Personalized Progressive Federated Learning with Leveraging Client-Specific Vertical Features

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Personalized Progressive Federated Learning with Leveraging Client-Specific Vertical Features

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부족한 저를 믿어 주시고 연구에 집중할 수 있도록 지도해주신 박유랑 교수님께 진심으로 감사드립니다. 또한 같이 연구를 하며 많은 도움을 주시고 의지가 되었던 여러 연구실 선생님들에게도 감사의 말씀을 드립니다. 언제나 따뜻한 격려와 응원으로 다독여 주신 가족들에게도 고맙다는 말을 전하고 싶습니다.

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ABSTRACT

Personalized Progressive Federated Learning with Leveraging Client-Specific Vertical Features

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Federated learning (FL) has been used for model building across distributed clients. However, conventional horizontal federated learning (HFL) cannot leverage vertically partitioned features to increase model complexity, and vertical federated learning (VFL) requires all clients to share a large number of overlapping sample-ids. On the other hand, the main challenge of FL is the distributed setting of data heterogeneity and non-independent and identically distributed (non-I.I.D) data among clients. In this study, we proposed a personalized progressive federated learning (PPFL) model, which is a multi-model-based personalization that allows the leveraging of vertically partitioned client-specific features. The performance of PPFL was evaluated using two datasets: the Physionet Challenges 2012 dataset and a real-world dataset composed of eICU data and highly intensive care unit (HICU) data from the Severance Hospital, Seoul, South Korea. We compared the performance of in-hospital mortality and length of stay task prediction between our model and the comparison models based on the accuracy and area under receiver operating characteristic (AUROC). The PPFL showed an accuracy of 0.849 and AUROC of 0.790 in in-hospital mortality prediction, which are the highest scores compared to comparison models. For length-of-stay prediction, PPFL also showed an AUROC of 0.808 in average which was the highest among all comparators.

Key words: Personalized federated learning, vertically partitioned data, Non-IID data

Chapter 1

Introduction

Federated learning (FL) is a collaborative machine-learning approach used for solving data problems, such as data leakage, while preserving privacy in distributed environments across multiple devices and institutions in a communication-efficient manner [1–3]. Despite the numerous advantages of FL, such as privacy preservation, fulfillment of data requirements, and communication efficacy, it is still limited regarding the availability of information from conventional FL designs that are generally based on a distributed environment. FL designs (e.g., horizontal federated learning (HFL) and vertical federated learning (VFL)) can be categorized based on the data distribution among various parties (i.e., whether data are distributed based on the feature space or sample-ID space) [2]. HFL [3–9] can analyze large volumes of data using "identical feature spaces" from multiple clients. VFL [10, 11] can be built from distributed feature spaces using only "identical sample IDs" across different clients.

However, in an HFL scenario, some clients might have specific feature information that is generated only within specific clients or is not allowed in a federated manner because of critical privacy concerns. For instance, there may be differences in the features collected among hospitals participating in federated learning, and these client-specific features may be excluded from the HFL scenario. Under a real-world VFL scenario, it is difficult for distributed clients to obtain sufficient identical samples to build a ma-chine-learning model. These issues may degrade the performance of the model.

In contrast, the main challenge for FL is the distributed setting of data heterogeneity and non-independent and identically distributed (non-IID) data from clients [12]. Previous studies [13, 14] have demonstrated that a global FL model with a federated averaging algorithm might perform poorly using statistical data heterogeneity, which slows down FL convergence.

The limitations of FL designs and data heterogeneity have motivated the development of a new approach to overcome both problems. In real-world situations, client-specific vertical features can be ignored in an HFL design, whereas identical sample IDs are insufficient in a VFL design, and data heterogeneity degrades performance. Therefore, we focused on leveraging client-specific vertical features while implementing a model that is well adapted to the heterogeneity of data across clients in a cross-silo environment.

In this study, we propose a novel approach called personalized progressive federated learning (PPFL) combining FL with variants of progressive neural networks [15]. In PPFL, building a personalized model allows the learning of client-specific distributions from a globally learned FL model by transmitting layer-wise knowledge to different network columns. The proposed model learns global knowledge from common feature information and expands the feature space related to client-specific vertical features by creating new column networks.

We applied the lateral connection in a progressive neural network [15] to expand the layer-wise feature space from a globally pre-trained FL model. Additionally, a progressive neural network was proposed to address the forgetting problem [15, 16]. Therefore, our model prevents the forgetting of previously learned global knowledge during the personalization phase.

Although PPFL is a domain agnostic framework that can be applied to various fields, in this study, we experiment and validate the algorithm with real-world medical data. Federated learning has gained increasing attention in the medical domain as a possible privacy preserving machine learning framework [17]. To this end, we additionally tested the PPFL with real-world medical data utilizing highly intensive care unit (HICU) data from the Severance Hospital, Seoul, South Korea.

To the best of our knowledge, this study is the first federated learning study that considers the common and vertical features of each client by applying personalized progressive learning and intends to verify whether our PPFL algorithm performs higher than the existing federated learning models based on real-world medical data from multiple hospitals.

Chapter 2

Background

2.1 Federated Learning and Design

FL is a machine-learning approach in which multiple clients collaboratively build a learning task while considering privacy issues and communication efficacy [3]. FL can be classified into HFL and VFL, depending on how the data are distributed among various clients [2]. HFL deals with a scenario in which each client has an identical feature space but different sample-id spaces. FedAvg [3] is a collaborative machine-learning framework proposed for this HFL scenario. HFL approaches cannot utilize vertically partitioned features, which are specifically generated by individual clients and are not shared with the HFL frameworks, increasing the model complexity.

VFL deals with a scenario in which each client has a different feature space and identical sample ID space. Although secured machine-learning methods [10, 32–35] for distributed features have been proposed, such methods cannot be used as deep learning approaches. In addition, despite the proposal of VFL approaches for deep learning [11, 36, 37], these methods have a limitation, in which every client must learn sufficient “identical sample-IDs” using a deep learning model.

2.2 Federated Learning on Non-IID Data

Data heterogeneity and non-IID data complicate the construction of a global FL model that can be applied to individual clients. FedAvg demonstrates a reduced model performance, including accuracy, under statistical data heterogeneity [14]. Additionally, the heterogeneity of the data slows down and destabilizes the convergence of FedAvg [13].

Previous studies [14, 30, 38, 39] have focused on utilizing the data augmentation method in an FL manner to address the weight divergence on non-IID data during the FL process. This method has been proposed to smoothen the statistical heterogeneity across distributed clients. However, when data augmentation approaches FL, it suffers from privacy leakage because data sharing has not been eliminated. Client selection approaches, such as FAVOR [29] used to build the FL model from the more homogeneous data distributions, also exist.

Previous studies [31, 40–45] proposed a personalized globally trained FL model for heterogeneous clients. Meta-learning-based approaches, such as personalized federated average (Per-FedAvg) [31], have been proposed to personalize an FL model by finding an optimal initialization for local personalization and learning of task-specific local representations based on a single global model design through meta-learning [40]. Multi-model personalization based on hierarchical clustering [41] was used to train an FL model for each cluster of clients. This framework involves training clusters of clients during each round of FL training. PFL approaches based on multi-task learning, model interpolation, and transfer learning build a model for each individual client through the FL process. The MOCHA algorithm was proposed as a personalization method for combining distributed multi-task learning and FL [42]. The model interpolation method [43] was proposed to handle the trade-off between a globally learned model and locally learned models with an adjustable penalty parameter. Transfer-learning-based approaches [44,45] aim to transfer the globally trained knowledge to the local models of individual clients through fine-tuning.

2.3 Federated Learning with Medical Data

FL has gained increasing attention in the medical field for its ability to enable machine learning in a distributed environment without sharing raw data. Moreover, the need for generalizable and robust models is another factor that motivates the interest in FL in medical data [17]. Various studies have applied FedAvg and other methods of FL on medical data. However, most research topics focused on HFL settings. There are only few works done in terms of VFL in its applications in medical data [46]. Although the vertical data problem is a domain agnostic problem, there are cases where different medical data for a patient are split throughout clinical institutions. Vepakomma et al. (2018) presented split learning algorithm as a possible framework for vertical learning in the healthcare sector [47]. However, the limitation is that this study does not utilize medical data. Further research in VFL in medical data is required and PPFL aims to target this issue.

Chapter 3

Method

We proposed a PPFL algorithm for achieving client-specific personalized inferences on data heterogeneity and non-IID data settings. PPFL also addresses the limited information availability of FL design by leveraging not only common features but also client-specific vertical features across distributed clients. Figure 3.1 shows the overview of our proposed framework. The proposed process involves two major steps. First, we built a horizontal federated model (HFL) on a central server using only the common features of the client from the distributed clients. Second, the pre-trained horizontal federated model was deployed for each client, learning personalized knowledge for client-specific inference tasks through a personalized progressive network (PersonalizedNet). The PersonalizedNet considers both a horizontal FL network (HorizontalNet), which receives input as weights from a globally trained model based on the common features of the client, and a vertical network (VerticalNet), which learns the specific feature of the client.

