Universal EHR Federated Learning Framework

Junu Kim
Kyunghoon Hur
Seongjun Yang
Edward Choi
KAIST

Abstract
Federated learning (FL) is the most practical multi-source learning method for electronic healthcare records (EHR). Despite its guarantee of privacy protection, the wide application of FL is restricted by two large challenges: the heterogeneous EHR systems, and the non-i.i.d. data characteristic. A recent research proposed a framework that unifies heterogeneous EHRs, named UniHPF. We attempt to address both the challenges simultaneously by combining UniHPF and FL. Our study is the first approach to unify heterogeneous EHRs into a single FL framework. This combination provides an average of 3.4% performance gain compared to local learning. We believe that our framework is practically applicable in the real-world FL.

Keywords: Electronic Healthcare Record, Federated Learning, Multi-Source Learning, Centralized Learning, UniHPF

1. Introduction
Electronic healthcare record (EHR) is a rich data source that records whole hospital events for each patient. Using EHR in machine learning (ML) allows us to make useful predictions for patients’ future health status (Choi et al., 2016a,b). Since the predictions can affect the life of the patients, accurate prediction is vital. Due to the nature of ML, using more data is helpful to improve the model accuracy (Sordo and Zeng, 2005; Prusa et al., 2015). Considering that each EHR is maintained by each hospital, the size of the single-source data is limited. Therefore, employing multiple hospitals’ data (multi-source learning) is required to improve the accuracy.

Unfortunately, this is not straightforward due to the privacy issue of EHR. Since healthcare data contains personal information, exporting data outside the hospital is highly restricted. Therefore, traditional centralized learning (CL) has limited practicality, because it need to gather all data into a central server (Algorithm 1).

In this situation, federated learning (FL) can be a solution since it does not need to share data among clients (hospital). It only has to share model weights that are trained only on each client data. The global server aggregates the weights and sends the global model to each client in each communication round (Algorithm 2). For this mechanism, FL is the most appropriate method for achieving multi-source learning on EHR while protecting patient privacy.

Despite its benefits, the application of FL is limited due to the heterogeneity of EHR system. In each EHR system (i.e. client, hospital), the medical codes and the database schema are typically not shared (Figure 1 (1)). Therefore, most of the previous studies conduct FL experiments only with clients using a single system (Lee and
Kim Hur Yang Choi

Shin, 2020; Huang et al., 2019; Yang et al., 2022). However, these approaches are not able to handle the system heterogeneity of the real-world EHRs. Unifying all EHR systems into a standard format (common data model, CDM) can resolve this limitation (Rajkomar et al., 2018; Li et al., 2019b). However, it is not yet examined due to the cost- and time-consuming nature.

On the other hand, UniHPF (Hur et al., 2022b) is a framework that can effectively handle heterogeneous EHR systems in the cost- and time-efficient manner. It replaces medical codes with text and linearizes different database schemas to mutually compatible free text format (Figure 1). However, the success of UniHPF was only shown in the CL setting, which has the aforementioned practical limitations. In FL, as opposed to CL, we have to consider the differences among the clients’ data distributions (non-i.i.d. problem, Figure 1 (2)) (Rieke et al., 2020; Li et al., 2022).

Therefore, we combine UniHPF with multiple FL methods to resolve the non-i.i.d. problem and compare among the methods. Since the performance is increased in FL compared to without multi-source learning, we successfully resolve both the privacy problem and the non-i.i.d. problem. Our main contributions can be summarized as follows:

- We suggest a practically applicable EHR multi-source learning framework by combining UniHPF and FL.
- Our proposed framework demonstrated improved prediction performance compared to local learning, and even occasionally showed similar performance to centralized learning.
- To the best of our knowledge, it is the first attempt to unify heterogeneous time-series EHRs into a single FL framework.
Figure 2: Visualization of UniHPF (Hur et al., 2022b). UniHPF first makes the text representation of each event by linearizing the schema and replacing the medical codes to its descriptions. The text representations are encoded independently by the event encoder, and aggregated by the event aggregator to make a prediction. Since UniHPF treats EHRs as free text, this is capable of handling heterogeneous EHR systems with a single model. Note that the sub-word tokenizer and word embedding layer is omitted in this figure.

