

Communication Size Reduction of Federated Learning based on Neural ODE Model

Yuto Hoshino, Hiroki Kawakami, and Hiroki Matsutani
Keio University, 3-14-1 Hiyoshi, Kohoku-ku, Yokohama, Japan 223-8522
Email: {hoshino,kawakami,matsutani}@arc.ics.keio.ac.jp

Abstract—Federated learning is a machine learning method in which data is not aggregated on a server, but is distributed to the edges, in consideration of security and privacy. ResNet is a classic but representative neural network that succeeds in deepening the neural network by learning a residual function that adds the inputs and outputs together. In federated learning, communication is performed between the server and edge devices to exchange weight parameters, but ResNet has deep layers and a large number of parameters, so communication size becomes large. In this paper, we use Neural ODE as a lightweight model of ResNet to reduce communication size in federated learning. In addition, we newly introduce a flexible federated learning using Neural ODE models with different number of iterations, which correspond to ResNet with different depths. The CIFAR-10 dataset is used in the evaluation, and the use of Neural ODE reduces communication size by approximately 90% compared to ResNet. We also show that the proposed flexible federated learning can merge models with different iteration counts.

1. Introduction

In the task of image recognition, one of the methods to improve accuracy is to increase the number of convolutional layers to build a deeper neural network. ResNet [1] is one of the high-performance CNN models that stack many layers by learning residual function, but ResNet has a large number of parameters. Neural ODE [2] utilizes a similarity to ODE (Ordinary Differential Equation) to reduce the parameters of ResNet. ResNet uses different weight parameters for each layer, but Neural ODE uses the same weight parameters repeatedly. Thereby, Neural ODE significantly reduces model size compared to ResNet and can be implemented in resource-limited edge devices. Because the computation cost of the convolutional layer is expensive, high-performance deep CNN models are sometimes too large for resource-limited edge devices. A CNN model with reduced computation cost is developed in [3]. It uses two convolutional steps, depthwise and pointwise, instead of an ordinary convolutional layer.

Recently, sending personal data to cloud servers has become problematic from a privacy perspective. Federated learning [4] is used as an alternative to the traditional learning systems that aggregate data on a server. In the federated learning, each device downloads a model from the server, trains on the device, aggregates the resulting

weight parameters on the server, and distributes the weight parameters again to the device. This eliminates the need to aggregate personal data on a server. However, federated learning needs communication between the server and each device, and state-of-the-art CNN models have a lot of parameters, so its communication size is large. Devices that participate in the federated learning are assumed to use the same model, but the computation power of each device may not be the same, and the appropriate model size may vary depending on the device.

Neural ODEs reduce the number of parameters. It can represent a processing equivalence to ResNet at different depths by changing the number of iterations of the same weights without increasing the number of parameters. In this paper, we propose a flexible federated learning that reduces the communication size by using Neural ODEs and allows devices to use models with different layer iteration counts. Federated learning technologies are surveyed in [5]. This work is related to effective and model specialized algorithms. Different models are aggregated in [6]. This work also aggregates models with different depths. In particular, our contributions are summarized below.

- We use Neural ODE as a federated learning model, so that clients can use the models with different iteration counts and a server can make a global model by aggregating them. This can relax a constraint of traditional federated learning where all the clients use the same model.
- We use dsODENet as a federated learning model. dsODENet [7] is a lightweight model based on the idea of Neural ODE. It can achieve the above benefit while further reducing the communication size.

The rest of this paper is organized as follows. Section 2 introduces the baseline technologies behind our proposal. Section 3 proposes the combination of federated learning and Neural ODE method. Section 4 shows evaluation results. Section 5 analyzes the results with different algorithm and parameter settings. Section 6 concludes this paper.

2. Related Work

2.1. Depthwise Separable Convolution

CNN is composed of multiple layers, such as convolutional layers, pooling layers, and fully-connected layers.

CNN has good accuracy in image recognition, but each convolutional layer uses many parameters. Let N , M , and N_K be the number of input channels, the number of output channels, and the kernel size of one side, respectively. The number of parameters in one convolutional layer is NMN_K^2 .

