Resource-Aware Heterogeneous Federated Learning using Neural Architecture Search

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Abstract

Federated Learning (FL) is extensively used to train AI/ML models in distributed and privacy-preserving settings. Participant edge devices in FL systems typically contain non-independent and identically distributed (Non-IID) private data and unevenly distributed computational resources. Preserving user data privacy while optimizing AI/ML models in a heterogeneous federated network requires us to address data heterogeneity and system/resource heterogeneity. Hence, we propose Resource-aware Federated Learning (RaFL) to address these challenges. RaFL allocates resource-aware models to edge devices using Neural Architecture Search (NAS) and allows heterogeneous model architecture deployment by knowledge extraction and fusion. Integrating NAS into FL enables on-demand customized model deployment for resource-diverse edge devices. Furthermore, we propose a multi-model architecture fusion scheme allowing the aggregation of the distributed learning results. Results demonstrate RaFL’s superior resource efficiency compared to SoTA.

1. Introduction

The massive data generated at the edge (e.g., mobile phones and IoT devices) have become a valuable resource for improving the performance of AI models. However, increasing privacy concerns make it unrealistic to collect data at a central location and train practical ML models on powerful machines. Hence, Federated Learning (FL) emerges as a privacy-aware decentralized AI/ML model training and optimizing paradigm which has been widely adopted by the technology industry. FL involves the participation of local client nodes which distributively train and optimize AI models, facilitated by an aggregating server to integrate the decentralized training results without accessing user private data.

Despite FL’s significant contributions to decentralized AI, it also introduces two key challenges: data heterogeneity and resource/system heterogeneity, which make it difficult to scale. The private data collected on edge devices is often described as non-independent and identically distributed (Non-IID). Data decentralization and heterogeneity causes uncertainties and optimization failures when training with naive decentralized training methods [12]. Additionally, the presence of system heterogeneity, where edge devices in an FL system have different resources and computational capacities, leads to poor resource use efficiency. Furthermore, expensive communication overhead produced by frequently sharing weights/gradients between edge clients and server becomes a bottleneck for scaling up the network. Cross-device FL settings, for instance, involve the participation of possibly hundreds of thousands or even millions of edge devices resulting in massive bandwidth consumption.

Despite these challenges, state-of-the-art (SoTA) FL baselines mainly focus on addressing data heterogeneity (i.e., Non-IID data on edge devices), while ignoring system and resource heterogeneity among edge devices. In practice, computational resources among edge devices vary vastly, especially in cross-device FL settings. Hence, simply deploying a common model architecture leads to poor resource utilization. This sub-optimal deployment will cause resource-hungry edge devices to consume precious energy supplies while underutilizing more capable edge devices with idle resources.

In this paper, we consider both data and system heterogeneity and propose Resource-aware Federated Learning (RaFL). RaFL deploys resource-aware neural architectures on edge devices, and uses heterogeneous model architecture fusion to aggregate decentralized training re-
sults. Specifically, we integrated Neural Architecture Search (NAS) into the FL system for conducting on-demand neural architecture search based on the edge clients’ local computational capacities. RaFL optimizes the clients’ computational resources by providing a near-optimal network architecture under the given resource constraints. The RaFL server additionally supplies all its clients with a common smaller knowledge (student) network that will serve as a knowledge medium in the heterogeneous network environment. RaFL clients engage in deep mutual learning [33] to co-train their network pairs and diffuse knowledge into their knowledge networks. Meanwhile, the RaFL server aggregates local knowledge from clients to combine decentralized training results. Furthermore, given the availability of public data, RaFL server provides the option of using ensemble distillation to improve the robustness of knowledge fusion. More importantly, our FL pipeline shows a considerable drop in communication overhead while addressing device and data heterogeneity.

In essence, RaFL makes the following contributions:

- We maximize resource utilization based on clients’ resource constraints in the FL system.
- We are able to accelerate inference time thanks to our heterogeneous resource-aware networks that computationally benefit their corresponding edge clients.
- We reduce FL communication overhead by deploying a small interceding knowledge network (subnetwork) derived from the super-network pool.
- We provide flexible options for RaFL to take advantage of transfer learning, ensemble learning, and public data. This makes RaFL scalable and applicable in real-world scenarios.