2. Background and Methods

2.1. Federated Learning

Federated learning is a kind of distributed learning that trains a model without sharing data among clients (McMahan et al., 2017) (Algorithm 2). It enables to train the model without the hazard of data leakage by aggregating the parameters or gradients (Brisimi et al., 2018). An obstacle to applying FL is that the data among clients is often not independent and identically distributed (non-i.i.d.). This makes optimizing a global model challenging (Rieke et al., 2020). We examine four well-known FL algorithms with UniHPF.

- **FedAvg** (McMahan et al., 2017), a de facto algorithm of FL, simply averages the local model weights. Since this method does not fully consider the non-i.i.d. problem, various FL algorithms have been developed.
- **FedProx** (Li et al., 2020) regularizes the local model with $L_2$ distance between local and global parameters. It prevents the weights of the local optimal points from taking the global point.
- **FedBN** (Li et al., 2021) handle the feature heterogeneity among clients, by excluding the batch normalization layers from the aggregation step.
- **FedPxN** (Yang et al., 2022) combined the advantages of FedProx and FedBN, and it is reported to show best performance for FL with EHRs.
2.2. UniHPF

As mentioned earlier, the EHR system heterogeneity is the biggest obstacle to performing multi-source learning. To overcome this problem, unifying the input format is required. Recently, UniHPF (Hur et al., 2022b) has successfully addressed this problem without using domain knowledge and excessive preprocessing (Figure 2).

The two key concepts of UniHPF are treating EHR as free text, and utilizing the EHR hierarchy. A patient \( P \) in any EHR system is composed of multiple medical events \( m_i \in P \), and each event has its type \( e_i \), such as “labevents” or “prescriptions”. The events are composed of the corresponding features, which is composed of name and value \((n_{i,j}, v_{i,j}) \in m_i\). Some of the values are in the form of the medical codes \( c \), and these differ among the EHR systems. Thus, UniHPF replace the code \( c \) with its text description \( d \) (Hur et al., 2022a). For example, the lab measurement code “50912” can be converted into “Glucose”. UniHPF makes a free text representation \( R_i \) of each event \( m_i \) by linearizing the schema as

\[
R_i = (e_i \oplus n_{i,1} \oplus v_{i,1} \oplus n_{i,2} \oplus v_{i,2} \oplus \cdots)
\]

where \( \oplus \) is a concatenation operator. Note that UniHPF does not perform the feature selection, which is time- and cost-consuming. Since these text representations are mutually compatible among the heterogeneous EHR systems, UniHPF is a suitable framework to perform FL. To make a prediction \( \hat{y} \), UniHPF uses sub-word tokenizer (Tok) and word embedding layer (Emb), and encodes the text-represented events individually with the event encoder (Enc).

\[
z_i = \text{Enc}(\text{Emb}(\text{Tok}(R_i)))
\]

The encoded events are aggregated by the event aggregator (Agg).

\[
\hat{y} = \text{Agg}(z_1, z_2, \cdots)
\]

This helps the model to understand the patient-event level hierarchy of EHRs. Since no medical domain knowledge is used in any of the above steps, UniHPF can unify heterogeneous EHR systems efficiently.

3. Experiments and Discussion

3.1. Datasets

We use three open-sourced EHR datasets: MIMIC-III (Johnson et al., 2016), MIMIC-IV (Johnson et al., 2022), and Philips eICU (Pollard et al., 2018). The first two are composed of data from a single hospital, and the last one is a combination of data from multiple hospitals. MIMIC-III is recorded with two heterogeneous EHR systems, so we split it into MIMIC-III-CV (CareVue) and MIMIC-III-MV (Metavision) based on the systems. Since different hospitals have different data distributions, we treat the 7 largest hospitals in eICU dataset as independent clients. To summarize, we have a total of 10 clients from 4 different EHR systems and 10 different cohorts: MIMIC-IV, MIMIC-III-CV, MIMIC-III-MV, and 7 hospitals in eICU. Note that the clients are heterogeneous enough in terms of the demographic information and label distributions (Appendix B). The data is split into train, valid, and test set with 8:1:1 ratio in a stratified manner for each task.

3.2. Experimental Setting

Our cohorts include the patients over 18 years of age who stayed in intensive care unit (ICU) longer than 24 hours. We only use the first 12 hours of the first ICU stay from each hospital admission to make predictions. We follow the settings of Hur et al. (2022b), except that we use GRU (Chung et al., 2014) as the event encoder of UniHPF. All experimental resources and hyperparameters are available on github\(^1\). We adopt 5 prediction tasks from McDermott et al. (2020).