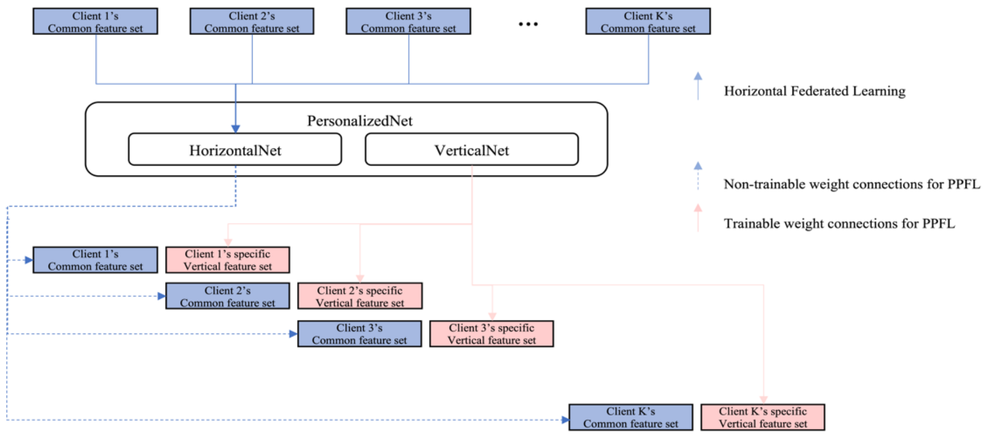

Figure 3.1: Overview of the PPFL framework

3.1 Problem Formulation

This study aims to solve the case where the features of each client are common and client-specific cases exist (Figure 3.2 A). All common feature information should be shared among clients. Suppose that an individual client k has a dataset $D_k \coloneqq \{\boldsymbol{x}_i^k, \boldsymbol{s}_i^k, y_i^k\}_{i=1}^{m^{(k)}}$ consisting of $m^{(k)}$ samples, where the client $k \in \mathcal{K} \coloneqq \{1, \ldots, K\}$. The i-th sample of D_k can be represented using a common feature vector with p -dimension $\boldsymbol{x}_i^k \coloneqq \{x_i^{1(k)}, x_i^{2(k)}, \ldots, x_i^{p(k)}\}$; the client's specific vertical feature vector with q-dimension $\boldsymbol{s}_i^k \coloneqq \{s_i^{1(k)}, s_i^{2(k)}, \ldots, s_i^{q(k)}\}$, and the corresponding target variable y_i^k. Note that the attributes and dimension $p^{(k)}$ of the common feature vector $\boldsymbol{x}_i^k$ are identical for all clients

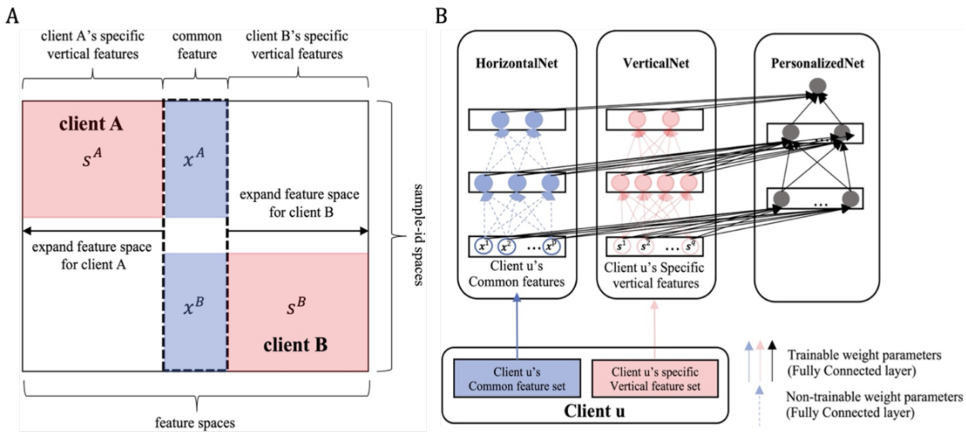

Figure 3.2: Problem setting and network architecture of the PPFL

$k \in \mathcal{K}$. However, the attributes and dimension $q^{(k)}$ of the client's specific vertical feature vector $\boldsymbol{s}_i^k$ may not be the same for all clients.

3.2 Horizontal Federated Learning

A horizontal federated model learns global knowledge related to common features across multiple clients in a federated manner. The proposed model is generic and can be applied to other collaboratively aggregated method based on the deep-learning model. However, in this study, we applied our algorithm to the FedAvg as a base method for building a horizontal federated model because it is the most well-known and commonly used method.

FedAvg is an algorithm that aggregates the weight parameters of the models within each client using weighted averaging. m is the total sample size of K clients. In addition,

$f_i(\boldsymbol{\omega})$ is the loss function of the prediction on example $(\boldsymbol{x}_i, y_i)$. Therefore, the objective function for solving the empirical risk minimization is

$$\begin{gathered} \min_{\boldsymbol{\omega}^c \in \mathbb{R}^d} F(\boldsymbol{\omega}^c) \coloneqq \sum_{k=1}^{K} \frac{m^{(k)}}{m} F_k(\boldsymbol{\omega}^k), \\ \text{where } F_k(\boldsymbol{\omega}^k) \coloneqq \sum_{\boldsymbol{x}_i \in D_k} f_i(\boldsymbol{\omega}^k) \end{gathered} \tag{1}$$

3.3 Personalized Progressive Federated Learning

PPFL contains three network columns: HorizontalNet, VerticalNet, and PersonalizedNet. PPFL is a multi-model-based approach that generates differently for every client at the deployment step and aims to solve the trade-off problem between globally generalized knowledge and client-specific knowledge. Hence, we utilized the concept of lateral connection in progressive neural networks [15], which is proposed for leveraging transfer and avoiding catastrophic forgetting in multi-task learning. Figure 3.2 B shows the architecture of the PPFL model.

3.3.1 Horizontal Network

HorizontalNet, which is the first column of PPFL, is a network that is transferred from the horizontal federated model. The internal weight parameters of the HorizontalNet column $\boldsymbol{\omega}^{c^{int}}$ were initialized using parameter $\boldsymbol{\omega}$ of the horizontal federated model described in Section 2.2. This network column aims to pass generalized knowledge to personalized networks with the common feature data of the client $\boldsymbol{x^k}$ as input information. Note that the internal weight matrix $\boldsymbol{\omega}^{c^{int}}$ in HorizontalNet, which is not connected with PersonalizedNet, is "frozen" to train. However, the lateral weight parameter $\boldsymbol{\omega}^{c^{lat}}$, which is the weight parameter between HorizontalNet and PersonalizedNet, can be updated using an optimization algorithm. This approach avoids forgetting the generalized knowledge that has already been learned. The hidden layers $\boldsymbol{h}_l^c$ in the HorizontalNet column for the client's common feature vector $\boldsymbol{x}_k$ are computed using the internal weight parameter $\boldsymbol{\omega}_l^{c^{int}}$ of the HorizontalNet as

$$\boldsymbol{h}_{l+1}^c = \sigma\left(\boldsymbol{\omega}_l^{c^{int}} \boldsymbol{h}_l^c + \boldsymbol{b}_l^c\right),\ where \quad \boldsymbol{h}_0^c = \boldsymbol{x}^k. \qquad (2)$$

The output values for the HorizontalNet hidden layers $\boldsymbol{h}_l^c$ are transferred to PersonalizedNet via the lateral weight parameter $\boldsymbol{\omega}^{c^{lat}}$ without overlaying the original internal weight parameter $\boldsymbol{\omega}^{c^{int}}$ of HorizontalNet. Therefore, the internal parameter of HorizontalNet $\boldsymbol{\omega}^{c^{int}}$ is not a trainable weight parameter for retaining the globally learned knowledge for the common feature space, and its lateral weight parameter $\boldsymbol{\omega}^{c^{lat}}$ allows the transfer of proper knowledge from $\boldsymbol{h}_l^c$ to the personalizedNet layer $\boldsymbol{h}_l^p$.