2. Related Works

2.1. Traditional Federated Learning

The pioneer FL implementation of [19] ushered in a novel FedAvg algorithm. FedAvg combined local stochastic gradient descents (SGDs) with global model averaging. Several spin-offs of FedAvg have since sprouted further optimizing FL convergence. FedProx [17] was proposed to address convergence issues associated with data and device heterogeneity. This was conducted by permitting the participation of “straggler” devices and introducing a proximal term in the local loss. FedNova [27] normalizes and scales local updates modifying weights to mitigate gradient bias. SCAFFOLD [13] introduced gradient-based control variates to correct client drift and speed up convergence. These SoTA methods involve weight aggregation and gradient control methods which inherently assume uniformity in edge resource capacities by deploying architecturally identical models onto resource-heterogeneous edge devices. Moreover, while these algorithms consider client computational diversity, they only focus on possible variations in local training speeds. In contrast, diverse edge computational capacities require the deployment of heterogeneous client network architectures. As such, accounting for potential network architectural diversity is imperative.

2.2. Personalized FL

Recent research on personalized FL [6–8,11,32] showed uniform FL models can degrade overall performance and demonstrated how personalized models increase robustness. Personalized FL is an active research area that focuses on the issue of statistical heterogeneity. Personalization questions the viability of a single global model satisfying the needs of all clients equitably. Intuitively, the presence of data heterogeneity implies the global model will have varying performances on the differing local datasets. As such, rather than deploy an identical global model, personalized FL allows edge clients to tune the model weights to better fit local data. Nevertheless, these approaches still adopt the same model architecture, which fails to address the heterogeneity of computational capacities.

2.3. Knowledge Distillation in Federated Learning

Knowledge distillation has been adopted in FL as a means to address model heterogeneity [9, 15, 18, 22, 25]. For example, Fed-ensemble [25] ensembles the prediction output of all client models; FedKD [28] proposes an adaptive mutual distillation framework to learn a student and a teacher model simultaneously on the client side; FedDF [18] distills the ensemble of client and teacher models to a server student model. [15], proposes the application of a public dataset as medium of exchanging knowledge among customized client models. [31] proposes the use of KD where the global network and student network involve in knowledge transfer rather than direct assignment.

In contrast, our approach utilizes local deep mutual learning [33] coupled with an optional ensemble-based multi-model fusion in the cloud whenever public data is available. In the absence of public data, we perform global model aggregation. This makes our pipeline quite flexible and applicable in real-world scenarios.
2.4. Model Compression in Federated Learning

Model compression techniques such as network pruning and quantization [3, 23, 30] have been adopted in FL to relieve resource stress and reduce communication overhead. However, such methods usually suffer from accuracy loss and introduce dynamically changing architectures complicating the server aggregation step. In this work, we propose an FL pipeline to jointly address data and device (architectural) heterogeneity. We setup a framework using NAS querying, deep mutual learning and knowledge distillation. Naturally, the NAS-DML-KD setup induces favorable grounds for reducing communication overhead.

2.5. Neural Architecture Search

The outstanding performance of modern NAS frameworks has inspired us to integrate NAS into our FL settings as a means to address system heterogeneity. We are mostly interested in exploring two-stage weight-sharing NAS frameworks for their convenient methods to derive resource-aware subnetworks. [1] proposed progressive shrinking to train Once-for-All (OFA) weight-sharing super-networks from which subnetworks are then extracted. In BootstrapNAS, [20] propose a scheme for training super-networks based on arbitrary pre-trained models. In their work, subnetworks of comparable or even higher performance to that of the pre-trained model are derived using the Non-Dominated Sorting Genetic Algorithm II [5]. In FairNAS [4], a new fairness constraint is introduced to improve subnetwork sampling. AttentiveNAS [26] introduced the BestUp and WorstUp subnetwork sampling strategies and was able to produce SoTA subnetworks. Recently, [29] proposed DecNAS, where neural architecture search is adapted to the decentralized environment. In the proposed system, the FL server and clients iteratively shrink an initial pre-trained network to fit the constraints of the edge client.

