

Android On-device Federated Learning of PyTorch Models with Flower

Michael Cho, Dr. Afra Mashhadi

Ubiquitous Computing Laboratory, University of Washington Bothell



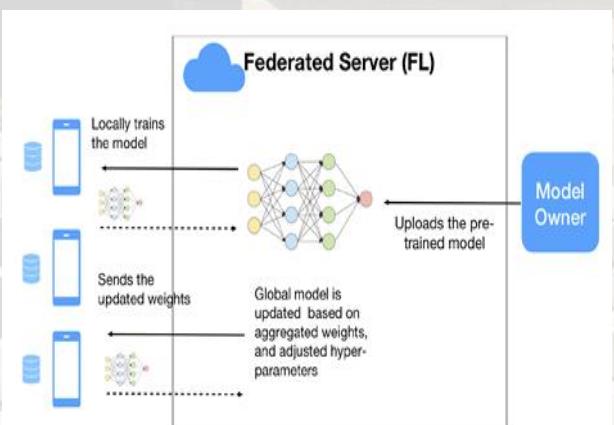
Question



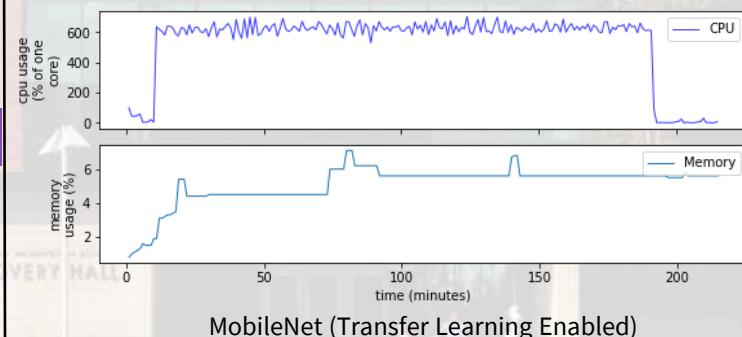
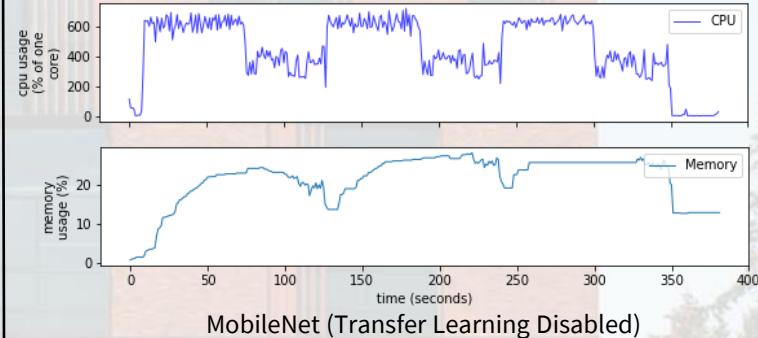
Research Question: Compared to centralized machine learning, can federated learning on mobile phones reduce computational complexity and restrictions while enhancing data privacy?

Methodology

- Developed an Android client interface for models based on PyTorch
- Integration with the Flower federated learning framework
- Training data set contained object detection classes (20 images per class)
- Leveraged CNNs (MobileNet and SqueezeNet) to help train data
- Measured memory, CPU, energy consumption, and training time
- Experimented on a Samsung S21 Ultra with 8GB of RAM and eight CPU cores



Results



Model	Time (per one round)	Max Memory
MobileNet (TL)	180 s	728 MB
MobileNet (No TL)	340 s	2.8 GB
SqueezeNet (TL)	7 s	384 MB
SqueezeNet (No TL)	32 s	1.2GB

On-device measurements of memory usage and training time for one round of local training

The table shows the memory and training time for both models. The comparison of the two models suggests that the **memory usage is approximately between 300MB-700MB** (3-7% of the total RAM) for SqueezeNet and MobileNet respectively when the models are leveraging transfer learning. One round of training (of MobileNet without TL) **consumed 10.3 mAh on average**, which corresponds to **less than 0.15%** of the total available battery on a fully charged device.

Conclusion

Federated learning on mobile phones is a viable alternative to centralized machine learning methods. With Flower, mobile phones can participate in training while maintaining **efficient use of computational resources** and **improving the privacy of data**. Future implementations of federated learning on edge devices **may provide more accessibility** to machine learning platforms **while promoting sustainability of resources**.