3.3.2 Vertical Network

The second network column was the VerticalNet column. This network progressively expanded the feature space with respect to the specific vertical features of the client. The input of VerticalNet is the specific vertical feature data of the client $\boldsymbol{s}^k \in D_k$. The weight parameter $\boldsymbol{\omega}^{v^{int}}$ is the internal weight parameter of VerticalNet, which is not connected to PersonalizedNet. The lateral weight parameter $\boldsymbol{\omega}^{v^{lat}}$ consists of the parameters of the VerticalNet and PersonalizedNet columns. Both $\boldsymbol{\omega}^{v^{int}}$ and $\boldsymbol{\omega}^{v^{lat}}$ can be learned through the training step because these parameters are newly constructed to expand the feature space and to connect with PersonalizedNet, which is the network column used for an inference task. Thus, the internal weight parameter $\boldsymbol{\omega}^{v^{int}}$ and lateral weight parameter $\boldsymbol{\omega}^{v^{lat}}$ learn client-specific vertical feature information and transmit their knowledge to PersonalizedNet. The hidden layers $\boldsymbol{h}_l^v$ in the VerticalNet column with respect to the client-specific vertical feature $\boldsymbol{s}^k$ and internal weight parameter $\boldsymbol{\omega}^{v^{int}}$ are

$$\boldsymbol{h}_{l+1}^v = \sigma\left(\boldsymbol{\omega}_l^{v^{int}} \boldsymbol{h}_l^v + \boldsymbol{b}_l^v\right), \quad where\ \boldsymbol{h}_0^v = \boldsymbol{s}^k \qquad (3)$$

3.3.3 Personalized Network

The PersonalizedNet layers learn the specific personalized knowledge of the client by acquiring the value of HorizontalNet, VerticalNet, and its previous layer as inputs. The computation between network columns is made possible through a lateral connection, the parameters of which, $\boldsymbol{\omega}^{c^{lat}}$ and $\boldsymbol{\omega}^{v^{lat}}$, are lateral weight parameters. Therefore, $\boldsymbol{\omega}^{c^{lat}}$ and $\boldsymbol{\omega}^{v^{lat}}$ determine the amount of activation of the globally learned common feature information and vertical feature information within the client, respectively. Its internal parameters $\boldsymbol{\omega}^{p}$ are the internal weight parameters used to mix the information from both HorizontalNet and VerticalNet and learn more complex information to achieve the inference tasks of individual clients. The hidden layers $\boldsymbol{h}_l^p$ in the PersonalizedNet column are computed using Equation (4).

$$\boldsymbol{h}_{l+1}^{p} = \sigma\left(\boldsymbol{\omega}_{l+1}^{c^{lat}}\boldsymbol{h}_{l+1}^{c} + \boldsymbol{\omega}_{l+1}^{v^{lat}}\boldsymbol{h}_{l+1}^{v} + \boldsymbol{\omega}_{l+1}^{p}\boldsymbol{h}_{l+1}^{p} + \boldsymbol{b}_{l}^{p}\right) \qquad (4)$$

Note that the proposed method can be applied even in the absence of client-specific vertical features. In this case, the hidden layer of a personalized progressive network is expressed as

$$\boldsymbol{h}_{l+1}^{p} = \sigma\left(\boldsymbol{\omega}_{l+1}^{c^{lat}}\boldsymbol{h}_{l+1}^{c} + \boldsymbol{\omega}_{l+1}^{p}\boldsymbol{h}_{l+1}^{p} + \boldsymbol{b}_{l}^{p}\right). \qquad (5)$$

Algorithm 1 Learning procedure of horizontal federated model

Input: The Dataset $D_k^{common} := \{(\boldsymbol{x}_i^k, y_i^k)\}_{i=1}^{m^k}, where\ client\ k \in K := \{1, \dots K\}$; is the local mini-batch size, E is the number of local epochs, and η is the learning rate.
Output: The horizontal federated model C and its weight parameter $\boldsymbol{\omega}^c$
1: **Central server execute:**
2: Construct the horizontal federated model C and initialize its weight parameter $\boldsymbol{\omega}^c$
3: **for** each round t = 0, 1, 2 … , N **do**
4: Randomly set the S_t from the clients with the number of $m \leftarrow \max(S \cdot K, 1)$, where $0 < S \leq 1$
5: **for** each client $k \in S_t$ **in parallel do**

$\omega_{t+1}^{k} \leftarrow \boldsymbol{ClientCommonUpdate}(k,\ \omega_t;\ x_i^k)$
end for
$\boldsymbol{\omega}_{t+1}^{c} \leftarrow \sum_{k=1}^{K} \frac{m_k}{m} \omega_{t+1}^{k}$
end for
return $\boldsymbol{\omega}^c$ to all clients

$\boldsymbol{ClientCommonUpdate}(k, \boldsymbol{\omega}^k;\ \boldsymbol{x}_i,\ y_i)$: *//Run on client k*
$\boldsymbol{\mathcal{B}} \leftarrow$ (split D_{k}^{common} into batches of size B)
for each local epoch e from 1 to E **do**
for batch $b \in \boldsymbol{\mathcal{B}}$ **do**
$\boldsymbol{\omega^{k+1}} \leftarrow gradientdescent(\boldsymbol{\omega}^k;\ \ell, \eta^p; \mathrm{b})$
end for
end for
return $\boldsymbol{\omega}_{t+1}^{k}$ to central server

Algorithm 2 Learning procedure of personalized progressive federated learning model

Input: The Dataset $D_k := \{(\boldsymbol{x}_i^k, (\boldsymbol{s}_i^k),\ y_i^k)\}_{i=1}^{m(k)}, where\ client\ k \in K := \{1, \dots K\}$; B^p is the local mini-batch size for personalization, E^p is the number of epochs for personalization, and η^p is the learning rate for personalization
Output: The personalized progressive FL model $\mathcal{P}$
Client execute: // *Run on specific client* k
Receive the ω^c from central server
$\boldsymbol{\mathcal{B}} \leftarrow$ (split D_k into batches of size B^p)
if client k has client-specific vertical feature $\boldsymbol{s}^k$ **then**
$\mathcal{P} \leftarrow \textbf{PersonalizedVertical}(\boldsymbol{x}^{\mathbf{k}}, \boldsymbol{s}^{\boldsymbol{k}})$
else
$\mathcal{P} \leftarrow \textbf{PersonalizedVertical}(\boldsymbol{x}^{\mathbf{k}})$
end if

$\textbf{PersonalizedVertical}(\boldsymbol{x}^{\mathbf{k}}, \boldsymbol{s}^{\boldsymbol{k}})$
Construct the PPFL model
$\mathcal{P} \leftarrow f(\boldsymbol{\omega}^{c^{int}},\ \boldsymbol{\omega}^{v^{lat}}, \boldsymbol{\omega}^{v^{int}}, \boldsymbol{\omega}^{v^{lat}}, \boldsymbol{\omega}^{p};\ \boldsymbol{x}^k,\ \boldsymbol{s}^k)$
initialize $\boldsymbol{\omega}^{c^{int}}$ to $\boldsymbol{\omega}^{c}$, and freeze the training of $\boldsymbol{\omega}^{c^{int}}$
initialize $\boldsymbol{\omega}^{c^{lat}}, \boldsymbol{\omega}^{v^{int}}, \boldsymbol{\omega}^{v^{lat}}, \boldsymbol{\omega}^{p}$
for each personalization epoch e from 1 to E^p **do**
for batch $b^p \in \boldsymbol{\mathcal{B}}$ **do**

$(\boldsymbol{\omega}_{e+1}^{c^{lat}}, \boldsymbol{\omega}_{e+1}^{v^{int}}, \boldsymbol{\omega}_{e+1}^{v^{lat}}, \boldsymbol{\omega}_{e+1}^{p})$
$\leftarrow \boldsymbol{gradientdescent}(\boldsymbol{\omega}_{e}^{c^{lat}}, \boldsymbol{\omega}_{e}^{v^{int}}, \boldsymbol{\omega}_{e}^{v^{lat}}, \boldsymbol{\omega}_{e}^{p};\ \ell, \eta^{p}; b^{p})$
end for
end for
return the PPFL model $\mathcal{P}$

PersonalizedCommon$(\boldsymbol{x}^{\mathbf{k}})$
Construct the PPFL model
$\mathcal{P} \leftarrow f(\omega^{c^{int}},\ \omega^{c^{lat}}, \omega^{p}; x^{k})$
initialize $\omega^{c^{int}}$ to ω^{c}, and freeze the training of $\omega^{c^{int}}$
initialize $\omega^{c^{lat}}, \omega^{p}$
for each personalization epoch e from 1 to E^{p} **do**
for batch $b^{p} \in \boldsymbol{\mathcal{B}}$ **do**
$(\boldsymbol{\omega}_{e+1}^{c^{lat}}, \boldsymbol{\omega}_{e+1}^{p}) \leftarrow \boldsymbol{gradientdescent}((\boldsymbol{\omega}_{e}^{c^{lat}}, \boldsymbol{\omega}_{e}^{p};\ \ell, \eta^{p}; b^{p})$
end for
end for
return the PPFL model $\mathcal{P}$