Depthwise Separable Convolution [3] divides this convolutional layer into two convolutional steps, depthwise convolutional step and pointwise convolutional step. In the depthwise convolutional step, a convolutional operation involving only spatial direction (the size is N_K^2) is applied for each input feature map. Different weight parameters are used for each of N input channels; thus its weight parameter size is NN_K^2 . Then, an output feature map of the depthwise convolutional step is fed to the pointwise convolutional step as an input. A 1×1 convolutional operation is applied for each input feature map and for each output channel; thus its weight parameter size is NM . The weight parameter size of Depthwise Separable Convolution is $NN_K^2 + NM$ in total, which is approximately N_K^2 times reduction, assuming that $N, M \gg N_K$.

2.2. Neural ODE

ResNet [1] is a well-known neural network architecture that can increase the number of stacked layers or building blocks by introducing shortcut connections. Using a shortcut connection, an input feature map to a building block is temporarily saved, and then it is added to the original output of the building block to generate the final output of the block.

ODE is composed of an unknown function and its ordinary derivatives. To obtain an approximate numerical solution, an ODE solver such as the first-order Euler method and higher-order Runge-Kutta method can be used. Based on a similarity between the network structure with shortcut connections and the ODE solver, one building block can be interpreted as one step in the ODE solver as suggested in [2]. Assuming that the Euler method is used as an ODE solver, it can be interpreted that a first-order approximation is applied to solve the output of the building block. In this paper, one building block is called ODEBlock, and the whole network architecture consisting of ODEBlocks is called ODENet.

2.3. Federated Learning

Mobile devices have a lot of data that can be used to train models which can contribute to improve user experiences, such as predictive conversion and image search. However, since such data should be carefully treated from a privacy perspective, centralized learning systems that aggregate data in one place may not be appropriate. To address this issue, a federated learning is proposed in [4]. It can train a shared model without aggregating the training data but keeping it distributed, and then it aggregates the weight parameters. The algorithm is Federated Averaging, which is shown in Algorithm 1.

In Algorithm 1, K represents the total number of clients, k is their index, and \mathcal{P}_k is data at client k . Also, B is the

size of the local mini-batch, E is the number of epochs to be trained in mobile devices, and η is the learning rate. In this algorithm, the first step is to initialize the weight parameters of the model to be used. Then, m clients are randomly selected from among all the clients, and the server sends the weight parameters w to the selected clients. The size of m is determined by client fraction C . The weights w are updated at each epoch (E epochs in total) at each client based on the formula in line 13. After E updates, the weight parameters w are aggregated by the server and the weights w are updated by taking the average based on the formula in line 8, where n is total number of data and n_k is total number of data at client k . The above steps are repeated for t rounds. The average of the weight parameters sent from the clients is calculated by the server, so this algorithm is called Federated Averaging.

However, when the data on each device is unbalanced, although this algorithm can achieve a good accuracy in the local model on each device, the accuracy is not high in the global model that has aggregated all the local models. Since the goal of federated learning is that the global model achieves a good accuracy both locally and globally, new federated learning algorithms have been proposed to replace Federated Averaging, such as Personalized Federated Averaging [8] and Adoptive Personalized Federated Learning [9]. These algorithms are similar to Federated Averaging, but instead of training directly, meta-learning is performed using a portion of the data before training. By the meta-learning, the model is tuned for each device based on the trend of the data.

Algorithm 1 Federated Averaging

```

1: function ExecuteServer()
2:   Initialize  $w_0$ 
3:   for each round  $t = 1, 2, \dots$  do
4:      $m \leftarrow \max(C \cdot K, 1)$ 
5:      $S_t \leftarrow$  (random set of  $m$  clients)
6:     for each client  $k \in S_t$  in parallel do
7:        $w_{t+1}^k \leftarrow$  ClientUpdate( $k, w_t$ )
8:      $w_{t+1} \leftarrow \sum_{k=1}^K \frac{n_k}{n} w_{t+1}^k$ 
9:   function ClientUpdate( $k, w$ )  $\triangleright$  Run on client  $k$ 
10:     $\mathcal{B} \leftarrow$  (split  $\mathcal{P}_k$  into batches of size  $B$ )
11:    for each local epoch  $i$  from 1 to  $E$  do
12:      for each batch  $b \in \mathcal{B}$  do
13:         $w \leftarrow w - \eta \nabla \ell(w; b)$ 

```

3. Proposed Federated Learning Method

In the federated learning, it is necessary to reduce the communication size involved in exchanging weight parameters between the server and each device. In addition, when ResNet is used as a federated learning model, ResNet models with different layer depths cannot share their weight parameters. However, it is likely that some devices participating in a federated learning have less available memory

and computation power. Since the federated learning basically does not allow different models to be mixed together, a model commonly used in all the devices should be carefully selected. In this paper, we use ODENet to reduce the communication size and enable federated learning between models with different layer iteration counts.