In RaFL, we deploy heterogeneous subnetworks generated with OFA on the edge clients. Despite the effectiveness of addressing device heterogeneity, the diverse client subnetworks require further training to handle data heterogeneity. Furthermore, heterogeneous architectures demand unconventional aggregation techniques. As such, we apply Knowledge Distillation (KD) and Deep Mutual Learning (DML) to address these issues.

3. Methodology

RaFL consists of three main components: resource-aware neural architecture search, local knowledge fusion with deep mutual learning, and cloud knowledge aggregation (Figure 1). Unlike mainstream FL systems which deploy an identical model architecture on all edge devices, RaFL performs an on-demand model architecture search to tailor to the resource utilization requirements of edge devices (θ in Figure 1). Local devices train their customized model on local data and transfer the model’s knowledge to a smaller knowledge network via deep mutual learning (θ). After local training, edge clients communicate their local knowledge to the cloud server (θ). The server aggregates the received local knowledge into a global knowledge network (θ). Moreover, in the case where public data is available, RaFL provides an optional ensemble distillation to further improve the robustness of knowledge aggregation (θ). Lastly, the RaFL server transfers over the global knowledge to the edge devices (θ).

3.1. Resource-aware Federated NAS

Mainstream FL solutions assume the presence of homogeneous resource capacities across participant clients. In practice however, computational resource among edge devices varies vastly, especially in a cross-device FL settings. Thus simply deploying an identical model architecture leads to poor resource utilization; while powerful clients are left with idle resources, resource-limited clients may struggle to train a large architecture while consuming limited energy supplies.

RaFL proposes a resource-aware federated neural architecture search to search for resource-tailored models for edge devices as shown in Figure 1 θ. Specifically, we first deploy a pre-trained Once-For-All (OFA) [1] NAS super-network (SoTA NAS solution) from [1] on the cloud, and in the FL initialization stage, clients query the super-network to obtain resource-aware models on first contact. The OFA super-network has been trained by minimizing the objective function shown in Equation 1.

\[
\min_{\Theta} \sum_{\text{arch}_i} L_{\text{eval}}(C(\Theta, \text{arch}_i))
\]

Where Θ is the weights of the super-network, arch_i is the subnetwork configuration, which represent a neural architecture, the function C samples the sub-network from the supernet Θ via a given architecture configuration. The objective function optimizes Θ to get minimal loss on all sampled architectures.

RaFL efficiently queries neural architectures from the NAS supernet on behalf of requesting clients. RaFL maintains two conditions when integrating NAS into the FL pipeline. First, the NAS supernet is pre-trained on public data. Second, an asynchronous querying mechanism continuously runs in the cloud. Pre-training a NAS supernet requires a considerable effort thus burdening the FL server. Despite this however, the NAS supernet can be reused in other similar tasks without the need of another pre-training. This is because transfer learning [1] demonstrates that architectures trained on one dataset usually produce good performance on other Non-IID datasets.
It is important to note that the super-network is pre-trained on a completely different data distribution or even a different task. Edge client devices easily download a customized model architecture by simply specifying their computational constraints. Because NAS supplies pre-trained models, it has the added benefit of enabling transfer learning right from the start. This however, might cause an unfair advantage during baseline comparisons (i.e., since baseline models start from an untrained model). To level the field, we propose communicating extracted knowledge from local model parameters/gradients between clients and the server, aging will not work. Hence, rather than communicating are deployed across the FL clients, a simple weight averaging will not work. Hence, rather than communicating model parameters/gradients between clients and the server, we propose communicating extracted knowledge from local models instead. To do this, we utilize local knowledge fusion via deep mutual learning (DML) [33] (as shown in Figure 1).

