Multimodal Federated Learning

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Abstract

Federated learning is proposed as an alternative to centralized machine learning since its client-server structure provides better privacy protection and scalability in real-world applications. In many applications, such as smart homes with IoT devices, local data on clients are generated from different modalities such as sensory, visual, and audio data. Existing federated learning systems only work on local data from a single modality, which limits the scalability of the system.

In this paper, we propose a multimodal and semi-supervised federated learning framework that trains autoencoders to extract shared or correlated representations from different local data modalities on clients. In addition, we propose a multimodal FedAvg algorithm to aggregate local autoencoders trained on different data modalities. We use the learned global autoencoder for a downstream classification task with the help of auxiliary labelled data on the server. We empirically evaluate our framework on different modalities including sensory data, depth camera videos, and RGB camera videos. Our experimental results demonstrate that introducing data from multiple modalities into federated learning can improve its accuracy. In addition, we can use labelled data from only one modality for supervised learning on the server and apply the learned model to testing data from other modalities to achieve decent accuracy (e.g., approximately 70% as the best performance), especially when combining contributions from both unimodal clients and multimodal clients.

1 Introduction

The long-debated privacy issues in centralized machine-learning (ML) systems have motivated researchers to design and implement machine learning in decentralized fashions. Federated learning (FL) (McMahan et al. 2017), which allows different parties to jointly train Deep Neural Network (DNN) models without releasing their local data, is a system paradigm that has gained much popularity in both research communities and real-world ML applications.

FL is specifically suitable for privacy sensitive applications such as smart homes (Aïvodji, Gambs, and Martin 2019, Liu et al. 2020a, Zhao et al. 2020) based on IoT technologies. These applications often deploy different types of IoT sensors or devices that generate data from different modalities (e.g., sensory, visual, and audio). For example, on one FL client, activities of a person in a smart home can be recorded by body sensors in a smartwatch worn by the person, and also by a video camera in the room at the same time. Meanwhile, for FL clients with different device setups, some of them may have multimodal local data (i.e., multimodal clients) while the others may have unimodal local data (i.e., unimodal clients). Many centralized ML systems (Ngiam et al. 2011, Wang et al. 2015, Ohi et al. 2013, Radu et al. 2018, Xing et al. 2018) have shown that combining data from different modalities can improve their performance. To work on multimodal data, existing FL systems either use data fusion (Liang et al. 2020), which requires all the data (i.e., training and testing) in the system to be aligned multimodal data and does not work on unimodal clients, or need clients to send data representations to the server (Liu et al. 2020b), which may break the privacy guarantee of FL since the representations can be used to recover local data.

In this paper, we propose a multimodal FL framework that takes advantage of aligned multimodal and unlabelled data on clients. Our assumption is that data from different modalities (e.g., sensory data and visual data) on a client inherently have some alignment information (e.g., through synchronized local timestamps of sensory data samples and video frames), based on which we can train models to extract multimodal representations from the data. We utilise multimodal autoencoders (Ngiam et al. 2011, Wang et al. 2015) to encode the data into shared or correlated hidden representations. To enable the server in our framework to aggregate trained local autoencoders into a global autoencoder, we propose a multimodal version of the FedAvg algorithm (McMahan et al. 2017) that can combine local models trained on data from both unimodal and multimodal clients.

In a semi-supervised fashion (van Berlo, Saeed, and Ozcelebi 2020, Zhao et al. 2021), we use the global autoencoder and an auxiliary labelled dataset on the server to train a classifier for activity recognition tasks and evaluate its performance on a variety of multimodal datasets. Compared with existing FL systems (Liang et al. 2020, Liu et al. 2020b), our proposed framework does not share representations of local data to the server. Additionally, instead of requiring the clients and the server to have aligned data from all modalities, our framework conducts local training on both multimodal and unimodal clients and only needs unimodal labelled data on the server.

We make the following contributions in this paper:

• We propose a multimodal FL framework that works on
data from different modalities and a multimodal FedAvg algorithm.

• We find that introducing data from more modalities into FL leads to better classification accuracy.

• We show that classifiers trained on labelled data on the server from one modality work well on testing data from other modalities.

• We show that combining contributions from both unimodal and multimodal clients further improves the classification accuracy.

