

Stochastic setting

Here, we consider the stochastic setting, where each of the functions f_c can be written as

$$f_c(\theta) = \mathbb{E}_{Z^c \sim \xi_c} \left[f_c^{Z^c}(\theta) \right] ,$$

where for each $c \in [M]$, Z^c is a random variable with a certain distribution ξ_c . We assume that each client has access to its own function f_c through stochastic sampling of $f_c^{Z^c}$. In this setting, **FedAVG** solves the global optimization problem by performing local stochastic gradient updates on each client. Starting from an initial point θ_0 shared by the central server, the learning procedure is as follows:

- The server sends the current parameter θ_r to all the clients.
- Starting from θ_r , each client performs H local updates:

$$\theta_{r,h+1}^c = \theta_{r,h}^c - \eta \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) , \quad \text{for } h = 0, \dots, H-1 ,$$

where $Z_{r,h}^c$ is sampled from the distribution ξ_c .

- Finally, the clients send to the central server their last iterate $\theta_{r,H}^c$, and the server averages all the iterates before broadcasting the updated global model again to all the agents.

For convenience of notation, given $Z := (Z^1, \dots, Z^M)$, we define the following *virtual* unbiased estimator of $\nabla F(\theta)$:

$$\nabla F^Z(\theta) = \frac{1}{M} \sum_{c=1}^M \nabla f_c^{Z^c}(\theta) .$$

We make the following assumption on the noise of the gradient:

FL-4. *There exists $\sigma^2 \geq 0$ such that for every agent $c \in [M]$, the gradient estimator satisfies*

$$\mathbb{E}_{Z^c \sim \xi_c} \left[\|\nabla f_c^{Z^c}(\theta) - \nabla f_c(\theta)\|^2 \right] \leq \sigma^2 .$$

Under **FL-4**, it holds that

$$\begin{aligned} \mathbb{E} [\|\nabla F^Z(\theta) - \nabla F(\theta)\|_2^2] &= \frac{1}{M^2} \sum_{c=1}^M \sum_{c'=1}^M \mathbb{E} \left[\langle \nabla f_c^{Z^c}(\theta) - \nabla f_c(\theta), \nabla f_{c'}^{Z^{c'}}(\theta) - \nabla f_{c'}(\theta) \rangle \right] \\ &= \frac{1}{M^2} \sum_{c=1}^M \mathbb{E} \left[\|\nabla f_c^{Z^c}(\theta) - \nabla f_c(\theta)\|_2^2 \right] \leq \frac{\sigma^2}{M} , \end{aligned} \quad (33)$$

where in the last inequality, we used that for $c \neq c'$, $\mathbb{E} \left[\langle \nabla f_c^{Z^c}(\theta) - \nabla f_c(\theta), \nabla f_{c'}^{Z^{c'}}(\theta) - \nabla f_{c'}(\theta) \rangle \right] = 0$ by the independence of Z^c and $Z^{c'}$ and **FL-4**.

F.1. Convergence of **FedAVG** when $\alpha = 1$

Denote by $F^* = \frac{1}{M} \sum_{c=1}^M f_c^*$ and where $(f_c^*)_{c \in [M]}$ are defined in **FL-2**. First, we prove the following lemma, which bounds the local drift

Lemma F.1. *Assume **FL-1**, **FL-2** with $\alpha = 1$, **FL-3** and **FL-4**. Then, for any $\eta > 0$ that satisfies $\eta \leq \frac{1}{LH}$, the iterates θ_R of Algorithm **FedAVG** satisfies*

$$\frac{1}{MH} \sum_{c=1}^M \sum_{h=1}^{H-1} \mathbb{E} [\|\theta_r - \theta_{r,h}^c\|_2^2 | \theta_r] \leq 4\eta^2(H-1)^2 \|\nabla F(\theta_r)\|_2^2 + 4\eta^2(H-1)^2 \zeta^2 + 4\eta^2(H-1)\sigma^2 . \quad (34)$$

