Label Hungry? Not Anymore: Towards Federated Semi-supervised Learning

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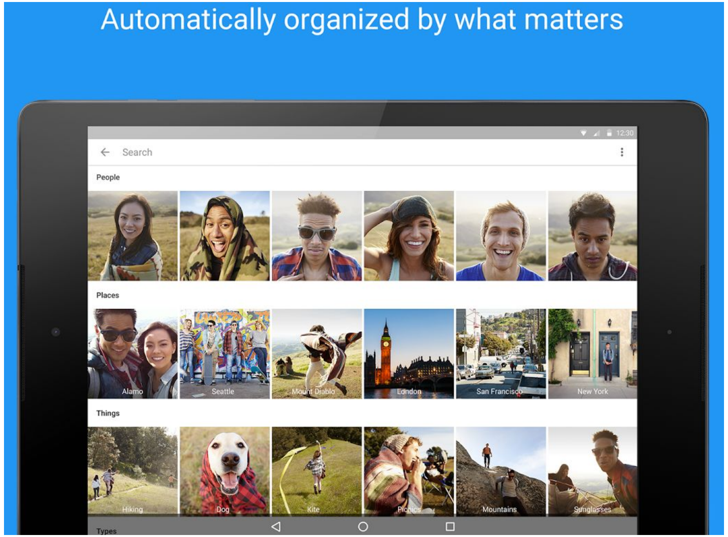
Challenge for FL

- While users generate a wealth of rich data, **labeled data** is scarce on client devices
  - ~1.2 trillion photos taken on mobile devices in 2017 [1]
- Limits usability of FL in domains where deep learning has shown high performance, such as image classification



[1] Richter, Felix. “Infographic: Smartphones Cause Photography Boom.” *Statista Infographics*, 31 Aug. 2017, www.statista.com/chart/10913/number-of-photos-taken-worldwide/.

Problem Formulation

- Apply semi-supervised learning in federated setting to leverage unlabelled data
- EMNIST federated digit recognition dataset
- Study model performance while varying the ratio of labelled to unlabeled data

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Related Work

- **Federated learning** [2]:
  - Privacy-preserving ML training on a large corpus of decentralized data residing on devices like mobile phones.
- **Semi-supervised learning:**
  - Combines small amount of labelled data with large amounts of unlabelled data during training [3].
- **Representation Learning:**
  - Supervision is derived from the data itself using auxiliary tasks
    1. Autoencoder network
    2. Image rotations [4]

[2] McMahan, et al. "Communication-efficient learning of deep networks from decentralized data." arXiv preprint arXiv:1602.05629 (2016).
[3] Chapelle, et al. *Semi-supervised learning*. Cambridge, Mass.: MIT Press. ISBN 978-0-262-03358-9
[4] Gidaris, et al. "Unsupervised representation learning by predicting image rotations." arXiv preprint arXiv:1803.07728 (2018).

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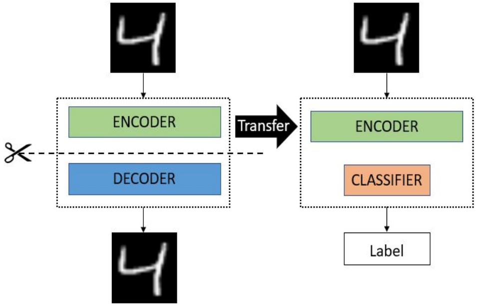
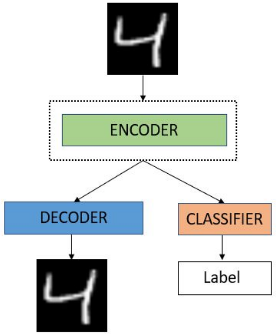
Self-supervised pre-training (SSPT)

- Train autoencoder in federated computation
- Transfer encoder layer weights to classifier
- Train classifier in second federated computation



Semi-supervised joint optimisation (SSJO)

- Single federated computation
- All examples generate unsupervised loss
- Labeled examples generate additional supervised loss



