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2022_Fall

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Reliability and Performance Assessment of Federated Learning on Clinical Benchmark Data, https://arxiv.org/abs/2005.11756
Federated Learning on Clinical Benchmark Data: Performance Assessment, https://www.jmir.org/2020/10/e20891

삼성병원: 신수용 교수
https://sooyongshin.wordpress.com/2020/11/22/federated-learning/

이제 유명해져서 아는 사람은 다 아는 federated learning..
특히 개인정보 보호가 큰 이슈가 되는 헬스케어 데이터 분석에서 중요한 기술이라고 말이 많은 federated learning..
(*개인적으로 몇년 전부터 이런 기술을 도입해서 사용해야 한다고 강력히 주장하기도 했고.. 특히 가명처리의 대안으로 적극 주장*)
근/데/ 논문이든 뭐든 말만 하지 실제로 하는 사람은 의외로 많지 않은 federated learning.. (*국외 포함. 나도 이 논문 전에는 말만 하던 사람*)
솔직히 말만 많지, 하는 사람이 많이 없어서 그냥 시작했다..

목적은
1. 실제 헬스케어 데이터에서 동작하는지 검증
2. 실제 network 환경에서 동작하는지 검증

의료 데이터에 쓰면 좋다는 논문은 진짜 많은데..
실제로 검증한 논문은 거의 없다.

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[CVPR 2022, NVIDIA] Closing the Generalization Gap of Cross-Silo Federated Medical Image Segmentation, https://openaccess.thecvf.com/content/CVPR2022/html/Xu_Closing_the_Generalization_Gap_of_Cross-Silo_Federated_Medical_Image_Segmentation_CVPR_2022_paper.html
Github: https://github.com/NVIDIA/NVFlare/examples/FedSM
Github: https://github.com/NVIDIA/NVFlare/tree/dev/examples

Cross-silo federated learning (FL) has attracted much attention in medical imaging analysis with deep learning in recent years as it can resolve the critical issues of insufficient data, data privacy, and training efficiency.

However, there can be a generalization gap between the model trained from FL and the one from centralized training. This important issue comes from the non-iid data distribution of the local data in the participating clients and is well-known as client drift.

In this work, we propose a novel training framework FedSM to avoid the client drift issue and successfully close the generalization gap compared with the centralized training for medical image segmentation tasks for the first time. We also propose a novel personalized FL objective formulation and a new method SoftPull to solve it in our proposed framework FedSM.

We conduct rigorous theoretical analysis to guarantee its convergence for optimizing the non-convex smooth objective function. Real-world medical image segmentation experiments using deep FL validate the motivations and effectiveness of our proposed method.

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Reward Systems for Trustworthy Medical Federated Learning, https://arxiv.org/abs/2205.00470
Github: https://github.com/kpandl/Reward-System-for-Trustworthy-Medical-Federated-Learning

Federated learning (FL) has received high interest from researchers and practitioners to train machine learning (ML) models for healthcare. Ensuring the trustworthiness of these models is essential. Especially bias, defined as a disparity in the model's predictive performance across different subgroups, may cause unfairness against specific subgroups, which is an undesired phenomenon for trustworthy ML models.

In this research, we address the question to which extent bias occurs in medical FL and how to prevent excessive bias through reward systems.

- We first evaluate how to measure the contributions of institutions toward predictive performance and bias in cross-silo medical FL with a Shapley value approximation method.
- In a second step, we design different reward systems incentivizing contributions toward high predictive performance or low bias.
- We then propose a combined reward system that incentivizes contributions toward both. We evaluate our work using multiple medical chest X-ray datasets focusing on patient subgroups defined by patient sex and age.

Our results show that we can successfully measure contributions toward bias, and an integrated reward system successfully incentivizes contributions toward a well-performing model with low bias. While the partitioning of scans only slightly influences the overall bias, institutions with data predominantly from one subgroup introduce a favorable bias for this subgroup. Our results indicate that reward systems, which focus on predictive performance only, can transfer model bias against patients to an institutional level. Our work helps researchers and practitioners design reward systems for FL with well-aligned incentives for trustworthy ML.

