDrop scheme is elaborated in Section III-A.

2) Dropout: To facilitate the discussion of FedDrop, the original dropout scheme as presented in [15] is introduced as follows. First of all, dropout is only applied to the fully connected layers in a DNN (or a fully connected neural network) since other layers (e.g., convolutional layers) have much fewer parameters. Consider a fully connected layer in a DNN. The output of the $i$-th neuron in the $l$-th layer is denoted as $f_{l,i}(w_{l,i})$ where $f_{l,i}(\cdot)$ is the activation function [e.g., rectified linear unit (ReLU)], and $w_{l,i}$ is the parameter vector. The dropout technique generates a subnet by deactivating each neuron (together with its connections) with a probability of $p_k$ in each round of model training. The probability $p_k$ is called the dropout rate and $(1 - p_k)$ the presence rate. Specifically, with random dropout, an arbitrary neuron, say the $i$-th neuron in the $l$-th layer, can be expressed as a random variable:

$$\hat{f}_{l,i}(w_{l,i}) = m_{l,i}^{(k)} f_{l,i}(w_{l,i}), \quad \forall (l,i),$$  (1)

where $m_{l,i}^{(k)}$ is the dropout mask, defined as

$$m_{l,i}^{(k)} = \begin{cases} 
1, & \text{w.p. } (1 - p_k), \\
1 - p_k, & \text{w.p. } p_k.
\end{cases}$$  (2)
In (2), the scaling factor $1/(1 - p_k)$ guarantees that the expectation of $\hat{f}_{\ell,i}(w_{\ell,i})$ is $f(w_{\ell,i})$. As a result, the expectation of all neurons’ outputs in the subnet is equal to those in the original DNN.

As mentioned, in a subnet generated by dropout, each neuron in the subnet is randomly deactivated with a probability of $p_k$. In this case, the size of the subnet is random and the $C^2$ overhead to train it can not be determined. This further leads to uncertain learning latency. To address issue, an approach of progressive random parametric pruning is adopted for realizing the dropout scheme to generate a subnet with deterministic size, as described below.

- **Step 1**: For an arbitrary fully connected layer in the DNN, randomly select a neuron with a uniform probability and deactivate it.
- **Step 2**: Repeat Step 1 until the dropout rate is satisfied, i.e., exactly $p_k$ of the neurons in the layer are deactivated.

3) **Per-Round Latency**: Consider an arbitrary round and an arbitrary device, say the $k$-th device. It is assigned by the server with a subnet, which is generated using the dropout technique with a dropout rate of $p_k$. Then, the latency for device $k$ to update its subnet in this round includes two parts. One is the communication latency for downloading the subnet and uploading the corresponding updates, given by

$$T_{k}^{\text{com}} = \frac{M_k Q}{B_k R_k^{dl}} + \frac{M_k Q}{B_k R_k^{ul}}, \quad 1 \leq k \leq K,$$

where the first term is the downloading latency, the second term is the uploading latency, $M_k$ is the number of parameters of the subnet and will be analyzed later [see (7)]. $Q$ is the quantization bits used for one parameter, $B_k$ is the bandwidth assigned to device $k$, and $R_k^{dl}$ and $R_k^{ul}$ are the downlink and uplink spectrum efficiencies of device $k$, respectively. The other is the computation latency for local calculation. According to [17], it is given by

$$T_{k}^{\text{cmp}} = \frac{C_k D_k}{f_k}, \quad 1 \leq k \leq K,$$

where $C_k$ is the number of processor operations required for updating the subnet regarding one data sample and will be analyzed later [see (8)]. $D_k$ is the number of samples trained on device $k$, and $f_k$ is the computation speed of device $k$. Overall, the latency of device $k$ in this round is

$$T_k = T_{k}^{\text{com}} + T_{k}^{\text{cmp}}, \quad 1 \leq k \leq K,$$

where $T_{k}^{\text{com}}$ is the communication latency defined in (3) and $T_{k}^{\text{cmp}}$ is the computation latency defined in (4). Finally, due to the synchronized updates property (see e.g., [12]), i.e., the server can not finish one training round before all devices upload their updates, the latency of this round depends on the slowest device:

$$T = \max_k T_k.$$

### III. FEDERATED DROPOUT

#### A. Federated Learning with FedDrop

The scheme of federated learning scheme enhanced by FedDrop is described as follows. The feature of FedDrop is to generate subnets of different sizes for distributed updating at devices such that the sizes are adapted to their $C^2$ capacities. In each training round of FL with FedDrop, the operations are shown in Fig. 1 and are elaborated below.

1) **Subnets generation**: For each device, the server generates a subnet, say $S_k$, for the $k$-th device, with the FedDrop rate defined in (9).

2) **Model downloading**: Each device downloads its assigned subnet from the server.

3) **Local model updating**: All devices update their corresponding local subnets based on their local datasets.

4) **Local model uploading**: Each device uploads its updated local model to the server.

