FedH2L: Federated Learning with Model and Statistical Heterogeneity

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Abstract

Federated learning (FL) enables distributed participants to collectively learn a strong global model without sacrificing their individual data privacy. Mainstream FL approaches require each participant to share a common network architecture and further assume that data are sampled IID across participants. However, in real-world deployments participants may require heterogeneous network architectures; and the data distribution is almost certainly non-uniform. To address these issues we introduce FedH2L, which is agnostic to the model architecture and robust to different data distributions across participants. In contrast to approaches sharing parameters or gradients, FedH2L relies on mutual distillation, exchanging only posteriors on a shared seed set between participants in a decentralized manner. This makes it extremely bandwidth efficient, model agnostic, and crucially produces models capable of performing well on the whole data distribution when learning from heterogeneous silos.

1 Introduction

Today, artificial intelligence (AI) is showing its strengths in almost every walk of life. To fully realize AI’s benefits, we wish to learn models across as much data as possible, but this data is often held privately across diverse users or organizations. To enable collective benefit from AI while maintaining data privacy, Federated Learning (FL) \cite{bonawitz2017practical, mcmahan2017communication, konecnny2016federated} algorithms aim to train a global model based on the efforts of distributed participants’ data and resources. There are a number of actively researched challenges however to achieving this vision \cite{li2020federated}, including system/model heterogeneity, statistical heterogeneity, bandwidth requirements, and residual privacy concerns. Different FL methods provide different trade-offs in their requirements on these axes along in the accuracy they ultimately provide \cite{li2020federated}. We propose a novel FL method FedH2L, which primarily aims to support significant statistical and model heterogeneity across participants, and also provides benefits for bandwidth and privacy.

System heterogeneity usually refers to different compute and bandwidth resources among participants leading to different update rates among them, and mainstream research aims to alleviate the impact of stragglers in FL setting \cite{li2020federated}. However, participants more generally may require fundamentally different model architectures \cite{li2019federated}. This can occur in edge or device-based FL due to devices’ different memory constraints, or in B2B FL due to each organization wishing to keep their particular optimised model architecture private. Statistical heterogeneity refers to the diversity in each user’s data distribution \cite{li2020federated, mohri2019federated}. We aim to learn a strong federated system capable of performing on the global data distribution, although learning takes place locally in each user’s private data silo.

Mainstream FL methods typically proceed by sharing parameters or gradients at each iteration \cite{mcmahan2017communication}. This means they are often bandwidth-constrained, as contemporary models can have millions of parameters. Furthermore, many FL methods require a centralized server to aggregate results from each participant. This requires a globally trusted authority, and provides a single point of failure.

In contrast, we present a decentralized peer-to-peer approach that is robust and extremely communication efficient. Parameter and gradient sharing strategies also incur a residual privacy risk due to attack vulnerability \cite{zhu2019federated, luca2018federated}. Our FedH2L shares no parameters, thus eliminating this vulnerability.

In this paper, we present a novel FL algorithm FedH2L, which significantly advances the practical applicability of FL by enabling simultaneous system and statistical heterogeneity across participants. Instead of exchanging gradients/parameters, FedH2L exchanges predictions on small shared seed set distributed to participants in advance \cite{li2019federated}, and performs decentralized global optimization.
by mutual learning [Zhang et al., 2018], thus enabling model-agnostic FL. This strategy also eliminates privacy concerns of parameter/gradient sharing, and requires orders of magnitude lower communication cost than sharing models/gradients. However, there is still the issue of managing statistical heterogeneity across participants [Li et al., 2020a; Peng et al., 2020; Quiñonero-Candela et al., 2009]. In FedH2L, each participant optimizes a multi-task objective of fitting its local data, and distillation on the seed set for knowledge sharing across peers. This multi-task optimization is challenging when there is significant distribution shift, which can lead to gradient conflict [Yu et al., 2020] and poor solutions. To this end, we introduce a new optimization strategy to find the best non-conflicting gradient for simultaneously fitting local data and incorporating feedback from peers. Our contributions are:

