

A APPENDIX

A.1 PROOF OF THEOREM 1

During the Procrustes alignment, we define $\mathbf{Z}^{t+1} = (\mathbf{U}^{t+1})^\top \mathbf{S}^{t+1} \mathbf{V}^{t+1} \in \mathbb{R}^{r' \times r'}$. Therefore, $\mathbf{S}^{t+1}$ satisfies

$$\mathbf{S}^{t+1} = \mathbf{U}^{t+1} \mathbf{Z}^{t+1} (\mathbf{V}^{t+1})^\top. \quad (1)$$

Note that $(\mathbf{S}^{t+1})^\top \mathbf{S}^{t+1} = \mathbf{I}_{r'}$. In addition, since matrices $\mathbf{U}^{t+1}$ and $\mathbf{V}^{t+1}$ have orthogonal columns, we have

$$\begin{aligned} \text{Tr} \left(\mathbf{A}^t (\tilde{\mathbf{A}}^{t+1})^\top (\mathbf{S}^t)^\top \right) &= \text{Tr} \left(\mathbf{U}^{t+1} \boldsymbol{\Sigma}^{t+1} (\mathbf{V}^{t+1})^\top \mathbf{V}^{t+1} (\mathbf{Z}^{t+1})^\top (\mathbf{U}^{t+1})^\top \right) \\ &= \text{Tr} \left(\boldsymbol{\Sigma}^{t+1} (\mathbf{Z}^{t+1})^\top \right) \\ &= \sum_{j=1}^{r'} \sigma_j^{t+1} z_{j,j}^{t+1}. \end{aligned} \quad (2)$$

Since matrix $\mathbf{Z}^{t+1}$ satisfies $(\mathbf{Z}^{t+1})^\top \mathbf{Z}^{t+1} = \mathbf{I}_{r'}$, each element $z_{j,j}^{t+1}$ yields $z_{j,j}^{t+1} \leq 1$, we have $\text{Tr} \left(\mathbf{A}^t (\tilde{\mathbf{A}}^{t+1})^\top (\mathbf{S}^t)^\top \right) \leq \sum_{j=1}^{r'} \sigma_j^{t+1}$, with the equality achieved at $\mathbf{Z}^t = \mathbf{I}_{r'}$. Therefore, when the maximum objective is achieved, matrix $\mathbf{S}^{t,*}$ satisfies

$$\mathbf{S}^{t,*} = \mathbf{U}^{t+1} \mathbf{I}_{r'} (\mathbf{V}^{t+1})^\top = \mathbf{U}^{t+1} (\mathbf{V}^{t+1})^\top. \quad (3)$$

This completes the proof of Theorem 1.

A.2 ALGORITHM FOR FLORG

Algorithm 1 FLORG

- 1: **Input:** Local fine-tuning datasets $\mathcal{D}_n$, $n \in \mathcal{N}$; learning rate η ; pretrained model $\mathbf{W}^0$; initialized low-rank matrix $\mathbf{A}^1$.
 - 2: The central server initializes $\mathbf{L}$ and $\mathbf{R}$ with orthogonal columns and broadcasts them to all clients.
 - 3: $\mathbf{W}^1 := \mathbf{W}^0 + \mathbf{L}(\mathbf{A}^1)^\top \mathbf{A}^1 \mathbf{R}$.
 - 4: **For** $t \in \mathcal{T}$ **do**
 - 5: The central server broadcasts $\mathbf{A}^t$ to all clients.
 - 6: **For** client $n \in \mathcal{N}$ **in parallel do**
 - 7: $\mathbf{A}_n^{t+\frac{1}{2}} := \mathbf{A}^t - \eta \nabla_{\mathbf{A}} F_n(\mathbf{W}^t; \xi_n)$.
 - 8: Transmits $\mathbf{A}_n^{t+\frac{1}{2}}$ to the central server.
 - 9: **End for**
 - 10: $\mathbf{Q}^{t+1} := \frac{1}{N} \sum_{n \in \mathcal{N}} \left(\mathbf{A}_n^{t+\frac{1}{2}} \right)^\top \mathbf{A}_n^{t+\frac{1}{2}}$.
 - 11: Perform eigendecomposition to $\mathbf{Q}^{t+1}$ and obtain $\tilde{\mathbf{A}}^{t+1} := (\Lambda^{t+1})^{\frac{1}{2}} \mathbf{P}^{t+1}$.
 - 12: Perform Procrustes alignment to $\tilde{\mathbf{A}}^{t+1}$ and obtain $\mathbf{S}^{t,*} := \mathbf{U}^{t+1} (\mathbf{V}^{t+1})^\top$.
 - 13: $\mathbf{A}^{t+1} := \mathbf{S}^{t,*} \tilde{\mathbf{A}}^{t+1}$.
 - 14: $\bar{\mathbf{W}}^{t+1} := \mathbf{W}^0 + \mathbf{L}(\mathbf{A}^{t+1})^\top \mathbf{A}^{t+1} \mathbf{R}$.
 - 15: **End for**
 - 16: **Output:** Average fine-tuned model $\bar{\mathbf{W}}^{T+1}$.
-