Proof. Using the expression of $\theta_{r,h}^c$, and decomposing each gradient as $\nabla f_c^{Z_{r,\ell}}(\theta_{r,\ell}^c) = \nabla f_c^{Z_{r,\ell}}(\theta_{r,\ell}^c) - \nabla f_c(\theta_{r,\ell}^c) + \nabla f_c(\theta_{r,\ell}^c) - \nabla f_c(\theta_r^c) + \nabla f_c(\theta_r)$ we obtain by Young's inequality

$$\begin{aligned} \frac{1}{H} \sum_{h=1}^{H-1} \mathbb{E} [\|\theta_r - \theta_{r,h}^c\|_2^2 | \theta_r] &= \frac{\eta^2}{H} \sum_{h=1}^{H-1} \mathbb{E} \left[\left\| \sum_{\ell=0}^{h-1} \nabla f_c^{Z_{r,\ell}}(\theta_{r,\ell}^c) \right\|_2^2 \middle| \theta_r \right] \\ &\leq \frac{\eta^2}{H} \sum_{h=1}^{H-1} 2\mathbb{E} \left[\left\| \sum_{\ell=0}^{h-1} \nabla f_c(\theta_r) \right\|_2^2 \middle| \theta_r \right] + 4\mathbb{E} \left[\left\| \sum_{\ell=0}^{h-1} \nabla f_c(\theta_r) - \nabla f_c(\theta_{r,\ell}^c) \right\|_2^2 \middle| \theta_r \right] + 4\mathbb{E} \left[\left\| \sum_{\ell=0}^{h-1} \nabla f_c(\theta_{r,\ell}^c) - \nabla f_c^{Z_{r,\ell}}(\theta_{r,\ell}^c) \right\|_2^2 \middle| \theta_r \right] \\ &\leq \frac{2\eta^2}{H} \sum_{h=1}^{H-1} h^2 \mathbb{E} [\|\nabla f_c(\theta_r)\|_2^2 | \theta_r] + \frac{4\eta^2}{H} \sum_{h=1}^{H-1} \mathbb{E} \left[\left\| \sum_{\ell=0}^{h-1} \nabla f_c(\theta_r) - \nabla f_c(\theta_{r,\ell}^c) \right\|_2^2 \middle| \theta_r \right] + \frac{4\eta^2}{H} \sum_{h=1}^{H-1} h\sigma^2, \end{aligned}$$

where we used the fact that $\mathbb{E} [\nabla f_c(\theta_{r,\ell}^c) - \nabla f_c^{Z_{r,\ell}}(\theta_{r,\ell}^c) | \theta_{r,\ell}^c] = 0$ in the last inequality. Using the smoothness of the f_c , Jensen's inequality, and the fact that $\sum_{h=1}^{H-1} h^2 \leq \frac{H(H-1)^2}{2}$, we obtain

$$\begin{aligned} \frac{1}{H} \sum_{h=1}^{H-1} \mathbb{E} [\|\theta_r - \theta_{r,h}^c\|_2^2 | \theta_r] &\leq \eta^2(H-1)^2 \|\nabla f_c(\theta_r)\|_2^2 + \frac{4\eta^2 L^2}{H} \sum_{h=1}^{H-1} \sum_{\ell=0}^{h-1} h \mathbb{E} [\|\theta_r - \theta_{r,\ell}^c\|_2^2 | \theta_r] + 4\eta^2(H-1)\sigma^2 \\ &\leq \eta^2(H-1)^2 \|\nabla f_c(\theta_r)\|_2^2 + \frac{2\eta^2 H(H-1)L^2}{H} \sum_{h=1}^{H-1} \mathbb{E} [\|\theta_r - \theta_{r,h}^c\|_2^2 | \theta_r] + 2\eta^2(H-1)\sigma^2, \end{aligned}$$

