

Adaptive Dynamic Pruning for Non-IID Federated Learning

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Abstract

Federated Learning (FL) has emerged as a new paradigm of training machine learning models without sacrificing data security and privacy. Learning models at edge devices such as cell phones is one of the most common use case of FL. However, the limited computing power and energy constraints of edge devices hinder the adoption of FL for both model training and deployment, especially for the resource-hungry Deep Neural Networks (DNNs). To this end, many model compression methods have been proposed and network pruning is among the most well-known. However, a pruning policy for a given model is highly dataset-dependent, which is not suitable for non-Independent and Identically Distributed (Non-IID) FL edge devices. In this paper, we present an adaptive pruning scheme for edge devices in an FL system, which applies dataset-aware dynamic pruning for inference acceleration on Non-IID datasets. Our evaluation shows that the proposed method accelerates inference by $2\times$ (50% FLOPs reduction) while maintaining the model’s quality on edge devices.

1. Introduction

Federated learning (FL) approach is developed as a decentralized machine learning approach to cope with not only the privacy issue but also the large size of data at the at a single central location (McMahan et al., 2017). Efficiently deploying machine learning models to limited resource edge devices (e.g., mobile-phone, self-driving car) is one of the critical issues of FL. Machine learning models’ increasing memory and computing power requirements (such as deep neural networks) make their deployment on edge devices a grand challenge.

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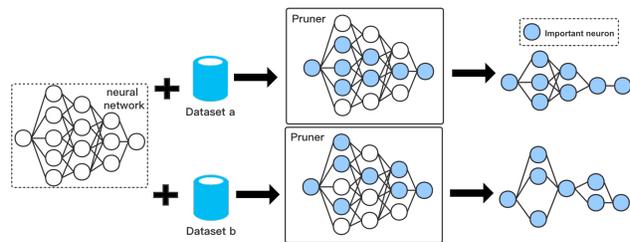


Figure 1. An example of traditional pruning policy under Non-IID datasets. The neurons in the neural network react different for the two datasets lead to different structure of pruned neural networks.

Traditional model compression methods, such as network pruning (Jiang et al., 2019), can reduce the computing pressure and accelerate the inference on the edge devices. However, the pruning policy is highly dataset-dependent, which is not well suitable for federated learning scenarios, where the edge devices’ local dataset on FL scenarios is inherently non-independent and identically distributed (Non-IID).

The key idea of network pruning is to permanently remove deep neural networks’ (DNNs) redundant weights by evaluating the saliency of neurons for the input data (Gao et al., 2019). Figure 1 shows an example of network pruning policies on different datasets. For different input data, the neurons react differently, and a pruning policy under a given dataset transferred to another dataset might lead a poor performance. Notably, for the edge devices with Non-IID datasets, a universal pruning policy for all edge devices might cause a poor result in some devices. Additionally, if we apply different pruning policies for each Non-IID device, it will lead to model structure mismatch when we aggregate the local model to the data center. Moreover, there is a fine-tuning process after pruning to compensate for the accuracy loss, which creates an extra challenge for federated learning.

To overcome the above limitations, in this paper, we design a adaptive federated learning pruning scheme (FLP for short) to reduce the computing pressure and accelerate the inference on the edge devices. The FLP applies the local dataset-aware dynamic pruning (Li et al., 2021a) on FL edge devices. Instead of permanently removing some parameters of neural networks (NNs), for each edge device, we accelerate the model by only selecting a partial neural net-

work (e.g., a subset of channels) predicted to be significant at run-time to compute. The subnetwork selection is made by dynamic pruning gates, which train simultaneously with the neural network. So we do not need a post-fine-tuning or retraining after pruning is finished. To our best knowledge, we are the first to apply the dataset-aware dynamic pruning on Non-IID federated learning scenarios. The experiment demonstrates that the FLP can significantly accelerate the inference on edge devices and with no extra communication cost.