3.1. Lightweight Model based on Neural ODE

Federated learning requires the exchange of trained weight parameters between the server and devices at each round. Since the weight parameters are exchanged at each round, the larger the size of the weight parameters, the more the burden on the devices and users. In this paper, we propose to use ODENet and dsODENet [7], lightweight models based on the idea of Neural ODE, as a method to reduce the communication size. First, we explain the structure of ResNet and ODENet.

Figures 1 and 2 show the basic structure of the 7-block ResNet- N and the corresponding 7-block ODENet- N , where N is the number of model depths. The Residual Block is denoted as ResBlock. In general, in deep learning, the accuracy improves as the number of layers increases. As the neural network becomes deep, the feature map size tends to be small and the number of channels tends to be increased. In ResNet, particular ResBlocks reduce the feature map size while increasing the number of channels. In Figure 1, conv1 performs convolutional operations as a preprocessing layer, and C physically-stacked ResBlocks are executed in block1. block2_1 is a down-sampling ResBlock to reduce the feature map size, and C physically-stacked ResBlocks on the output of block2_1 are executed in block2_2. The same operation is performed for block3_1 and block3_2.

ODENet replaces ResBlocks in Figure 1 with ODE-Blocks as shown in Figure 2. In ResNet, C ResBlocks are physically-stacked in block1, block2_2, and block3_2, but ODENet replaces these C ResBlocks with a single ODEBlock. Instead, ODEBlock is executed C times in block1, block2_2, and block3_2, whereas it is executed only once in block2_1 and block3_1.

Here we consider the difference in the number of parameters between ResNet and ODENet. Let $O(L)$ be the number of parameters in one ResBlock and ODEBlock. In ResNet, C ResBlocks are stacked in one block, so the number of parameters is $O(CL)$. In contrast, ODENet repeats ODEBlock C times in one block, so the number of parameters is $O(L)$. The parameter size reduction by ODENet becomes large as C is increased. Thus, the communication size can be reduced by using ODENet as a federated learning model instead of ResNet.

In addition, the number of parameters can be further reduced by using dsODENet [7], which combines ODENet and Depthwise Separable Convolution [3]. As mentioned in Section 2, Depthwise Separable Convolution reduces the number of parameters in the convolutional operation. In Figure 3, Conv1 and Conv2 are convolutional layers, and ReLU (Rectified Linear Unit) is an activation function. Figure 3 left shows a structure of an ODEBlock in ODENet, while Figure

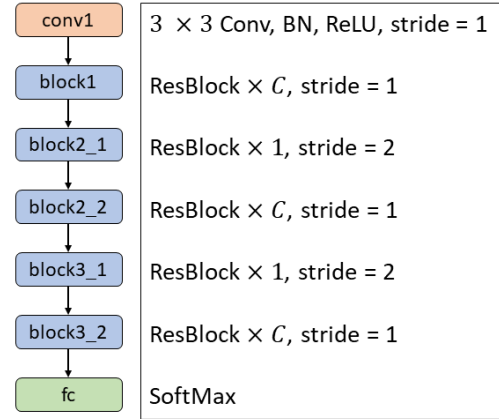


Figure 1. Structure of 7-block ResNet

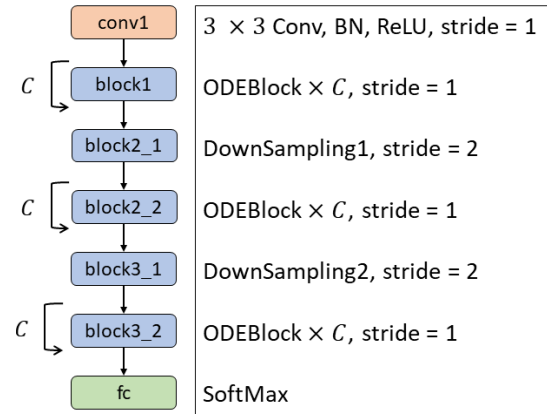


Figure 2. Structure of 7-block ODENet

3 right shows that of dsODEBlock in dsODENet, in which each convolutional layer of the ODEBlock is replaced with two convolutional steps: the depthwise convolutional step and the pointwise convolutional step. This modification can further reduce the communication size.

