Auto-FedRL: Federated Hyperparameter Optimization for Multi-institutional Medical Image Segmentation

—— Supplementary Material ——

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1 Supplementary Introduction

In this supplementary document, we first perform a convergence analysis of federated learning under the proposed federated hyperparameter optimization framework (Sec. 2.1) and then provide details of the network architectures used for our classification (Sec. 2.2) and segmentation experiments. Finally, we analyze the learning process for the pancreas segmentation task (Sec. 3.1).

2 Supplementary Method

2.1 Convergence Analysis

In Eq. 1 of main manuscript, we define the FL optimization problem as follows:

$$\min_{x \in \mathbb{R}^d} \frac{1}{m} \sum_{i=1}^{m} L_i(x),$$

where $m$ is the number of clients and $L_i(x) = \mathbb{E}_{z \sim \mathcal{D}_i}[f_i(x, z)]$ is the loss function of the $i^{th}$ client. $z \in Z$, and $\mathcal{D}_i$ represents the data distribution of the $i^{th}$ client. Following the proof originally proposed in adaptive federated optimization [6], we have the unbiased stochastic gradient $g_i(x)$ and the client’s true gradient $\nabla L_i(x)$. Then we make the following three common assumptions:

* Work done during an internship at NVIDIA.
**Assumption 1** (Lipschitz Gradient):

\[ ||\nabla L_i(x) - \nabla L_i(y)|| \leq L||x - y||, \forall x, y \in \mathbb{R}^d \]

**Assumption 2** (Bounded Global Variance):

\[
\left( \frac{1}{m} \right) \sum_{i=1}^{m} ||\nabla [L_i(x)]_j - [\nabla f(x)]_j||^2 \leq \sigma^2_{g,j}, \\
\forall x \in \mathbb{R}^d \text{ and } j \in [d]
\]

**Assumption 3** (Bounded Gradients):

For any \( i \in [m], x \in \mathbb{R}^d \) and \( z \in Z \),

We have \( ||[\nabla f_i(x, z)]_j|| \leq G, \forall j \in [d] \)

As discussed in [6], the three assumptions are widely adopted in the non-convex optimization [7,8,5] and federated learning literature [4,10]. For the illustration purpose, we assume the server optimizer is the commonly used Adam optimizer.

Let \( \sigma^2 = \sigma^2_l + 6K\sigma^2_g \), where \( \sigma^2_l = \sum_{j=1}^{d} \sigma^2_{l,j} \) and \( \sigma^2_g = \sum_{j=1}^{d} \sigma^2_{g,j} \). Suppose the client learning \( \gamma_l \) is bounded by the search space and satisfies \( \gamma_l \leq \frac{1}{16}LK \) and

\[
\gamma_l \leq \frac{1}{6K} \min \left\{ \left[ \frac{\alpha}{GL} \right]^{1/2}, \left[ \frac{2\alpha^2}{GL^3\gamma} \right]^{1/4}, \left[ \frac{\alpha}{GL^2} \right]^{1/3} \right\},
\]

where \( \alpha \) controls the algorithms’ degree of adaptivity. To highlight the dependency of \( K \) (the number of clients) and \( Q \) (the number of rounds) for the convergence rate, we can assume \( \gamma_l, \gamma \) and \( \alpha \) are specifically chosen as follows:

\[
\gamma_l = \Theta\left( \frac{1}{KL\sqrt{Q}} \right), \\
\gamma = \Theta\left( \sqrt{KM} \right), \\
\alpha = \frac{G}{L}.
\]

Based on the proof of FedAdam [6], when \( Q \) is sufficiently large, the proposed methods satisfies:

\[
\min_{0 \leq q \leq Q-1} \mathbb{E}||\nabla f(x_q)||^2 = O\left( \frac{f(x_0) - f(x^*)}{\sqrt{mKQ}} + \frac{2\sigma^2_L}{G^2\sqrt{mKQ}} + \frac{\sigma^2}{GKQ} + \frac{\sigma^2_L\sqrt{m}}{G^2\sqrt{KQ}^{3/2}} \right).
\]

Hence, when \( Q \gg K \), the proposed method can achieve a convergence rate of \( O\left( \frac{1}{\sqrt{mKQ}} \right) \) under the adaptive federated optimization framework. Readers are referred to [6] for a complete convergence analysis of the adaptive federated optimization.
Auto-FedRL: Federated Hyperparameter Optimization

2.2 Network Architectures

We use a 3D U-Net [2] style encoder-decoder architecture for the segmentation networks. The encoder and decoder networks can be described as shown in Table 1, where ResConvBlockWD represents a 3D ResConvBlock with downsampling layer and network modules are expressed by (in-channel, out-channel).