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서울과기대 박종혁 교수, https://scholar.google.com/citations?hl=en&user=IshTErgAAAAJ&view_op=list_works&sortby=pubdate
- FusionFedBlock: Fusion of Blockchain and Federated Learning to Preserve Privacy in Industry 5.0, https://www.sciencedirect.com/science/article/abs/pii/S1566253522001658
- Federated Learning-based secure Electronic Health Record sharing scheme in Medical Informatics, https://ieeexplore.ieee.org/abstract/document/9774951

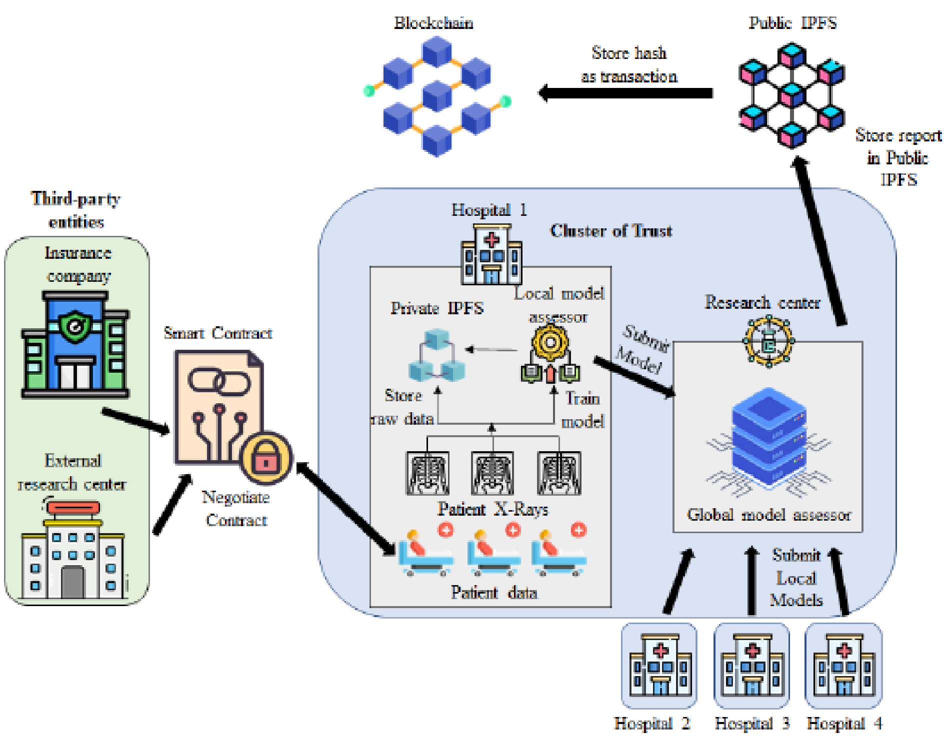

Fig. 1. Secure EHR Sharing Scheme Overview

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Federated Learning-based secure Electronic Health Record sharing scheme in Medical Informatics, https://ieeexplore.ieee.org/abstract/document/9774951