Formally, we specify the $l^{th}$ edge client as $C_l$. $C_l$ initially downloads a small sized knowledge network $\theta_l^k$ from the cloud. $\theta_l^k$ contains aggregated knowledge from other clients (or untrained weights for initial step; see section 3.3). Afterwards, $C_l$ jointly optimizes the $\theta_l^k$ alongside it’s local resource-aware model $\theta_l$ on its local Non-IID dataset using DML (as shown in Algorithm 1 ClientUpdate). For a given input batch of local Non-IID data, DML first calculates the dataset loss (e.g., cross-entropy loss as shown in equation 2) for both networks independently.

$$L_c(\theta; B) = -\frac{1}{|B|} \sum_{x,y \in B} y^T \log(\sigma(\theta(x)))$$  \hspace{1cm} (2)

Here $\theta \in \{\theta_l, \theta_l^k\}$, $B$ is the input batch, $x$ and $y$ is the data point, and $\sigma$ is the softmax function.

Afterwards, DML measures the distance between the two predicted distributions using the Kullback Leibler (KL) divergence. Equation 3 shows the KL distance $D_{KL}(\theta_l||\theta_l^k)$ from $\theta_l^k$ to $\theta_l$.

$$D_{KL}(\theta_l||\theta_l^k; B) = \frac{1}{|B|} \sum_{x,y \in B} \sigma(\theta_l(x))^T \log \frac{\sigma(\theta_l(x))}{\sigma(\theta_l^k(x))}$$  \hspace{1cm} (3)

Similarly, we compute the $D_{KL}(\theta_l||\theta_l^k; B)$ by swapping $\theta_l$ and $\theta_l^k$ in the equation 3.

Finally we define the DML loss as shown in equations 4 and 5. DML loss combines a conventional loss function (eg. cross-entropy) with the objective of minimizing the Kullback Leibler (KL) divergence between the predictions of the participating networks (equation 4 and 5). This dual objective function enables learning from data while simultaneously gravitating the two networks towards each other.

$$L_{\theta_l} = L_c(\theta_l; B) + D_{KL}(\theta_l^k||\theta_l; B)$$  \hspace{1cm} (4)

$$L_{\theta_l^k} = L_c(\theta_l^k; B) + D_{KL}(\theta_l||\theta_l^k; B)$$  \hspace{1cm} (5)

An intuition as to why DML outperforms solo learning has to do with the dissimilarity of the participating models. In this case, the varying architectures coupled with the
successive DML steps further converge both subnetwork and forth between the server, they engage in sharing local powerful co-learner network boosts its performance. Additionally, while the smaller student’s intermittent global aggregation entail the learning of differing data representations. As such, varying outputs allows them both to capture each other’s internal representations/knowledge. Thus, varying out- student’s intermittent global aggregation entail the learning of differing data representations. As such, varying outputs allows them both to capture each other’s internal representations/knowledge. Additionally, while the smaller student helps reduce network bandwidth, having a larger (more powerful) co-learner network boosts its performance.

As clients communicate their student networks back and forth between the server, they engage in sharing local knowledge and receiving global knowledge. Consequently, successive DML steps further converge both subnetwork ($θ_l$) and student ($θ^k_l$) networks on the global data distribution. Overall, initializing clients with resource-specific NAS subnetworks paired with a smaller student network addresses device heterogeneity and reduces communication overhead.

3.3. Cloud Knowledge aggregating and Ensemble Distillation

As we mentioned before, RaFL utilizes the knowledge network as an medium to support interoperability among multi-model FL clients. As shown in Figure 1 $\mathcal{O}$ and $\mathcal{O}$, the function of the knowledge network is to exchange knowledge among Non-IID clients. The objective of the cloud updates is to ensure the global knowledge network contains all the knowledge from selected edge clients. As the Figure 1 $\mathcal{O}$ and $\mathcal{O}$ shows, RaFL provides two model fusion solutions, weight aggregating and ensemble knowledge distillation, to support comprehensive FL practical scenarios.