The algorithms for building the horizontal federated model and PPFL models are

The algorithms for building the horizontal federated model and PPFL models are presented in Algorithms 1 and 2, respectively. In Algorithm 1, the input is a common feature vector from the participating clients and target variables. As an output of Algorithm 1, the horizontal federated model can be learned using common feature information from the participating clients in the FL. The outputs of Algorithm 1 and the dataset, including common features, vertical features, and target variables from the participating clients, are the inputs of Algorithm 2. Subsequently, the PPFL model, consisting of the HorizontalNet, VerticalNet, and PersonalizedNet columns, is generated for each client. The HorizontalNet column of the PPFL model $\boldsymbol{\omega}^{c^{int}}$ is initialized using the weight parameter $\boldsymbol{\omega}^{c}$ from the horizontal federated model. The input is a common feature vector and a client-specific vertical feature vector from the individual client and target variables. The weight parameter $\boldsymbol{\omega}^{c^{int}}$ of the HorizontalNet column are frozen to retain globally learned knowledge related to common features, where $\boldsymbol{\omega}^{v^{int}}$ is the internal weight parameter of VerticalNet for client-specific vertical features. The lateral weight parameters $\boldsymbol{\omega}^{c^{lat}}$ and $\boldsymbol{\omega}^{v^{lat}}$ transmit knowledge of layer-wise network columns, including HorizontalNet and VerticalNet, respectively. The PersonalizedNet weight parameter $\boldsymbol{\omega}^{p}$ allows learning of more complex information from the PersonalizedNet layer $\boldsymbol{h}_l^p$, which receives the values of $\boldsymbol{h}_l^c$ and $\boldsymbol{h}_l^v$. As an output for Algorithm 2, these parameters can be learned using optimization methods such as gradient descent optimization algorithms [18]. Through this process, the proposed model can be personalized, except for the VerticalNet column, if there are no client-specific vertical features.

Chapter 4

Experiments

4.1 Study Design

To validate the performance of our model on specific datasets in the medical domain, we compared the combinations of input data from the Physionet Challenge 2012 [19], eICU data [20], and HICU data from Severance Hospital, Seoul, Korea to evaluate the performance of the PPFL algorithm. Details of the data are provided in the data section.

We compared PPFL with the models described below. (x) indicates that the model has learned only the common feature space, and (x, s) indicates the model has learned both common features and client-specific vertical features.

- **FedAvg (*x*):** HorizontalNet learned by the FedAvg algorithm with common features.
- **FedProx (x):** HorizontalNet learned by the FedProx algorithm with common features.
- **PPFL (*x*):** The PPFL model learns on individual clients by leveraging only common features.
- **PPFL (*x, s*):** The PPFL model learns on individual clients by leveraging both common features and client-specific vertical features.
- **Local (*x*):** Multi-layer perceptron (MLP) models learned only from common feature data of a specific client.

- **Local (*x, s*):** MLP models learned from both common and vertical feature data for a specific client.

We divided the training, validation, and test datasets in the ratio of 6:2:2 for each client participating in PPFL training. The validation dataset was used to search for hyperparameters using a random-search algorithm. We optimized the weight parameters of the models by stochastic gradient descent using the Adam optimizer [21]. We utilized the cross-entropy loss as a loss function for the application of our proposed and comparison models to binary classification. For hyperparameter tuning, 100 epochs were set for local training in federated learning, and 30 rounds were used to aggregate the local models.

We implemented them while providing accuracy and an area under the receiver operating characteristic (AUROC) score for each ICU client to demonstrate the performance improvement for individual clients and the robustness of the unseen distribution for the proposed model.

4.2 Dataset

The performance of the PPFL model was evaluated on two datasets: (1) a public EMR dataset called Physionet Challenge 2012 [19] and (2) a distributed ICU dataset from four types of ICUs from 208 institutions from the eICU [20] and Severance Hospital in South Korea. First, the Physionet Challenge 2012, which was extracted from the MIMIC-II database [22], consists of information regarding 8,000 ICU patients. These records contained 36 time-series features (i.e., laboratory tests, vital signs, and mechanical ventilation) and five demographic features, including ICU-type information. In this study, we aggregated ICU information for 48 h in an average manner because we did not focus on time-series data. Each ICU, with a total of 6,000 samples, was considered an individual client. Coronary care unit (CCU), cardiac surgery recovery unit (CSRU), medical ICU (MICU), and surgical ICU (SICU) retained 889, 1,219, 2,216, 1,676, and 2,000 ICU stay samples, respectively. The remaining 2,000 samples were used as external ICUs, configured without client separation. The external ICU was not used during the PPFL training. In this dataset, we assumed that the common feature set comprised demographic and mechanical ventilation information. In contrast, client-specific vertical features comprised vital signs and laboratory tests for all clients. The description of data distribution by the ICU for common features of the Physionet Challenge 2012 data set is presented in Supplementary Table 1-3.

Second, the distributed ICU dataset was composed of the eICU dataset [20] and Severance Hospital in Seoul, Korea, to predict in-hospital mortality. From the eICU (208 hospitals), 14,550 patients admitted to the MICU and 10,664 patients from the SICU were selected. From the Severance Hospital, 5,306 patients admitted to the high ICU (HICU) were selected. For external validation, we selected 12,706 patients from the neuro-surgical ICU (NSICU) from the eICU dataset. We identified 14 common features for each ICU, and different client-specific features were selected for each client using an L1-based feature selection method that utilizes linear models with an L1 penalty (L1-norm) added to the loss function [23]. The description of data distribution by the ICU for common features of the distributed ICU dataset is presented in Supplementary Table 4. This study was approved by the Institutional Review Board of Severance Hospital (IRB approval no. “4-2021-0820”).

4.2 Experiment Details

PPFL performance was evaluated using the Physionet Challenge 2012 dataset from CCU, CSRU, MICU, and SICU. Each ICU was selected as an independent client. For each client, we compared the performance of FedAvg (x), PPFL (x), PPFL (x, s), Local (x), and Local (x, s) for both internal and external validations. Internal performance was measured using a test set from a local client. For external validation, we used 2,000 samples that were set aside when partitioning ICU data. We evaluated the performance of binary classifications for the following two cases: in-hospital mortality as a binary class (dead or alive) and length of stay as a binary class for more than seven days after 48 h of ICU admission.

We computed feature importance using the SHAP value computed by Deep SHAP to investigate the concept shift after the application of PPFL [24]. SHAP is a method used for computing the value of a data instance. Deep SHAP approximates the SHAP value using DeepLIFT [25].

We compared the loss of in-hospital mortality prediction tasks while training PPFL (x) and PPFL (x, s) with transfer learning to evaluate the effects of the personalizing mechanism on PPFL. We simulated PPFL in two ways. First, we compared the loss of PPFL (x) and PPFL (x) without freezing FedAvg (x) and transfer learning for each training epoch to evaluate personalized learning in a horizontal data environment. Additionally, we compared PPFL (x, s) with PPFL (x, s) without freezing and transfer learning to evaluate the effects of personalized learning in the presence of the client-specific vertical features.

Moreover, we conducted a performance comparison with distributed ICU dataset to evaluate the effectiveness of PPFL and the performance of the PPFL in an extreme data environment. We compared the performance of the local models (x) and (x, s) and FedAvg (x) with PPFL (x) and PPFL (x, s). The task was to predict in-hospital mortality. The training and evaluation details were the same as those described in the study design section.

4.3 Experiment Setting

All experimental settings were implemented using TensorFlow 2.5.0 [26]. The models were trained on a machine equipped with two NVIDIA QUADRO RTX 8000 CUDA 11.0, 128 GB memory and one Intel Xeon Platinum 8253 2.2 GHz CPU.