A.3 PROOF OF LEMMA 1

$$\begin{aligned} &\langle \mathbf{H}^t, (\mathbf{A}^t)^\top \mathbf{A}^t (\mathbf{H}^t + (\mathbf{H}^t)^\top) + (\mathbf{H}^t + (\mathbf{H}^t)^\top) (\mathbf{A}^t)^\top \mathbf{A}^t \rangle_F \\ &\stackrel{(a)}{=} \left\langle \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2}, (\mathbf{A}^t)^\top \mathbf{A}^t (\mathbf{H}^t + (\mathbf{H}^t)^\top) + (\mathbf{H}^t + (\mathbf{H}^t)^\top) (\mathbf{A}^t)^\top \mathbf{A}^t \right\rangle_F \\ &= 2 \left\langle \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2}, (\mathbf{A}^t)^\top \mathbf{A}^t \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2} \right\rangle_F + 2 \left\langle \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2}, \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2} (\mathbf{A}^t)^\top \mathbf{A}^t \right\rangle_F \end{aligned}$$

$$\begin{aligned}
& \stackrel{(b)}{\geq} 2 \lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t) \left\| \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2} \right\|_F^2 + 2 \lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t) \left\| \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2} \right\|_F^2 \\
& = 4 \lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t) \left\| \frac{\mathbf{H}^t + (\mathbf{H}^t)^\top}{2} \right\|_F^2 \\
& = 4 \lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t) \left\| \mathbf{H}^t \right\|_F^2,
\end{aligned} \tag{4}$$

where equality (a) is obtained due to the fact that the second factor within the inner product is symmetric. Thus, the skew-symmetric part of $\mathbf{H}^t$ is orthogonal. inequality (b) result from $(\mathbf{A}^t)^\top \mathbf{A}^t \succeq \lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t) \mathbf{I}_k$.

This completes the proof of Lemma 1.

A.4 PROOF OF LEMMA 2

We expand $\left\| \mathbf{S}^t \tilde{\mathbf{A}}^{t+1} - \mathbf{A}^t \right\|_F^2$ as follows:

$$\left\| \mathbf{S}^t \tilde{\mathbf{A}}^{t+1} - \mathbf{A}^t \right\|_F^2 = \left\| \tilde{\mathbf{A}}^{t+1} \right\|_F^2 + \left\| \mathbf{A}^t \right\|_F^2 - 2 \text{Tr} \left(\mathbf{S}^t \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top \right). \tag{5}$$

Similarly, we have

$$\left\| \mathbf{S}^{t,*} \tilde{\mathbf{A}}^{t+1} - \mathbf{A}^t \right\|_F^2 = \left\| \tilde{\mathbf{A}}^{t+1} \right\|_F^2 + \left\| \mathbf{A}^t \right\|_F^2 - 2 \text{Tr} \left(\mathbf{S}^{t,*} \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top \right). \tag{6}$$

Therefore, $\Delta_{\text{proc}}^{t+1}$ satisfies

$$\Delta_{\text{proc}}^{t+1} = 2 \left(\text{Tr} \left(\mathbf{S}^{t,*} \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top \right) - \text{Tr} \left(\mathbf{S}^t \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top \right) \right). \tag{7}$$