2 Related work

2.1 Federated learning

McMahan et al. (2017) proposed federated learning (FL) as an alternative system paradigm to centralized ML. Given its decentralized feature, FL is especially suitable for edge computing (Shi et al. 2016; Chen and Ran 2019), which moves computation to the place where data are generated. In order to solve the difficulty of having labelled data on FL clients, recent research in FL has been focusing on unsupervised and semi-supervised FL frameworks through data augmentation (Jeong et al. 2020; Liu et al. 2020; Zhang et al. 2021; Long et al. 2021; Kang, Liu, and Chen 2020; Wang et al. 2020; Yang et al. 2021; Saeed, Ozcelebi, and Luukkien 2019; Saeed et al. 2021) to generate pseudo labels for local data, or through learning to extract hidden representations from unlabelled local data (van Berlo, Saeed, and Ozcelebi 2020; Zhao et al. 2021). Our work in this paper follows the path of the latter category. Compared with the existing research, we enable semi-supervised FL to learn from multiple data modalities.

2.2 Heterogeneity in federated learning

Heterogeneity is one of the most challenging issues (Kairouz et al. 2021; Li et al. 2020) in FL because models are locally trained on clients. Different clients may vary in terms of computational capabilities, model structures, distribution of data, or distribution of features. Among all these issues, the heterogeneity in distribution of data (i.e., non-IID local data) has attracted most research efforts (Smith et al. 2017; Zhao et al. 2018; Li et al. 2019; Chen et al. 2020). In order to learn from heterogeneous models, Lin et al. (2020) proposed to use knowledge distillation (Hinton, Vinyals, and Dean 2015) to train global models of FL based on the output probability distribution from local models, instead of directly averaging the parameters of them. Existing research, however, neglected the heterogeneity in data modalities in FL, which is commonplace in many scenarios such as edge computing, IoT environments, and mobile computing.

A recent study by Liu et al. (2020b) applies FL on data from two modalities (i.e., images and texts) and treats each modality individually, which is the same as running two individual FL instances for them. In the study, to align the two modalities on a server, representations of local data need to be uploaded to the server. This breaks the privacy guarantee of FL because the server has the global model that generates the representations from raw data and could recover the raw data if it has those representations. The framework proposed by Liang et al. (2020) can work on multimodal data only when the clients’ local data, the server’s labelled data, and testing data are all aligned data from both modalities. Instead of aligning the representations from different modalities, it conducts early fusion (i.e., element-wise multiplication) on the representations. Thus unimodal data cannot contribute to the local training and the trained model cannot be used on unimodal data. Compared to the existing work, we use the alignment information in local data to learn to extract shared or correlated hidden representations from multiple modalities, which does not require sending representations of local data to the server and allows models to be trained and used on unimodal data.

3 Methodology

3.1 Framework overview

We propose an FL framework wherein clients’ unlabelled local data can be from either one single modality or multiple modalities. In our framework, as shown in Fig. 1, unimodal clients (e.g., Clients 1 and 3) only deploy one type of devices due to reasons such as budget or privacy. Multimodal clients (e.g., Client 2) deploy both types of devices and thus have multimodal local data. For multimodal clients, we assume that there is alignment information between the data from two modalities, based on which we can align the hidden representations of two modalities.

Similar to existing semi-supervised FL frameworks (van Berlo, Saeed, and Ozcelebi 2020; Zhao et al. 2021), on clients we learn to extract hidden representations from un-
labelled data. On multimodal clients, we train local models to extract shared or correlated representations since we have aligned pairs of multimodal data. On unimodal clients, we train models to extract representations from one single modality. Local models from both types of clients are sent to the server and are aggregated into a global model by using a multimodal version of the FedAvg algorithm (McMahan et al. 2017). The server uses the global model to encode a labelled dataset from either modality into a labelled representation dataset, based on which a classifier is trained through supervised learning.

3.2 Learning to extract representations

Autoencoders Autoencoders (Baldi 2012) are one of the commonly used DNNs in unsupervised ML. A typical autoencoder, as shown in Fig. 2a, has two building blocks, which are an encoder (f) and a decoder (g). The encoder maps unlabelled data (X) into a hidden representation (h). The decoder tries to generate a reconstruction (X′) of the input data from the representation. When training an autoencoder, the objective is to minimize the difference between X and X′, which is measured by a loss function L(X, X′).

Split autoencoders In order to extract shared representations from aligned multimodal data, Ngiam et al. (2011) proposed a split autoencoder (SplitAE) that takes input data from one modality and encode the data into a shared h for two modalities. With the shared h, two decoders are used to generate the reconstructions for two modalities. Fig. 2b shows the structures of SplitAEs for two data modalities.