3.2. Federated Learning between Different Models

In the federated learning, the same model is typically used by all the participating devices. However, in a real environment, these devices are not the same and are likely to have different compute resources, such as memory capacity and computation power. If the common model is accurate but requires a high computation power, low-end edge devices cannot join the federated learning. However, using the simplest model may limit the system-wide accuracy. To fully utilize the performance of each device, it is necessary to use a well-fitting model for each device.

In the case of ResNet, different models have different numbers of stacked ResBlocks (i.e., different C) in block1, block2_2, and block3_2. In the federated learning, these different ResNet models cannot be aggregated directly at the

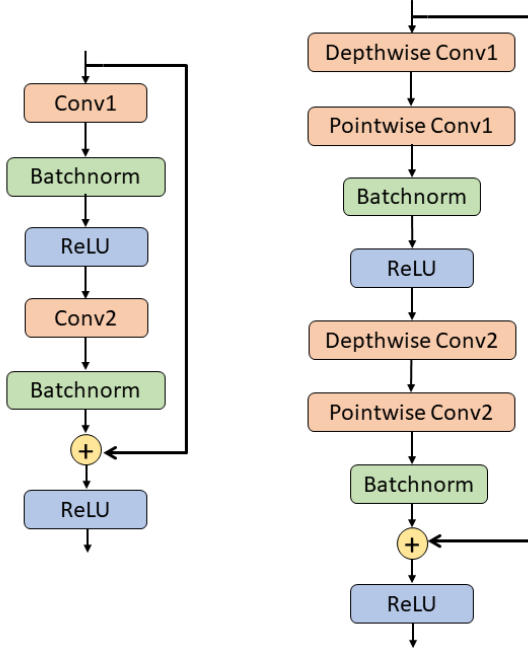


Figure 3. Structure of ODEBlock and dsODEBlock in ODENet and dsODENet

server due to the model incompatibility between them. In the case of ODENet, as shown in Figure 2, one ODEBlock is repeated C times in block1, block2_2, and block3_2 of ODENet. In other words, ODENet models with different C values differ only in the numbers of iterations of ODEBlocks, not in the number of weight parameters. In this case, the structure of the ODENet models is the same, so these models with different C values can be aggregated at the server. Using ODENet as a federated learning model enables federated learning between models with different iteration counts in order to fully utilize the performance of each device. dsODENet also enables federated learning between models with different iteration counts for the same reasons as ODENet.

4. Evaluations

In this section, we evaluate the federated learning method proposed in Section 3 using an image recognition task. ODENet- N , dsODENet- N , and ResNet- N are used in the federated learning and are compared in terms of the communication size, computation size, and accuracy. N represents the layer depth in ResNet, ODENet, and dsODENet. More specifically, we assume $N = 6C + 6$ in this experiment¹ and use $N = 34, 50$, and 101. The numbers of epochs, batch size, and communication rounds in the federated learning are 100, 100, and 20, respectively.

1. In Figure 1, ResBlocks are executed $3C + 2$ times, each contains two convolutional layers. The pre- and post-processing (conv1 and fc) layers are also included in N ; thus $N = 2(3C + 2) + 2$.

Federated Averaging (FedAvg) is used as a federated learning algorithm. CIFAR-10 dataset [10] is used for training and inference. Python 3.8.5, PyTorch 1.8.1, and torchvision 0.9.1 are used for model implementation. A machine with Ubuntu 18.04.5 LTS (64-bit), Intel Core i7-10700K CPU @ 3.8GHz, 32GB DDR4 SDRAM, and NVIDIA GeForce RTX 3090 GPU is used for the evaluation in this paper.