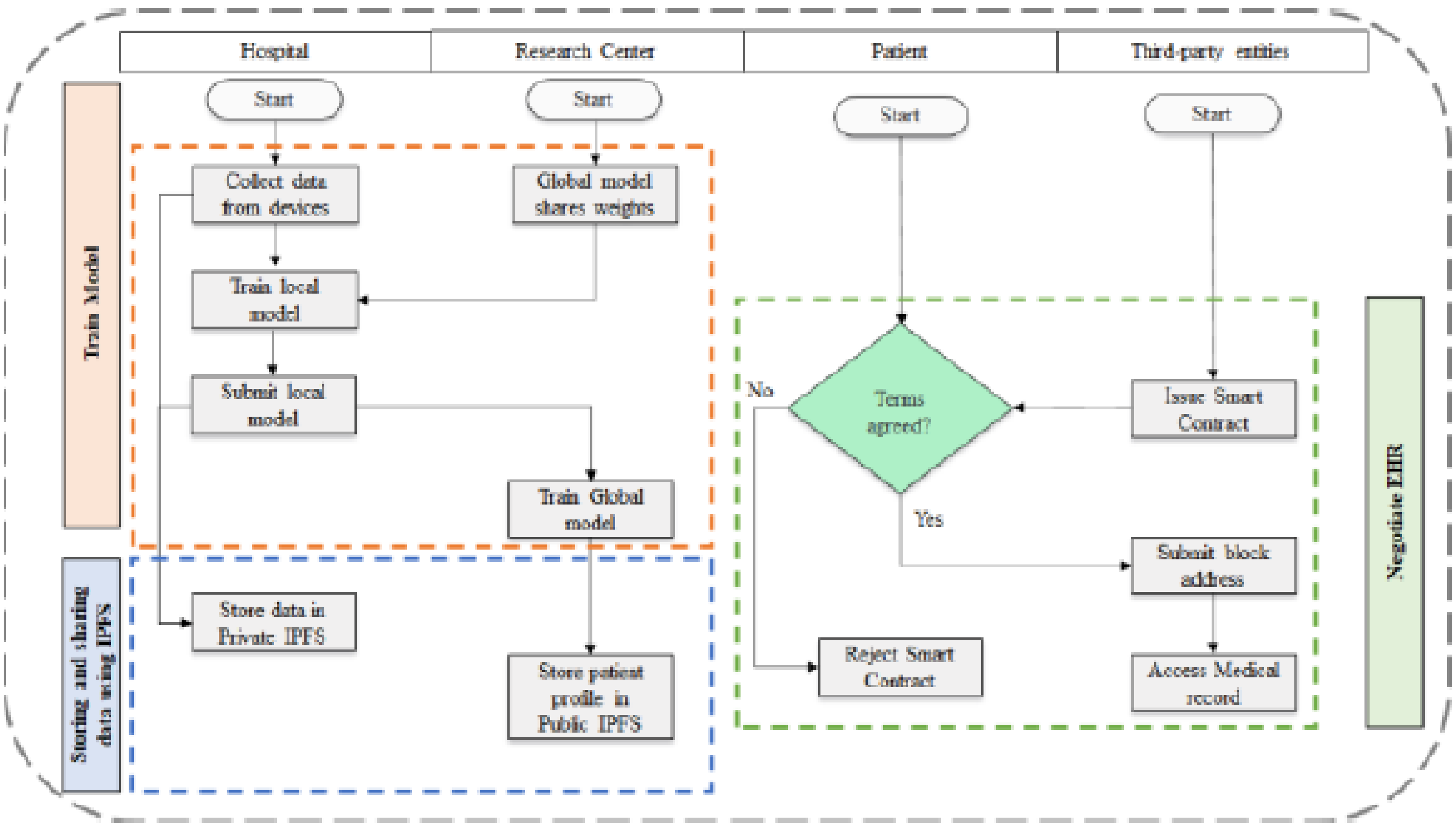

Fig. 2. Secure EHR Scheme process-flow

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smart Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

It provides fair and explainable FL participant contribution evaluation in an efficient and privacy-preserving manner, and optimizes the FL model aggregation approach based on the evaluation results.

- Since its deployment in Yidu Cloud Technology Inc. in March 2021, CAreFL has served 8 well-established medical institutions in China to build healthcare decision support models.
- It can perform contribution evaluations 2.84 times faster than the best existing approach, and has improved the average accuracy of the resulting models by 2.62% compared to the previous system (which is significant in industrial settings). To our knowledge, it is the first contribution-aware federated learning successfully deployed in the healthcare industry.