where the second inequality comes from completing the sum from $\ell = 0$ to h until $\ell = H-1$, and the fact that $\sum_{h=1}^{H-1} h = \frac{H(H-1)}{2}$. Using the fact that $\eta HL \leq 1/2$, we have $2\eta^2 H(H-1)L^2 \leq 1/2$. Reorganizing the terms and multiplying the previous inequality by 2, we obtain

$$\frac{1}{H} \sum_{h=1}^{H-1} \mathbb{E} [\|\theta_r - \theta_{r,h}^c\|_2^2 | \theta_r] \leq 2\eta^2(H-1)^2 \|\nabla f_c(\theta_r)\|_2^2 + 4\eta^2(H-1)\sigma^2.$$

Averaging this inequality for $c = 1$ to M and using Lemma C.1 to bound $\frac{1}{M} \sum_{c=1}^M \|\nabla f_c(\theta_r)\|_2^2 \leq 2\|\nabla F(\theta_r)\|_2^2 + 2\zeta^2$ gives the result. \square

Theorem F.2. Assume **FL-1**, **FL-2** with $\alpha = 1$, **FL-3** and **FL-4**. Then, for any $\eta > 0$ that satisfies $\eta \leq \frac{1}{18LH}$, the iterates θ_R of Algorithm FedAVG satisfies:

$$\mathbb{E}[F(\theta_R)] - F^* \leq \left(1 - \frac{\eta H \mu}{4}\right)^R (F(\theta_0) - F^*) + \frac{8\zeta^2}{\mu} + \frac{16\eta L}{M} \sigma^2 + 12\eta^2(H-1)L^2 \sigma^2.$$

Case $H = 1$ The algorithm in this setting can be rewritten as stochastic gradient descent on the objective F . Using **FL-1**, setting $Z_r := (Z_{r,0}^1, \dots, Z_{r,0}^M)$ and taking the conditional expectation over θ_r , we have

$$\begin{aligned} \mathbb{E}[F(\theta_{r+1}) | \theta_r] &\leq \mathbb{E} \left[F(\theta_r) + \langle \nabla F(\theta_r), \theta_{r+1} - \theta_r \rangle + \frac{L}{2} \|\theta_{r+1} - \theta_r\|_2^2 \middle| \theta_r \right] \\ &= F(\theta_r) - \eta \mathbb{E} [\|\nabla F(\theta_r)\|_2^2 | \theta_r] + \frac{L\eta^2}{2} \mathbb{E} [\|\nabla F^{Z_r}(\theta_r)\|_2^2 | \theta_r] \\ &\leq F(\theta_r) - \eta \|\nabla F(\theta_r)\|_2^2 + L\eta^2 \mathbb{E} [\|\nabla F^{Z_r}(\theta_r) - \nabla F(\theta_r)\|_2^2 | \theta_r] + L\eta^2 \|\nabla F(\theta_r)\|_2^2 \\ &= F(\theta_r) - \eta(1 - L\eta) \|\nabla F(\theta_r)\|_2^2 + \frac{L\eta^2 \sigma^2}{M}, \end{aligned} \tag{35}$$

where in the last inequality we used (33). Using (19), and subtracting F^* from both sides of the inequality yields

$$\mathbb{E}[F(\theta_{r+1}) | \theta_r] - F^* \leq (1 - \eta\mu(1 - L\eta)) (F(\theta_r) - F^*) + \eta(1 - L\eta)\zeta^2 + \frac{L\eta^2 \sigma^2}{M}.$$

Since $\eta \leq 1/2L$, taking the expectation with respect to all the stochasticity and expanding the recursion gives

$$\mathbb{E}[F(\theta_r)] - F^* \leq \left(1 - \frac{\eta\mu}{2}\right)^r (F(\theta_0) - F^*) + \frac{\zeta^2}{\mu} + \frac{2L\eta\sigma^2}{\mu M}.$$

which concludes the proof.