Assume $θ^k$ is the global knowledge network, and $θ^k_l$ as the $l^{th}$ client’s knowledge network. The cloud update process is shown in Algorithm 2. We select a set of communication clients $S$ in the current communication round. Once we receive the knowledge from edges, we aggregate the knowledge networks (as shown in step $\mathcal{O}$). Equation 6 shows the mathematical representation of this process.

$$\theta^k \leftarrow \frac{n_l}{N_S} \sum_{l \in S} \theta^k_l$$  \hspace{1cm} (6)

Here, $N_S$ is the total data size in selected clients $S$, and $n_l$ is data samples in $l^{th}$ client.

Recent FL works [1] demonstrate how public data can improve FL performance. In line with such works, in the case where public data is available, RaFL provides an ensemble knowledge distillation option for boosting cloud aggregating. As step $\mathcal{O}$ in Figure 1 shows, RaFL ensembles knowledge networks using the average logits strategy $\theta_{ens}(x) = \text{Avg}(\theta^k_l(x))_{l \in S}$ to produce a combined output on the public dataset. The outputted soft labels is then coupled with the unlabeled dataset to train the global knowledge network in tandem. The distillation loss is defined in equation 7.

$$L_d = D_{KL}(\theta_{ens}||\theta^k; B)$$  \hspace{1cm} (7)

It is noteworthy to mention that the knowledge network is a small-sized network derived from the NAS supernet. Intuitively, a larger knowledge network might seem to have a better performance. In our ablation study however, we show the trade-off between the size and the overall performance of the knowledge network. Results show there is no significant gain in increasing the size of the knowledge network.

4. Experiments

We conducted several experiments to extensively evaluate RaFL and summarized our experiments into five sections: learning efficiency, communication efficiency, system heterogeneity, resource utilization, and ablation study. In learning efficiency, we analyze the optimization ability for training the target model. The communication efficiency experiment investigates the communication cost incurred by client-server updates. In our system heterogeneity experiment, we highlight the advantage of RaFL across systems.
with varying resources. In the utilization experiment, we measure the overall resource use efficiency. Lastly, we conduct a comprehensive ablation study.

4.1. Experimental Setup

Datasets and models. We conduct experiments on datasets inline with baselines: CIFAR-10/100 [14] and FEMNIST [2] under Non-IID benchmark settings [16]. We deploy resource-aware deep learning models sampled from MobileNet-v2/v3 [11] or ResNet [10] super-network in different cases. In contrast, in baselines, we deploy a uniformed architecture sampled from MobileNet-v2/v3 and ResNet correspondingly. To avoid confusion, we identify networks by their capacity (via FLOPs), eg. we identify ResNet-18 as: ResNet with 76 MFLOPs. Additionally, our experiments also involves in over-parameterized models, such as VGG-11/16 [24], for highlight comparison.

Federated learning settings. We consider three following scenarios: (a) traditional FL settings, (b) public data with ensemble knowledge distillation, and (c) transfer learning with NAS. With CIFAR-10/100, we experiment on different number of clients from 30 to 100 and sample 10% to 70% clients for communication, while with FEMNIST, we experiment on 3000 clients and sample 10% clients in each communication round. All our experiments are conducted on benchmark Non-IID settings [16].

NAS settings. We conduct neural architecture search on pre-trained OFA [1] super-networks on ImageNet [21]. Super-network architectures involved in the experiments include ResNet, MobileNetv2 and MobileNetv3. Resource-aware models will be sampled from the super-networks. According to the FL settings, pre-trained weights inherited from super-network can be reset or transferred accordingly. Detailed information is specified in subsection.

Knowledge Net setting. We sampled a tiny network (in terms of FLOPs) from super-network as the knowledge network. Typically 28 ± 1 MFLOPs on ResNet architecture and 8 ± 0.5 on MobileNet architecture.

Baselines. We compare RaFL with state-of-the-art (SoTA) FL algorithms, including FedAvg [19], FedProx [17], FedNova [27].