TABLE 1. COMMUNICATION SIZE

Model	Number of parameters to be transferred	Size / MB
ResNet-34	21,780,648	83.09
ResNet-50	25,505,232	97.29
ResNet-101	44,447,912	169.55
ODENet-34	1,937,034	7.39
ODENet-50	1,937,034	7.39
ODENet-101	1,937,034	7.39
dsODENet-34	1,249,381	4.76
dsODENet-50	1,249,381	4.76
dsODENet-101	1,249,381	4.76

TABLE 2. COMPUTATION SIZE

Model	Number of parameters to be processed	Size / MB
ResNet-34	21,797,672	83.15
ResNet-50	25,557,032	97.49
ResNet-101	44,549,160	169.94
ODENet-34	8,952,010	34.15
ODENet-50	16,742,730	63.87
ODENet-101	26,091,594	99.53
dsODENet-34	2,075,480	7.92
dsODENet-50	2,989,670	11.40
dsODENet-101	4,086,698	15.59

4.1. Communication Size

Table 1 shows the communication size of the ResNet, ODENet, and dsODENet models with different depths (i.e., N). Here, the communication size means the sum of the weight parameters of the convolutional layers and fully-connected layers in a given federated learning model. The communication is required between the server and device in each federated learning round. The size is measured using torchsummary in PyTorch which is a tool that reports the size information.

Table 1 shows that both ODENet and dsODENet have fewer communication size than the corresponding ResNet model. Comparing ResNet and ODENet, the communication size of ODENet-50 is 7.6% of the original ResNet model. In the case of ResNet and dsODENet, the communication size of dsODENet-50 is 4.9% of the ResNet model. The results show that the use of ODENet and dsODENet can significantly reduce the communication size between the server and devices.

The communication size increases as the depth N is increased in ResNet. In the cases of ODENet and dsODENet, on the other hand, their communication size is constant regardless of the N parameter. This is because the number of physically-stacked blocks is the same in ODENet and dsODENet with different N depths, and only the number of

iterations of each block is different. Please note that, since the model size is also small in ODENet and dsODENet, the required memory capacity is reduced by ODENet and dsODENet compared to the original ResNet model.

4.2. Computation Size

Table 2 shows the computation size of the three models with different depths N . Here, the computation size is the cumulative total number of weight parameters to be processed. All these sizes are measured using torchsummary.

Table 2 shows that both ODENet and dsODENet have fewer computation size than the corresponding ResNet model. Comparing ResNet and ODENet, the computation size of ODENet-50 is 65.5% of the original ResNet model. In the case of ResNet and dsODENet, the computation cost of dsODENet-50 is 11.7% of the ResNet model. The results show that the use of ODENet and dsODENet can reduce the computation cost in addition to the communication size.

Please note that the communication sizes of ODENet and dsODENet are constant regardless of the depths N . However, the number of parameters to be processed is increased when N is increased in the ODENet and dsODENet cases. This is because the number of iterations of the ODEBlock and dsODEBlock is increased as the depth N is increased, and the computation cost also increases.

4.3. Federated Learning with Different Depths

In the federated learning, different ResNet models with different N parameters cannot be aggregated. But ODENet and dsODENet models with different N parameters are structurally the same and can be aggregated. To investigate the possibility of federated learning between different ODENet depths, we selected two models from $N = 34, 50, 101$ and trained them using CIFAR-10 dataset. The same experiment is also performed for dsODENet.

Figures 4 and 5 show training curves (epoch number vs. loss value) when ODENet and dsODENet are trained using non-iid data, respectively. In this case, one model is trained with only five classes of CIFAR-10, while the other is trained with the remaining five classes. In Figure 4, the red, green, and blue lines show the loss value when federated learning is performed between ODENet-34 and ODENet-50, between ODENet-50 and ODENet-101, and between ODENet-34 and ODENet-101, respectively. Similarly, in Figure 5, the red, green, and blue lines show the loss value when federated learning is performed between dsODENet-34 and dsODENet-50, between dsODENet-50 and dsODENet-101, and between dsODENet-34 and dsODENet-101, respectively. The horizontal axis of Figures 4 and 5 represents the number of epochs, and the vertical axis represents the loss value. In all the models, the loss values decrease as the number of epochs is increased and converged around 50 epochs. This indicates that both ODENet and dsODENet are trained successfully. In other words, ODENet and dsODENet are capable of federated learning between models with different N parameter.