In essence, this paper makes the following contributions:

- A adaptive network pruning method for Non-IID edge devices with no additional communication cost.
- Fairness-aware pruning policy for each edge device on federated learning network.
- To the best of our knowledge, this work is the first one addressing network pruning on the heterogeneity problem in federated learning by accelerating inference on each edge device.

2. Related work

2.1. Federated learning

Federated learning is a decentralized machine learning approach by communication with the model parameters by leaving the training data on each client’s devices in order to keep the clients’ privacy (Lim et al., 2020). General Federated learning involves two entities, the server and the clients (edges), and consists of three phases such as downstream, upstream, and edge computation (McMahan et al., 2017). The downstream means transmitting the initialized model from the server to clients and then training the model on each local data in the edge computation phase. After that, the clients have the upstream phase uploading the weights (parameters) trained on each client to the server and aggregate the local models. The key idea is to train the model on each local device, which results in the computation and storage limitation on the edges’ device. The compression scheme is one of the directions in order to improve communication efficiency. Konečný et al. (Konečný et al., 2016) proposed structure updates and sketched updates in the client upstream phase by enforcing the size of update parameters and sub-sampling the update using quantization and random rotations, respectively. Caldas et al. (Caldas et al., 2018) suggested adopting the lossy compression on downstream phase from server to clients and dropout on upstream phase and local round in order to decrease the communication cost.

Reducing the computation on clients’ devices is also related to achieving the efficient strategy of Federated learning (Li

et al., 2020b). Moreover, theoretical schemes, following Independent and Identical Distributed (IID) data, could not be applied in a practical environment (Lim et al., 2020). Therefore, the Non-IID issue is also one of the challenges in federated learning because data on each device is following different distribution. McMahan et al. (McMahan et al., 2017) proposed Federated Averaging algorithm (*FedAvg*) to resolve the Non-IID issue by iterative model averaging with local stochastic gradient descent (SGD) on each local client’s data. Moreover, they demonstrated the robustness of *FedAvg* to train convolutional neural networks (CNNs) on benchmark image classification datasets (e.g., MNIST (LeCun et al., 1998) and CIFAR-10 (Krizhevsky & Hinton, 2009)).

To improve Federated learning with model compression from Non-IID distribution, Sattler et al. (Sattler et al., 2019) proposed the communication efficient federated learning with Non-IID data distribution with compressing the model on both phases, upstream and downstream, using k-sparsification. Xu et al. (Xu et al., 2021) suggested accelerating the Federated learning model with three stages: pruning, quantization, and selective updating. However, the pruning is to adopt structured pruning as a static pruning model. This limits the flexibility of the Non-IID issue because the structured pruning reduces the model size without considering the current input. Jiang et al. (Jiang et al., 2019) proposed PruneFL that employs adaptive and distributed pruning for efficient federated learning on edge devices, which leads to continuously tracking the parameters according to the model size and automatically adapting the model size. This means PruneFL is a feasible result for Non-IID by maintaining the connection and the model’s parameters.

This paper focuses on pruning for efficient federated learning with Non-IID distribution with CIFAR-10 dataset (Krizhevsky & Hinton, 2009).

2.2. Model compression

Model compression such as network pruning (Li et al., 2020a; Ye et al., 2020; Yu et al., 2021; 2020), knowledge distillation (Chen et al., 2017), and network quantization (Polino et al., 2018) focus on efficient deployment of DNNs on edge devices. Within the scope of this paper, we mainly discuss network pruning. Network pruning can be categorised to static pruning (Chin et al., 2020; Guo et al., 2020; Li et al., 2020a) and dynamic pruning (Li et al., 2021a; Gao et al., 2019). Static pruning evaluates model parameters’ importance and removes those with a lower rank permanently. The static pruning can reduce the model size but will permanently lose pruned parameter’s information. Otherwise, the static pruning policy is highly input-dependent, a universal pruning policy for Non-IID edge devices is not practical. The dynamic pruning, instead

