Privacy-preserving decentralized learning methods for biomedical applications

Mohammad Tajabadi, Roman Martin, and Dominik Heider

Philip Frese

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Outline

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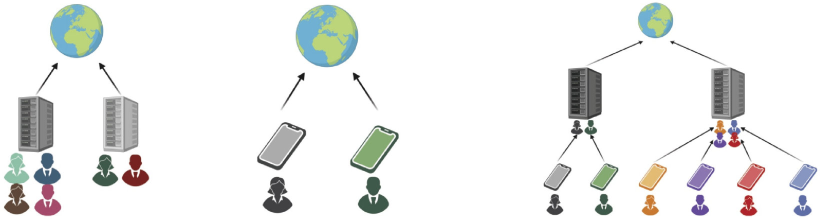
Motivation

- Great potential for artificial intelligence methods in biomedical field
  - Development and repurposing of drugs
  - Epidemiological modeling
  - New treatments, prognostics, and monitoring methods
- Traditional learning methods require massive amounts of data
  - Often not available at a single site, e.g., hospital
  - Regulations like GDPR limit sharing of medical patient data
- Decentralized learning methods allow for training new models without sharing data
- Common procedure: Multiple participants independently train models on their local datasets and share model parameters

Tajabadi et al. [10]

Outline

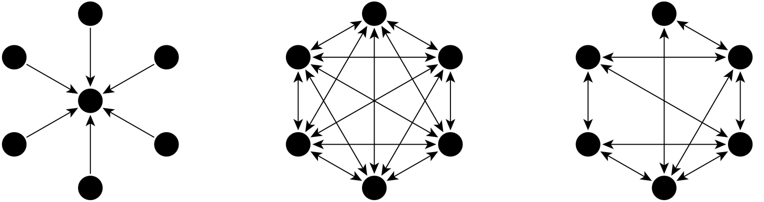
Decentralized Learning Settings



(a) Cross-silo learning (b) Cross-device learning (c) Cross-device forming ad hoc silos

Figure: Tajabadi et al. [10]

Network Topologies



(a) Centralized learning network (b) Fully meshed peer-to-peer network (c) Partially meshed peer-to-peer network

Figure: Tajabadi et al. [10]

Outline

Gossip Learning

- Partially meshed peer-to-peer network, entirely decentralized
- Each peer trains a model using local data
- Perform random walks over partial network to share models with other peers
- Peers merge models and update them using local data (online learning)
- All peers have the same model parameters at convergence

Ormándi et al. [8], Tajabadi et al. [10]

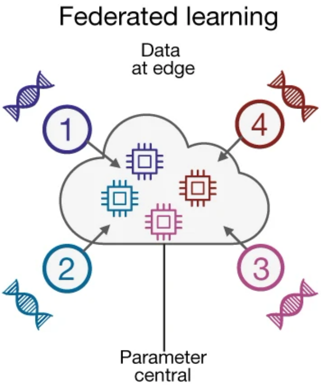
Gossip Learning: Applications

- Pros/Cons:
  - \+ No single point of failure, better robustness and scalability
  - − High data transfer, less efficient than federated learning in some experiments
- Brain tumor segmentation on multi-parametric MRI [1]
  - Introduce Gossip Mutual Learning (GML) for aggregating models in peers
  - Performance is higher than local models, comparable to federated learning (although 25% communication overhead), and lower than pooled model

Chen and Yuan [1], Hegedűs et al. [4]

Federated Learning

- Centralized learning network with one server and multiple clients
- Each client trains a local model with the local dataset
- Model parameters are sent to the server
- Server aggregates the local models, resulting in a global model which is distributed to clients



McMahan et al. [6], Tajabadi et al. [10], Figure: Warnat-Herresthal et al. [11]

Federated Learning: Applications

- Pros/Cons:
  - \+ Less data traffic than in gossip learning
  - − Potential single point of failure
- Federated Random Forest (FRF) models for disease prediction and classification [3]
  - Examined diseases: Liver disease, hepatocellular carcinoma, breast cancer, lung tumors
  - Performance comparable to centralized model, outperform local models
  - More stable for imbalanced datasets, no significant performance decrease when increasing number of datasets and decreasing their size

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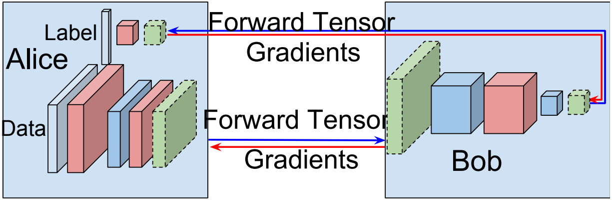
Hauschild et al. [3], Hegedűs et al. [4]