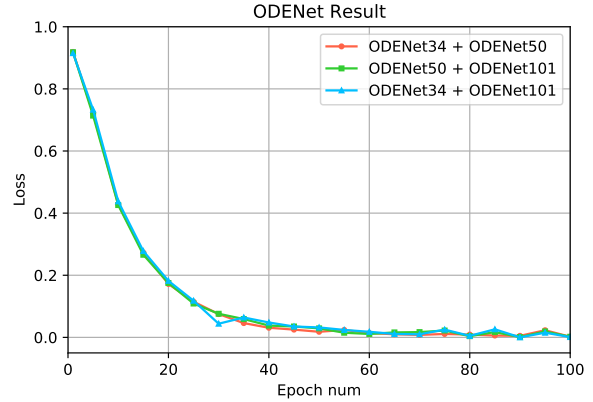


Figure 4. Training curve (epoch number vs. loss value) of ODENet

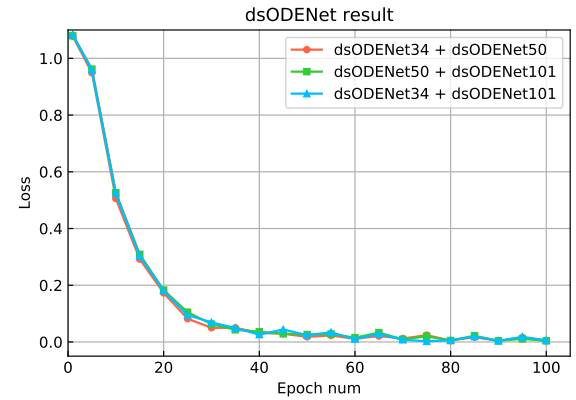


Figure 5. Training curve (epoch number vs. loss value) of dsODENet

4.4. Accuracy

Table 3 shows the inference accuracy trained without using federated learning (i.e., stand-alone learning). Table 4 shows the inference accuracy trained using federated learning. The accuracy is calculated by taking the average of two clients. In Table 4, federated learning is performed between two clients that use models with different depths. For example, 34+50 means ODENet-34 and ODENet-50, 34+101 means ODENet-34 and ODENet-101, and 50+101 means ODENet-50 and ODENet-101. dsODENet is also trained under similar conditions. From Tables 3 and 4, both ODENet and dsODENet are less accurate when trained by federated learning than those trained by the stand-alone learning. A similar tendency is observed in ResNet models with and without federated learning.

Table 4 shows that accuracy of dsODENet is higher than ODENet for iid data. In the iid data case, the dataset is randomly distributed to two models. In the non-iid data case, each client has five classes. In the ODENet, 50+101 outperforms 34+50 and 34+101 by 0.7% and 0.9% for iid data and by 4.7% and 5.0% for non-iid data. In the dsODENet, 50+101 outperforms 34+50 and 34+101 by 1.4%

and 1.5% for iid data and by 0.9% and 0.4% for non-iid data. These results show that the combination of models with larger iteration counts increases accuracy. Table 3 shows that deeper models achieve better accuracy. In Table 4, accuracies are calculated by averaging those of two clients. Therefore, increasing the number of deeper models increases global accuracy. Comparing the accuracy of iid and non-iid data cases, both ODENet and dsODENet show a significant decrease in accuracy for non-iid data.

TABLE 3. ACCURACY [%] OF ODENET AND DSODENET USING STAND-ALONE LEARNING

N	34	50	101
ODENet	74.3	75.8	76.2
dsODENet	74.2	74.6	75.3

TABLE 4. ACCURACY [%] OF ODENET AND DSODENET USING FEDERATED LEARNING

Data	iid data			non-iid data		
	N	34+50	34+101	50+101	34+50	34+101
ODENet	73.6	73.4	74.3	42.5	42.2	47.2
dsODENet	69.4	69.3	70.8	49.7	50.2	50.6

5. Discussions

In this section, we discuss the causes of degradation of accuracy in non-iid data. The training curve is converged as shown in Figure 5. The accuracy is high enough for iid data, so it seems that there is no problem with the model. ResNet-50 is trained using federated learning under the same conditions, and the inference accuracy is 83% for the iid data, while it is decreased to 55% for the non-iid data. As with ODENet and dsODENet, the result also shows a significant drop in accuracy for non-iid data in ResNet. This suggests that the cause of the accuracy degradation is related to the federated learning algorithm.