---

\(^1\) https://github.com/starmpcc/UniFL
Figure 3: Test AUPRC of the local learning (LL), federated learning (FL), and centralized learning (CL) experiments. Note that the graphs are ordered by the client size from left top to right bottom. ⋆ mark indicates the p-value of the Student’s t-test is lower than 0.05.

- Diagnosis (Dx): Predict all categorized diagnosis codes during the whole hospital stay of a patient.
- Length of Stay (LOS3, LOS7): Predict whether a patient would stay in ICU longer than 3 or 7 days.
- Mortality (Mort): Predict whether a patient would be alive or die within 60 hours.
- Readmission (Readm): Predict whether a patient would readmit to ICU within the same hospital admission.

To compare with multi-source learning, we examine the performance of Local Learning (LL), which is training and evaluating with each client’s data alone. We used Area Under Precision-Recall Curve (AUPRC) as the metric. We assume a stable internet connection and full participation because the hospitals are generally connected by LAN. All the experiments are repeated with five random seeds with one NVIDIA A100 80G or two RTX A6000 48G gpus.

3.3. Experimental Result

The experimental results are shown in Figure 3. The average performance for each task and client are reported in Appendix C. First, we evaluate whether our framework successfully handles the EHR system heterogeneity. Second, we compare the FL algorithms with respect to the non-i.i.d. problem.

Consistent with Hur et al. (2022b), UniHPF always gets an average of 10.4% performance increase by using CL compared with LL. This means that UniHPF properly overcomes the EHR system heterogeneity.

Overall, the FL shows an average of 3.4% performance increase compared to LL. This implies that UniHPF is helpful in aggregating the clients’ data into a single FL model,
demonstrating its potential since this combined method is practically applicable in real-world heterogeneous EHRs.

We compare the performance among the algorithms with respect to the non-i.i.d. problem. Our results agree with Choudhury et al. (2019); Niu et al. (2020), which showed CL is the upper bound of the FL performance. In the CL setting, the clients’ data is pooled before start the training, which prevents the non-i.i.d. problem. Therefore, CL has the best performance among the learning methods. In contrast, FedAvg can be treated as an empirical lower bound among the FL algorithms with some non-i.i.d. data (Li et al., 2019a; Hsu et al., 2019). Although FedProx is an algorithm that handles the non-i.i.d. problem, the performance is lower than FedAvg. The reason for this result seems that the performance of FedProx heavily depends on the hyperparameter \( \mu \). The performance of FedBN and FedPxN are higher than FedAvg, and lower than CL. This suggests that these algorithms do address the non-i.i.d. problem in EHRs to some extent, but not completely.

Nevertheless, our framework shows its potential when the data distribution is extremely heterogeneous. Contrary to the other clients, eICU-73 and eICU-443 do not have drug infusion information. Even in these extreme cases, performing FL with FedBN or FedPxN resulted in some performance increment compared to LL.

For the training time, FL requires an average of 1.9 times more communication rounds than CL epochs until satisfying the same early stopping criterion. Nevertheless, the performance of FL is inferior to CL. This result denotes that the gradient update is relatively less accurate for each communication round. We expect that this can be improved by developing a better EHR-specific FL algorithm.

4. Conclusion

In this paper, we empirically show that the combination of UniHPF and FL successfully resolves both the EHR system heterogeneity and the non-i.i.d. problem simultaneously. The lower performance of FL compared to CL implies that there is still a room for improvement with a new FL algorithm in EHR. We leave the investigation of EHR-specific pretraining with FL as our future work.

Acknowledgments

This work was supported by Institute of Information & Communications Technology Planning & Evaluation (IITP) grant (No.2019-0-00075), Korea Medical Device Development Fund grant (Project Number: 1711138160, KMDF_PR_20200901_0097), and the Korea Health Industry Development Institute (KHIDI) grant (No.HR21C0198), funded by the Korea government (MSIT, MOTIE, MOHW, MFDS).
References

Theodora S Brisimi, Ruidi Chen, Theofanie Mela, Alex Olshevsky, Ioannis Ch Paschalidis, and Wei Shi. Federated learning of predictive models from federated electronic health records. *International journal of medical informatics*, 112:59–67, 2018.

Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F Stewart, and Jimeng Sun. Doctor ai: Predicting clinical events via recurrent neural networks. In *Machine learning for healthcare conference*, pages 301–318. PMLR, 2016a.

Edward Choi, Mohammad Taha Bahadori, Jimeng Sun, Joshua Kulas, Andy Schuetz, and Walter Stewart. Retain: An interpretable predictive model for healthcare using reverse time attention mechanism. *Advances in neural information processing systems*, 29, 2016b.

Olivia Choudhury, Yoonyoung Park, Theodoros Salonidis, Aris Gkoulalas-Divanis, Issa Sylla, et al. Predicting adverse drug reactions on distributed health data using federated learning. In *AMIA Annual symposium proceedings*, volume 2019, page 313. American Medical Informatics Association, 2019.

Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

Tzu-Ming Harry Hsu, Hang Qi, and Matthew Brown. Measuring the effects of non-identical data distribution for federated visual classification. *arXiv preprint arXiv:1909.06335*, 2019.

Li Huang, Andrew L Shea, Huining Qian, Aditya Masurkar, Hao Deng, and Dianbo Liu. Patient clustering improves efficiency of federated machine learning to predict mortality and hospital stay time using distributed electronic medical records. *Journal of biomedical informatics*, 99:103291, 2019.

Kyunghoon Hur, Jiyoung Lee, Jungwoo Oh, Wesley Price, Younghak Kim, and Edward Choi. Unifying heterogeneous electronic health records systems via text-based code embedding. In *Conference on Health, Inference, and Learning*, pages 183–203. PMLR, 2022a.

Kyunghoon Hur, Jungwoo Oh, Junu Kim, Min Jae Lee, Eunbyeol Cho, Jiyoun Kim, Seong-Eun Moon, Young-Hak Kim, and Edward Choi. Unihpf: Universal healthcare predictive framework with zero domain knowledge. *arXiv preprint arXiv:2207.09858*, 2022b.

Alistair Johnson, Lucas Bulgarelli, Tom Pollard, Steven Horng, Leo Anthony Celi, and Roger Mark. Mimic-iv. *PhysioNet. 2.0).* https://doi.org/10.13026/7vcr-e114., 2022.

Alistair EW Johnson, Tom J Pollard, Lu Shen, Li-wei H Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G Mark. Mimic-iii, a freely accessible critical care database. *Scientific data*, 3(1):1–9, 2016.

Geun Hyeong Lee and Soo-Yong Shin. Federated learning on clinical benchmark data: performance assessment. *Journal of medical Internet research*, 22(10):e20891, 2020.

Qinbin Li, Yiqun Diao, Quan Chen, and Bingsheng He. Federated learning on non-iid data silos: An experimental study. In *2022 IEEE 38th International Conference
on Data Engineering (ICDE), pages 965–978. IEEE, 2022.

Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. Federated optimization in heterogeneous networks. Proceedings of Machine Learning and Systems, 2:429–450, 2020.

Xiang Li, Kaixuan Huang, Wenhao Yang, Shusen Wang, and Zhihua Zhang. On the convergence of fedavg on non-iid data. arXiv preprint arXiv:1907.02189, 2019a.

Xiaoxiao Li, Meirui Jiang, Xiaofei Zhang, Michael Kamp, and Qi Dou. Fedbn: Federated learning on non-iid features via local batch normalization. arXiv preprint arXiv:2102.07623, 2021.

Ziyi Li, Kirk Roberts, Xiaojian Jiang, and Qi Long. Distributed learning from multiple ehr databases: contextual embedding models for medical events. Journal of biomedical informatics, 92:103138, 2019b.

Matthew McDermott, Bret Nestor, Evan Kim, Wancong Zhang, Anna Goldenberg, Peter Szolovits, and Marzyeh Ghassemi. A comprehensive evaluation of multi-task learning and multi-task pre-training on ehr time-series data. arXiv preprint arXiv:2007.10185, 2020.

Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In Artificial intelligence and statistics, pages 1273–1282. PMLR, 2017.

Chaoyue Niu, Fan Wu, Shaojie Tang, Lifeng Hua, Rongfei Jia, Chengfei Lv, Zhihua Wu, and Guihai Chen. Billion-scale federated learning on mobile clients: A sub-model design with tunable privacy. In Proceedings of the 26th Annual International Conference on Mobile Computing and Networking, pages 1–14, 2020.