- We introduce FedH2L, which uniquely provides simultaneous support for a challenging set of real world conditions including heterogeneous models across peers, robust decentralized learning, privacy preserving parameter/gradient-free communication, while being desired to maximise performance under heterogeneous data statistics across peers.
- To provide best performance under conditions of heterogeneous data statistics across peers we introduce a new optimization strategy to find the gradient update that does not conflict between local and global update cues.
- We conduct extensive experiments on several multi-domain datasets: Rotated MNIST [Ghifary et al., 2015], PACS [Li et al., 2017], and Office-Home [Venkateswara et al., 2017a]. Compared to the baselines, we improve the model performance across all domains, demonstrating the effectiveness of FedH2L.

### 2 Related Work

**System and Statistical Heterogeneity** FL aims to train models over remote devices, while keeping data localized. FL faces many challenges [Li et al., 2020a], and the important one is the heterogeneity on the system and statistical aspects. Participants may vary on hardware, compute and bandwidth resources. These system characteristics make issues such as stragglers prevalent. Existing studies mainly focus on the active sampling [Kang et al., 2019; Nishio and Yonetani, 2019]. However, a more severe challenge in system heterogeneity is the model heterogeneity of different architectures among participants. Li and Wang [2019] introduce FedMD for model heterogeneity based on knowledge distillation but with a centralized communication server. FML [Shen et al., 2020] trains extra heterogeneous models by learning from participants’ distributed homogeneous models. FedGKT [He et al., 2020] trains small CNNs on edges and periodically transfer their knowledge (e.g., extracted features) instead of data by knowledge distillation to a server-side large CNN.

In almost every substantive use case of FL (e.g., medical data across hospitals, industrial data across corporations) participants generate and collect data in a Non-IID distributed manner, leading to statistical shift among them. To tackle such statistical heterogeneity, FedProx [Li et al., 2020b] provides convergence guarantees based on FedAVG [McMahan et al., 2017] over Non-IID data. FedAgnostic [Mohri et al., 2019] learns a centralized model that is optimized for any target distribution formed by a mixture of participants’ distributions. FML [Shen et al., 2020], FedGKT [He et al., 2020] and FedMD [Li and Wang, 2019] also have the opportunities to cope with the Non-IID data because they have individualized models for each user but still controlled by a central server. We aim to handle both model and statistical heterogeneity in a decentralized manner without the need of a centralized model or extra local models.

**Bandwidth and Privacy Requirements** Communication is a critical bottleneck in FL. The current communication-efficient methods mainly consider: (1) Reducing the total number of communication rounds; (2) Reducing the size of transmitted messages at each round. But such methods [McMahan et al., 2017; Li et al., 2020b; Shen et al., 2020; Mohri et al., 2019] still typically proceed by sharing the millions of model parameters or gradients as the communicated messages, which means the best case bandwidth requirement is still orders of magnitude worse than FedH2L. Additionally, sharing parameters create attack vulnerability [Luca et al., 2018; Zhu et al., 2019], increasing privacy risk. The aggregation of parameters and gradients also usually asks for a centralized trusted authority [McMahan et al., 2017; Li et al., 2020b] which may lead to the single point of failure. FedH2L provides a communication-efficient decentralized peer-to-peer method without sharing any high-overhead and privacy compromising model parameters/gradients.

**Multi-task Optimization** Instead of learning a single global model, we simultaneously learn distinct local models with a multi-task objective based on local and remote teaching signals. A similar federated work in multi-task setting is MOCHA [Smith et al., 2017], but each local model only focuses on the performance on its own task, instead of the multi-task objective. A key challenge in multi-task learning [Yu et al., 2020; Kendall et al., 2018] is the conflicting gradients, especially when there is statistical heterogeneity across tasks/participants. Yu et al. [2020] propose a gradient surgery to train a single model for multiple tasks by projecting each task gradient onto normal plane of the other. In contrast, we propose a novel optimization strategy to get non-conflicting gradients for each participant’s model so as to fit local data and learn from other peers reliably and simultaneously.
3 Methodology