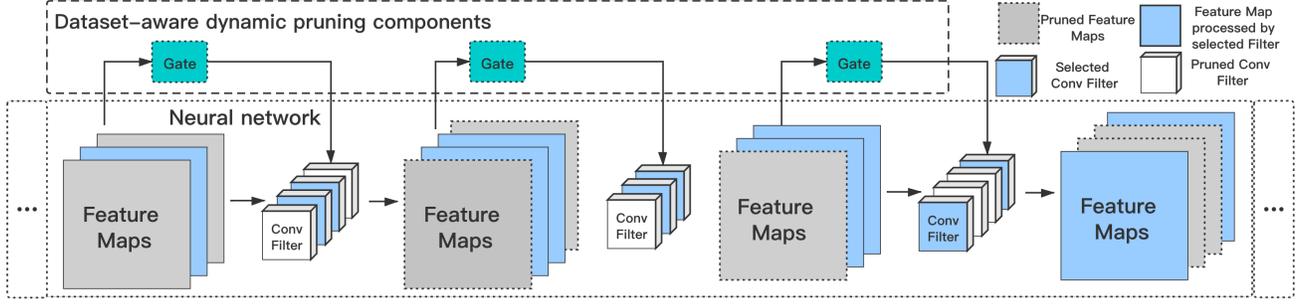


Figure 2. Dynamic pruning on CNN model.

of simply reducing model size at the cost of accuracy with pruning, accelerate convolution by selectively computing only a subset of channels predicted to be important at runtime while considering the sparse input from the preceding convolution layer. In addition to saving computational resources, a dynamic model preserves all neurons of the full model, which minimizes the impact on task accuracy. However, only dynamic pruning fails to shrink the model size and will not improve the communication efficiency.

3. Approach

This section explains our approach by performing channel pruning on convolutional neural networks (CNNs). However, our method is not limited to CNNs and can be easily extended to sequence models and other popular machine learning models. Figure 3 illustrates the high-level overview of FLP. To prune the CNN model on Non-IID edge devices, we first deploy a dataset-aware local dynamic pruning component on each edge device. The dynamic pruning component is constituted by several channel selection gates, as shown in Figure 2, which select a partial neural network predicted to be important at run-time to compute. The channel selection gate is a linear layer with negligible computation. When we train the neural network, for instance, the *FedAvg* (McMahan et al., 2017), we train the dynamic pruning component simultaneously with the neural network. However, we only send the neural network’s parameter to data cent for aggregation, the dynamic pruning component will store locally, so it will not add extra communication cost. After training, the local dynamic components will predict a customize pruning policy for each Non-IID device, and avoid the high bias of a universal pruning policy on the Non-IID situation.

3.1. Dynamic pruning

Straightforwardly, as depicted in Figure 2, here we perform pruning on CNNs. To prune a neural network, we introduced a dynamic pruning gate for each hidden layer. The gate will take the feature maps (previous layer’s output) as input,

predict which channels (Conv Filter) are important in the current layer, and select them for calculation.

Formally, we formulate a l -hidden-layer neural network as:

$$F(x) = f_l(f_{l-1}(\dots f_1(x_0)\dots)) \quad (1)$$

, where the x_i is the feature map in i -th layer, $F(x)$ is the forward propagate function of the neural network, and the f_k is the k -th hidden layer, which projects the feature maps from $(k - 1)$ -th layer to k -th layer. In the CNN model, the

$$f_k(x_{k-1}) = \text{ReLu}(\text{norm}(\text{Conv}_k(x_{k-1}, \theta_k))) \quad (2)$$

, where the $\theta_k \in \mathbb{R}^{C_{out} \times C_{in} \times K \times K}$ is the learnable parameter, C_{out} and C_{in} is the output and input channel, K is the kernel size, Conv_k is the convolutional operation, norm is the normalization, and ReLu is the activation function.