Tom J Pollard, Alistair EW Johnson, Jesse D Raffa, Leo A Celi, Roger G Mark, and Omar Badawi. The eicu collaborative research database, a freely available multicenter database for critical care research. Scientific data, 5(1):1–13, 2018.

Joseph Prusa, Taghi M Khoshgoftaar, and Naeem Seliya. The effect of dataset size on training tweet sentiment classifiers. In 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA), pages 96–102. IEEE, 2015.

Alvin Rajkomar, Eyal Oren, Kai Chen, Andrew M Dai, Nissan Hajaj, Michaela Hardt, Peter J Liu, Xiaobing Liu, Jake Marcus, Mimi Sun, et al. Scalable and accurate deep learning with electronic health records. NPJ digital medicine, 1(1):1–10, 2018.

Nicola Rieke, Jonny Hancox, Wenqi Li, Fausto Milletari, Holger R Roth, Shadi Albarqouni, Spyridon Bakas, Mathieu N Galtier, Bennett A Landman, Klaus Maier-Hein, et al. The future of digital health with federated learning. NPJ digital medicine, 3(1):1–7, 2020.

Margarita Sordo and Qing Zeng. On sample size and classification accuracy: A performance comparison. In International Symposium on Biological and Medical Data Analysis, pages 193–201. Springer, 2005.

Seongjun Yang, Hyeonji Hwang, Daeyoung Kim, Radhika Dua, Jong-Youp Kim, Eunho Yang, and Edward Choi. Towards the practical utility of federated learning in the medical domain. arXiv preprint arXiv:2207.03075, 2022.
Appendix A. Federated and Centralized Learning Algorithms

In federated learning (Algorithm 2), each client has an individual model weight copy. The copies are initialized with the same weights and trained locally with corresponding client’s data. After the local training, the weights of the clients are gathered into the central server, aggregated, and synchronized. Each FL algorithms have different corresponding Aggregate function.

Algorithm 1: Centralized Learning
Input: clients $C_1, \cdots, C_N$, data $D_1, \cdots, D_N$, total epochs $T$, learning rate $\eta$
Output: model parameter $w_T$

main:
  for $i = 1$ to $N$ do
    Copy $D_i$ to server;
  end
initialize server model with $w$;
$D = \text{shuffle}(D_1, \cdots, D_N)$;
for $t = 0$ to $T - 1$ do
  for batch $b \leftarrow (x,y)$ of $D$ do
    $w \leftarrow w - \eta \nabla L(w; b)$;
  end
end
return $w$

Algorithm 2: Federated Learning
Input: clients $C_1, \cdots, C_N$, data $D_1, \cdots, D_N$, total communication rounds $T$, local epochs $L$, learning rate $\eta$
Output: model parameter $w_T$

main:
initialize client models with $w_0$;
for $t = 0$ to $T - 1$ do
  for $i = 1$ to $N$ do
    $w_{t,i} \leftarrow w_i$;
    $w_{t,i} \leftarrow \text{LocalTrain}(w_{t,k}, D_i)$;
  end
  $w_{t+1} = \text{Aggregate}(w_1, \cdots, w_N)$;
end
return $w_T$

def LocalTrain($w, D$):
  for $l = 0$ to $L - 1$ do
    for batch $b \leftarrow (x,y)$ of $D_k$ do
      $w \leftarrow w - \eta \nabla L(w; b)$;
    end
  end
return $w$;
## Appendix B. Clients Statistics

### Table 1: Cohort Statics and Label Distributions

| Dataset | MIMIC-IV | MIMIC-III-MV | MIMIC-III-CV | eICU-264 | eICU-420 | eICU-338 | eICU-73 | eICU-243 | eICU-458 | eICU-443 | Micro Avg. | Macro Avg. |
|---------|----------|--------------|--------------|-----------|-----------|-----------|---------|----------|-----------|-----------|------------|------------|
| No. of Unique codes | 1923 | 3226 | 347 | 320 | 367 | 384 | 306 | 284 | 281 | 1844.43 | 934.60 |
| No. of samples | 65594 | 21160 | 16831 | 3637 | 3153 | 2636 | 2612 | 2423 | 2368 | 2367 | 12278.10 | 99.07 |
| Average no. of events per sample | 112.89 | 91.43 | 100.46 | 53.69 | 87.60 | 47.32 | 58.13 | 51.80 | 58.69 | 51.82 | 99.07 | 71.32 |