For modalities A and B, given a pair of matching samples (X_A, X_B) (e.g., accelerometer data and video data of the same activity), the SplitAE (f_A, g_A, g_B) for input modality A is:

$$\text{arg min}_{f_A,g_A,g_B} L_A(X_A, X'_A) + L_B(X_B, X'_B)$$

where X'_A and X'_B are the reconstructions for two modalities. L_A and L_B are the loss functions for two modalities, respectively. Similarly, for input modality B, its SplitAE is (f_B, g_A, g_B).

Deep canonically correlated autoencoders In order to combine deep canonical correlation analysis (Andrew et al. 2013) and autoencoders together, Wang et al. (2015) proposed a deep canonically correlated autoencoder (DCCAE). It keeps an individual autoencoder for each modality and tries to maximize the canonical correlation between the hidden representations from two modalities. Fig. 2c shows the structure of a DCCAE for two modalities.

For modalities A and B, given aligned input (X_A, X_B), the DCCAE (f_A, g_A, f_B, g_B) is:

$$\lambda(L_A + L_B) + L_C$$

where L_A and L_B are the reconstruction losses and L_C is the canonical correlation objective. L_C can be defined as:

$$L_C = -\text{tr}(U^T f_A(X_A) f_B(X_B) V)$$

where U and V are canonical correlation analysis directions. Apart from minimizing reconstruction losses, DCCAE uses another objective to increase the canonical correlation between representations from two modalities (i.e., minimizing its negative value L_C). The two objectives are balanced by a parameter λ.

3.3 Multimodal federated averaging

During each round t, the server sends a global multimodal autoencoder w_t^A to selected clients. The local training on w_t^A depends on the modality of data on a selected client. As shown in Fig. 3a, a multimodal client (e.g., Client 2) locally updates the encoders and decoders for both modalities. A unimodal client (e.g., Client 1 or 3) only updates the encoder and decoder for its data modality through standard autoencoder training. The encoder and decoder for the other modality will be frozen during the local training.

We propose a multimodal FedAvg (Mm-FedAvg) algorithm to aggregate autoencoders received from both unimodal clients and multimodal clients. Fig. 3b shows which parts of different local autoencoders are used when generating a new global model. Given a global multimodal autoencoder w_t^A" at round t represented as (f_A, g_A, f_B, g_B), (f_A, g_A) is the encoder and decoder for modality A. Similarly, a local multimodal autoencoder updated by client k is w^k_{A,B} and the client’s modality m_k is one of A, B and AB. The Mm-FedAvg algorithm is shown in Alg. 1.

We aggregate local models from multimodal clients and unimodal clients, the contribution from multimodal clients is controlled by a weight parameter α. Increasing α can give more weights to multimodal clients because they play a key role in aligning two modalities.

4 Evaluation

We evaluated our framework through simulations to answer research questions as follows:

- Q1. Does introducing data from multiple modalities into FL improve its performance?
- Q2. Does a classifier trained on labelled data from one modality work on testing data from other modalities?
Figure 2: In an autoencoder (a), an encoder \( f \) maps input data \( X \) into a hidden representation \( h \). A decoder \( g \) maps \( h \) into a reconstruction \( X' \). In split autoencoders (b) for aligned input \((X_A, X_B)\) from two modalities, data from one modality are input into its encoder to generate an \( h \), which is then used to reconstruct the data for both modalities through two decoders. In a canonically correlated autoencoder (c) data from both modalities are input into their encoders to generate two representations.

(a) Autoencoder

(b) Split autoencoder

(c) Canonically correlated autoencoder

Figure 3: During local training (a), clients only update the \( f \) and \( g \) that are related to the modalities of their data. When conducting multimodal FedAvg (b) on the server, only the updated parts of each local model will be aggregated.

(a) Multimodal local training.

(b) Multimodal FedAvg

| Dataset   | Modality  | \( X \) size | \( h \) size | Classes |
|-----------|-----------|--------------|--------------|---------|
| Opp       | Acce      | 24           | 15           | 10      | 18      |
|           | Gyro      |              |              |         |         |
| mHealth   | Acce      | 9            | 6            | 4       | 12      |
|           | Gyro      | 6            |              |         |         |
|           | Mag       | 6            |              |         |         |
| UR Fall   | Acce      | 3            | 512          | 2,4     | 3       |
|           | RGB       |              |              |         |         |
|           | Depth     | 8            |              |         |         |

Table 1: Multimodal datasets in our experiments

4.1 Datasets

As human activity recognition (HAR) is a domain often relies on multimodal data, we used three HAR datasets that contain different data modalities in our experiments. Table 1 shows the modalities, \( X \) sizes, \( h \) sizes, and the number of classes in the datasets.

