Compression Study on Federated Learning

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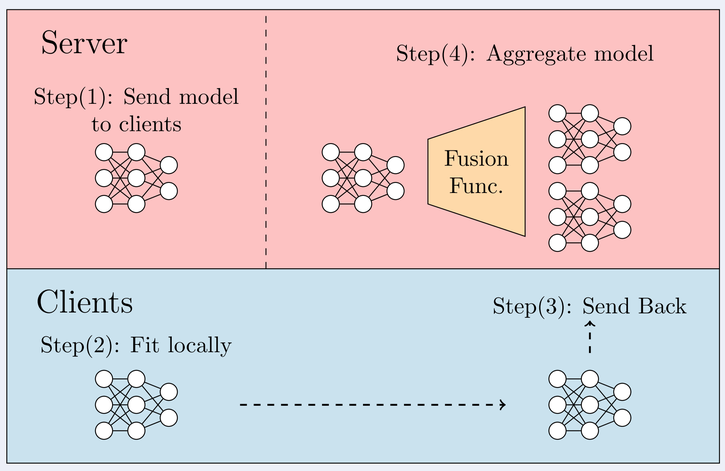
Lucas Grativol[*,§], Mathieu Léonardon[*], Guillaume Muller[†], Virginie Fresse[§], Matthieu Arzel[*] *IMT Atlantique, Lab-STICC, UMR CNRS 6285, Brest, France*[*]
Hubert Curien Laboratory, Saint-Etienne, France[§]
Mines Saint-Etienne, Institut Henri Fayol, Saint-Etienne, France[†]

Context

Federated Learning (FL) is used distributed/collaborative learning algorithm, for a more private machine learning.



Federated Learning standard setup.

Clients are usually embedded devices, with low hardware specifications but access to real-world, possibility private, data. In this scenarios, **how can neural networks compression techniques improve the FL framework ?**

Setup

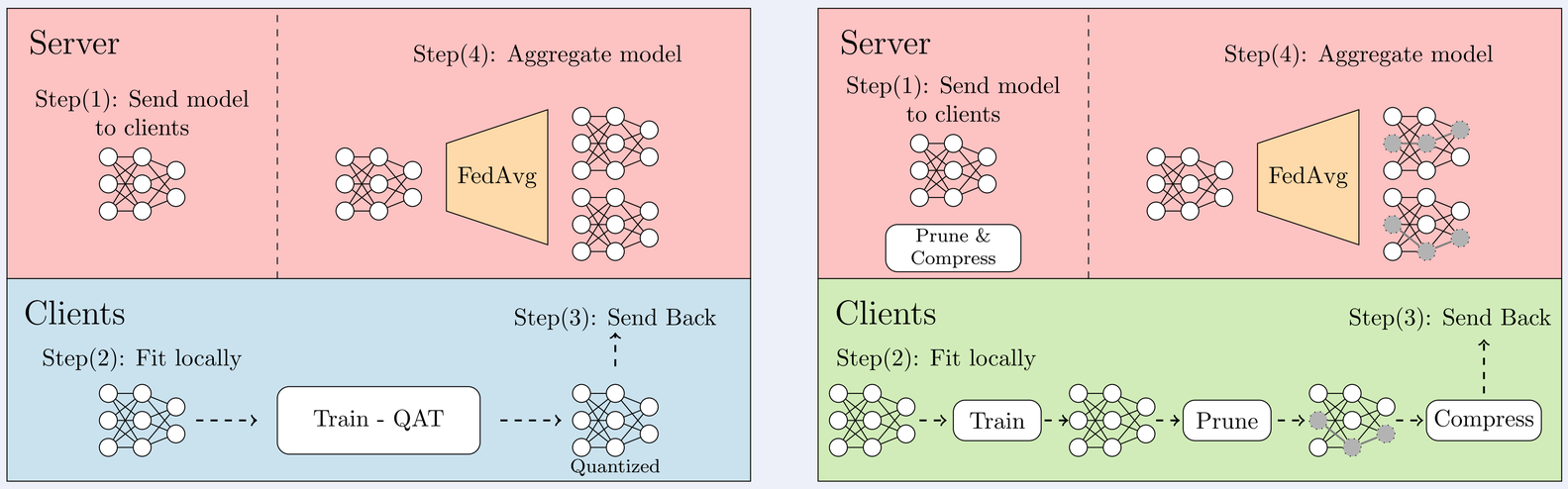
FL Setup: We used Flower's framework [1] to simulate 10 FL clients, with 40 % sampling rate, for 100 rounds of communication. The client's learning rate was fixed to 0.0316 and a batch-size of 20, as per [2]. On the server side, we use FedAvg as aggregation strategy.

Simulation: The experiments are done for image classification on CIFAR-10 and CIFAR-100, where each client hold a fraction of the trainset, accordiantly to a Latent Dirichlet Allocation [3] with parameter equals to 100. Each client trains a ResNet-12, with GroupNorm instead of a BatchNorm.

Quantization: We chose to work with quantization levels that are easily exploitable on embedded systems, 1-bit, 4-bit and 8-bit (weights only). For 4- and 8-bit, we use the brevitas framework [4] to implement QAT.