Let $\mathbf{M}^t = \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top = \mathbf{U}_M^t \Sigma_M^t \mathbf{V}_M^t$, where matrices $\mathbf{U}_M^t \in \mathbb{R}^{r' \times r'}$ and $\mathbf{V}_M^t \in \mathbb{R}^{r' \times r}$ have orthogonal columns. $\Sigma_M^t \in \mathbb{R}^{r' \times r'}$. Let $\mathbf{P}^t = \mathbf{U}_M^t (\mathbf{S}^t)^\top (\mathbf{V}_M^t)^\top$ and $\mathbf{P}^{t,*} = \mathbf{U}_M^t (\mathbf{S}^{t,*})^\top (\mathbf{V}_M^t)^\top = \mathbf{I}_{r'}$. Then, we have

$$\text{Tr} \left(\mathbf{S}^t \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top \right) = \text{Tr} \left(\mathbf{P}^t \Sigma_M^t \right) = \sum_{j=1}^{r'} \sigma_j p_{j,j}. \tag{8}$$

Similarly, we have

$$\text{Tr} \left(\mathbf{S}^{t,*} \tilde{\mathbf{A}}^{t+1} (\mathbf{A}^t)^\top \right) = \sum_{j=1}^{r'} \lambda_j. \tag{9}$$

By combining eqn. (7), (8), and (9), we obtain

$$\Delta_{\text{proc}}^{t+1} = 2 \sum_{j=1}^{r'} \lambda_j (1 - p_{j,j}). \tag{10}$$

Since matrices $\mathbf{U}_M^t$ and $\mathbf{V}_M^t$ have orthogonal columns, we have

$$\begin{aligned}
\left\| \mathbf{S}^t - \mathbf{S}^{t,*} \right\|_F^2 &= \left\| \mathbf{P}^t - \mathbf{I} \right\|_F^2 \\
&= \text{Tr} \left((\mathbf{P}^t - \mathbf{I})^\top (\mathbf{P}^t - \mathbf{I}) \right) \\
&= 2r' - \text{Tr}(\mathbf{P}^t) - \text{Tr}((\mathbf{P}^t)^\top) \\
&= 2 \sum_{j=1}^{r'} (1 - p_{j,j}).
\end{aligned} \tag{11}$$

By combining eqns. (10) and (11), we have

$$\begin{aligned}
\Delta_{\text{proc}}^{t+1} &= 2 \sum_{j=1}^{r'} \lambda_j (1 - p_{j,j}) \\
&\geq 2\lambda_{\min} \left(\tilde{\mathbf{A}}^{t+1}(\mathbf{A}^t)^\top \right) (1 - p_{j,j}) \\
&= 2\lambda_{\min} \left(\tilde{\mathbf{A}}^{t+1}(\mathbf{A}^t)^\top \right) \|\mathbf{P}^t - \mathbf{I}\|_F^2 \\
&= 2\lambda_{\min} \left(\tilde{\mathbf{A}}^{t+1}(\mathbf{A}^t)^\top \right) \|\mathbf{S}^t - \mathbf{S}^{t,*}\|_F^2.
\end{aligned} \tag{12}$$

By rearranging this inequality, we have

$$\|\mathbf{S}^t - \mathbf{S}^{t,*}\|_F^2 \leq \frac{\Delta_{\text{proc}}^{t+1}}{\lambda_{\min} \left(\tilde{\mathbf{A}}^{t+1}(\mathbf{A}^t)^\top \right)}. \tag{13}$$

This completes the proof of Lemma 2.

A.5 PROOF OF THEOREM 2

Based on Assumption 1, we expand $\mathbb{E}[f(\mathbf{W}^{t+1})]$ as

$$\mathbb{E}[f(\mathbf{W}^{t+1})] \leq \underbrace{\mathbb{E}[f(\mathbf{W}^t)] + \mathbb{E}[\langle \nabla f(\mathbf{W}^t), \mathbf{W}^{t+1} - \mathbf{W}^t \rangle_F]}_{T_1} + \underbrace{\frac{L}{2} \mathbb{E}[\|\mathbf{W}^{t+1} - \mathbf{W}^t\|_F^2]}_{T_2}. \tag{14}$$