5) **Global model updating**: In the server, for an arbitrary subnet, say $S_k$, a complete DNN, say $N_k$, is first constructed, where the parameters included in $S_k$ are updated and the other parameters use the same values in the last round. Then, the global model is updated by averaging all complete DNNs, say $\{N_k\}$.

#### Remark 1 (FL versus FL with FedDrop)

In FL, a global model is used in each round and broadcast is used for model downloading. In FL with FedDrop, each device can adaptively select a subnet for updating based on its $C^2$ capacities.

### B. Analysis and Optimization of FedDrop

In each training round of the FedDrop scheme, devices are assigned by a server with different subnets generated via different dropout rates. In the sequel, we first analyze the $C^2$ overhead of each device. Then, the adaptive FedDrop rate of each device is designed based on given per-round latency $T$, varying spectrum efficiencies $\{R_k^{dl}, R_k^{ul}\}$, and the allocated bandwidth $\{B_k\}$.

1) **Communication overhead analysis**: Consider an arbitrary device, say the $k$-th. Its communication overhead in each round depends on the number of parameters of its assigned subnet. First, consider any two adjacent fully connected layers in the original DNN, say the $\ell$-th layer with $N_\ell$ neurons and the $(\ell + 1)$-th layer with $N_{\ell+1}$ neurons. The number of parameters to connect these two layers is $N_\ell \times N_{\ell+1}$. Then, the dropout technique is used to randomly generate a subnet for the device with a dropout rate of $p_k$. In the subnet, the numbers of neurons in the two layers can be derived as $(1 - p_k)N_\ell$ and $(1 - p_k)N_{\ell+1}$, respectively. Furthermore, the number of parameters to connect these two layers in the subnet can be derived as $(1 - p_k)^2N_\ell \times N_{\ell+1}$. Next, as the dropout technique is applied in all fully connected layers, it’s easy to derive the number of parameters in the fully connected layers of the subnet as $(1 - p_k)^2M_{\text{full}}$, where $M_{\text{full}}$ is the total number of parameters in these layers. Hence, the total number of parameters in the subnet is given by

$$M_k = M_{\text{conv}} + (1 - p_k)^2M_{\text{full}}, \quad 1 \leq k \leq K,$$

where $M_{\text{conv}}$ and $M_{\text{full}}$ are the numbers of parameters in the convolutional layers and fully connected layers of the original DNN, respectively.
2) Computation overhead analysis: Similarly, consider the $k$-th device, the $\ell$-th and the $(\ell + 1)$-th layers in the original DNN. The computation between these two layers have two phases. One is the forward phase, whose operations contain $N_\ell \times N_{\ell+1}$ multiplications, $(N_\ell - 1) \times N_{\ell+1}$ additions, and $N_{\ell+1}$ activation operations. The other is the backward phase, which calculates the gradients of $N_\ell \times N_{\ell+1}$ parameters. Then, a subnet is randomly generated for the device with a dropout rate of $p_k$. In the forward phase, the numbers of multiplications, additions, and activation operations to update the subnet are $(1 - p_k)^2 N_\ell \times N_{\ell+1}$, $(1 - p_k)N_\ell - 1$ and $(1 - p_k)N_{\ell+1}$, respectively. In the backward phase, the number of gradients to be calculated in the subnet is $(1 - p_k)^2 N_\ell \times N_{\ell+1}$.

Next, for analysis simplicity, we approximate the computation overhead between these two layers in the subnet to be the ratio, say $(1 - p_k)^2$, of that in the original DNN for the following reason: The ratio of additions’ number approaches $(1 - p_k)^2$ and the number of activation operations is far less than that of other operations. Finally, as all fully connected layers are applied with the dropout technique, the total operations to update these layers in the original DNN can be approximated to $(1 - p_k)^2 C_{\text{full}}$ with $C_{\text{full}}$ being the computation overhead to update these layers in the original DNN. Hence, the overall computational overhead can be written as

$$C_k = C_{\text{conv}} + (1 - p_k)^2 C_{\text{full}},$$

where $C_{\text{conv}}$ and $C_{\text{full}}$ are the computational overhead for convolutional layers and fully connected layers to update the original DNN, respectively.

3) Optimization of FedDrop rates: By substituting the $C^2$ overhead in (7) and (8) into the per-round latency in (6), the minimum FedDrop rate of device $k$ can be derived as

$$p_k^{\text{min}} = 1 - \sqrt{\frac{T - T_{\text{conv}}}{T_{\text{full}}}}, \quad 1 \leq k \leq K,$$

where $T_{\text{conv}}$ and $T_{\text{full}}$ are the sum $C^2$ latencies for device $k$ to update all convolutional layers and all fully connected layers in the original DNN, respectively. They are given by

$$T_{\text{conv}} = \frac{M_{\text{conv}}}{B_k} \left( \frac{1}{R_k^d} + \frac{1}{R_k^a} \right) + \frac{C_{\text{conv}} D_k}{f_k},$$

and

$$T_{\text{full}} = \frac{M_{\text{full}}}{B_k} \left( \frac{1}{R_k^d} + \frac{1}{R_k^a} \right) + \frac{C_{\text{full}} D_k}{f_k},$$

where the notations follow that in (3), (4), (7), and (8). One can observe from (9) and (10) that the dropout rate of a device is a monotone decreasing function of the associated communication rate and computation speed.