Experimental Setup

- **Mask ratio**: the fraction of data for which labels are removed
  - Varied over {0.0, 0.8, 0.9, 0.95, 0.98, 0.99}

Models:

- **FSL:** Fully Supervised Learning (baseline)
- **SSPT:** Self-Supervised Pre-Trained model
- **SSJO:** Semi-Supervised Jointly Optimized model

Architecture:

- **Classification head:** (Input-size: 784) → (embedding dense-layer: 256) → (Output-size: 10)
- **Reconstruction head:** (Input-size: 784) → (embedding dense-layer: 256) → (Output-size: 784)

Federated Setting

Batch Size	20
Client Learning Rate	1e-3
Client Momentum	0.99
Epochs/Client	10
Clients/Round	100
Communication Rounds	100

Central Setting

Batch Size	20
Learning Rate	1e-4
Momentum	0.99
Epochs	10

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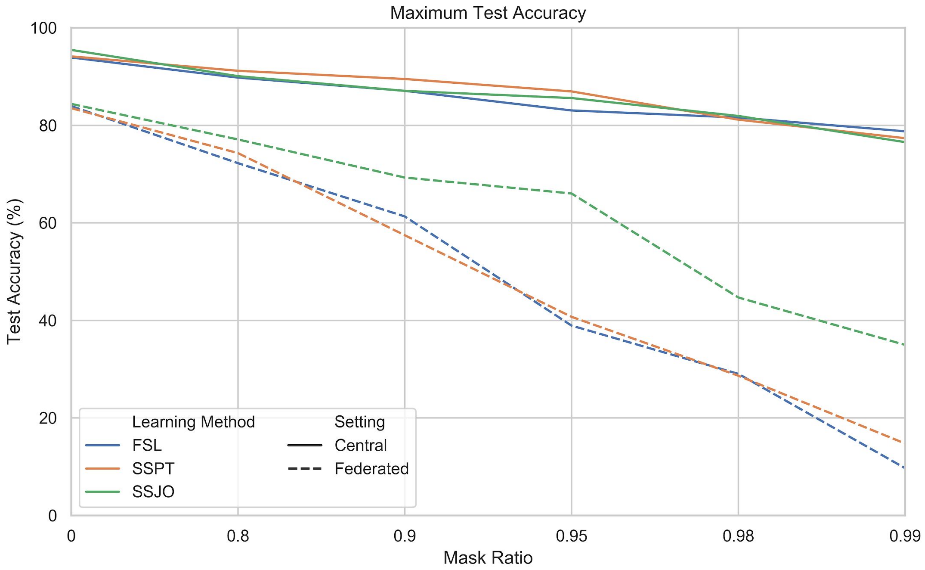
Results

- Central Setting:
  - similar results across three methods
  - Marginal increase in test accuracy for SSJO and SSPT methods over FSL

- Federated Setting:
  - SSJO outperforms SSPT and FSL by greater margin as mask ratios increase

- As expected, lower test accuracy for Federated vs. Central
  - Possibility for higher federated accuracy with refined hyperparameter search and additional communication rounds