Chapter 5

Results

5.1 Performance Evaluation

PPFL (x, s) showed the highest performance for every ICU client on external validation. The PPFL(x) showed an average of 0.790 AUROC for the in-hospital mortality task and 0.808 AUROC for the length of the stay task (Figures 5.1 A and 5.1 B, respectively). Where FedAvg(x) and FedProx(x) showed performance (AUROC) by 0.616 and 0.615 in mortality prediction, respectively. In addition, PPFL(x, s) higher performance than FedAvg(x) and FedProx(x) both in hospital mortality and length of stay prediction. The average AUROC of FedAvg(x) was 0.643 and 0.643 for FedProx(x) in length of stay prediction. Compared with Local(x, s), PPFL (x, s) show that all AUROC performances of PPFL(x, s) outperform in external validations. The average AUROC for local(x, s) in external validation was 0.743 in in hospital mortality prediction, and 0.773 in length of stay prediction. In average, PPFL(x, s) showed higher performance than local(x, s) models in external validation(Figure 5.1 A, Figure 5.1 B, Supplementary Table 5). Comparing the average AUROC of PPFL(x, s) to Local(x, s) in Figure 2C and Figure 2D, our model showed higher performance in in hospital mortality task. However, in length of stay prediction, the SICU showed 0.865, which was higher than the average AUROC performance than PPFL(x, s). Overall, PPFL(x, s) showed the highest AUROC compared to other local model(x, s) in average (Figure 5.1 C, Figure 5.1 D). Figures 5.2 shows the

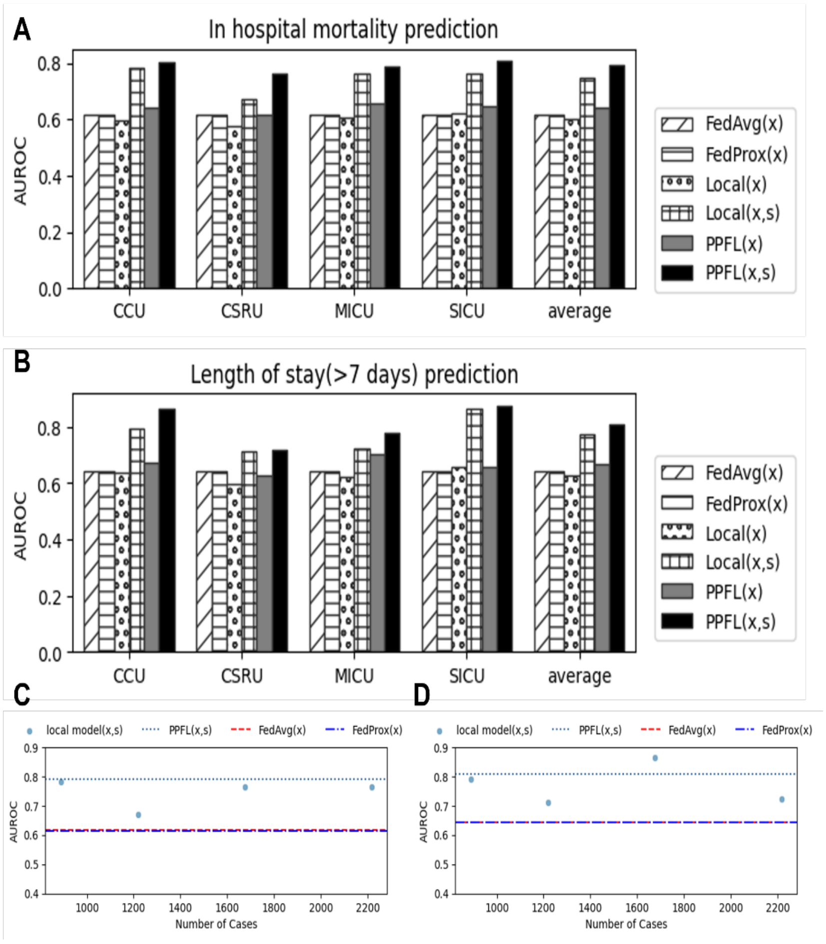

Figure 5.1: Performance evaluation on Physionet 2012. PPFl was evaluated compared to FedAvg (x), FedProx (x), Local (x), and Local (x, s) in terms of AUROC on external validation. PPFL (x, s) shows the highest score in every task. A. AUROC comparison for in-hospital mortality prediction task. B. AUROC score comparison for the length of stay prediction task. C. AUROC score compared for each ICUs for in-hospital mortality prediction task among Local (x, s), PPFL (x, s), and FedAvg (x) D. AUROC score compared for each ICUs for the length of stay (>7) prediction task among Local (x, s), PPFL (x, s), FedProx (x), and FedAvg (x).

contributions of common and vertical features for all clients in predicting in-hospital mortality. Within common features, age and mechanical ventilation (MechVent) features had the highest shape value in all clients (age was 0.5 or more in all clients and MechVent

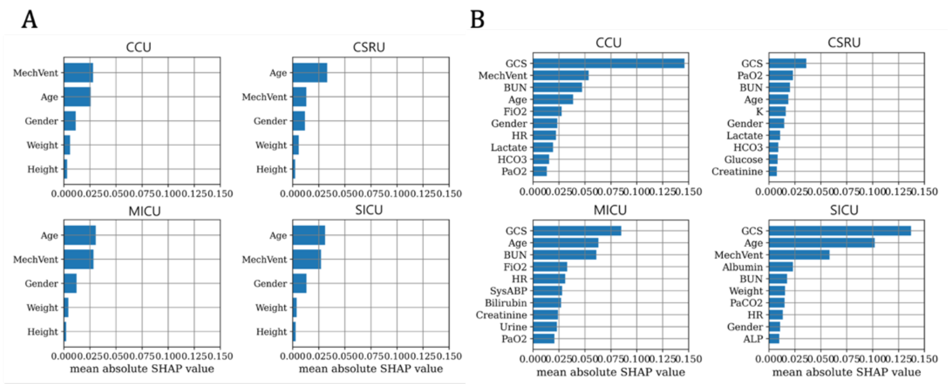

Figure 5.2: Mean absolute SHAP values of common and vertical features in predicting in-hospital mortality. A. SHAP values in common features. B. top 10 highest SHAP value features with vertical features.

was 0.3 or more in three clients). Among the vertical features, the Glasgow Coma Scale (GCS) had the highest shape value for all clients (0.025 or higher for all clients). Mechanical ventilation still had a high ranking for CCU and SICU.

We also compared FedAvg (x) to PPFL (x, s) to evaluate whether leveraging client specific features shows high performance. PPFL (x, s) showed higher performance than FedAvg (x) (Supplementary Table 6). For the MICU, the SHAP value for MechVent was not lower than those of the other clients. However, in terms of vertical features, vital signs, such as GCS, blood urea nitrogen, fraction of inspired oxygen, heart rate, and absolute blood pressure, have higher SHAP values than those for mechanical ventilation.

5.2 Effectiveness of Progressive Model

Figure 5.3 shows the results of the cross-entropy loss for the mortality prediction task for the personalized models for each client. The loss was evaluated by an external client

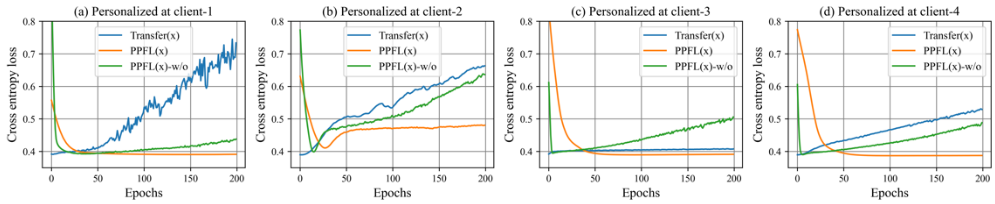

Figure 5.3: Loss comparison of the PPFL, PPFL without freezing and transfer in each client using common features. Client-1: CCU, Client-2: CSRU, Client-3: MICU, Client-4: SICU

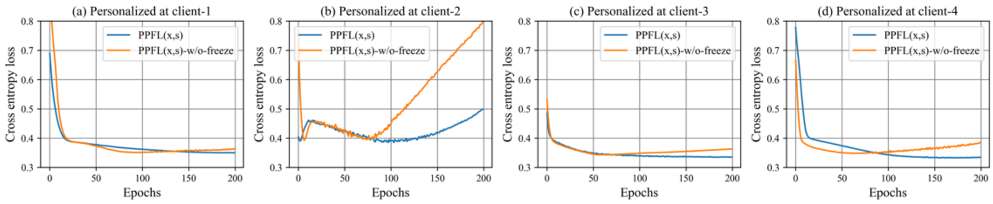

Figure 5.4: Loss comparison of the PPFL and PPFL without freezing using common and client-specific vertical features. Client-1: CCU, Client-2: CSRU, Client- 3: MICU, Client-4: SICU

during the training process. The loss without a weight freeze (green line) and the loss without a personalized progressive network (blue line) increased as the number of epochs increased compared with the loss of PPFL (x). We also observed a loss increase in PPFL (x, s) without a weight freeze compared with PPFL (x, s) with a loss freeze (Figure 5.4). In this comparison, we observed that: (1) Personalizing through simple transfer learning to HorizontalNet (x) makes unstable the learning procedure related to loss. (2) Personalizing using PPFL without freezing the internal parameters of HorizontalNet also makes unstable the learning procedure. (3) The proposed PPFL method showed a continuous decrease in loss compared to comparison models. (4) This improvement was more effectively observed as the client-specific distribution became increasing different