Split Learning

- Deep neural network is split between nodes and server
- Node performs forward pass and sends output (*smashed data*) to server for completion of forward pass, inverse for back propagation
- Loss computation can optionally be performed by node to avoid sharing labels (wrapped network)
- Multiple nodes: Round robin; server (centralized mode) or previous node (peer-to-peer mode) sends parameters to next node



Gupta and Raskar [2], Tajabadi et al. [10], Figure: [2]

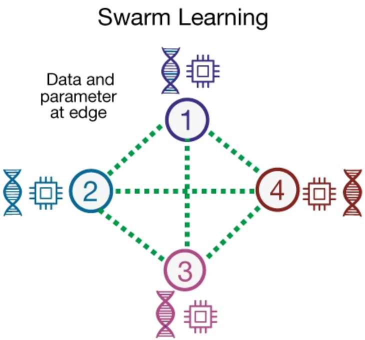
Split Learning: Applications

- Pros/Cons:
  - \+ Training is partially offloaded to server (reduced computation in nodes), configurable privacy-efficiency trade-off
  - – Nodes are processed sequentially (improved in variant *SplitFed*), only suitable for deep neural networks
- Split learning for biomedical image classification and clinical concept predictions on electronic health record (EHR) datasets [5]
  - Convolutional neural network for image classification, transformer (nodes) and fully connected network (server) for EHR data
  - Performance similar to federated learning and centralized learning

Li et al. [5]

Swarm Learning

- Decentralized form of collaborative learning
- Fully meshed peer-to-peer network, mainly for cross-silo settings
- Nodes train models using local data
- Parameters are exchanged via Swarm API and nodes merge models
- New nodes enroll via blockchain smart contract for enhanced security



Tajabadi et al. [10], Warnat-Herresthal et al. [11], Figure: [11]

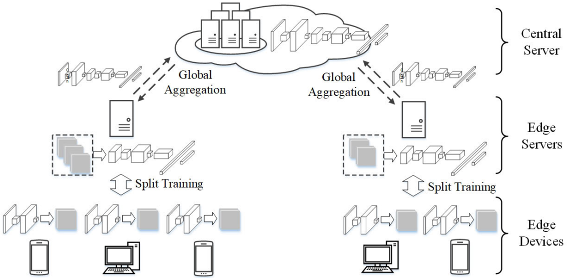
Swarm Learning: Applications

- Pros/Cons
  - \+ No central entity, enhanced security
  - − High data transfer including redundant data
- Disease diagnosis in human nails [7]
  - Image classification using transfer learning (from VGG16 and InceptionV3)
  - Results comparable to central model, slight improvement when data is split unevenly

Mohammed et al. [7]

Edge Learning

- *Edge* refers to edge devices (data collection) and edge servers (one step away from edge devices)
- Edge computing: Perform computations near the data, Fog computing: Computations on edge servers
- Example architecture EdgeFed:



Tajabadi et al. [10], Ye et al. [12], Figure: [12]

Edge Learning: Applications

- Pros/Cons:
  - \+ Increased privacy (depending on architecture), reduced communication cost
  - − Limited processing power in edge devices
- DeepFog healthcare monitoring system [9]
  - Three-layer architecture: physical (data collection), fog (data processing), and cloud layers
  - Tasks: Prediction of diabetes and hypertension attacks, stress type classification

Priyadarshini et al. [9]

Outline

Categories of Decentralized Learning Systems

Categories	**Systems with a centralized authority**	**Peer-to-peer systems**
Learning methods	federated learning, split learning, edge learning	gossip learning, swarm learning
Collaboration	all nodes connect to a central server	direct communication between nodes
Advantages	facilitated collaboration	enhanced fault tolerance
Disadvantages	server has sole authority over training process, single point of failure	higher data transfer
Settings	cross-device & cross-silo	cross-device (GL), cross-silo (SL)

Tajabadi et al. [10]

Privacy Limitations

- Privacy preservation is not inherently guaranteed and depends on architecture and models
- Model parameters may leak training data (and thereby sensitive information)
- Additional security measures to be considered:
  - Secure multi-party computation
  - Homomorphic encryption
  - Differential privacy

Tajabadi et al. [10]

Conclusion

- Decentralized learning methods often match performance of traditional methods
- Factors for selecting a learning method:
  - Model type
  - Network capacity
  - Network stability
  - Computational power
  - Desired level of control
- Methods could be combined in hybrid architectures
- Significant role in growing potential to connect institutions for, e.g., studying rare diseases

Tajabadi et al. [10]

Thank you for your attention!

Questions?

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