In particular, $\mathbf{W}^{t+1} - \mathbf{W}^t$ satisfies

$$\begin{aligned}
&\mathbf{W}^{t+1} - \mathbf{W}^t \\
&= \frac{1}{N} \sum_{n \in \mathcal{N}} (\mathbf{L}(\mathbf{A}^{t+1})^\top \mathbf{A}^{t+1} \mathbf{R} - \mathbf{L}(\mathbf{A}^t)^\top \mathbf{A}^t \mathbf{R}) \\
&= \mathbf{L} \frac{1}{N} \sum_{n \in \mathcal{N}} \left((\mathbf{A}_n^{t+\frac{1}{2}})^\top \mathbf{A}_n^{t+\frac{1}{2}} - (\mathbf{A}^t)^\top \mathbf{A}^t \right) \mathbf{R} \\
&= \mathbf{L} \frac{1}{N} \sum_{n \in \mathcal{N}} \left((\mathbf{A}^t - \eta \nabla_{\mathbf{A}} F_n(\mathbf{W}^t; \boldsymbol{\xi}_n))^\top (\mathbf{A}^t - \eta \nabla_{\mathbf{A}} F_n(\mathbf{W}^t; \boldsymbol{\xi}_n)) - (\mathbf{A}^t)^\top \mathbf{A}^t \right) \mathbf{R} \\
&= \mathbf{L} \left((\mathbf{A}^t)^\top \mathbf{A}^t - \eta ((\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \mathbf{A}^t) + \eta^2 (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t - (\mathbf{A}^t)^\top \mathbf{A}^t \right) \mathbf{R} \\
&= \mathbf{L} \left(\eta^2 (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t - \eta ((\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \mathbf{A}^t) \right) \mathbf{R},
\end{aligned} \tag{15}$$

where $\bar{\mathbf{G}}_{\mathbf{A}}^t = \frac{1}{N} \sum_{n \in \mathcal{N}} \nabla_{\mathbf{A}} F_n(\mathbf{W}^t; \boldsymbol{\xi}_n) = \mathbf{A}^t (\mathbf{H}^t + (\mathbf{H}^t)^\top)$. We first bound T_1 as follows:

$$\begin{aligned}
&T_1 \\
&= -\eta \mathbb{E}[\langle \nabla f(\mathbf{W}^t), \mathbf{L}((\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \mathbf{A}^t) \mathbf{R} \rangle_F] + \eta^2 \mathbb{E}[\langle \nabla f(\mathbf{W}^t), \mathbf{L}(\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \mathbf{R} \rangle_F] \\
&= \underbrace{\eta \mathbb{E}[\langle \nabla f(\mathbf{W}^t), \mathbf{L}((\mathbf{A}^{t,*} - \mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top (\mathbf{A}^{t,*} - \mathbf{A}^t)) \mathbf{R} \rangle_F]}_{T_3} \\
&\quad - \eta \mathbb{E}[\langle \nabla f(\mathbf{W}^t), \mathbf{L}((\mathbf{A}^{t,*})^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \mathbf{A}^t) \mathbf{R} \rangle_F] \\
&\quad + \eta^2 \mathbb{E}[\langle \nabla f(\mathbf{W}^t), \mathbf{L}(\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \mathbf{R} \rangle_F] \\
&\stackrel{(a)}{=} T_3 - \eta \mathbb{E}[\langle \mathbf{H}^t, ((\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \mathbf{A}^t) \rangle_F] + \eta^2 \mathbb{E}[\langle \mathbf{H}^t, (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \rangle_F] \\
&= T_3 - \eta \mathbb{E}[\langle \mathbf{H}^t, (\mathbf{A}^t)^\top \mathbf{A}^t (\mathbf{H}^t + (\mathbf{H}^t)^\top) + (\mathbf{H}^t + (\mathbf{H}^t)^\top) (\mathbf{A}^t)^\top \mathbf{A}^t \rangle_F] \\
&\quad + \eta^2 \mathbb{E}[\langle \mathbf{H}^t, (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \rangle_F],
\end{aligned} \tag{16}$$

where equality (a) is obtained due to the fact that for an arbitrary matrix $\mathbf{X}$, we have $\langle \mathbf{G}^t, \mathbf{L}\mathbf{X}\mathbf{R} \rangle = \langle \mathbf{H}^t, \mathbf{X} \rangle$. T_3 can be bounded as follows:

$$\begin{aligned}
T_3 &\leq \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{\eta}{2} \mathbb{E} \left[\left\| \mathbf{L} \left((\mathbf{A}^{t,*} - \mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top (\mathbf{A}^{t,*} - \mathbf{A}^t) \right) \mathbf{R} \right\|_F^2 \right] \\
&\stackrel{(a)}{\leq} \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + 2\eta \mathbb{E} \left[\left\| (\mathbf{A}^{t,*} - \mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \right\|_F^2 \right] \\
&\stackrel{(b)}{\leq} \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + 2\eta \|\mathbf{A}^{t,*} - \mathbf{A}^t\|_F^2 \mathbb{E} \left[\left\| \bar{\mathbf{G}}_{\mathbf{A}}^t \right\|_F^2 \right] \\
&\stackrel{(c)}{\leq} \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{2\eta}{N^2} \|\mathbf{A}^{t,*} - \mathbf{A}^t\|_F^2 \sum_{n \in \mathcal{N}} \|\nabla_{\mathbf{A}} F_n(\mathbf{W}^t; \xi_n)\|_F^2 \\
&\stackrel{(d)}{\leq} \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{2\eta\psi}{N} \|\mathbf{A}^{t,*} - \mathbf{A}^t\|_F^2 \\
&= \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{2\eta\psi}{N} \left\| (\mathbf{S}^{t,*} - \mathbf{S}^t) \tilde{\mathbf{A}}^t \right\|_F^2 \\
&\stackrel{(e)}{\leq} \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{2\eta\psi}{N} \|\mathbf{S}^{t,*} - \mathbf{S}^t\|_F^2 \left\| \tilde{\mathbf{A}}^t \right\|_F^2 \\
&\stackrel{(f)}{\leq} \frac{\eta}{2} \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{2\eta\psi \tilde{C}_{\mathbf{A}}^2 \Delta_{\text{proc}}^t}{N \lambda_{\min} \left(\tilde{\mathbf{A}}^t (\mathbf{A}^{t-1})^\top \right)}, \tag{17}
\end{aligned}$$

where inequalities (a) and (c) result from Jensen's inequality. Inequalities (b) and (e) is obtained by using the fact $\|\mathbf{AB}\|_F \leq \|\mathbf{A}\|_F \|\mathbf{B}\|_F$. Inequality (d) results from Assumption 2. Inequality (f) results from Assumption 3 and Lemma 2. Then, we further bound the second term of T_1 as

$$\begin{aligned}
& -\eta \mathbb{E} \left[\langle \mathbf{H}^t, (\mathbf{A}^t)^\top \mathbf{A}^t (\mathbf{H}^t + (\mathbf{H}^t)^\top) + (\mathbf{H}^t + (\mathbf{H}^t)^\top) (\mathbf{A}^t)^\top \mathbf{A}^t \rangle_F \right] \\
& \stackrel{(a)}{\leq} -4\eta \lambda_{\min} \left((\mathbf{A}^t)^\top \mathbf{A}^t \right) \left\| (\mathbf{L})^\top \nabla f(\mathbf{W}^t) (\mathbf{R})^\top \right\|_F^2, \tag{18}
\end{aligned}$$

where inequality (a) results from Lemma 2. Then, we bound $\eta^2 \mathbb{E} [\langle \mathbf{H}^t, (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \rangle_F]$ as follows:

$$\begin{aligned}
\eta^2 \mathbb{E} [\langle \mathbf{H}^t, (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \rangle_F] &\stackrel{(a)}{\leq} \eta^2 \left(\frac{1}{2} \|\mathbf{H}^t\|_F^2 + \frac{1}{2} \|\bar{\mathbf{G}}_{\mathbf{A}}^t\|_F^4 \right) \\
&= \eta^2 \left(\frac{1}{2} \|(\mathbf{L})^\top \nabla f(\mathbf{W}^t) (\mathbf{R})^\top\|_F^2 + \frac{1}{2} \|\bar{\mathbf{G}}_{\mathbf{A}}^t\|_F^4 \right) \\
&\stackrel{(b)}{\leq} \frac{\eta^2}{2} \|(\mathbf{L})^\top \nabla f(\mathbf{W}^t) (\mathbf{R})^\top\|_F^2 + \frac{\eta^2 \psi^2}{2}, \tag{19}
\end{aligned}$$

where inequality (a) results from Jensen's inequality. Inequality (b) is obtained by using Lemma 2. By combining inequalities (16), (17), (18), and (19), we have

$$T_1 \leq \frac{2\eta\psi \tilde{C}_{\mathbf{A}}^2 \Delta_{\text{proc}}^t}{N \lambda_{\min} \left(\tilde{\mathbf{A}}^t (\mathbf{A}^{t-1})^\top \right)} + \left(-4\eta \lambda_{\min} \left((\mathbf{A}^t)^\top \mathbf{A}^t \right) + \frac{\eta^2}{2} + \frac{\eta}{2} \right) \|\nabla f(\mathbf{W}^t)\|_F^2 + \frac{\eta^2}{2} \psi^2. \tag{20}$$