5.1. Federated Learning Algorithm

To validate the hypothesis above, we evaluate a different federated learning algorithm namely APFL (Adoptive Personalized Federated Learning) [9] instead of FedAvg for training and inference. FedTroch [11] is used as an evaluation platform in this case. CIFAR-10 and CIFAR-100 are used as datasets. FedTorch is built with distributed APIs of PyTorch. It uses MPI to parallelize the federated learning over multiple computers, even on a single CPU. We use ODENet-50 and dsODENet-50 as the federated learning models. The number of clients is varied between 10 and 20, the number of classes for each client is varied between 2 and 5, and the impact of these factors is discussed.

Tables 5 and 6 show the results of ODENet and dsODENet with different federated learning algorithms: FedAvg and APFL. The numbers of clients are 10 and 20 in Tables 5 and 6, respectively. In these tables, (10, 5) means the number of clients is 10 and the number of classes is 5. Comparing

TABLE 5. ACCURACY OF ODENET AND DSODENET USING APFL WHEN THE NUMBER OF CLIENTS IS 10 [%]

	Algorithm (Clients, Classes)	FedAvg		APFL	
		(10, 2)	(10, 5)	(10, 2)	(10, 5)
CIFAR-10	ODENet-50	24.8	55.2	38.6	59.4
	dsODENet-50	24.3	57.4	36.1	61.0
CIFAR-100	ODENet-50	28.7	29.8	27.1	27.9
	dsODENet-50	27.0	31.3	27.3	28.2

TABLE 6. ACCURACY OF ODENET AND DSODENET USING APFL WHEN THE NUMBER OF CLIENTS IS 20 [%]

	Algorithm (Clients, Classes)	FedAvg		APFL	
		(20, 2)	(20, 5)	(20, 2)	(20, 5)
CIFAR-10	ODENet-50	31.4	58.7	53.7	64.3
	dsODENet-50	32.8	57.5	53.9	65.8
CIFAR-100	ODENet-50	15.2	18.1	20.1	16.8
	dsODENet-50	18.0	16.6	17.0	16.4

FedAvg and APFL, the accuracy of APFL is higher than that of FedAvg in the cases of ODENet and dsODENet. In the case of (10, 5), APFL improves the accuracy of ODENet and dsODENet by 4.2% and by 3.6%, respectively. In the case of (20, 5), it improves their accuracy by 5.6% and by 8.3%, respectively. This suggests that the use of the FedAvg algorithm is a cause of the low accuracy in the case of non-iid data. As shown in Table 3, FedAvg does not degrade accuracy in iid data. However, considering actual situations where federated learning is used, it is unlikely that users will use the same data in each device, so data distribution will be unbalanced. In this case, APFL is better than FedAvg as a federated learning algorithm. Please note that APFL uses a meta-learning at the local devices in order to tune the model parameters, which increases the computational complexity compared to FedAvg. The results of CIFAR-100 when the number of clients is 10 are fair. However, those when the number of clients is 20 are lower than expected. It is expected that increasing the number of epochs can improve accuracy. In the rest of this section, we discuss the accuracies using CIFAR-10 as a dataset.

5.2. Number of Clients

Here we focus on the impact of the number of clients on accuracy. Tables 5 and 6 show the results when the number of clients are 10 and 20, respectively. Comparing the results of (10, 5) and (20, 5) when using FedAvg, the increase of the number of clients from 10 to 20 improves the accuracy of ODENet and dsODENet by 3.5% and 0.1%, respectively. Comparing the results when using APFL, the increase of the number of clients improves the accuracy of ODENet and dsODENet by 4.9% and 4.8%, respectively. The actual federated learning involves many clients, not just a small number of clients such as 10 or 20. In reality, there is a possibility that the accuracy will further increase because a large number of clients are expected to participate in the federated learning.

5.3. Number of Classes

Then we focus on the impact of the number of classes. Comparing the results of (10, 2) and (10, 5) when using APFL, the increase of the number of classes from 2 to 5 improves the accuracy of ODENet and dsODENet by 20.8% and 24.9%, respectively. Comparing the results of (20, 2) and (20, 5), the increase of the number of classes improves the accuracy of ODENet and dsODENet by 10.6% and 11.9%, respectively.

In the cases of (10, 2), the accuracies of ODENet and dsODENet are exceptionally low. Because the experiment is performed with 10 clients, the total number of data is also decreased when the number of classes is decreased to 2. That is, when the number of clients is 10, using only 2 classes is insufficient, and increasing the number of clients or the number of classes can recover the accuracy.