Here we introduce the details of FedH2L. Assume there are \( N \) nodes in the FL network, holding data with potentially distinct distributions \( D = \{ D_1, D_2, \ldots, D_N \} \). The data on each node contains a set of data-label pairs, i.e., \( D_i = \{ X_i, Y_i \} \). We also split \( D_i \) into its private data which must only be kept locally, the shared public seed data, validation data and test data, i.e., \( D_i = \{ D_i^\text{pri}, D_i^\text{pub}, D_i^\text{val}, D_i^\text{test} \} \). We aim to learn a federated system that aggregates knowledge from all nodes, but without sacrificing each node’s data privacy, and without assuming a common model architecture. We consider the homogeneous multi-domain setting [Li et al., 2017], where all nodes share the same label set \( Y \) covering the same \( M \) classes, but have different data distributions. For example, consider medical images of the same set of diseases, but collected by different machines in different hospitals. Each node \( i \) uses a network parameterized by \( \theta_i \), which can be uniquely customized and private to each node. No centralized model is used in FedH2L. But the goal is that after learning, each node’s model \( \theta_i \) should incorporate the knowledge of all nodes’ datasets, and be able to perform well on any node’s data distribution. The workflow is divided into two iterative phases: local and global optimization.

3.1 Local Optimization

Local optimization for a node follows the conventional supervised learning paradigm using locally available data. Denoting \( i \)-th node’s network as \( f_{\theta_i} \); we optimize the cross-entropy (CE) loss to obtain gradient \( g_{\theta_i}^{\text{loc}} \):

\[
\min_{\theta_i} \ell^{\text{(CE)}}(f_{\theta_i}(x_i^{\text{loc}}), y_i^{\text{loc}}),
\]

\[ g_{\theta_i}^{\text{loc}} = \nabla_{\theta_i} \ell^{\text{(CE)}}(f_{\theta_i}(x_i^{\text{loc}}), y_i^{\text{loc}}), \quad \tag{1} \]

Here \( d_i^{\text{loc}} = (x_i^{\text{loc}}, y_i^{\text{loc}}) \in \{ D_i^\text{pri}, D_i^\text{pub} \} \) is a batch of the \( i \)-th domain’s data. There is also an alternative setup \( d_i^{\text{loc}} = (x_i^{\text{loc}}, y_i^{\text{loc}}) \in \{ D_i^\text{pri}, \sum_{n=1}^{N} D_n^\text{pub} \} \) that uses all domains’ public seed data. We use the latter option of \( d_i^{\text{loc}} \) by default for it behaves slightly better in our experiment, and this is consistent with the data usage strategy in the FL studies with public data [Li and Wang, 2019; Zhao et al., 2018]. Note that \( f_{\theta_i}(x_i^{\text{loc}}) \) provides soft labels \( p_i^{\text{loc}} \) corresponding to the output of the final softmax layer of the network, which are compared against the ground truth one-hot labels.

3.2 Global Mutual Optimization

The next step is for each node to learn from its peers. To achieve this in a decentralized manner and under conditions of heterogeneous model architecture, we exploit model distillation. Different from the conventional distillation [Hinton et al., 2015] where a strong teacher trains multiple students, the federated network in FedH2L acts as an ensemble of students that all teach each other.

**Preparation for mutual learning** We randomly sample a batch \( d_i^{\text{pub}} = (x_i^{\text{pub}}, y_i^{\text{pub}}) \) from \( D_i^\text{pub} \) in each domain/node and compute the soft labels \( p_i^{\text{pub}} \). Note that the superscript \( i \) denotes the domain the data is drawn from (from the \( i \)-th domain \( d_i^{\text{pub}} \)), and the subscript \( i \) denotes the network \( f_{\theta_i} \) making the prediction. To assess the quality of predictions, we also get the accuracy \( \text{Acc}_{\text{pub}} \) over the batch public data in each domain. Each node \( i \) broadcasts \( [p_i^{\text{pub}(i)}, \text{Acc}_{\text{pub}}(i)] \) as its teaching signal, and associated teaching confidence, to others in the cohort. Note that the predictions in the teaching signal \( p_i^{\text{pub}(i)} \) are with respect to public data \( x_i^{\text{pub}} \), but contain knowledge from the local private data due to being made with the locally optimized network \( f_{\theta_i} \). The quantities \( [p_i^{\text{pub}(i)}, \text{Acc}_{\text{pub}}(i)] \) are the only parameters exchanged during the federated global mutual optimization step. So this approach is highly communication efficient, and does not disclose any node’s private data.