In CNNs, the convolutional operation consumes most of the computation resources. One efficient way to reduce the computation cost is to lessen the channels. So, we introduced a dynamic pruning gate for each convolutional layer to select high response channels according to the input data. For example, in k -th hidden layer, the gate convolutional layer is defined as equation 3 and 4.

$$\hat{\theta}_k = \theta_k[\text{Gate}_k(x_{k-1}), \text{Gate}_{k-1}(x_{k-2}), :, :] \quad (3)$$

$$\hat{f}_k(x_{k-1}) = \text{ReLu}(\text{norm}(\text{Conv}_k(x_{k-1}, \hat{\theta}_k))) \quad (4)$$

The $\text{Gate}_k(x_{k-1})$ predict the important channels and produces the channel index tensor with shape $\mathbb{R}^{\hat{C}_{out} \times 1}$, where the \hat{C}_{out} is number of channels predicted to be important for k -th convolution layers. In the gate convolutional layer, we have the selected parameter $\hat{\theta}_k$ with size $\mathbb{R}^{\hat{C}_{out} \times \hat{C}_{in} \times K \times K}$.

In the gate convolutional layers, we apply the matrix slicing operation to choose the important channels. Instead of permanently delete the unimportant channels like the traditional pruning policy, those not selected channels are ready to be re-activated when they have a high response for the input data.

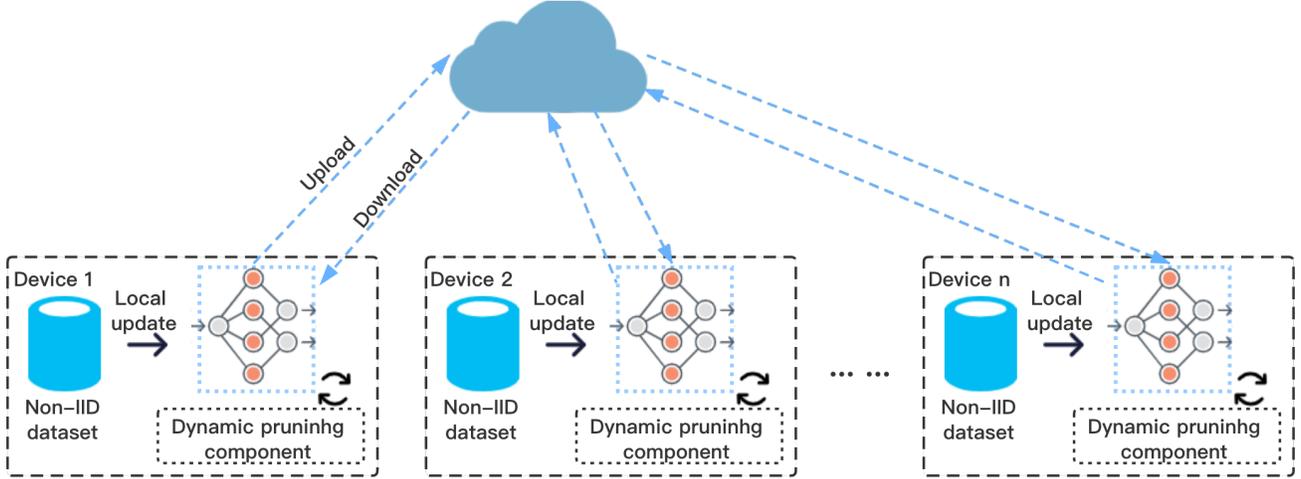


Figure 3. Overview of FLP. The dynamic pruning component and the neural network trains simultaneously when local updating. When communicating, we only transmit the neural network’s parameter.