5.4. Limitations

Without federated learning, the inference accuracy of ResNet-50 is 87.3%, which is 11.5% higher than that of ODENet-50 and 12.7% higher than that of dsODENet-50. When APFL is used as a federated learning algorithm with 10 clients and 5 classes, the inference accuracy of ResNet-50 is 72.3%. This result is 12.9% higher than ODENet and 11.3% higher than dsODENet under the same conditions. Since ResNet achieves a higher accuracy than ODENet and dsODENet even in stand-alone learning, the reason for this lower accuracy of ODENet and dsODENet is not related to federated learning. Actually, it is pointed out that there is room for improving the performance of ODENet. ANODE [12] is an extended approach of ODENet that introduces a checkpointing technique to compute more precise gradients. Improving the base accuracy of our ODENet and dsODENet models by introducing the ANODE approach is thus our future work.

6. Summary

In this paper, we use two lightweight CNN models, ODENet and dsODENet, for the federated learning and compared in terms of the communication size, the number of parameters to be processed, and accuracy. Compared to ResNet-50, ODENet-50 and dsODENet-50 successfully reduce the communication size by 92.4% and by 95.1%, respectively. These results show that ODENet and dsODENet can be used to reduce the communication size between the server and devices in federated learning. We also perform federated learning on two different models, such as ODENet-50 and ODENet-101, and show that federated learning of ODENet and dsODENet models with different iteration counts or depths is possible. This enables the use of ODENet and dsODENet as the federated learning model that can take full advantage of the performance of each device.

As a future work, we will evaluate the federated learning accuracy when the number of clients is increased to 100 or 1000. We will revise the base ODENet and dsODENet

models by introducing ANODE [12]. We will also examine state-of-the-art federated learning algorithms in addition to FedAvg and APFL.

Acknowledgements This work was partially supported by JST CREST Grant Number JPMJCR20F2, Japan.

References

- [1] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.
- [2] R. T. Q. Chen, Y. Rubanova, J. Bettencourt, and D. Duvenaud, "Neural Ordinary Differential Equations," in *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS)*, Dec. 2018, pp. 6572–6583.
- [3] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv preprint arXiv:1704.04861, Apr. 2017.
- [4] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in *Proceedings of the International Conference on Artificial Intelligence and Statistics (AISTATS)*, Apr. 2017, pp. 1273–1282.
- [5] Q. Li, Z. Wen, Z. Wu, S. Hu, N. Wang, Y. Li, X. Liu, and B. He, "A Survey on Federated Learning Systems: Vision, Hype and Reality for Data Privacy and Protection," *IEEE Transactions on Knowledge and Data Engineering*, pp. 1–1, 2021.
- [6] T. Lin, L. Kong, S. U. Stich, and M. Jaggi, "Ensemble Distillation for Robust Model Fusion in Federated Learning," arXiv preprint arXiv:2006.07242, Mar. 2021.
- [7] H. Kawakami, H. Watanabe, K. Sugiura, and H. Matsutani, "dsODENet: Neural ODE and Depthwise Separable Convolution for Domain Adaptation on FPGAs," in *Proceedings of the Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP)*, 2022, pp. 152–156.
- [8] A. Fallah, A. Mokhtari, and A. Ozdaglar, "Personalized Federated Learning with Theoretical Guarantees: A Model-Agnostic Meta-Learning Approach," in *Proceedings of the Annual Conference on Neural Information Processing Systems (NeurIPS)*, 2020, pp. 3557–3568.
- [9] Y. Deng, M. M. Kamani, and M. Mahdavi, "Adaptive Personalized Federated Learning," arXiv preprint arXiv:2003.13461, Mar. 2020.
- [10] A. Krizhevsky and G. Hinton, "Learning Multiple Layers of Features from Tiny Images," University of Toronto, Tech. Rep. 0, 2009.
- [11] F. Haddadpour, M. M. Kamani, A. Mokhtari, and M. Mahdavi, "Federated Learning with Compression: Unified Analysis and Sharp Guarantees," arXiv preprint arXiv:1704.04861, 2020.
- [12] A. Gholaminejad, K. Keutzer, and G. Biro, "ANODE: Unconditionally Accurate Memory-Efficient Gradients for Neural ODEs," in *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI)*, Aug 2019, pp. 730–736.