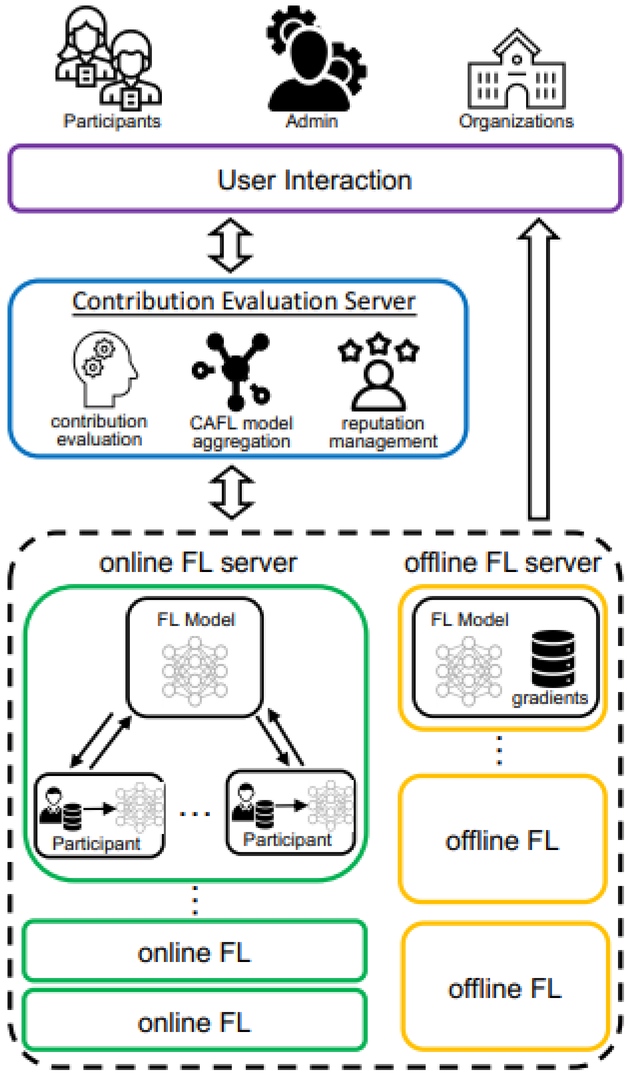

Figure 1: The CAreFL system architecture.

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smart Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

FL participant **contribution evaluation** is an active subfield of FL (Ghorbani and Zou 2019; Jia et al. 2019; Song, Tong, and Wei 2019; Wang et al. 2020; Wei et al. 2020). The aim is to estimate the value of each FL participant by evaluating its impact on the performance of the resulting FL model, without exposing their sensitive local data. To bridge the aforementioned gaps in FL frameworks for smart healthcare, we propose the Contribution-Aware Federated Learning (CAreFL) framework.

The advantages are:

1. **Fast and Accurate Contribution Evaluation**: it is incorporated with our proposed GTG-Shapley (Liu et al. 2022) approach, which can evaluate fair and accurate FL participant contribution in a highly efficient manner.
2. **Contribution-Aware FL Model Aggregation**: during the contribution evaluation process, GTG-Shapley builds a large number of aggregated FL sub-models involving local model updates from different combinations of FL participants. With this knowledge, CAreFL provides a novel FL aggregation approach which selects the best performing sub-model to be distributed to the FL participants for the next round of local training. This differs from FedAvg-based approaches (which always aggregate all received local models), and can better deal with data heterogeneity issues.
3. **Contribution-based FL Participant Reputation Management**: historical contribution evaluation records are converted into reputation values for the FL participants. This information can serve as a basis stakeholder management decision support.

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smart Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

- Hence, the canonical SV cannot be directly used for contribution evaluation in the context of FL.
- The key idea of GTG-Shapley is to opportunistically reduce the need for sub-model retraining with model reconstruction and strategic sampling of combinations of participants. It truncates unnecessary sub-model evaluations to reduce computational costs, while maintaining high accuracy of estimated SVs.