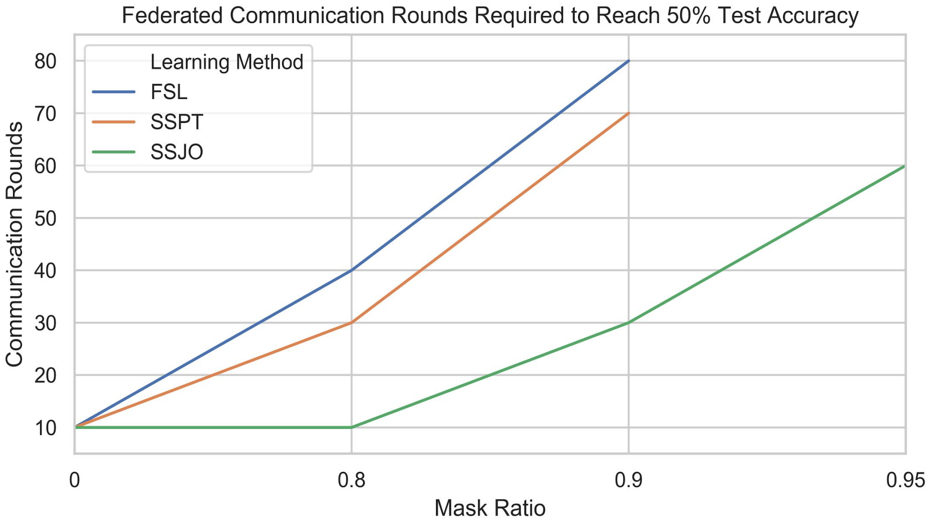
FSL: Fully Supervised Learning

SSPT: Self-supervised Pre-Training

SSJO: Semi-supervised Joint Optimization

Results

- FSL requires more communication rounds than SSPT and SSJO
- SSJO requires the least communication rounds



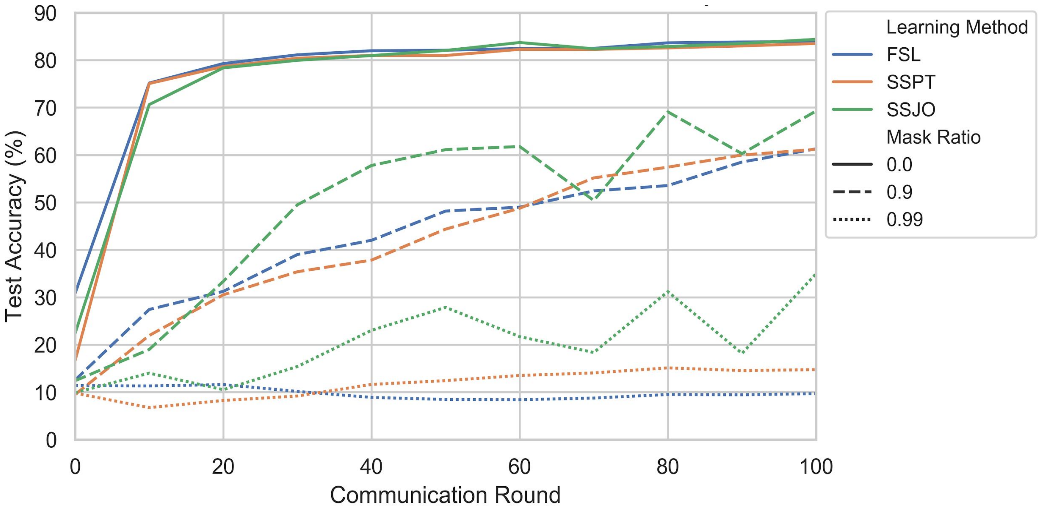
FSL: Fully Supervised Learning

SSPT: Self-supervised Pre-Training

SSJO: Semi-supervised Joint Optimization

Results

- SSJO test accuracy is unstable during training as mask ratio increases
- Model might be oscillating between local optima in the two heads



FSL: Fully Supervised Learning SSPT: Self-supervised Pre-Training SSJO: Semi-supervised Joint Optimization

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- In our experiments, SSL:
  - achieved similar (low mask-ratio) or higher (high mask-ratio) test accuracy to FSL
  - required fewer communications rounds to reach a threshold of 50% test accuracy

- Joint optimization: higher test accuracy but more unstable training

- Future work:
  - learning rate decay to stabilize SSJO training
  - the use of more specialized auxiliary tasks such as predicting rotations
  - the performance of these methods on richer datasets such as federated CIFAR 100

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END OF
PRESENTATION!!

Questions?

Appendix: Rotation Model

- Convolution model on EMNIST
- SSPT only
- No major difference in performance
    - Dataset: EMNIST may not be ideal for rotation prediction task
    - Model architecture: may not be ideal for pretraining