**Mutual Learning** Each node \( i \) will act both as a student and a teacher, so there are \( (N-1) \) teachers for each student \( f_{\theta_i} \). To improve each student node \( i \)’s model based on teacher node \( j \)’s data, it is trained to mimic the teacher’s soft predictions on the teacher’s public data. Specifically, each student \( i \) uses the Kullback Leibler (KL) Divergence loss \( \ell_i^{\text{(KL)}} \) as

\[
\ell_i^{\text{(KL)}} = \frac{1}{N-1} \sum_{j=1, j\neq i}^{N} \text{Acc}_{j} \cdot D_{KL}(p_j^{\text{pub}(j)} || p_i^{\text{pub}(i)}),
\]

where each teacher’s contribution is weighted by its teaching confidence \( \text{Acc}_{j} \), and where

\[
D_{KL}(p_j^{\text{pub}(j)} || p_i^{\text{pub}(i)}) = \mathbb{E}_{p_j^{\text{pub}(j)}} \log p_j^{\text{pub}(j)} - \log p_i^{\text{pub}(i)}.
\]

In addition, besides the KL mimicry loss, we can also take advantage of the conventional supervised loss (CE loss):

\[
\ell_i^{\text{(CE)}} = \frac{1}{N-1} \sum_{j=1, j\neq i}^{N} \ell^{\text{(CE)}}(f_{\theta_i}(x_j^{\text{pub}}), y_j^{\text{pub}}),
\]

Thus we obtain the total mutual learning gradient for node \( i \) learning from the other nodes in the cohort:

\[
g_i^{\text{pub}} = \nabla_{\theta_i} (\ell_i^{\text{(KL)}} + \ell_i^{\text{(CE)}}).
\]

**Summary** In summary, each node trains using \( g_i^{\text{loc}} = \nabla_{\theta_i} \ell_i^{\text{(CE)}} \) on local data, and \( g_i^{\text{pub}} = \nabla_{\theta_i} (\ell_i^{\text{(KL)}} + \ell_i^{\text{(CE)}}) \) using other domains’ public seed data.

3.3 Dealing with Statistical Heterogeneity

Our algorithm described so far enables decentralized FL of heterogeneous models. However, a key challenge is to best support the practically ubiquitous situation of statistical heterogeneity across domains. We hope that the local gradient \( g_i^{\text{loc}} \) can help to improve the performance on other domain’s data (Cross-Domain Performance), and the remote teacher gradient \( g_i^{\text{pub}} \) can help to improve the performance on the local data (Within-Domain Performance). However this is challenging to achieve from a multi-task learning perspective, because the local learning gradient and peer learning gradient may conflict [Yu et al., 2020; Lopez-Paz and Ranzato, 2017; Wei and Yijing, 2021] under significant statistical shift.
Mutual Learning robust to statistical shift  To perform student-teacher learning that is robust to distribution-shift across nodes, we propose to enforce the constraint:

$$\langle g_i^{\text{loc}}, g_i^{\text{pub}} \rangle \geq 0. \quad (7)$$

If this constraint is satisfied, then the remote teaching signal $g_i^{\text{pub}}$ is unlikely to increase $\ell(\text{CE})$ on each domain’s local data, and we can safely use $g_i^{\text{pub}}$ to directly update $\theta_i$ without risking negative within-domain performance. Thus we check across nodes, we propose to enforce the constraint:

$$\text{Mutual Learning robust to statistical shift}$$

To perform $\tilde{g}_i$ after projection

$$\text{Computation of } \tilde{g}_i \text{ We set } \tilde{g}_i \leftarrow \text{project}(g_i^{\text{pub}}, g_i^{\text{loc}}). \text{ Here }$$

project is the optimization of dual problem of Quadratic Program (QP). To solve (8) efficiently, recall the primal of a QP

$$\text{Aggregation (AGG): Node only uses its own domain (pri+pub) data for conventional training (SGD on CE).}$$

$$\text{Aggregation (AGG): Node aggregates its own (pri+pub) data and the shared public data from other nodes for conventional training. AGG is usually a strong baseline to beat in multi-domain learning [Li et al., 2019].}$$

$$\text{FedMD [Li and Wang, 2019]: A state of the art centralized approach to model-heterogeneity in FL.}$$

$$\text{FedAvg [McMahan et al., 2017]: The classic FL method that uses a central server to aggregate gradients and distribute parameters.}$$

$$\text{FedProx [Li et al., 2020b]: A FedAvg-based approach that provides convergence guarantees for learning over statistical heterogeneity.}$$

4 Experiments

We evaluate on digit classification (Rotated MNIST) and image recognition (PACS, Office-Home) tasks. These datasets contain multiple sub-domains with statistical shift. We use Ray [Moritz et al., 2018] framework to implement distributed applications. We compare FedH2L to the alternatives:

- **Independent (IND):** Node only uses its own domain (pri+pub) data for conventional training (SGD on CE).
- **Aggregation (AGG):** Node aggregates its own (pri+pub) data and the shared public data from other nodes for conventional training. AGG is usually a strong baseline to beat in multi-domain learning [Li et al., 2019].
- **FedMD [Li and Wang, 2019]:** A state of the art centralized approach to model-heterogeneity in FL.
- **FedAvg [McMahan et al., 2017]:** The classic FL method that uses a central server to aggregate gradients and distribute parameters.
- **FedProx [Li et al., 2020b]:** A FedAvg-based approach that provides convergence guarantees for learning over statistical heterogeneity.

Metrics  In our decentralized approach, each node has its own model, and our goal is all models should outperform that of a centralized competitor such as FedAvg. So we report the average test performance across all nodes’ models. Considering the statistical heterogeneity, we report the following three metrics, where $F$ evaluates test accuracy.

- **Within-Domain Performance:** $WDP_i = F_i(D_i^{\text{test}})$. WDP is the performance of $f_{\theta_i}$ on the node $i$’s test data. Higher WDP
values indicate the learning experience from other nodes improve the performance on the current node. This is not guaranteed by a simple FL algorithm as other nodes’ gradients can potentially cause conflict or forgetting [Yu et al., 2020; McCloskey and Cohen, 1989]. FedH2L aims to improve WDP by projecting away conflicting gradients.

**Cross-Domain Performance:** \( CDP_i = F_i \left( \sum_{n=1, n \neq i}^N D_n^{\text{test}} \right) \).

CDP is the performance of \( f_{\theta_i} \) on all other nodes’ test data. If FL nodes do not learn from their peers then CDP will be low due to statistical shift.

**Average accuracy:** \( ACC_i = F_i \left( \sum_{n=1}^N D_n^{\text{test}} \right) \). ACC is the all-domain performance of \( f_{\theta_i} \) on all nodes’ test data.

### 4.1 Evaluation on Rotated MNIST

**Dataset and settings** Rotated MNIST [Ghifary et al., 2015] contains different domains with each one corresponding to a degree of roll rotation in MNIST dataset. The basic view (M0) is formed by randomly choosing 100 images each of ten classes from MNIST dataset, and we create 3 rotating domains from M0 with 20° rotation each in clockwise direction, denoted M20, M40, M60. The data on each node is split by default 65%/10%/10%/15% for \( D_i^{\text{pri}} / D_i^{\text{pub}} / D_i^{\text{val}} / D_i^{\text{test}} \).