Now, we bound T_2 . In particular, it satisfies

$$\begin{aligned}
T_2 &= \mathbb{E} \left[\left\| \mathbf{L} \left(\eta^2 (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t - \eta \left((\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t + (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \mathbf{A}^t \right) \right) \mathbf{R} \right\|_F^2 \right] \\
&\stackrel{(a)}{\leq} 3\eta^4 \mathbb{E} \left[\left\| \mathbf{L} \eta^2 (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \mathbf{R} \right\|_F^2 \right] + 6\eta^2 \mathbb{E} \left[\left\| \mathbf{L} \eta (\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \mathbf{R} \right\|_F^2 \right] \\
&\stackrel{(b)}{\leq} 3\eta^4 \mathbb{E} \left[\left\| (\bar{\mathbf{G}}_{\mathbf{A}}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \right\|_F^2 \right] + 6\eta^2 \mathbb{E} \left[\left\| (\mathbf{A}^t)^\top \bar{\mathbf{G}}_{\mathbf{A}}^t \right\|_F^2 \right] \\
&\stackrel{(c)}{\leq} 3\eta^4 \mathbb{E} \left[\left\| \bar{\mathbf{G}}_{\mathbf{A}}^t \right\|_F^4 \right] + 6\eta^2 \mathbb{E} \left[\left\| \mathbf{A}^t \right\|_F^2 \right] \mathbb{E} \left[\left\| \bar{\mathbf{G}}_{\mathbf{A}}^t \right\|_F^2 \right] \\
&\stackrel{(d)}{\leq} 3\eta^2 \psi \left(\eta^2 \psi + 2C_{\mathbf{A}}^2 \right). \tag{21}
\end{aligned}$$

where inequality (a) is obtained by using Jensen’s inequality. Inequality (b) is obtained since $\mathbf{L}$ and $\mathbf{R}$ have orthogonal columns. Inequality (c) results from the fact $\|\mathbf{AB}\|_F \leq \|\mathbf{A}\|_F \|\mathbf{B}\|_F$. Inequality (d) is obtained by using Lemma 4 and Assumption 3.

Then, we combine inequalities (14), (20), and (21), we have

$$\begin{aligned} \mathbb{E} [f(\bar{\mathbf{W}}^{t+1})] &\leq \mathbb{E} [f(\bar{\mathbf{W}}^t)] + \left(\frac{\eta^2}{2} + \frac{\eta}{2} - 4\eta\lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t) \right) \|\nabla f(\mathbf{W}^t)\|_F^2 \\ &\quad + \frac{\eta^2\psi^2}{2} + \frac{3L\eta^2\psi(\eta^2\psi + 2C_{\mathbf{A}}^2)}{2} + \frac{2\eta\psi\tilde{C}_{\mathbf{A}}^2\Delta_{\text{proc}}^t}{N\lambda_{\min}(\tilde{\mathbf{A}}^t(\mathbf{A}^{t-1})^\top)}. \end{aligned} \quad (22)$$

We denote $\Omega = 4\eta \min_{t \in \mathcal{T}} \{\lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t)\} - \frac{\eta^2}{2} - \frac{\eta}{2}$. By rearranging inequality (22) and summing over all T fine-tuning rounds, we have

$$\begin{aligned} &\Omega \sum_{t \in \mathcal{T}} \|\nabla f(\mathbf{W}^t)\|_F^2 \\ &\leq \sum_{t \in \mathcal{T}} (f(\bar{\mathbf{W}}^t) - f(\bar{\mathbf{W}}^{t+1})) + T \left(\frac{\eta^2\psi^2}{2} + \frac{3L\eta^2\psi(\eta^2\psi + 2C_{\mathbf{A}}^2)}{2} \right) + \sum_{t \in \mathcal{T}} \frac{2\eta\psi\tilde{C}_{\mathbf{A}}^2\Delta_{\text{proc}}^t}{N\lambda_{\min}(\tilde{\mathbf{A}}^t(\mathbf{A}^{t-1})^\top)} \\ &\stackrel{(a)}{\leq} f(\bar{\mathbf{W}}^1) - f(\bar{\mathbf{W}}^*) + T \left(\frac{\eta^2\psi^2}{2} + \frac{3L\eta^2\psi(\eta^2\psi + 2C_{\mathbf{A}}^2)}{2} \right) + \sum_{t \in \mathcal{T}} \frac{2\eta\psi\tilde{C}_{\mathbf{A}}^2\Delta_{\text{proc}}^t}{N\lambda_{\min}(\tilde{\mathbf{A}}^t(\mathbf{A}^{t-1})^\top)}, \end{aligned} \quad (23)$$