3.2. Dynamic pruning Gate

The dynamic pruning gate takes the current layer’s feature map as input and predicts the important channels (convolutional filters) to be selected. Essentially, the dynamic pruning gate sub-samples the spatial dimensions of the feature map to scalars and a linear layer to make the prediction. The $Gate_k(x_{k-1})$ can be formulate as equation 5 and 6.

$$s_k = \text{subsample}(x_k) \in \mathbb{R}^{\hat{C}_{in} \times 1 \times 1} \quad (5)$$

$$g_k = \text{K-argmax}(\text{softmax}(\text{linear}(s_k))) \in \mathbb{R}^{\hat{C}_{out} \times 1 \times 1} \quad (6)$$

In the implementation, we use the average pool to subsample the feature map, and the K-argmax operation will return the top-K most significant values’ index. The K is a hyper-parameter, which defines the dynamic channel pruning ratio for hidden layers. Similar to the (Gao et al., 2019), we train the gate together with the neural network, and regularize all layers with the Lasso $\mathcal{L}_g = \lambda \sum_{k=1}^l \mathbb{E}[\|\text{linear}(s_k)\|_1]$ in the total loss, where s_k is the subsample vector of x_k .

3.3. Dataset-aware dynamic pruning with federated learning

We use *FedAvg* (McMahan et al., 2017) federated learning algorithm to train the dynamic pruning component and neural network. Algorithm 1 shows the federated learning process. In the server execution, the procedure is exactly the same as the *FedAvg*, where the server aggregates the parameter from the selected clients. When updating the client site, the client first downloads the neural network’s parameter w from the cloud server. Then, training the neural network and dynamic pruning component together using the local dataset. After training is finished, the client will

upload the neural network’s parameter to the server, and the dynamic pruning component’s parameter w_g is stored locally. Therefore, the client updates the model to the server would not add extra communication cost. The loss function is defined in equation 7.

$$\mathcal{L}(w, w_g; \mathcal{B}) = \mathcal{L}_{nn} + \mathcal{L}_g \quad (7)$$

, where the \mathcal{L}_{nn} is the Cross Entropy loss of the neural network, the \mathcal{L}_g is the gate loss defines in section 3.2, and the \mathcal{B} is the local data.

Algorithm 1 Dataset-aware dynamic pruning with federated learning algorithm

Server executes:

```

initialize  $w_0$ 
for each round  $t = 1, 2, \dots$  do
     $C \leftarrow$  random set of  $m$  clients
    for each client  $c \in C$  in parallel do
         $w_{t+1}^c \leftarrow$  ClientUpdate( $c, w_t$ )
    end for
     $w_{t+1} \leftarrow \sum_{c \in C} \alpha_c w_{t+1}^c$ 
end for
    
```

ClientUpdate(c,w):

```

 $\mathcal{B} \leftarrow$  split local dataset into batches
 $w \leftarrow$  download global model parameter  $w$ 
for epoch = 1, 2, ... do
    for batch  $b \in \mathcal{B}$  do
         $w \leftarrow w - \eta \nabla \mathcal{L}(w, w_g; b)$ 
         $w_g \leftarrow w_g - \eta \nabla \mathcal{L}(w, w_g; b)$ 
    end for
end for
return  $w$  to server
    
```

4. Experiment

Since most federated learning approaches focus on communication efficiency, and there is little reference to perform network pruning on the FL system, we cannot find a proper baseline to compare our work. To show the effectiveness of the FLP, we have the following experiment:

- Pruning effectiveness
- Inference acceleration and local accuracy

4.1. Implementation details

Dataset. The experiments are done on CIFAR-10 (Krizhevsky & Hinton, 2009). We used distribution-based label imbalance to simulate label imbalance between each client (Li et al., 2021b). Here, each client is allocated a proportion of the samples of each label according to Dirichlet distribution (with concentration β). Specifically, we sample $p_k \sim \text{Dir}_N(\beta)$ and allocate a $p_{k,j}$ proportion of the instances of class k to party j . Here we choose the $\beta = 0.1$. Moreover, to test the FLP’s dataset-aware pruning policy on each device, we further allocate a local validation dataset for

Federated learning settings. We have a total of 10 client devices with Non-IID datasets. 100-rounds *FedAvg* (McMahan et al., 2017) federated learning process is applied to the neural network when training, and for each round, we apply 10 epochs local update. We use the SGD optimizer, where the $\alpha = 5 \times 10^{-3}$, the learning rate is 0.1, batch size is 64, and the weight decay is 5×10^{-4} . In each epoch, the cosine learning rate decay is applied. Since we only have 10 clients, for each round, we sample all the clients to participate in the aggregate process.