We first experiment by easily deploying homogeneous networks (e.g. LeNet [LeCun et al., 1998]). We train using AMSGrad [Reddi et al., 2018] optimizer (\( lr = 1e-3 \), weight decay=1e-4) for 10,000 rounds and set batch_size=32. We explore performance considering several factors: (1) \( \alpha \), the proportion of \( D_i^{\text{pub}} \). We set the proportion of \( (D_i^{\text{pri}} + D_i^{\text{pub}}) \) as 75%, and \( D_i^{\text{val}} \) and \( D_i^{\text{test}} \) account for 10% and 15% unchanged respectively. Note that the performance of IND, FedAvg and FedProx is independent of \( \alpha \). (2) In FedH2L, \( E \) is the ratio between global and local update rounds. Local optimization is carried out each round, and global optimization every \( E \) rounds. So when calculating the global update \( \tilde{g}_i \), \( g_i^{\text{loc}} \) is actually \( (\tilde{g}_i^{\text{loc}} - g_i^{\text{val}}) \) over \( E \) rounds. Here we set default \( E = 1 \), and then ablate the hyperparameter sensitivity on \( E \). (3) We explore both homogeneous and heterogeneous architectures. Note that even in the homogeneous architecture case, decentralized FedH2L nodes have independent parameters.

**Results** Table 2 shows the results including varying \( \alpha \) of FedH2L. We evaluate using the validation data every 50 rounds and keep the model with the maximal ACC for the final test on three metrics. Max value on each metric is bold. We draw the following conclusions: (1) FedH2L generally outperforms competitors for a range of \( \alpha \). (2) FedH2L generally performs better with increased public data proportion \( \alpha \). (3) FedH2L outperforms the AGG and IND baselines at every \( \alpha \) operating point. (4) Compared to state of the art competitors, FedH2L outperforms FedMD at every operating point. The poor performance of FedMD compared to FedH2L and AGG shows that it is vulnerable to distribution shift between domains. The vanilla centralized FedAvg/FedProx require over 1000× the communication bandwidth of FedH2L, and we now restrict their bandwidth to match that used by FedH2L and get the results in Table 2. FedH2L outperforms FedAvg/FedProx clearly at \( \alpha = 15\% \).

**Qualitative Results** We perform PCA projections of the features on all domains’ test data in Figure 1. FedH2L provides the improved overall separability on all domains’ data.

### 4.2 Evaluation on PACS dataset

**Dataset and settings** PACS [Li et al., 2017] is a multi-domain object recognition benchmark with 9991 images of 7 categories across 4 different domains. The original PACS dataset has a fixed split for train, validation and test. We separate out 10% of its test part as the public seed data, and directly use the train part as our private data. Here we mainly consider the heterogeneous model case where we randomly deploy ResNet18, ResNet34, AlexNet and VGG11. The heterogeneous model case where all nodes use a ResNet18 is reported in the supplementary material, and it also shows the benefits of FedH2L. We use AMSGrad (\( lr = 1e-4 \), weight decay=1e-5) to train 10,000 rounds and set batch_size=32.

**Results** We can see from Table 3: (i) In the heterogeneous case, FedAvg and FedProx are inherently inapplicable and FedH2L surpasses the other alternatives. (ii) We observe that although VGG11 does not perform well in the sketch domain (see IND/AGG WDP), when used with FedH2L, it still benefits rather than harms the other nodes’ performance thanks in part due to the teaching confidence signal (Eq. (3)).

### 4.3 Evaluation on Office-Home dataset

**Dataset and settings** The Office-Home [Venkateswaran et al., 2017b] dataset is initially proposed to evaluate domain adaptation. It consists 4 different domains with each containing images of 65 object categories. We split each domain data into \( \{D_i^{\text{pri}}, D_i^{\text{pub}}, D_i^{\text{val}}, D_i^{\text{test}}\} \) according to the default \([65\%, 10\%, 10\%, 15\%]\). We randomly apply ResNet34, MobileNet, AlexNet and ResNet50 as their heterogeneous models and use the same hyperparameters as in the PACS experiment. The homogeneous model case is also reported in the supplementary material where FedH2L shows consistent benefits.