5.3 Performance Evaluation Using Real-World Clinical Data

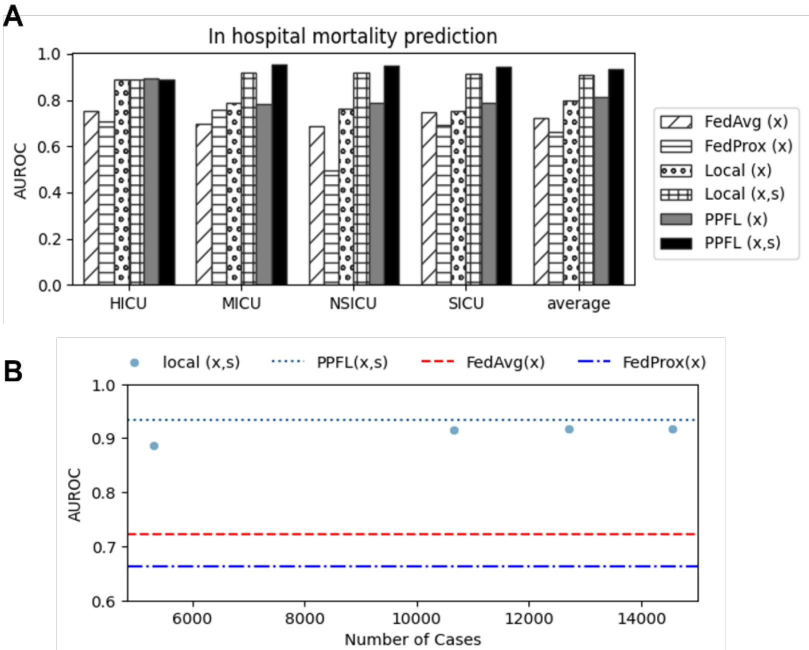

Figure 5.5: **Performance evaluation on real-world clinical data**. PPFL was evaluated compared to FedAvg, FedProx, and local models using real-world data in terms of AUROC. PPFL (x, s) shows the highest score in every task A. AUROC comparison for in-hospital mortality prediction task. B. AUROC score compared for each ICUs for in-hospital mortality prediction task.

In the performance evaluation of the actual experiment, PPFL(x, s) showed the highest score, with an accuracy of 0.939 and AUROC of 0.934 (Figure 5.5 A and Supplementary Table 7). In most ICU clients, PPFL (x, s) shows the highest AUROC, except for HICU. In the HICU, PPFL (x) showed the highest performance, with an AUROC of 0.892 and accuracy of 0.932 (Supplementary Table 7), which were 0.1% and 0.3% higher than that of PPFL (x, s), respectively. Compared with the models Local (x, s), FedAvg (x), and

FedProx (x), the AUROC values of the PPFL (x, s) model for predicting in-hospital mortality improved in the internal assessments (Figure 5.5 B). FedAvg (x) showed an average AUROC of 0.722, and FedProx (x) performed 0.663 which was the lowest score in all models. However, PPFL (x, s) performed 0.935 in average. Figure 5.5 B shows that the local models show higher performance than FedAvg (x), while PPFL (x, s) achieves the highest AUROC. In addition, the AUROC increases for all clients as the number of clients increases. In external evaluation with NSICU from the eICU dataset, PPFL (x, s) showed an AUROC of 0.948, which was 3.1% higher than that of the Local (x, s) model.

Chapter 6

Discussion

The usage of federated learning in analyzing distributed medical data is a well-known research topic [17, 27]. Therefore, research on federated learning that can potentially protect data privacy has been conducted in various medical fields [28]. However, most current studies consider learning common features among clients. In this study, we proposed a personalized progressive federated learning (PPFL) algorithm for heterogeneously distributed clients that expands the feature space for client-specific vertical features. This study is the first federated learning study that considers common features and client-specific vertical features by applying progressive learning. PPFL shows a robust performance compared to other algorithms based on the comparison of PPFL with existing federated learning models and local models in various settings.

Compared to FedAvg, which is suitable for a horizontally partitioned data environment [3–9], PPFL is a novel federated learning framework that leverages the idea of progressive learning to perform learning in both horizontally and vertically partitioned environments. PPFL can utilize more features and samples than other models (Figure 5.1, Supplementary Table 5, Figure 5.5), resulting in better performance compared to existing local and federated learning models. For example, FedAvg and FedProx have a limited feature space because only the common features from multiple clients are input into the model in terms of its structure. The local model uses only the sample of each client; thus, the number of samples is inevitably smaller than that of the PPFL input dataset. PPFL demonstrated a higher performance than the existing model by inputting all the collected features and samples of multi-clients.

A learning weight based on a common feature is delivered to each client, and the effect of transfer learning is confirmed by running the delivered running weight and vertical feature together (Figure 5.3, Figure 5.4, and Supplementary Table 5). Wang et al. reported that client transfer learning is effective in learning client-specific features [29]. The effectiveness of the proposed model is the greatest for clients who are significantly different from the overall data distribution since CSRU has the most different label distribution from an external client and the most severe class imbalance problem.

In addition, an important known problem of federated learning is the unstable convergence of weights and performance degradation in heterogeneous data environments [14, 30]. In this study, the PPFL model showed stable convergence of loss in a heterogeneous multi-client environment compared to transfer learning (Figure 5.3 and Figure 5.4).

For all internal validations of the clients, except for the in-hospital mortality task for some clients, HorizontalNet(x), learned through FedAvg, exhibits a degraded performance compared to that with Local(x). Previous studies have confirmed that FL performance may decrease when the distribution among clients is heterogeneous [13, 14]. Additionally, the data we tested was statistically significant heterogeneous across clients (Supplementary Table 1). We found that the hospital stay of SICU patients was significantly longer than that of other ICU patients (Supplementary Table 1). Moreover, we found that the performance of the local(x) model using only local data was higher than our proposed PPFL(x, s) (Figure 5.1 D). This indicates that extreme data heterogeneity in FL can lead to lower performance than that of local models. However, we emphasize that our model still outperforms FedAvg and FedProx, and the performance difference with the local model (SICU) is negligible.

Although client-specific vertical features contain more information, our proposed model is effective in terms of robustness. This shows that PPFL is robust to the global knowledge forgetting problem in the personalization process of the FL models. Since there are few studies conducted with real-world data scenarios on federating learning and demands on experiments using real-world data are emphasized [30, 31], this is the first study to use real-world clinical data from multiple ICU clients from different countries. In this study, real-world data considering all ICU features showed higher performance compared to the Physionet challenge 2012 dataset with limited features. This is the rationale for PPFL to become a clinically applicable algorithm.

Federated Learning generally performs better in terms of privacy than local models. Yang et al. (2019) reports possibility of indirect privacy leakage in FL systems [2]. Since PPFL utilizes horizontal features in the training process, the client specific features are secure, having advantage than other FL algorithms. Indirect data leakage may occur only in the horizontal features. However, the client specific vertical features progressively learned in each client are safe from any direct or indirect privacy leakage compared to other FL frameworks.

Our study has several limitations. First, there is little difference in the computing time and resources when verifying the PPFL in the same network bandwidth. However, additional research on the computation time and resources between physically distant networks is required for multi-client from multi-country studies. Second, this PPFL algorithm was written assuming that information on the features of multiple clients is shared; however, information about common and vertical features of each client may not be provided in the real world. Research on an automatic feature selection process based on the characteristics of input data among the features of multiple clients is essential. Third, Yang et al. (2019) reported that there is a possibility of indirect privacy leakage to raw federated learning systems [2]. We plan to further our studies in strengthening PPFL from these issues. Fourth, although only MLP modules based on linear layer have been applied to the PPFL framework in this study, we will also apply them to other neural network structures such as sequential-based layers in future studies.

Chapter 7
Conclusion

We proposed the PPFL algorithm to personalize federated algorithms for heterogeneously distributed clients and expand the feature space for client-specific vertical feature information. Moreover, we investigated the performance improvement and robustness of our proposed model using real-world EHR data and validated the usefulness of the model. Our model showed higher performance than FedAvg and FedProx. We plan to further our studies in improving the PPFL compared to other models in FL.

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Appendix

		CCU (n = 889)	CSRU (n = 1,219)	MICU (n = 2,216)	SICU (n = 1,676)	External ICU (n = 2,000)	P-value
Age		69.4 (14.6)	67.6 (13.1)	63.5 (18.1)	60.3 (19.3)	64.1 (12.2)	< 0.001
Gender	Female	357 (40.2)	453 (35.8)	1075 (50.1)	706 (41.6)	241 (45.2)	< 0.001
	Male	531 (59.8)	812 (64.2)	1070 (49.9)	992 (58.4)	292 (54.8)	
Height		170.6 (17.8)	169.9 (10.5)	168.3 (19.7)	170.1 (17.3)	169.3 (23.2)	< 0.001
Weight		80.7 (21.8)	87.4 (20.0)	82.3 (27.2)	83.0 (25.8)	81.9 (23.3)	< 0.001
In-hospital death	Alive	773 (87.0)	1205 (95.2)	1724 (80.3)	1457 (85.8)	453 (85.0)	< 0.001
	Death	115 (13.0)	61 (4.8)	423 (19.7)	242 (14.2)	80 (15.0)	
Length of stay	<7 days	396 (44.6)	455 (35.9)	801 (37.3)	453 (26.7)	189 (35.5)	< 0.001
	>7 days	492 (55.4)	811 (64.1)	1346 (62.7)	1246 (73.3)	344 (64.5)	

* One-way analysis of variance (ANOVA) for continuous features; χ^2-test for categorical features.