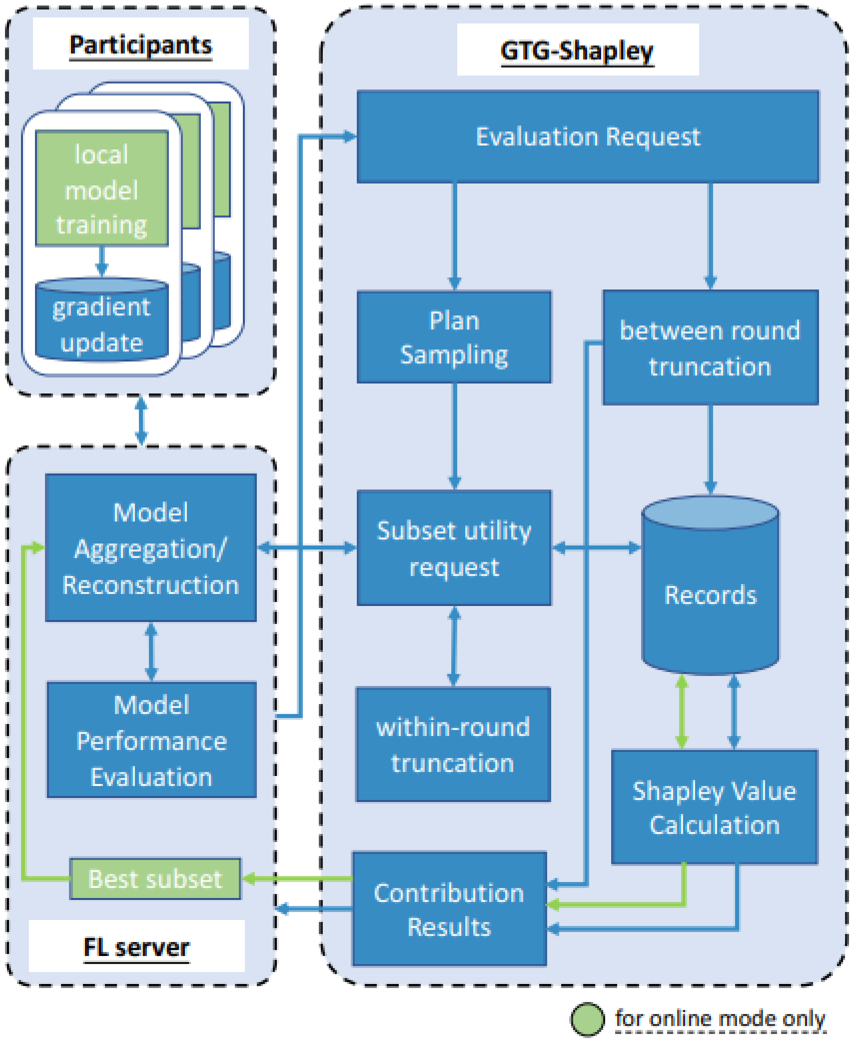

Figure 3: The CAreFL AI Engine

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[AAAI 2022] CAreFL: Contribution-Aware Federated Learning for Smar Healthcare, https://ojs.aaai.org/index.php/AAAI/article/view/21505

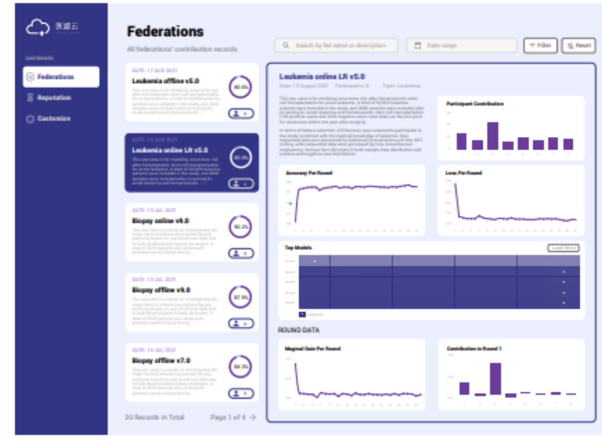

Figure 5: The main user interface of CAreFL.

Application Use and Payoff

The CAreFL framework has been deployed in Yidu Cloud Technology I lines of their business:

1. clinical research services : Clinical research focuses on training FL m from multiple hospitals.
2. real-world trial research services. : Real world trial research is often initiated by a pharmaceutical company which aims to leverage data from multiple hospitals to build models.

Both services require data which need to be collected by the hospitals over months or years under their respective Institutional Review Board (IRB) supervision. So far, CAreFL has been used to help eight well-known medical institutions in China to train AI models for risk prediction, disease diagnosis and influence factor analysis.

Conclusions and Future Work

In future, we will continue the explore the applicability of CAreFL in other smart healthcare application scenarios. We will also extend the CAreFL framework with contribution-based data pricing mechanisms (Pei 2020) to support the emergence of an **FL-based healthcare data exchange marketplace**. Eventually, we aim to incorporate these functionalities into the opensource FATE framework and make them available to more developers, researchers and practitioners.