### Demographic Information

#### Gender (%)
- M: 55.81, 56.31, 56.74, 51.61, 57.78, 55.73, 54.98, 55.78, 54.88, 55.92
- F: 43.69, 43.69, 43.26, 48.39, 42.22, 44.27, 45.02, 44.43, 45.82, 42.98

#### Ethnicity (%)
- White: 67.78, 72.78, 70.67, 87.82, 86.08, 92.87, 75.61, 64.05, 64.02, 42.97
- Black: 10.84, 10.25, 8.74, 7.26, 4.19, 1.52, 13.51, 31.82, 29.10, 52.68
- Hispanic: 3.82, 4.07, 2.80, 0.33, 0.03, 1.29, 7.66, 0.00, 0.00, 1.10
- Asian: 2.96, 3.26, 2.10, 3.77, 2.64, 1.27, 0.99, 3.43, 1.43
- Other: 14.60, 10.18, 15.69, 3.77, 8.21, 5.62, 2.87, 14.87, 7.90

### Label Ratio

#### Dx (%)
- 1: 4.73, 4.81, 4.99, 3.78, 3.26, 0.48, 4.49, 3.40, 3.10, 3.85, 3.00, 3.69
- 2: 3.99, 4.25, 4.16, 2.56, 1.75, 1.54, 2.50, 1.98, 1.23, 4.81, 1.30, 2.89
- 3: 10.36, 10.87, 12.16, 5.55, 12.40, 8.87, 12.25, 11.75, 5.04, 7.09, 3.43, 9.63
- 4: 6.77, 6.55, 6.24, 2.47, 8.97, 1.87, 3.31, 5.23, 1.55, 1.25, 2.38, 4.20
- 5: 7.33, 6.60, 5.18, 2.49, 5.35, 1.90, 2.67, 2.11, 1.98, 3.55, 2.81, 3.85
- 6: 6.38, 5.76, 4.27, 9.24, 5.83, 6.12, 4.82, 5.98, 6.63, 8.69, 2.34, 6.35
- 7: 11.15, 11.92, 15.35, 23.57, 11.55, 22.44, 18.75, 24.62, 23.34, 19.63, 4.38, 18.21
- 8: 6.95, 7.52, 9.24, 17.27, 9.91, 18.52, 12.81, 13.47, 15.40, 15.92, 2.96, 12.70
- 9: 7.25, 7.43, 7.46, 6.94, 5.95, 5.99, 4.19, 3.88, 4.96, 3.12, 3.26, 5.80
- 10: 6.98, 7.33, 7.53, 5.29, 6.93, 6.72, 6.58, 7.56, 12.60, 4.51, 3.30, 7.50
- 11: 0.08, 0.05, 0.07, 0.06, 0.03, 0.05, 0.09, 0.04, 0.12, 0.07, 0.04, 0.06
- 12: 1.53, 1.72, 1.88, 0.55, 0.88, 1.14, 0.46, 0.42, 0.56, 0.24, 0.77, 0.94
- 13: 4.34, 4.15, 2.96, 0.63, 0.58, 0.51, 0.46, 0.36, 0.40, 0.54, 2.20, 1.51
- 14: 0.56, 0.56, 0.57, 0.01, 0.02, 0.00, 0.08, 0.03, 0.00, 0.14, 0.31, 0.20
- 15: 0.01, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.01, 0.00, 0.00, 0.00
- 16: 5.78, 6.52, 8.12, 14.80, 10.85, 20.57, 18.70, 14.50, 18.32, 23.59, 3.03, 14.18
- 17: 6.67, 5.55, 3.81, 3.58, 5.58, 2.53, 2.20, 4.98, 3.83, 2.55, 3.71, 4.13
- 18: 8.91, 8.25, 6.04, 1.40, 10.25, 1.36, 2.73, 1.93, 1.25, 1.02, 5.23, 4.31

#### LOS (%)
- True: 32.50, 36.93, 42.24, 42.68, 48.24, 38.66, 37.10, 39.50, 39.74, 45.59, 36.26, 40.34
- False: 11.08, 12.51, 15.37, 12.48, 16.97, 11.87, 11.06, 10.94, 15.58, 17.66, 12.44, 13.55