Different sensory modalities The Opportunity (Opp) challenge dataset [Chavarriaga et al. 2013] contains 18 short-term and non-repeated kitchen activities. We used the accelerometer data (Acce) and gyroscope data (Gyro) as the two modalities in our experiments. We followed the experimental setup used by Hammerla et al. [2016] to generate training and testing data. As the training data are from 15 runs, when generating local data for a client, the size of the randomly sampled sequence is 1/15 of the training data.

The mHealth dataset [Banos et al. 2014] contains 12 daily living and exercise activities. We used the accelerometer data (Acce), gyroscope data (Gyro), and magnetometer data (Mag) in our experiments and tested the combinations of each two of them. For each replicate of our simulations, we used the Leave-One-Subject-Out method to randomly choose one participant and used her data as testing data. The other 9 participants’ data are used as training data. The size of the randomly sampled sequence for a client is 1/9 of the training data.

Sensory-Visual modalities The UR Fall Detection dataset [Kwolek and Kepski 2014] contains 70 video clips
recorded by a RGB camera (RGB) and a depth camera (Depth) of human activities including fall and daily living activities. Each video frame is labelled and paired with sensory data from accelerometers (Acce).

We use this dataset for our experiments on sensory-visual and visual-visual modality combinations. For the modality RGB, similar to the work by Srivastava et al. (2015), we use a pre-trained ResNet-18 (He et al. 2016) to convert each frame into a feature map. For the modality Depth, we use the extracted features provided in the dataset. The size of $h$ is 2 with Acce and is 4 without it. For each replicate of our simulations, we randomly sample 1/10 data (i.e., 7 video clips) as testing data and use the rest as training data. The size of the randomly sampled sequence for a client is 1/9 of the training data.

4.2 Simulation setup

In each replicate of our simulation, the server conducts 100 communication rounds with the clients and selects 10% clients for local training (2 epochs with a 0.01 learning rate) in each round, after which the cloud training (5 epochs with a 0.001 learning rate) is conducted. The labelled dataset on the server is randomly sampled from the training dataset and its size is the same as the size of a client’s local data. For DCCAE, we set $\lambda = 0.01$ as suggested by Wang et al. (2015). For the multimodal weight parameter $\alpha$, we tested $\{1, 2, 10, 50, 100, 500\}$ and found that $\alpha = 100$ provides the best performance. For each individual simulation setup, we use different random seeds to run 64 replicates.

**Baselines** To answer Q1, we consider a system in which clients have multimodal data and a server has two labelled unimodal datasets. Without multimodal representation learning, a baseline scheme can only use data from one modality, which we refer to as UmFL (30 unimodal clients, 1 label modality). Comparing UmFL with our multimodal scheme (30 multimodal clients, 2 label modalities) will reveal whether introducing more modalities in FL improves its performance. We tested both of them on the data from the modality of UmFL.

To answer Q2, we consider a system wherein clients have multimodal data and a server has a labelled dataset from one modality. A baseline scheme trains a global unimodal autoencoder for each modality with the same size of $h$. The classifier of the baseline is trained on the labelled data from one modality with the help from the autoencoder on that modality. We directly test the classifier on data from the other modality, since the sizes of $h$ from two modalities are the same. This baseline does not do any alignments and can be seen as an ablation study of effectiveness of multimodal representation learning. We refer to this baseline as Abl (30 unimodal clients for each modality, 1 label modality). Comparing Abl with our scheme (30 multimodal clients, 1 label modality) will indicate whether the multimodal autoencoders play any roles when training and testing on different modalities.

**Models** We implement all the deep learning components through the PyTorch library (Paszke et al. 2019). For training autoencoders on time-series data, we use long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997) autoencoders (Srivastava, Mansimov, and Salakhutdinov 2015) in our experiments for local training and use the bagging strategy (Guan and Pletsch 2017) to train our models with random batch sizes and sequence lengths. On the server, we use a classifier that has one MLP layer connected to one LogSoftmax layer as the model for supervised learning. On the mHealth dataset we introduce a Dropout layer (rate=0.5) before the MLP layer of the classifier to prevent overfitting.