**Results** In Table 4, FedH2L gives a clear boost to overall accuracy, within-domain and cross-domain performance.

### 4.4 Further Analysis

**Optimization and loss analysis** Figure 2(left) shows ACC on the validation data. FedH2L exhibits faster convergence to the higher performance. Figure 2(right) shows the consistent utility of KL loss during the first 1000 rounds for convergence and performance benefits as shown on ACC. Figure 2(middle) shows the loss during local optimization, which benefits FedH2L locally with the help of the global mutual learning.
Table 2: Test result (%) on three metrics on Rotated MNIST.

| Method            | M0-LeNet | M20-LeNet | M40-LeNet | M60-LeNet | Avg. |
|-------------------|----------|-----------|-----------|-----------|------|
|                   | ACC      | WDP       | CDP       | ACC       | WDP  | CDP   | ACC   | WDP   | CDP   |
| FedH2L (α=5%)     | 86.17    | 88.67     | 85.33     | 86.33     | 93.33 | 85.11 | 87.50 | 93.33 | 85.78 |
| AGG (α=5%)        | 85.50    | 92.67     | 83.11     | 87.50     | 93.33 | 85.56 | 83.67 | 90.00 | 81.56 |
| FedMD (α=5%)      | 84.17    | 87.33     | 83.11     | 85.33     | 91.33 | 83.33 | 86.67 | 96.00 | 83.56 |
| FedH2L (α=10%)    | 90.17    | 93.33     | 89.11     | 91.67     | 96.00 | 90.22 | 86.50 | 90.67 | 85.11 |
| AGG (α=10%)       | 86.50    | 90.00     | 85.33     | 87.17     | 92.67 | 85.33 | 86.67 | 94.00 | 84.22 |
| FedMD (α=10%)     | 85.00    | 88.67     | 83.78     | 87.67     | 95.33 | 85.11 | 82.00 | 90.00 | 79.11 |
| FedH2L (asynchronous) | 90.66   | 93.33     | 89.78     | 90.00     | 94.00 | 88.67 | 85.50 | 90.67 | 83.33 |
| FedH2L (α=15%)    | 89.67    | 91.33     | 89.11     | 90.00     | 92.67 | 89.11 | 90.50 | 94.00 | 89.33 |
| AGG (α=15%)       | 87.83    | 92.00     | 86.44     | 89.67     | 92.67 | 89.11 | 87.83 | 94.00 | 85.78 |
| FedMD (α=15%)     | 86.87    | 89.33     | 88.44     | 89.00     | 93.33 | 87.56 | 85.00 | 90.00 | 83.33 |
| IND               | 66.39    | 91.33     | 58.08     | 78.11     | 94.00 | 72.82 | 72.39 | 93.31 | 65.48 |
| FedAvg            | 86.50    | 77.33     | 89.56     | 86.50     | 90.87 | 86.44 | 86.50 | 92.67 | 84.44 |
| FedProx           | 86.67    | 80.00     | 88.89     | 86.67     | 90.00 | 85.56 | 86.67 | 91.33 | 85.11 |

Table 3: Test result (%) on three metrics on PACS with heterogeneous models.

| Method             | Photo-ResNet18 | Art_painting-ResNet34 | Cartoon-AlexNet | Sketch-VGG11 | Avg. |
|--------------------|----------------|-----------------------|----------------|-------------|------|
|                   | ACC            | WDP                   | CDP            | ACC         | WDP  | CDP   | ACC   | WDP   | CDP   |
| FedH2L             | 83.86          | 99.80                 | 80.66          | 90.91       | 99.95 | 88.57 | 81.68 | 99.67 | 76.16 |
| IND                | 51.08          | 99.57                 | 41.29          | 77.72       | 99.30 | 72.15 | 68.52 | 99.39 | 59.05 |
| AGG                | 84.90          | 100.00                | 81.90          | 89.50       | 100.00 | 86.85 | 80.80 | 98.77 | 75.28 |
| FedMD              | 80.05          | 100.00                | 78.05          | 86.90       | 99.08 | 83.75 | 78.07 | 95.65 | 72.67 |
| FedAvg/FedProx     | -              | -                     | -              | -           | -     | -     | 51.40 | 75.47 | 35.83 |