4.2. Learning Efficiency

In this section, we explore the learning efficiency and optimization ability of RaFL. We evaluate the training performance with respect to the communication rounds, and compare RaFL with other methods: FedAvg [19], FedNova [27], and FedProx [17]. Since RaFL provides highly flexible optimization options among various FL application scenarios, to make a fair and extensive comparison, we elaborately considered all the possible practical situations in our comparison.

(a) Traditional FL. Firstly, in the case where public data is absent, we aggregate the weights of knowledge networks to fuse the local training results (via Figure 1 step 6 and Equation 6). Figure 2 (I) shows the training performance via communication rounds on CIFAR-100 with 100 clients, and in each communication round, we sampled 10% clients to involve in training (Results of traditional FL setting are denoted as RaFL (a)). RaFL outperforms baselines with a large margin. For example, it converges at 65% compared to 40% of FedAvg while it’s bandwidth is only 80% of that of FedAvg. With even smaller bandwidth (one-eighth of FedNova), RaFL needs only 80 rounds to reach 40% accuracy opposed ~300 round from FedNova. Additionally, by carefully sifting through the training logs, we discovered our baseline methods suffered from over-fitting during local update as demonstrated in Figure 3. In contrasts, RaFL conducted NAS to search for small capacity models, which are nearly optimal architectures (i.e., that are lightweight and have high learning capacity) under given constraints. Moreover, RaFL gains the benefit of DML as the knowledge networks tend to drift to overall gradient directions. As a result, RaFL suffered less over-fittings.

(b) Public data with ensemble and knowledge distillation. Secondly, considering the case where public data is present, RaFL provides ensemble distillation option to improve the server aggregation (steps 7 and 8). As shown in Figure 2 RaFL-(b), RaFL achieves a higher convergence accuracy while requiring fewer rounds to achieve the target precision compared to baselines. For instance, in the 30 clients FL setting, it achieves at 70% final accuracy, which is 10% higher than other 3 baselines (Figure 2 (II)(1), (II)(3), (II)(4)). There are several exception where RaFL does not outperform the baselines in case of 100 clients with 40% sample rate (Figure 2 (II)(3)). RaFL with smaller sub-network reached a converged accuracy of 55%, slightly lower than 57% by FedAvg and FedNova. However, it is worth noting that RaFL uses far less bandwidth per communication rounds (1.6 GB versus 2.8GB and 5.6 GB for FedAvg and FedNova respectively) compared to the baselines. Thus with a small sacrifice in accuracy, we make a large gain in terms of communication cost. Despite the dissimilarity of the public data (Sampled 10k data points from TinyImagenet in this case) compared to the local dataset (CIFAR10/100), it improves the performance of both the global and local models. Ensemble distillation acquires knowledge from logits averaged over all knowledge networks. Thus mutually beneficial information is indirectly shared among all client architectures.

(c) Transfer learning with NAS. Thirdly, RaFL takes the advantage of transfer learning on its pre-trained NAS sub-networks when the networks are applied to the Non-IID FL dataset. Since the NAS super-network is pre-trained, we keep the pre-trained weights on sampled sub-networks (in previous two evaluations we drop the pre-trained weights).
perform baselines in most cases. Results show that RaFL has a clear advantage in scenarios where communication is a limiting factor. For instance, with a sample ratio of 10%, RaFL converges faster and with less communication cost compared to baselines. The figure illustrates that RaFL is able to show a superiority in communication efficiency, which is crucial in edge computing environments.

Finally, it’s worth mentioning that to further show the edge RaFL has under the above scenarios, we assigned small resources to the RaFL clients. Results show we outperform baselines in most cases.