4.3 Metrics

We test the classifier on the server against a labelled testing dataset. We use a sliding time window with length of 2,000 to extract time-series sequences (without overlap) from the testing dataset. We use the encoder of $w^\alpha$ for the modality of the testing data to convert the sequences into representations and test them on the classifier $w^\alpha$. We calculate the accuracy of a sequence as the percentage of correctly recognized samples among all the samples in the sequence. The average accuracy of all sequences is the accuracy of the classifier. We evaluate the accuracy of the classifier every other communication round until it converges and calculate its average value and standard error from 64 replicates. On each dataset, we evaluate both SplitAE and DCCAE and keep the one that has better accuracy.

5 Results

5.1 Multimodal data improve accuracy

On the Opp dataset, as shown in Fig. 4a, the accuracy of multimodal schemes (MmFL) that are trained on labelled datasets from two modalities (LAB) and tested on modality $A$ ($T_A$) is higher than that of UmFL. The converged accuracy on modality $B$ is the same for both UmFL and MmFL, which means that using only the gyroscope data (i.e., modality $B$) is enough to accurately recognize the activities.

On the mHealth dataset (Fig. 4b–4d), the results on three modality combinations show similar trends. On each testing modality, the converged accuracy of MmFL schemes is similar to that of their unimodal counterparts. The accuracy of MmFL schemes converges faster than UmFL schemes do.

On the UR Fall dataset, the sizes of $X$ from Acce and RGB are 3 and 512, respectively. Thus $h = 2$ is the biggest representation size that we can use for the modality combination Acce & RGB and it is not big enough to encode useful representations from RGB data. Therefore we only show the results from the other two modality combinations (Fig. 4e & 4f). The accuracy of MmFL schemes is higher than that of UmFL schemes on both modality combinations. Even the modalities of data in UR Fall are more heterogeneous (i.e., sensory & visual) than those in Opp or mHealth (i.e., sensory & sensory), multimodal FL can still align their representations.

Our results demonstrate that combining different modalities through multimodal representation learning can improve the performance (i.e., higher accuracy or faster convergence) of an FL system. Compared with existing work using early fusion (Liang et al. 2020), the labelled data source on the
server in our framework does not have to be aligned multimodal data. It can be individual unimodal datasets that are collected separately. This suggests that we can scale up FL systems across different modalities and utilize more data.

5.2 Labels can be used across modalities

Fig. 5 shows the accuracy of MmFL with different modalities for labelled data (e.g., $L_A$) and testing data (e.g., $T_A$), in comparison with a baseline scheme (Abi) and a unimodal scheme for the modality of the test data (e.g., UmFLA).

On the Opp dataset (Fig. 5a), using only multimodal clients (i.e., MmFLAB) achieves higher converged accuracy than baseline schemes do, which means that the multimodal representation learning on clients indeed aligns two modalities. When training classifiers on labelled Gyro data and testing them on Acce data (i.e., MmFLAB-LB-TA), the accuracy is close to that of a unimodal scheme using Acce data, which demands labelled Acce data on the server.

On the mHealth dataset (Fig. 5b), the converged accuracy of baseline schemes and unimodal schemes is close to each other. This means that different modalities can be correlated even without being aligned (similar to the findings reported by Malekzadeh et al. (2020)). MmFLAB schemes still improve the converged accuracy compared to Abi schemes and have faster convergence in two modality combinations (i.e., Acce & Gyro, Acce & Mag).

On the UR Fall dataset (Fig. 5c), MmFLAB schemes have higher accuracy than baselines do. It is worth to note that, when using labelled Depth data (i.e., $L_B$), the test accuracy on Acce and RGB data (i.e., MmFLAB-LB-TA) schemes in Fig. 5d & 5f is even higher than that when using labelled data from these two testing modalities (i.e., UmFLA).

In Sec. 5.1, results in Fig. 4e & 4f show that the unimodal schemes using Depth data have better performance than those using Acce or RGB data. Therefore, for MmFL with SplitAE, using labelled Depth data for the supervised learning on the server leads to better accuracy than that using Acce or RGB data's own labels.

Our results show that we can use the trained global autoencoder to share the label information from one modality to other modalities by mapping them into multimodal representations. The testing accuracy on the other modalities can be close to or even better than that of unimodal FL schemes using labels from the modalities. This allows us to scale up FL systems even with limited source of labelled data.

5.3 Training on mixed clients improve accuracy

To understand how mixed clients with different modalities, which is a more realistic scenario, affect the performance, for each MmFLAB scheme with 30 multimodal clients, we run one mixed-client scheme that has 10 more clients for modality $A$ (i.e., MmFLABA), one that has 10 more clients for modality $B$ (i.e., MmFLABB), and one that has 10 more clients for each modality (i.e., MmFLABAB). We compare them and keep the one that has the best accuracy.