Supplementary Table 1: Description of data distribution by icu for common variables of Physionet Challenge 2012

In hospital mortality										
Client	Client-specific vertical features									
1 CCU	DiasABP	PaO2	pH	SysABP	Lactate	HR	SaO2	Bilirubin	ALP	Platelets
2 CSRU	Na	Albumin	PaO2	FiO2	SaO2	Urine	pH	Lactate	Creatinine	SysABP
3 MICU	PaCO2	Temp	Na	K	PaO2	Creatinine	HCT	SysABP	Bilirubin	pH
4 SICU	pH	HCT	MAP	SysABP	Albumin	Mg	Platelets	DiasABP	K	FiO2

Supplementary Table 2: Selected client-specific vertical features of Physionet 2012

No.	Cite name	Feature name	Description
1	Common feature	Age	Patient age on initial visit.
2	Common feature	Gender	Patient's biological sex.
3	Common feature	Height	Patient's height on initial visit.
4	Common feature	Weight	Patient's weight on initial visit.
5	Common feature	In Hospital Death	Whether the patient died during admitted in hospital.
6	Common feature	Length of Stay	Patient's length of stay at ICU.
7	CCU	DiasABP	Patient's diastolic blood pressure.
8	CCU	Na	Sodium ion concentration in vein.
9	CCU	Albumin	Albumin concentration in vein.
10	CCU	PaO2	Partial pressure of Oxygen in arterial blood.
11	CCU	pH	Hydrogen ion concentration in vein.
12	CCU	SysABP	Patient's systolic blood pressure.
13	CCU	Lactate	Lactate concentration in vein.
14	CCU	HR	Patient's Heart rate.
15	CCU	SaO2	Oxygen saturation in arterial blood.
16	CCU	Bilirubin	Bilirubin concentration in vein.
17	CCU	ALP	Alkaline Phosphatase concentration in vein.
18	CCU	Platelet	Platelet counts in vein.
19	CSRU	Na	Sodium ion concentration in vein.
20	CSRU	Albumin	Albumin concentration in vein.
21	CSRU	PaO2	Partial pressure of Oxygen in arterial blood.
22	CSRU	FiO2	Fraction of inspired oxygen.
23	CSRU	SaO2	Oxygen saturation in arterial blood.
24	CSRU	Urine	Total urine output during first visit.
25	CSRU	pH	Hydrogen ion concentration in vein.
26	CSRU	Lactate	Lactate concentration in vein.
27	CSRU	Creatinine	Creatinine saturation in vein.
28	CSRU	SysABP	Patient's systolic blood pressure.
29	MICU	PaCO2	Partial pressure of carbon dioxide in arterial blood.
30	MICU	Temp	Patient's temperature on initial visit.

31	MICU	Na	Sodium ion concentration in vein
32	MICU	K	Potassium ion concentraion in vein
33	MICU	PaO2	Partial pressure of Oxygen in arterial blood.
34	MICU	Creatinine	Creatinine concentration in vein.
35	MICU	HCT	Hematocrit in vein. Measures the proportion of red blood cells in blood.
36	MICU	SysABP	Patient's systolic blood pressure.
37	MICU	Bilirubin	Bilirubin concentration in vein.
38	MICU	pH	Hydrogen ion concentration in vein.
39	SICU	pH	Hydrogen ion concentration in vein.
40	SICU	HCT	Hematocrit in vein. Measures the proportion of red blood cells in blood.
41	SICU	MAP	Mean arterial blood pressure.
42	SICU	SysABP	Patient's systolic blood pressure.
43	SICU	Albumin	Albumin concentration in vein.
44	SICU	Mg	Magnesium ion concentration in vein.
45	SICU	Platelet	Platelet counts in vein.
46	SICU	DiasABP	Patient's diastolic blood pressure.
47	SICU	K	Potassium ion concentration in vein.
48	SICU	FiO2	Fraction of inspired oxygen.

Supplementary Table 3: Description of the common and client-specific vertical features of Physionet Challenge 2012

No.	Cite name	Feature name	Description
1	Common feature	RBC Count	Red blood cell count from vein.
2	Common feature	Weight	Body weight on initial visit.
3	Common feature	temperature	Body temperature on initial visit.
4	Common feature	Bun	Blood Urea Nitrogen from urine.
5	Common feature	Creatinine	Creatinine from urine.
6	Common feature	Hct	Hematocrit from vein.
7	Common feature	Sodium	Sodium concentraion in vein.
8	Common feature	Gender	Biological sex.
9	Common feature	Respiratoryrate	Respiratory rate on initial visit.
10	Common feature	Height	Height on initial visit.
11	Common feature	Heartrate	Heartrate on initial visit.
12	Common feature	Age	Patient’s age on initial visit.
13	Severance HICU	PLT Count	Platelet count from vein.
14	Severance HICU	Height Z	Patient’s height on normal distribution.
15	Severance HICU	Height P	Patient’s height scaled on some distribution.
16	Severance HICU	Eosinophil (%)	Eosinophil percentage among other white blood cells in vein.
17	Severance HICU	Basophil (%)	Basophil percentage among other white blood cells in vein.
18	Severance HICU	Weight Z	Patient Weight on Z test.
19	Severance HICU	Monocyte (%)	Monocyte percentage among other white blood cells in vein.
20	Severance HICU	Neutrophil (%)	Neutrophil percentage among other blood cells in vein.
21	Severance HICU	foreign	Whether a patient is a foreigner.

22	Severance HICU	Body surface area	Body surface area of a patient.
23	Severance HICU	Cl	Chloride evaluated on vein.
24	Severance HICU	Weight P	Patient's weight scaled on some distribution.
25	Severance HICU	Hemoglobin	Hemoglobin count on vein.
26	Severance HICU	Albumin	Albumin concentration in vein.
27	Severance HICU	Total protein	Total protein amount in vein.
28	Severance HICU	FiO2	Fraction of inspired O2.
29	Severance HICU	GCS	Glasgow Coma Scale on initial visit.
30	Severance HICU	pH	Hydrogen ion concentration in water.
31	Severance HICU	Anion gap	Difference between positively charged ions.
32	Severance HICU	vent	Whether the patient used a ventilator.
33	Severance HICU	Bicarbonate	Bicarbonate concentration in vein.
34	Severance HICU	NARCAN	Brand name for Naloxone HCL.
35	Severance HICU	VANCOMYCIN HCL 1000 MG IV SOLR	Vancomycin injection through intravenous route.
36	eICU MICU	PANTOPRAZOLE SODIUM 40 MG PO TEBEC	Patient prescribed with Pantoprazole tablet through oral administration.
37	eICU MICU	1000 ML FLEX CONT : SODIUM CHLORIDE 0.9 % IV SOLN	Patient prescribed with Sodium chloride injection through intravenous route.
38	eICU MICU	POTASSIUM CHLORIDE CRYS	Potassium chloride through oral administration.

		ER 20 MEQ POP TBCR	
39	eICU MICU	Albumin	Albumin concentration in vein.
40	eICU MICU	fiO2	Fraction of inspired O2.
41	eICU MICU	Bicarbonate	Bicarbonate concentration in vein.
42	eICU MICU	GCS	Glasgow Coma Scale on initial visit.
43	eICU MICU	Anion gap	Difference between positively charged ions.
44	eICU MICU	Vent	Whether the patient used a ventilator.
45	eICU MICU	DEXTROSE 50%-WATER	Patient prescribed with Water with 50% of dextrose.
46	eICU MICU	SODIUM CHLORIDE 0.9%	Patient prescribed with sodium chloride 0.9%.
47	eICU MICU	METOPROLOL TARTRATE 25 MG PO TABS	Patient prescribed with Metoprolol 25MG tablet through oral administration.
48	eICU SICU	PANTOPRAZOLE SODIUM 40 MG PO TBEC	Patient prescribed with Pantoprazole tablet through oral administration.
49	eICU SICU	OXYCODONE	Patient prescribed with Oxycodone tablet through oral administration.
50	eICU SICU	ACETAMINOPHEN 5,325 MG PO TABS	Patient prescribed with acetoaminophen tablet through oral administration.
51	eICU SICU	POTASSIUM CHLORIDE CRYS ER 20 MEQ PO TBCR	Patient prescribed with Potassium chloride tablet through oral administration.
52	eICU SICU	DOCUSATE SODIUM 100 MG PO CAPS	Patient prescribed with docustate sodium 100MG tablet through oral administration.