4.3. Communication Efficiency

RaFL is able to show a superiority in communication efficiency compared to SoTAs via knowledge extraction and fusion, which communicates compacted knowledge networks between edge and server. To fully reveal the communication efficiency of RaFL, we conducted comprehensive experiments in order to achieve two objectives: target accuracy and converged accuracy. The communication cost

Figure 2 (I, II) RaFL(c) shows the results on different number of clients and sample rate. With the benefit of pretrained encoder, RaFL starts off with a high accuracy in the initial training stage and converges quickly during the fine tune process. For instance, in Figure 2 (II)(2), we train a light weight network sampled from MobileNetV3-based super-net and train VGG16 for baselines: RaFL converge fast with an accuracy of 46% in first round, and proceed to attain an incredible 80% converged accuracy, while produced a larger gap to baselines than ensemble setting. Moreover, with the fast convergence, our communication cost is smaller than baselines, for instance 3.9× less than FedNova (0.68 GB versus 2.67 GB).

Figure 3. Local training details: Rounds vs Accuracy.
Table 1. Comparison of communication cost with SoTAs to achieve target accuracy.

<table>
<thead>
<tr>
<th>Method</th>
<th>Model Arc.</th>
<th>Network Capacity</th>
<th>Dataset</th>
<th>Target Acc.</th>
<th>Round Cost</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>FedAvg</td>
<td>ResNet</td>
<td>76 MFLOPs</td>
<td>CIFAR100</td>
<td>40%</td>
<td>0.85 GB</td>
<td>388 GB</td>
</tr>
<tr>
<td></td>
<td></td>
<td>152 MFLOPs</td>
<td>CIFAR100</td>
<td>40%</td>
<td>1.6 GB</td>
<td>580 GB</td>
</tr>
<tr>
<td>FedNova</td>
<td>ResNet</td>
<td>76 MFLOPs</td>
<td>CIFAR100</td>
<td>40%</td>
<td>3.4 GB</td>
<td>323 GB</td>
</tr>
<tr>
<td></td>
<td></td>
<td>152 MFLOPs</td>
<td>CIFAR100</td>
<td>60%</td>
<td>6.4 GB</td>
<td>608 GB</td>
</tr>
<tr>
<td>FedProx</td>
<td>ResNet</td>
<td>76 MFLOPs</td>
<td>CIFAR100</td>
<td>40%</td>
<td>1.7 GB</td>
<td>496 GB</td>
</tr>
<tr>
<td></td>
<td></td>
<td>152 MFLOPs</td>
<td>CIFAR100</td>
<td>40%</td>
<td>3.2 GB</td>
<td>588 GB</td>
</tr>
<tr>
<td>RaFL</td>
<td>ResNet</td>
<td>28 MFLOPs</td>
<td>CIFAR100</td>
<td>40%</td>
<td>1.07 GB</td>
<td>31.0 GB</td>
</tr>
</tbody>
</table>

Figure 4. Communication cost to achieve target accuracy.

is calculated by bandwidth consumption between edge and server in the FL optimization process. Here we consider traditional FL setting (section 4.2 (a)).

The communication cost in reaching target accuracy is demonstrated in Figure 4, RaFL consistently outperforms SoTAs in communication overhead. For example, in ResNet architecture and CIFAR-100, RaFL reduced up to 31.25× communication cost compared to FedAvg [19], and up to 66.64× compared to FedNova. There are two reasons RaFL shows significant communicate efficiency, first, as shown in Figure 4, RaFL uses less communication rounds to achieve target accuracy. Second, RaFL communicates the knowledge networks with a tiny bandwidth of 0.66 GB per round.

Furthermore, we conducted experiments on optimizing target model to converge, Table 2 summarizes the results. In CIFAR-100 and ResNet, RaFL reaches 65% accuracy while the next best method FedNova only converges at 43%. More importantly, the total cost is significantly lower in the case of RaFL (being 1260 GB lower).

In general, RaFL requires fewer communication burden to reach both target accuracy and overall convergence across a wide range of FL settings. Additionally, it’s worth to mention that, the network capacity we deployed on edge also shows significant less resource consumption, where the average network capacity of RaFL is 47 MFLOPs (up to 3.25× less than baselines). Edge devices can further gain faster inference and react (Extensive experiments can be find in supplementary material communication efficiency).