In Fig. 5c, MmFLABAB schemes on the Opp dataset fur-
Figure 5: Accuracy of MmFL with labelled data from one modality (e.g., $L_B$) and test data from the other modality (e.g., $T_A$). MmFL schemes achieve higher converged accuracy or faster convergence than baselines (i.e., Abl schemes) in most cases. Combining contributions from both unimodal and multimodal clients (e.g., MmFLAB) further improves the accuracy.

6 Conclusions

Federated learning (FL) has shown great potentials to realize deep learning systems in the real world and protect the privacy of data subjects at the same time. In this paper, we propose a multimodal and semi-supervised framework that enables FL systems to work with clients that have local data from different modalities (unimodal and multimodal). Our experimental results demonstrate that introducing data from multiple modalities into FL systems can improve their performance. In addition, it allows us to apply models trained on labelled data from one modality to testing data from other modalities with the best performance being around 70\%. For future research, we plan to investigate broader applications of our framework in domains apart from multimodal human activity recognitions.
Tejani, A.; Chilamkurthy, S.; Steiner, B.; Fang, L.; Bai, J.; and Chintala, S. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Advances in Neural Information Processing Systems, volume 32.

Radu, V.; Tong, C.; Bhattacharya, S.; Lane, N. D.; Mascolo, C.; Marina, M. K.; and Kawser, F. 2018. Multimodal Deep Learning for Activity and Context Recognition. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(4).

Saeed, A.; Ozcelebi, T.; and Lukkien, J. 2019. Multi-task Self-Supervised Learning for Human Activity Detection. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 3(2).

Saeed, A.; Salim, F. D.; Ozcelebi, T.; and Lukkien, J. 2021. Federated Self-Supervised Learning of Multisensor Representations for Embedded Intelligence. IEEE Internet of Things Journal, 8(2): 1030–1040.

Shi, W.; Cao, J.; Zhang, Q.; Li, Y.; and Xu, L. 2016. Edge Computing: Vision and Challenges. IEEE Internet of Things Journal, 3(5): 637–646.

Smith, V.; Chiang, C. K.; Sanjabi, M.; and Talwalkar, A. 2017. Federated Multi-Task Learning. In Advances in Neural Information Processing Systems, volume 30.

Srivastava, N.; Mansimov, E.; and Salakhutdinov, R. 2015. Unsupervised Learning of Video Representations Using LSTMs. In Proceedings of the 32nd International Conference on Machine Learning, volume 37, 843–852.

van Berlo, B.; Saeed, A.; and Ozcelebi, T. 2020. Towards Federated Unsupervised Representation Learning. In Proceedings of the Third ACM International Workshop on Edge Systems, Analytics and Networking, 31–36.

Wang, B.; Li, A.; Li, H.; and Chen, Y. 2020. GraphFL: A Federated Learning Framework for Semi-Supervised Node Classification on Graphs. arXiv:2012.04187.

Wang, W.; Arora, R.; Livescu, K.; and Bilmes, J. 2015. On Deep Multi-View Representation Learning. In Proceedings of the 32nd International Conference on Machine Learning, volume 37, 1083–1092.

Xing, T.; Sandha, S. S.; Balaji, B.; Chakraborty, S.; and Srivastava, M. 2018. Enabling Edge Devices that Learn from Each Other. In Proceedings of the 1st International Workshop on Edge Systems, Analytics and Networking, 37–42.

Yang, D.; Xu, Z.; Li, W.; Myronenko, A.; Roth, H. R.; Harmon, S.; Xu, S.; Turkbey, B.; Turkbey, E.; Wang, X.; et al. 2021. Federated Semi-Supervised Learning for COVID Region Segmentation in Chest CT using Multi-National Data from China, Italy, Japan. Medical Image Analysis, 70: 101992.

Zhao, Y.; Haddadi, H.; Skillman, S.; Enshaeifar, S.; and Barnaghi, P. 2020. Privacy-Preserving Activity and Health Monitoring on Databox. In Proceedings of the Third ACM International Workshop on Edge Systems, Analytics and Networking, 49–54.

Zhao, Y.; Li, M.; Lai, L.; Suda, N.; Civin, D.; and Chandra, V. 2018. Federated Learning with Non-IID Data. arXiv:1806.00582.

Zhao, Y.; Liu, H.; Li, H.; Barnaghi, P.; and Haddadi, H. 2021. Semi-supervised Federated Learning for Activity Recognition. arXiv:2011.00851.