53	eICU SICU	ZOFRAN	Patient prescribed with ZOFRAN.
54	eICU SICU	LORazepam	Patient prescribed with Lorazepam.
55	eICU NSICU	Albumin	Albumin concentration in vein.
56	eICU NSICU	Hospitaldischargeyear	Patient’s hospital discharge year.
57	eICU NSICU	fiO2	Fraction of inspired O2.
58	eICU NSICU	GCS	Glasgow Coma Scale on initial visit.
59	eICU NSICU	ACETAMINOPHEN 650 MG RE SUPP	Patient prescribed with Acetaminophen 650MG.
60	eICU NSICU	Vent	Whether the patient used a ventilator.
61	eICU NSICU	PANTOPRAZOLE SODIUM 40 MG IV SOLR	Patient prescribed with Pantoprazole tablet through intravenous route.
62	eICU NSICU	LEVETIRACETAM 500 MG PO TABS	Patient prescribed with Levetiracetam tablet through oral administration.

Supplementary Table 4: Selected features for real-world clinical data validation.

		In hospital mortality				Length of stay (>7)			
		Internal		External		Internal		External	
Client	Model	Acc.	AUROC	Acc.	AUROC	Acc.	AUROC	Acc.	AUROC
1. CCU	FedAvg (x)	0.857	0.671	0.818	0.616	0.650	0.690	0.710	0.643
	FedProx (x)	0.861	0.766	0.835	0.615	0.539	0.628	0.647	0.604
	PPFL (x)	0.862	0.773	0.860	0.640	0.862	0.715	0.860	0.671
	PPFL (x, s)	**0.879**	**0.827**	**0.845**	**0.803**	**0.871**	**0.853**	**0.862**	**0.861**
	Local (x)	0.860	0.657	0.823	0.598	0.852	0.803	0.839	0.636
	Local (x, s)	0.871	0.810	0.835	0.781	0.864	0.822	0.847	0.792
2. CSRU	FedAvg (x)	0.951	0.614	0.818	0.616	0.535	0.661	0.710	0.643
	FedProx (x)	0.944	0.638	0.835	0.615	0.640	0.548	0.647	0.604
	PPFL (x)	0.937	0.643	0.814	0.617	0.923	0.690	0.816	0.625
	PPFL (x, s)	**0.954**	**0.873**	**0.836**	**0.762**	**0.954**	**0.833**	0.856	**0.719**
	Local (x)	0.952	0.635	0.818	0.576	0.927	0.691	0.851	0.596
	Local (x, s)	0.926	0.824	0.818	0.671	0.931	0.714	**0.860**	0.710
3. MICU	FedAvg (x)	0.809	0.616	0.818	0.616	0.640	0.593	0.710	0.643
	FedProx (x)	0.809	0.557	0.835	0.615	0.616	0.610	0.647	0.604
	PPFL (x)	0.812	0.643	0.820	0.655	0.815	0.643	0.860	0.703
	PPFL (x, s)	0.815	**0.715**	**0.847**	**0.789**	**0.864**	**0.695**	**0.868**	**0.779**
	Local (x)	0.809	0.631	0.818	0.604	0.805	0.619	0.860	0.619
	Local (x, s)	**0.818**	0.709	0.841	0.765	0.805	0.690	0.852	0.722
4. SICU	FedAvg (x)	0.833	0.659	0.818	0.616	0.643	0.617	0.710	0.643
	FedProx (x)	0.855	0.561	0.835	0.615	0.734	0.583	0.647	0.604
	PPFL (x)	0.855	0.672	0.860	0.648	0.851	0.689	0.860	0.659
	PPFL (x, s)	**0.860**	**0.835**	**0.867**	**0.807**	**0.856**	**0.853**	0.864	**0.873**
	Local (x)	0.803	0.665	0.818	0.622	0.741	0.692	0.858	0.657
	Local (x, s)	0.846	0.792	0.862	0.764	0.851	0.796	**0.871**	0.865
Average	FedAvg (x)	0.863	0.64	0.818	0.616	0.617	0.640	0.710	0.643
	FedProx (x)	0.867	0.631	0.835	0.615	0.632	0.592	0.647	0.604
	PPFL (x)	0.867	0.683	0.839	0.64	0.863	0.684	0.849	0.665
	PPFL (x, s)	**0.877**	**0.813**	**0.849**	**0.790**	**0.886**	**0.809**	0.863	**0.808**
	Local (x)	0.856	0.647	0.819	0.600	0.831	0.701	0.852	0.627
	Local (x, s)	0.866	0.784	0.839	0.745	0.862	0.755	**0.875**	0.772

Supplementary Table 5: Performance evaluation on Physionet 2012. PPFL was evaluated compared to FedAvg, FedProx, Local (using common features), Local (using common and specific features) in internal and external validation.

In hospital mortality					
		Internal		External	
Client	Model	Accuracy	AUROC	Accuracy	AUROC
CCU	FedAvg (x)	0.857	0.671	0.818	0.616
	PPFL (x,s)	**0.871**	**0.838**	**0.862**	**0.723**
CSRU	FedAvg (x)	0.951	0.614	0.818	0.616
	PPFL (x,s)	**0.954**	**0.847**	**0.861**	**0.760**
MICU	FedAvg (x)	**0.809**	0.616	0.818	0.616
	PPFL (x,s)	0.805	**0.774**	**0.860**	**0.745**
SICU	FedAvg (x)	0.833	0.659	0.818	0.616
	PPFL (x,s)	**0.860**	**0.781**	**0.865**	**0.772**

Supplementary Table 6: Internal and external validation of using client-specific features in each client on Physionet 2012.

In hospital mortality			
client	model	Accuracy	AUROC
Internal validation			
1. Sev-HICU	FedAvg (x)	0.929	0.753
	FedProx (x)	0.930	0.706
	PPFL (x)	**0.932**	**0.892**
	PPFL (x, s)	0.931	0.889
	Local (x)	0.930	0.886
	Local (x, s)	0.927	0.886
2. eICU-MICU	FedAvg (x)	0.812	0.697
	FedProx (x)	0.870	0.756
	PPFL (x)	0.867	0.785
	PPFL (x, s)	**0.928**	**0.955**
	Local (x)	0.881	0.789
	Local (x, s)	0.906	0.918
3. eICU-SICU	FedAvg (x)	0.890	0.747
	FedProx (x)	0.911	0.693
	PPFL (x)	0.916	0.790
	PPFL (x, s)	**0.957**	**0.946**
	Local (x)	0.911	0.752
	Local (x, s)	0.927	0.915

External validation			
4. NSICU	FedAvg (x)	0.890	0.780
	FedProx (x)	0.917	0.689
	PPFL (x)	0.918	0.787
	PPFL (x, s)	**0.941**	**0.948**
	Local (x)	0.915	0.765
	Local (x, s)	0.908	0.917

Supplementary Table 7: Performance evaluation on real-world clinical data. PPFL was evaluated compared to FedAvg, FedProx, Local (using common features), Local (using common and specific features) in internal and external validation using distributed real-world data.

국문초록

사용자 특징적인 수직 분할 데이터를 활용한

개인화된 점진 연합 학습

김태현

의생명시스템정보학과

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연합학습은 분산된 사용자들 사이에서 모델을 학습시키기 위한 방식이다. 하지만, 기존의 수평 연합 학습은 모델의 복잡성을 증가시키기 위해 수직 분할 데이터를 활용하지 못하며, 수직 연합 학습은 모든 사용자에게서 많은 양의 동일한 사용자가 공유 되어야한다. 반면, 연합 학습의 주요 과제 중 하나는 사용자 사이의 데이터 이질성과 독립-항등 분포가 아닌 환경에서의 학습이다. 본 연구에서 사용자 특징적인 수직 분할 데이터를 활용할 수 있는 다중 모델 기반 개인화된 알고리즘인 개인화된 점진 연합 학습 (Personalized Progressive Federated Learning, PPFL)을 제안한다. PPFL 의 성능은 Physionet

Challenge 2012 와 eICU 및 세브란스 병원 데이터로 이루어의 현실 세계 데이터의 두 데이터에서 평가되었다. 병원 내 사망과 병원 체류 기간 예측의 두 가지 문제에 대해 정확도와 수신자 조작 특성 곡선 면적 (Area Under Receiver Operating Characteristic, AUROC)에 기반하여 평가하였다. PPFL 은 병원 내 사망 예측에서 평균 0.849 의 정확도와 0.790 의 AUROC 의 성능을 보여주었으며, 다른 비교 모델들에 비해 가장 높은 점수를 보여주었다. 체류 기간 예측에서 PPFL 은 평균 0.808 AUROC 로 비교 모델들 중 가장 높은 성능을 보였다.

핵심 단어: 개인화된 연합학습, 수직 분할 데이터, 데이터 이질성