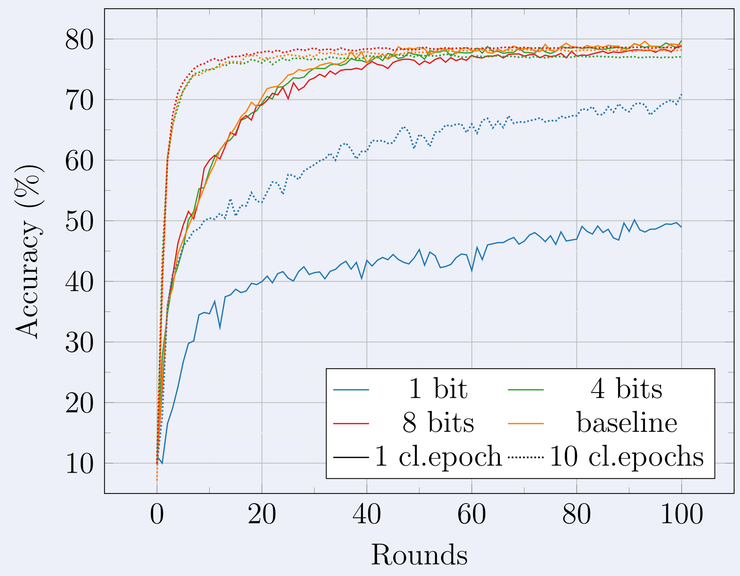
Pruning: We considered an unstructured magnitude based pruning method. To keep coherence between up and down streams, server and clients prune the same percentage of weights each round.

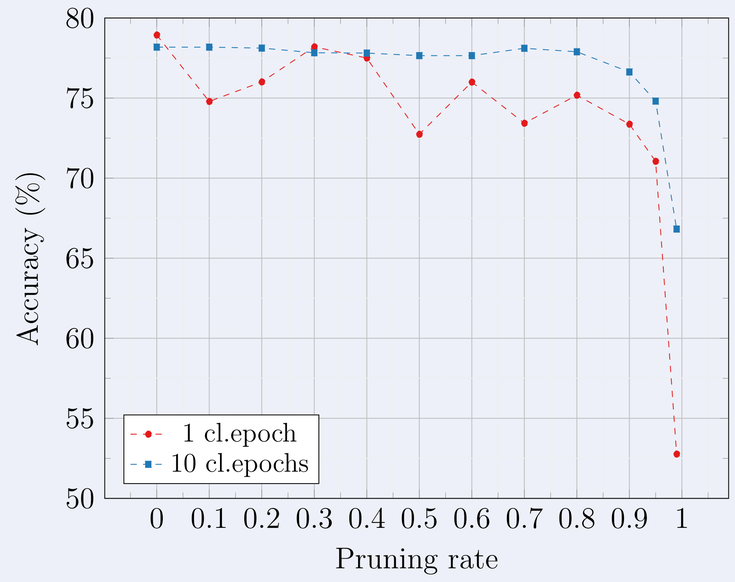
Our scheme



Proposed setups. On the left, each client trains a model using QAT (Quantization-Aware-Training). On the right, both client and server use magnitude prune to compress the model.

Experimental results – CIFAR10





Accuracy evolution comparison, for the quantization technique, between baseline (FP 32-bit), 1-bit, 4-bit and 8-bit, on the left. Pruning effect on the accuracy in function of the pruning rate, where the rate indicates the % of total parameters pruned, on the right. Experiments done for 1 and 10 cl.epochs (clients epochs)

Compression expectation

Technique	Accuracy (%)		Message (MiB)
	1 Lc. Epoch	10 Lc. Epochs	
Baseline	78.94	78.18	2.97
Pruning			
10 %	74.79	78.18	2.57
20 %	76.01	78.12	2.34
30 %	78.20	77.83	2.10
40 %	77.50	77.81	1.85
50 %	72.74	77.65	1.57
60 %	76.00	77.65	1.29
70 %	73.43	78.11	1.01
80 %	75.18	77.89	0.70
90 %	73.37	76.63	0.37
95 %	71.05	74.81	0.19
99 %	52.77	66.82	0.04
Quantization			
8-bits	78.80	78.58	0.75
4-bits	79.74	77.04	0.38
1-bit	48.93	70.89	0.10

Summary of message size and accuracy for the CIFAR-10 dataset.

Through the integration of common compression techniques to FL, where, depending on the compression used, it is possible to reduce the size of the message to be sent from 13% (10% pruning) to 96% (99%/1-bit pruning), after data compression. Where the trade-off between accuracy and message size is the main point.

Conclusions

- **Takeaways**: As seen in centralized training, reduced precision can achieve comparable accuracy to an FP32 model. Furthermore, in the quantization experiment, reaching 78% accuracy takes approximately 40 rounds with 1 local epoch, whereas with 10, it is achieved in just 10 rounds. By increasing the number of local epochs, it is possible to reduce communication, but at the same time, it increases device training time/energy.
- **Perspectives**: In order to go further with the adaptation of hardware constraints and the machine learning model, it could be interesting to integrate heterogeneous Federated Learning.

References

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[2] Reddi, Sashank and et al.: *Adaptive federated optimization*, ICLR (2021)
[3] Hsu, Tzu-Ming Harry and et al.: *Measuring the effects of non-identical data distribution for federated visual classification*, Neurips Workshop on Federated Learning (2019)
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