Follow up on A Naive Baseline in Heterogeneous Federated Learning

Durmus Alp Emre Acar*, Yue Zhao†

In this note, we tabulate more results to our comparison of naive baseline and HeteroFL. Recall that, in naive baseline, we group devices that share the same architecture and perform federated learning only over that group.

We report test results on CIFAR10 dataset, IID split, 100 devices, 10% activation rate where devices have two different complexity levels (complex and simple). To construct the simple model, we shrink the CNN layers using 0.0625 complexity level. We consider various splits such as 70 complex - 30 simple, 50 complex - 50 simple and 30 complex - 70 simple. For each of the splits, we experimented with fix and dynamic assignments as in [1]. We use the available HeteroFL code for ResNet experiments and our results validates reported test accuracies of [1]. For instance, we get 90.5% for HeteroFL global complex model accuracy in 50 complex - 50 simple split, dynamic assignment setting which is reported as 90.29% in [1]. Results for the two different experiments are reported in Table 1 - 4. We abbreviated decoupled FedAvg with complex model baseline as D-FedAvg-C. Similarly, decoupled FedAvg with complex model baseline is shown as D-FedAvg-S.

We discuss details of the naive baselines for the sake of completeness.

Fix assignments. In this assignment, complexity levels of each device is fixed. In each communication round, HeteroFL randomly selects 10 devices. To have a fair comparison, the naive baseline randomly selects 10% of the devices from one heterogeneity group. For example, consider 30 complex - 70 simple split. Naive baseline for complex clients selects 3 clients at random out of 30 complex clients at each round. Fixed assignment results are shown in Table 1 and 3.

Dynamic assignments. Complexity levels of each device dynamically changes. In each communication round, HeteroFL randomly selects 10 devices and then randomly assigns a complexity level to them based on the split ratio. On average, 7, 5 and 3 of the selected devices would have complex models for 70 complex - 30 simple, 50 complex - 50 simple and 30 complex - 70 simple splits respectively. Different from fix assignment, dynamic assignment allows every device to have both complexity levels. To have a fair comparison, the naive baseline selects devices at random among 100 devices where the activation rate depends on the complex vs. simple fraction. For instance, in 70 complex - 30 simple split, naive baseline for complex clients selects 7 clients at random out of 100 clients. Dynamic assignment results are tabulated in Table 2 and 4.

Discussion. As in the previous note, the performance of the naive baseline is on-par with HeteroFL across different architectures for the complex model. On the other hand, decoupled training for simple models outperforms HeteroFL. Even with different splits and assignments the question remains. As such, leveraging federated learning for training heterogeneous device models may result in loss of accuracy across different splits in both fixed and dynamic assignments. Namely, even though we have access to more data through different architectures, the task of transferring knowledge among different architectures is challenging.

*Boston University, Boston, MA
†Arm ML Research Lab, Boston, MA

Table 1: Complex model: Neural-Net consisting of three convolutional layers and includes group normalization. Fixed Assignment.

Complex - Simple Ratio	Algorithm	Server Complex Accuracy Architecture 'a'	Server Simple Accuracy Architecture 'e'
70 - 30	D-FedAvg-C	80.7	NA
	D-FedAvg-S	NA	65.5
	HeteroFL	80.0	61.3
50 - 50	D-FedAvg-C	79.9	NA
	D-FedAvg-S	NA	66.6
	HeteroFL	79.6	64.8
30 - 70	D-FedAvg-C	77.3	NA
	D-FedAvg-S	NA	67.5
	HeteroFL	77.3	67.2

Table 2: Complex model: Neural-Net consisting of three convolutional layers and includes group normalization. Dynamic Assignment.

Complex - Simple Ratio	Algorithm	Server Complex Accuracy Architecture 'a'	Server Simple Accuracy Architecture 'e'
70 - 30	D-FedAvg-C	81.2	NA
	D-FedAvg-S	NA	67.6
	HeteroFL	81.0	61.9
50 - 50	D-FedAvg-C	81.3	NA
	D-FedAvg-S	NA	67.0
	HeteroFL	80.8	65.3
30 - 70	D-FedAvg-C	80.3	NA
	D-FedAvg-S	NA	66.8
	HeteroFL	80.4	66.3

Table 3: Complex model: ResNet model with an sBN module as in [1]. Fixed Assignment.

Complex - Simple Ratio	Algorithm	Server Complex Accuracy Architecture 'a'	Server Simple Accuracy Architecture 'e'
70 - 30	D-FedAvg-C	90.5	NA
	D-FedAvg-S	NA	76.5
	HeteroFL	90.3	63.8
50 - 50	D-FedAvg-C	89.1	NA
	D-FedAvg-S	NA	77.4
	HeteroFL	89.3	74.3
30 - 70	D-FedAvg-C	87.3	NA
	D-FedAvg-S	NA	78.5
	HeteroFL	85.8	77.2

Table 4: Complex model: ResNet model with an sBN module as in [1]. Dynamic Assignment.

Complex - Simple Ratio	Algorithm	Server Complex Accuracy Architecture 'a'	Server Simple Accuracy Architecture 'e'
70 - 30	D-FedAvg-C	91.7	NA
	D-FedAvg-S	NA	76.8
	HeteroFL	91.3	67.7
50 - 50	D-FedAvg-C	90.7	NA
	D-FedAvg-S	NA	77.4
	HeteroFL	90.5	74.0
30 - 70	D-FedAvg-C	89.9	NA
	D-FedAvg-S	NA	78.7
	HeteroFL	89.1	77.2

References

[1] Enmao Diao, Jie Ding, and Vahid Tarokh. Hetero{fl}: Computation and communication efficient federated learning for heterogeneous clients. In *International Conference on Learning Representations*, 2021.