RSCFed: Random Sampling Consensus Federated Semi-supervised Learning – Supplemental Materials

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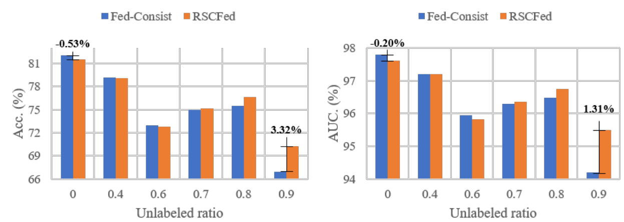
A. Ablation Study for Various Unlabeled Client Ratios when Partitioning Fixed

We demonstrate that the effectiveness of our RSCFed is ***due to uneven model reliability caused by the involved unlabeled clients.*** When each client is either fully labeled or fully unlabeled, with a fixed number of clients, the more unlabeled clients, the better our RSCFed is.

Fig. 1 shows the performance of our method and the baseline method Fed-Consist [1] under different labeled and unlabeled client ratios. We empirically set the number of clients to 10 and consider the ratio of unlabeled/total clients as 0, 0.4, 0.6, 0.7, 0.8, 0.9.

We can observe that as the ratio of unlabeled clients increases, the improvements of our RSCFed over Fed-Consist in Accuracy and AUC scores consistently grow. It is worth mentioning that when the unlabeled ratio is small, a slight performance drop can be observed from our RSCFed against Fed-Consist. This is because the increased number of labeled clients reduce the *uneven model reliability*, limiting the performance of our RSCFed. Notably, RSCFed exceeds Fed-Consist when the ratio of unlabeled clients comes to 0.7. When the unlabeled ratio is 0.9, our RSCFed can reach 3.32% and 1.31% improvements in Accuracy, and AUC scores, respectively. Therefore, we demonstrate that with a fixed number of clients, the more unlabeled clients involved, the better our RSCFed is.



(a) (b)

Figure 1. Performance curve of Fed-Consist [1] and our RSCFed under various unlabeled client ratios. The total number of clients is fixed to 10, and the x-axis refers to ratio of unlabeled clients among all clients.

B. Implementation Details

All local training in RSCFed is implemented with an SGD optimizer. The local learning rate is set according to the dataset. Specifically, for the SVHN dataset and CIFAR-100 dataset, we set the learning rate to 0.03 and 0.021 for labeled and unlabeled clients, respectively; For ISIC 2018 dataset, we set the learning rate to 2e-3 and 1e-3 for labeled and unlabeled clients, respectively. In each synchronization round, after the first global model is randomly initialized and assigned to the client-side, we firstly conduct supervised local training on the labeled client for 6 local epochs for SVHN and CIFAR-100 dataset, and 240 epochs for ISIC-2018 dataset, as a warming-up. The supervised pre-heated model then serves as the global model for training on labeled and unlabeled clients. In total, we train the model for 1,000 synchronization rounds [1].

References

[1] Dong Yang, Ziyue Xu, Wenqi Li, Andriy Myronenko, Holger R Roth, Stephanie Harmon, Sheng Xu, Baris Turkbey, Evrim Turkbey, Xiaosong Wang, et al. Federated semi-supervised learning for covid region segmentation in chest ct using multi-national data from china, italy, japan. *Medical image analysis*, 70:101992, 2021. 1

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[1]The code is available at https://github.com/XMed-Lab/RSCFed.