4.2. Pruning effectiveness

In this subsection, we compare the FLP with traditional pruning. Figure 1 shows the basic idea of the traditional network pruning. The traditional network pruning has the following steps:

1. Train the original model (neural network) through federated learning.
2. Perform pruning on the server site. The pruner evaluates the saliency of neurons on the neural network and permanently drops those unimportant neurons (the white neurons in Figure 1 have been deleted).
3. Pruned neural network send back to local devices.
4. Perform re-training or fine-tuning through federated learning on pruned neural networks to compensate for pruning accuracy loss.

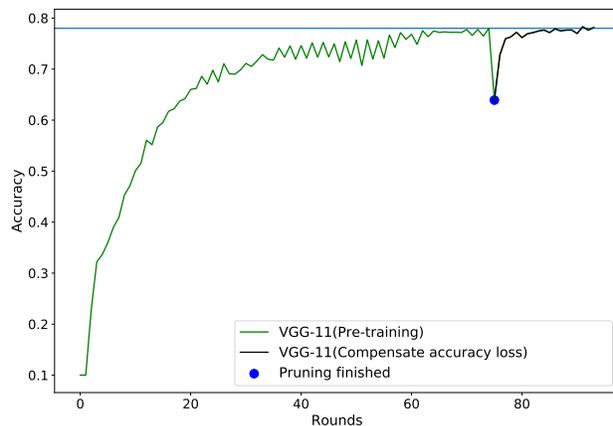


Figure 4. Training details on Uniform pruning policy.

Since we consider the Non-IID dataset in each local device, traditional pruning deploys on each local device would lead to a different neural structure and cause the parameter mismatch when the server aggregates the local model. We perform the traditional pruning on the server site after training and send the pruned model to each device in our experiment setting. We choose the uniform traditional pruning baselines (He et al., 2017), which prunes the hidden layers with a uniform pruning ratio and delete the convolution channels (filter) with a low l^1 -norm value.

Compare to the traditional network pruning, as shown below, the FLP steps are much straightforward:

1. Deploy dynamic pruning components on each device.
2. Train the neural network and dynamic pruning components together through federated learning.

There are two main benefits of FLP; first, we do not need to pre-train the neural network before pruning, and our pruning starts at the run-time. We train the dynamic pruning components together with the neural network. Second, the dynamic pruning components can adaptively select an optimal pruning policy for the Non-IID device. However, the universal pruning policy in traditional pruning may sub-optimal for some clients.

Figure 4 and 5 shows the training details of traditional pruning and FLP. Both the FLP and traditional pruning prune 50% FLOPs (floating point operations per second) on the VGG-11 (Simonyan & Zisserman, 2015). As shown in Figure 4, the traditional pruning starts pruning when we finish training the original neural network (starts at the 75 rounds), and the pruning will cause the accuracy loss. To get the 78% test accuracy, the model with a traditional pruning will need 19 extra rounds to compensate for the accuracy loss,

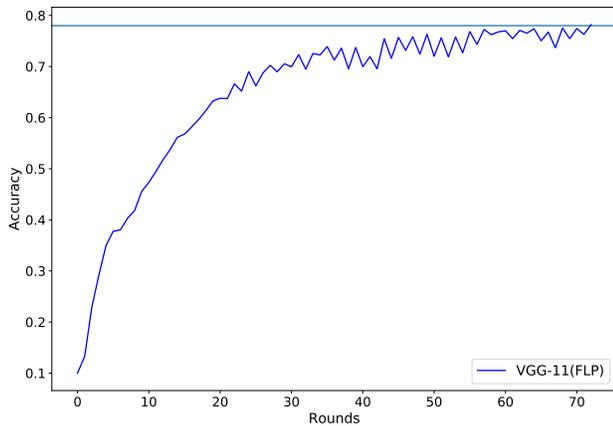


Figure 5. Training details of FLP.