where inequality (a) is obtained due to the fact that $f(\mathbf{W}^*) \leq f(\mathbf{W}^{T+1})$. If $\eta < 8 \min_{t \in \mathcal{T}} \{\lambda_{\min}((\mathbf{A}^t)^\top \mathbf{A}^t)\} - 1$, we have $\Omega > 0$. Then, we multiply $\frac{1}{T\Omega}$ on both sides of inequality (23) and obtain

$$\begin{aligned} \frac{1}{T} \sum_{t \in \mathcal{T}} \|\nabla f(\mathbf{W}^t)\|_F^2 &\leq \frac{f(\mathbf{W}^1) - f(\mathbf{W}^*)}{T\Omega} + \frac{\eta^2\psi^2}{2\Omega} + \frac{3L\eta^2\psi(\eta^2\psi + 2C_{\mathbf{A}}^2)}{2\Omega} \\ &\quad + \frac{1}{T\Omega} \sum_{t \in \mathcal{T}} \frac{2\eta\psi\tilde{C}_{\mathbf{A}}^2\Delta_{\text{proc}}^t}{N\lambda_{\min}(\tilde{\mathbf{A}}^t(\mathbf{A}^{t-1})^\top)}. \end{aligned} \quad (24)$$

This completes the proof of Theorem 2.

A.6 ADDITIONAL EXPERIMENTAL RESULTS

Table 1: Comparison of the testing accuracy.

Base Model	Dataset	FLoRG	FedIT	FeDeRA	FFA-LoRA	FedSA-LoRA
OPT-125M	MRPC	88.30	82.09	85.70	84.78	86.51
	QQP	89.72	84.18	87.09	86.30	87.92
RoBERTa-large	MRPC	90.80	85.16	88.30	87.50	89.21
	QQP	91.52	87.89	89.30	88.51	90.01

A.7 THE USE OF LARGE LANGUAGE MODELS (LLMs)

We used large language models (e.g., ChatGPT) for the general purpose of writing assistants to revise and polish the manuscript’s prose: improving grammar, wording, clarity, and fixing minor LaTeX/formatting issues. The models were not used for research ideation, designing algorithms/experiments, deriving proofs, selecting citations, or writing substantive technical content.

Table 2: Comparison of the testing accuracy under different ranks.

Rank	Dataset	FLoRG	FedIT	FeDeRA	FFA-LoRA	FedSA-LoRA
$r = 2$	MRPC	85.91	79.66	83.17	82.32	83.00
	QQP	87.62	81.88	84.90	84.09	85.65
	MNLI	86.14	80.70	83.44	82.64	84.22
	QNLI	89.70	86.67	87.22	86.40	88.10
$r = 4$	MRPC	90.80	85.16	88.30	87.50	89.21
	QQP	91.52	87.89	89.30	88.51	90.01
	MNLI	91.39	84.76	88.20	89.12	90.90
	QNLI	92.44	87.63	89.91	90.82	91.69
$r = 8$	MRPC	91.70	85.55	87.12	88.20	89.91
	QQP	91.80	86.39	89.26	88.45	90.10
	MNLI	91.70	86.40	89.29	90.44	90.41
	QNLI	92.50	87.77	90.20	90.41	91.13

Table 3: Comparison of the testing accuracy under different degrees of data heterogeneity.

Non-IIDness	Dataset	FLoRG	FedIT	FeDeRA	FFA-LoRA	FedSA-LoRA
$\rho = 0.1$	MRPC	85.06	78.19	81.91	81.00	83.01
	QQP	86.95	78.80	84.15	83.21	85.00
	MNLI	81.35	75.44	78.42	77.57	79.36
	QNLI	88.88	83.31	86.20	85.33	87.19
$\rho = 0.5$	MRPC	90.80	85.16	88.30	87.50	89.21
	QQP	91.52	87.89	89.30	88.51	90.01
	MNLI	91.39	84.76	88.20	89.12	90.90
	QNLI	92.44	87.63	89.91	90.82	91.69
$\rho = 1$	MRPC	90.76	85.77	89.26	88.91	88.20
	QQP	91.88	88.61	89.93	89.37	90.39
	MNLI	91.75	86.47	90.05	91.70	91.33
	QNLI	92.17	88.03	90.52	90.79	92.72