Table 1 shows the details of each block in our segmentation network. The VGG-9 [9] architecture used for CIFAR-10 experiments is presented in Table 3. For the Auto-FedRL(MLP), due to our online setting, we have to keep the learnable parameters in networks small but effective. The MLP can be described as following: Liner(in-channel, 256)-ReLu(256)-Liner(256, 256)-ReLu(256)-Liner(256, in-channel), where in-channel is decided by the size of mean vector $\mu$ and the covariance matrix $\Sigma$.

3 Supplementary Results

3.1 Learning Process for Pancreas Segmentation

Figure 1 presents the learning process of our best performing model in the pancreas segmentation task. As shown in Fig. 1(a), while in this task the number
Table 2. Configuration of Blocks in 3D Unet

| Block   | Layer    | Kernel size | Stride | Padding |
|---------|----------|-------------|--------|---------|
| ConvBlock | Conv3D   | 3           | 2      | 1       |
|         | InstanceNorm | -            | -      | -       |
|         | ReLu     | -            | -      | -       |
| ResConvBlock | Conv3D   | 3           | 1      | 1       |
|         | InstanceNorm | -            | -      | -       |
|         | ReLu     | -            | -      | -       |
| ResConvBlockD | Conv3D   | 3           | 2      | 1       |
|         | InstanceNorm | -            | -      | -       |
|         | ReLu     | -            | -      | -       |
|         | Conv3D   | 1           | 2      | 0       |
| UpSample | Conv3D   | 3           | 1      | 1       |
|         | InstanceNorm | -            | -      | -       |
|         | ReLu     | -            | -      | -       |
|         | Interpolate | -            | -      | -       |

Table 3. Configuration of VGG-9

| Block   | Layer    | In Channel | Out Channel | Kernel size | Stride | Padding |
|---------|----------|------------|-------------|-------------|--------|---------|
| Conv2D  | Conv2D   | 32         | 32          | 3           | 1      | 1       |
|         | ReLu     | 32         | 32          | -           | -      | -       |
|         | ReLu     | 64         | 64          | -           | -      | -       |
| MaxPool2d | Conv2D   | 64         | 128         | 3           | 1      | 1       |
|         | ReLu     | 128        | 128         | -           | -      | -       |
|         | ReLu     | 128        | 128         | -           | -      | -       |
|         | MaxPool2d | 128        | 128         | 2           | 2      | 0       |
|         | Dropout2d | -          | -           | -           | -      | -       |
| Conv2D  | Conv2D   | 128        | 256         | 3           | 1      | 1       |
|         | ReLu     | 256        | 256         | -           | -      | -       |
|         | Conv2D   | 256        | 256         | 3           | 1      | 1       |
|         | ReLu     | 256        | 256         | -           | -      | -       |
|         | MaxPool2d | 256        | 256         | 2           | 2      | 0       |
| FC      | Dropout  | -          | -           | -           | -      | -       |
|         | Linear   | 4096       | 512         | -           | -      | -       |
|         | ReLu     | 512        | 512         | -           | -      | -       |
|         | Linear   | 512        | 512         | -           | -      | -       |
|         | ReLu     | 512        | 512         | -           | -      | -       |
|         | Dropout  | 512        | 512         | -           | -      | -       |
|         | Linear   | 512        | 10          | -           | -      | -       |

Table 4. The additional computational details of different search strategies under the same setting on CIFAR-10.

| Search Space Type | Accuracy | Memory Usage | Running Time for Search | C3-Score |
|-------------------|----------|--------------|-------------------------|----------|
| Discrete          | 90.70    | 42.8 GB      | 8.246 s                 | 0.778    |
| Continuous        | 90.85    | 3.00 GB      | 0.012 s                 | 0.799    |
| Continuous MLP    | 91.27    | 3.13 GB      | 0.019 s                 | 0.803    |

of optimization steps is quite limited (i.e., 50), we still can observe that the RL agent is able to naturally form the training scheduler for each hyperparameter (e.g., the learning rate for clients and the server). Similar as the analysis of COVID-19 lesions segmentation, we use FANOVA [3] to assess the hyperparameter importance. As shown in Fig. 1(b), LR, AW2, and LI rank as top-3 most important hyperparameters, which implies that including aggregation weights into search space is also important in our setting.
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