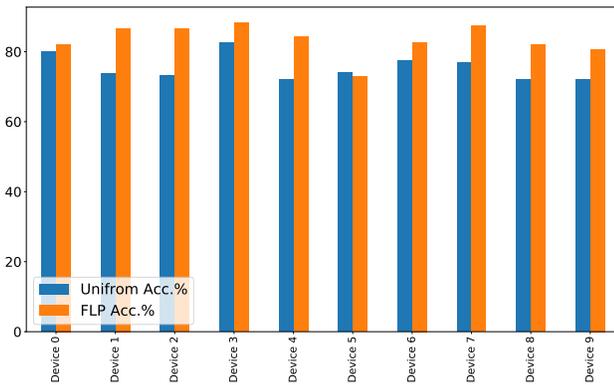


Figure 6. Validation accuracy on pruned VGG-11 under $2\times$ inference acceleration (50% FLOPs reduction).

a total of 94 rounds. This result in Figure 4 is based on the Unifrom tradition pruning policy. However, it can be extended to all traditional pruning methods because they require trained neural network information to generate a pruning policy. So even the SOTA pruning methods need extra rounds to compensate for accuracy loss.

As Figure 5 shows, the FLP only need 73 rounds to get the 78% test accuracy and 50% FLOPs reduction, and no extra rounds are needed to compensate for the test accuracy loss.

4.3. Inference acceleration and local accuracy

This section evaluates the FLP by inference and accuracy and compares it with the traditional uniform pruning policy. Since inference varies among different devices, we use the floating-point operations per second (FLOPs) to evaluate the inference of neural networks. The FLP produces the dataset-aware pruning policy for each local device. To test

the pruning policy, for each device, we split Non-IID local validation datasets for clients from the test set. Each local validation set has 1000 pictures.

Figure 6 shows the validation accuracy of 50% FLOPs VGG-11 pruned by uniform traditional pruning baseline and the FLP. On the total 10 clients, we outperform the traditional uniform pruning policy in most of the case. Additionally, the computation cost of the pruning components on each local device is negligible. The total FLOPs consumption of pruning components on VGG-11 is 1.024 Million FLOPs since the pruning components are essentially linear layers. However, the original VGG-11 has 8 Billion FLOPs. Under $2\times$ acceleration, we reduced 4 Billion FLOPs (50% FLOPs compared to the original model) and only added 1.024 Million extra FLOPs to decide the pruning policy.

5. Conclusion

There has been an increasing interest in running machine learning training on mobile or edge devices, and federated learning is a new paradigm for that while still maintaining data privacy. One key topic of federated learning is the limited computing power of edge devices. Communication and heterogeneity of federated learning made the network pruning on edge device a grand challenge. In this paper, we study non-IID data as one key challenge in federated learning and develop pruning methods to customize each device’s model further. We show that with dataset-aware dynamic pruning, the quality of the model is almost the same as the original or static-only pruning. Furthermore, the model size is reduced significantly with dynamic pruning as dynamic pruning can adapt different pruning policies for each clients’ data. Moreover, our method does not add extra cost to communication. This work is a starting point for addressing network pruning on the heterogeneity problem in federated learning. There are still many challenges left to make the idea more robust and applicable in real-life scenarios. In the future work, we want to extend dataset-aware dynamic pruning towards communication effectiveness to improve the robustness of the idea with federated learning and enable additional algorithms for better converging.

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