4.4. Resource-aware System Heterogeneity

RaFL with its resource-aware NAS shows superiority in various resource system heterogeneity. Since baselines fails to address system heterogeneity, we conduct ablation experiment to investigate the ability of RaFL dealing with different resource heterogeneous systems.

As shown in Table 3 and Figure 5, RaFL shows a stable optimizing ability under different system heterogeneity. Under extreme highlight settings, the 47.52 MFLOPs network capacity compare to 74.35 MFLOPs, where the training process shows they have similar learning trend and final accuracy even though the resource constraints is approximate 2× different. Furthermore, edge clients shows similar performance even though their network capacity varies, because NAS always searches for a nearly optimal architecture for a given constraints.

Additionally, RaFL shows incredible high resource utilization efficiency. In contrasts, baselines, fails to support multi-model in FL, have to satisfy the weak clients, in the same resource constraints setting, their resource use efficiency is only 75% on 79.70 MFLOPs constraints. RaFL

Table 2. Communication cost to achieve converged accuracy with 100 clients and 10% sample clients per round.

<table>
<thead>
<tr>
<th>Method</th>
<th>Model Arc.</th>
<th>Network Capacity</th>
<th>Dataset</th>
<th>Comm Cost per round</th>
<th>Total Cost</th>
<th>Converged Acc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FedAvg</td>
<td>ResNet</td>
<td>76 MFLOPs</td>
<td>CIFAR100</td>
<td>0.85 GB</td>
<td>425 GB</td>
<td>40%</td>
</tr>
<tr>
<td>FedNova</td>
<td>ResNet</td>
<td>76 MFLOPs</td>
<td>CIFAR100</td>
<td>1.7 GB</td>
<td>850 GB</td>
<td>42%</td>
</tr>
<tr>
<td>FedProx</td>
<td>ResNet</td>
<td>76 MFLOPs</td>
<td>CIFAR100</td>
<td>3.2 GB</td>
<td>1600 GB</td>
<td>43%</td>
</tr>
<tr>
<td>RaFL</td>
<td>ResNet</td>
<td>28 MFLOPs</td>
<td>CIFAR100</td>
<td>0.66 GB</td>
<td>340 GB</td>
<td>65%</td>
</tr>
</tbody>
</table>

Table 3. RaFL under different system-heterogeneous resource constraints.

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>ResNet</td>
<td>CIFAR100</td>
<td>48.01 MFLOPs</td>
<td>47.52 MFLOPs</td>
<td>99%</td>
<td>600</td>
<td>65%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>79.70 MFLOPs</td>
<td>74.35 MFLOPs</td>
<td>93%</td>
<td>500</td>
<td>61%</td>
</tr>
<tr>
<td>MobileNetV3</td>
<td>CIFAR100</td>
<td>11.37 MFLOPs</td>
<td>13.07 MFLOPs</td>
<td>90%</td>
<td>200</td>
<td>35%</td>
</tr>
</tbody>
</table>

Figure 5. RaFL under various system heterogeneous setting.
achieve 13.3% more resource utilization.

4.5. Scaled Federated Learning

We experiment with large scale FL setting by using FEMNIST dataset [2]. The total number of clients is 3000 with 300 active clients each communication round (10% sample rate). While RaFL has much smaller communication overhead, both methods achieve the same testing accuracy.

5. Conclusion

In this paper, we propose RaFL, a resource-aware FL pipeline for efficient heterogeneous federated learning using neural architecture search and dual knowledge distillation. The RaFL server initializes each client by supplying them with a pair of networks. The first network is a custom-made subnetwork that is tailored to fit the client’s computational need. The second is a common student network that will serve as a global knowledge medium. RaFL clients train their model pairs via deep mutual learning, while the RaFL server applies multi-model fusion for knowledge distillation. We conduct our experiments using an image classification task. In particular, we trained an array of heterogeneous clients on the CIFAR10 and CIFAR100 image datasets using baseline non-IID settings. Our experiments demonstrate the practicality of heterogeneous multi-model FL with improved convergence and increased communication efficiency. In the future, we intend on speeding up global model fusion and explore alternative ways of improving model fusion.

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