IV. EXPERIMENTS AND PERFORMANCE ANALYSIS

Consider a single-cell network in a disk with a radius of 0.15 kilometres. There are one server (AP) located at the center and $K = 10$ devices. The devices are uniformly distributed in the cell. The path loss between devices and the AP is 128.1 + 37.6 log $d$ with the distance $d$ in kilometre. Rayleigh fading is assumed. Each device is assumed to have $B = 1$ MHz bandwidth for uploading and downloading. The devices’ computation capacities are uniformly selected from the set $\{0.1, 0.2, \cdots, 1.0\}$ GHz. Two convolutional neural networks (CNNs) are trained using different settings, described as follows.

- **CNNCifar**: There are six convolutional layers and four fully connected layers. A pooling layer is followed after the 2rd, 4th, and 6th convolutional layers. The numbers of parameters in convolutional layers and fully connected layers are 7,776 and 74,000,960, respectively. It is trained on the Cifar-10 dataset with complex features.

- **CNNMnist**: There are two convolutional layers and two fully connected layers. A pooling layer is followed after each convolutional layer. The numbers of parameters in convolutional layers and fully connected layers are 750 and 16,500, respectively. It is trained on the MNIST dataset with simple features.

Besides FedDrop, two benchmarking schemes are considered. The first is the conventional FL without dropout. The other is called uniform dropout, where in each round, one single subnet is generated by the server by dropout and broadcast to all devices for updating. The dropout rate of each device is the same and should be the largest: $p = \max_k p_k^{\text{min}}$, where $p_k^{\text{min}}$ is defined in (9).

1) Learning Performance: The influence of dropout rate on the learning performance, say testing accuracy after convergence, is investigated, as shown in Fig. 2. The two schemes are compared by training the two models mentioned before. For fair comparison and explicitly showing the influence of dropout rate, all devices are set to have the same computation speed and spectrum efficiencies, and are assigned with same bandwidths. The channel is assumed to be static. Hence, all devices have the same dropout rate during the whole learning process. And the $C^2$ overhead of each device to update the fully connected layers in both schemes is reduced to $(1 - p)^2$ with $p$ being the dropout rate.

First, consider the case where the complex model, say CNNCifar, is trained on non independent and identical distributed (IID) local datasets. From Fig. 2, the testing accuracy of both schemes first increases and then decreases, as the dropout rate increases. The reasons are in the following. On the one hand, by applying the dropout technique, both schemes can
enjoy a model diversity to avoid overfitting during training.
On the other hand, high dropout rate is harmful for the model
expression ability. Besides, in Fig. 2 it can be observed that
the FedDrop scheme outperforms the uniform dropout scheme.
The reasons are two-fold. One is that the parameters of the
whole model are updated in the former instead of only a subnet
in the latter. The other is that FedDrop has a greater model
diversity gain by training different subnets in each round.

Then, consider the case for training the simple model, say
CNNMnist, on non-IID local datasets. From Fig. 2 similarly,
the FedDrop scheme outperforms the uniform dropout scheme
for similar reasons with the previous case. Besides, we can
observe that the testing accuracy of both schemes decreases
with increasing dropout rate. That’s because the training is
underfitting, i.e., a simple model is trained on the dataset
with simple features, and the dropout technique degrades the
expression ability of the CNNMnist model. However, the
performance degradation is slight in both schemes, when the
dropout rate is not large, i.e., \( p \leq 0.6 \).

From the experiments above, it can be summarized that
the learning performance can benefit from the dropout
technique when the training is overfitting. Moreover, the FedDrop
scheme can enjoy a better model diversity than the uniform
dropout scheme and thus has a better performance.

2) \( C^2 \) Overhead Comparison: To compare the \( C^2 \) overhead
of the two schemes in a more general case, the learning
performance of training the CNNMnist model is compared
when using the same \( C^2 \) resources. The schemes are compared
for training the model, say CNNMnist, on the non-IID local
datasets under the same per-round latency \( T \), as shown in
Fig. 3 First of all, FedDrop always outperforms uniform
dropout, demonstrating the effectiveness of the former design.
Moreover, allowing longer per-round latency improves the
two schemes with dropout. With lower latency, the performance
gap between the two schemes becomes larger. On the other
hand, one can observe that in this case without the issue of
overfitting, the \( C^2 \) overhead reduction of FedDropout and
uniform dropout is at the cost of some performance loss w.r.t.
to FL without dropout.

V. CONCLUDING REMARKS

In this paper, an efficient FL algorithm is proposed that
intelligently integrates the dropout technique to alleviate the
resource constraints of edge devices. The resultant FedDrop
scheme reduces the \( C^2 \) overhead and also acquires the ability of
coping with model overfitting. This work opens several
research directions. One is to quantify the tradeoff between
training latency and testing accuracy by adjusting the dropout
rate. Another is to jointly design the radio resource manage-
ment and load balancing in FedDrop systems.

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