Efficient Split-Mix Federated Learning for On-Demand and In-Situ Customization

Junyuan Hong\textsuperscript{1}, Haotao Wang\textsuperscript{2}, Zhangyang Wang\textsuperscript{2} and Jiayu Zhou\textsuperscript{1}

\textsuperscript{1}Michigan State University, \textsuperscript{2}University of Texas, Austin
Federated Learning

- *Training* is distributed to enormous clients and aggregated by parameter averaging.
- *Advantage*: Privacy protection, communication efficiency, flexible training with heterogeneous clients.
Run-time Dynamics & Model Customization

Client required trade-off

Accuracy

Accuracy

Memory/Time Efficiency

Adv. Robustness

Model width
(number of layer channels)

ideal customization by individual FedAvg Models

• More training time
• Inefficient customization
Challenges for In-situ Customization from Heterogeneous Federated Learning

- In-situ customization baseline: SHeteroFL (ICLR 2021)
- Co-existing heterogeneity
  - Resources
  - Data

Client data from different domains

MNIST  SVHN  USPS  SynDigits  MNIST_M
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Ineffective customization
Split-Mix

Flexible and affordable training
Split-Mix

Effective customization

width-flexible inference
Thank you!

More in our paper:

- Adversarial robustness customization.
- Joint customization of robustness and model sizes.

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Code: https://github.com/illidanlab/SplitMix