Table 4: Test result (%) on three metrics on Office-Home with heterogeneous models.

| Method             | Art-ResNet34 | Clipart-MobileNet | Product-AlexNet | Real_world-ResNet50 | Avg. |
|--------------------|--------------|-------------------|----------------|---------------------|------|
|                   | ACC          | WDP               | CDP            | ACC                 | WDP  | CDP   | ACC   | WDP   | CDP   |
| FedH2L             | 65.52        | 58.70             | 66.70          | 73.55               | 76.52 | 72.40 | 59.64 | 80.82 | 51.00 |
| IND                | 41.00        | 57.14             | 38.20          | 55.14               | 78.49 | 67.56 | 54.32 | 77.02 | 45.05 |
| AGG                | 57.34        | 51.86             | 58.30          | 70.61               | 78.49 | 67.56 | 54.32 | 77.02 | 45.05 |
| FedMD              | 55.46        | 55.59             | 55.44          | 67.49               | 77.50 | 63.61 | 53.17 | 75.59 | 44.02 |
| FedAvg/FedProx     | -            | -                 | -              | -                   | -     | -     | 51.74 | 59.42 | 48.72 |

Ablation on design components of global mutual optimization

- **KL mimicry loss** (Eq. 3), and the **project operation** for the calculation of $\hat{g}_i$ to achieve stable multi-domain learning (Eq. 8).
- We ablate them in Table 5 on Rotated MNIST ($\alpha = 10\%$).

**KL loss** plays an important role in both CDP and WDP. The robustness benefit of mutual learning by KL loss to find a wider minimum in the single domain has been analyzed in DML [Zhang et al., 2018]. Similarly, under our multi-domain setting, the matching with teachers’ posterior predictions increases the model’s generalization (CDP) to other domains. Meanwhile, the soft labels (for KL loss) help to alleviate the model shift interference of the domain’s hard true labels (for CE loss). Thus KL loss benefits optimization stability (WDP) during the global mutual optimization.

If we remove the **project operation**, then $\hat{g}_i$ will be updated by directly using $g_i^{\text{data}}$. The results confirm that WDP gets worse without the constrained $g_i$. Moreover, we compare with an alternative gradient projection PCGrad [Yu et al., 2020] which deals with conflicting gradients in a hand-crafted way. But PCGrad shows unsatisfactory performance even slightly worse than without the project operation.

**Hyperparameter sensitivity**

We ablate the hyperparameter of $\alpha$ in FedH2L in Table 6 on Rotated MNIST ($\alpha = 10\%$). FedH2L generally performs better with lower update interval $E$. Performance degrades smoothly with larger $E$ which lowers communication cost proportionally.

**Limitations**

A limitation of FedH2L is while our comms cost is $\approx 106\times$ lower than FedAvg at small scale (4 nodes), this advantage will be eroded if scaled to many participants. This could be alleviated by communicating between a subset of randomly chosen pairs at each global round, which prelim-
inary experiments of such asynchronous distributed learning in Table 2 show lead to similar performance.

5 Conclusion

We proposed FedH2L for FL with heterogeneous models and data statistics. Each node in the cohort acts as both student and teacher, providing effective communication efficient federated learning. FedH2L supports heterogeneous architectures, which is crucial for FL across diverse hardware platforms, and with institutions’ proprietary models; and is robust to heterogeneous data statistics, which – while not widely studied academically – is ubiquitous in practical FL.

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Table 6: Hyperparameter sensitivity of $E$ in FedH2L (Avg).

| Method           | ACC  | WDP  | CDP  |
|------------------|------|------|------|
| FedH2L ($E = 1$) | 89.13| 93.33| 87.72|
| FedH2L ($E = 5$) | 88.04| 92.17| 86.67|
| FedH2L ($E = 10$)| 87.25| 93.17| 85.28|

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