#### Mort (%)
- True: 1.68, 2.70, 2.84, 2.12, 3.55, 2.35, 0.54, 1.32, 3.04, 2.83, 2.11, 2.30
- False: 7.94, 5.81, 5.72, 8.83, 11.48, 8.35, 17.99, 12.30, 8.49, 10.31, 7.75, 9.72
Appendix C. Experimental Result

Table 2: Average performance for each task and client. The numbers in the parentheses mean the relative performance improvement compared to the local learning (LL). Red and blue texts mean the negative and more than 10% increments, respectively.

| Task      | Local | FedAvg | FedProx | FedBN | FedPxN | Centralized |
|-----------|-------|--------|---------|-------|--------|-------------|
| Dx        | 0.622 | 0.619  | 0.616   | 0.663 | 0.641  | 0.714       |
|           |       | (−0.38%) | (−0.87%) | (+6.67%) | (+3.08%) | (+14.81%)   |
| LOS3      | 0.603 | 0.603 | 0.609   | 0.609 | 0.613  | 0.623       |
|           |       | (+0.12%) | (+1.07%) | (+1.12%) | (+1.81%) | (+3.54%)   |
| LOS7      | 0.266 | 0.295  | 0.302   | 0.302 | 0.297  | 0.312       |
|           |       | (+11.33%) | (+12.67%) | (+13.88%) | (+11.94%) | (+17.51%)   |
| Mort      | 0.153 | 0.167  | 0.157   | 0.162 | 0.158  | 0.166       |
|           |       | (+9.33%) | (+2.76%) | (+5.76%) | (+3.35%) | (+8.90%)   |
| Readm     | 0.117 | 0.118  | 0.116   | 0.116 | 0.116  | 0.129       |
|           |       | (+1.62%) | (−0.34%) | (−0.75%) | (−0.59%) | (+10.70%)   |
| MIMIC-IV  | 0.414 | 0.428  | 0.410   | 0.424 | 0.412  | 0.417       |
|           |       | (+3.59%) | (−0.72%) | (+2.45%) | (−0.24%) | (+0.83%)   |
| MIMIC-III-MV | 0.384 | 0.431 | 0.423   | 0.437 | 0.423  | 0.428       |
|           |       | (+12.15%) | (+10.33%) | (+13.81%) | (+10.10%) | (+11.61%)   |
| MIMIC-III-CV | 0.41  | 0.416  | 0.411   | 0.423 | 0.409  | 0.427       |
|           |       | (+1.52%) | (+0.38%) | (+3.27%) | (−0.24%) | (+4.23%)   |
| eICU-264  | 0.283 | 0.282  | 0.289   | 0.299 | 0.300  | 0.336       |
|           |       | (−0.06%) | (+2.36%) | (+6.12%) | (+6.17%) | (+18.95%)   |
| eICU-420  | 0.457 | 0.445  | 0.445   | 0.458 | 0.450  | 0.483       |
|           |       | (−2.58%) | (−2.67%) | (+0.25%) | (−1.49%) | (+5.65%)   |
| eICU-338  | 0.269 | 0.289  | 0.286   | 0.304 | 0.300  | 0.322       |
|           |       | (+7.89%) | (+6.60%) | (+13.14%) | (+11.67%) | (+19.86%)   |
| eICU-73   | 0.31  | 0.327  | 0.326   | 0.334 | 0.327  | 0.380       |
|           |       | (+5.77%) | (+5.46%) | (+8.13%) | (+5.72%) | (+23.00%)   |
| eICU-243  | 0.356 | 0.367  | 0.368   | 0.375 | 0.381  | 0.382       |
|           |       | (+3.15%) | (+3.43%) | (+5.39%) | (+7.14%) | (+7.29%)   |
| eICU-458  | 0.343 | 0.330  | 0.349   | 0.349 | 0.350  | 0.359       |
|           |       | (+3.59%) | (+1.96%) | (+1.84%) | (+2.26%) | (+4.92%)   |
| eICU-443  | 0.296 | 0.291  | 0.286   | 0.300 | 0.298  | 0.355       |
|           |       | (−1.52%) | (−3.12%) | (+1.76%) | (+0.96%) | (+20.33%)   |
| Average   | 0.352 | 0.361  | 0.359   | 0.370 | 0.365  | 0.389       |
|           |       | (+2.54%) | (+2.19%) | (+5.29%) | (+3.76%) | (+10.57%)   |