General case Using Lemma D.1, we have

$$F(\theta_{r+1}) \leq F(\theta_r) + \langle \nabla F(\theta_r), \theta_{r+1} - \theta_r \rangle + \frac{L}{2} \|\theta_{r+1} - \theta_r\|_2^2.$$

Let $\beta = \frac{1}{\sqrt{\eta H}}$. Using the polarization identity $2\langle a, b \rangle = \|a + b\|_2^2 - \|a\|_2^2 - \|b\|_2^2$, we get

$$\begin{aligned} \mathbb{E}[F(\theta_{r+1})|\theta_r] - F(\theta_r) &\leq \mathbb{E}\left[\langle \beta^{-1}\nabla F(\theta_r), \beta(\theta_{r+1} - \theta_r) \rangle + \frac{L}{2}\|\theta_{r+1} - \theta_r\|_2^2 \middle| \theta_r\right] \\ &\leq \langle \beta^{-1}\nabla F(\theta_r), \beta\mathbb{E}[\theta_{r+1} - \theta_r|\theta_r] \rangle + \frac{L}{2}\mathbb{E}[\|\theta_{r+1} - \theta_r\|_2^2|\theta_r] \\ &= \frac{1}{2}\left(\|\beta^{-1}\nabla F(\theta_r) - \beta\mathbb{E}[\theta_r - \theta_{r+1}|\theta_r]\|_2^2 - \|\beta^{-1}\nabla F(\theta_r)\|_2^2 - \|\beta\mathbb{E}[\theta_r - \theta_{r+1}|\theta_r]\|_2^2\right) + \frac{L}{2}\mathbb{E}[\|\theta_{r+1} - \theta_r\|_2^2|\theta_r] \\ &= \underbrace{\frac{1}{2\beta^2}\|\nabla F(\theta_r) - \beta^2\mathbb{E}[\theta_r - \theta_{r+1}|\theta_r]\|_2^2 - \frac{1}{2\beta^2}\|\nabla F(\theta_r)\|_2^2}_{(\mathbf{A})} + \underbrace{\frac{L}{2}\mathbb{E}[\|\theta_{r+1} - \theta_r\|_2^2|\theta_r] - \frac{\beta^2}{2}\|\mathbb{E}[\theta_{r+1} - \theta_r|\theta_r]\|_2^2}_{(\mathbf{B})}. \quad (36) \end{aligned}$$

Bounding (A). Using the fact that $F = \frac{1}{M} \sum_{c=1}^M f_c$, the definition $\beta^2 = 1/\eta H$, the definition of θ_{r+1} and Jensen's inequality, we have

$$\begin{aligned} \left\|\nabla F(\theta_r) - \beta^2\mathbb{E}[\theta_r - \theta_{r+1}|\theta_r]\right\|_2^2 &= \left\|\mathbb{E}\left[\frac{1}{M}\sum_{c=1}^M\left(\nabla F(\theta_r) - \frac{1}{H}\sum_{h=0}^{H-1}\nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c)\right)\middle|\theta_r\right]\right\|_2^2 \\ &\leq \frac{1}{HM}\sum_{c=1}^M\sum_{h=0}^{H-1}\left\|\mathbb{E}\left[\nabla f_c(\theta_r) - \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c)\middle|\theta_r\right]\right\|_2^2. \end{aligned}$$

By independence of $Z_{r,h}^c$ and $\theta_{r,h}^c$, and using Jensen's inequality and the smoothness of the f_c (FL-1), we obtain

$$\begin{aligned} \left\|\nabla F(\theta_r) - \beta^2\mathbb{E}[\theta_r - \theta_{r+1}|\theta_r]\right\|_2^2 &\leq \frac{1}{HM}\sum_{c=1}^M\sum_{h=0}^{H-1}\left\|\mathbb{E}\left[\nabla f_c(\theta_r) - \nabla f_c(\theta_{r,h}^c)\middle|\theta_r\right]\right\|_2^2 \\ &\leq \frac{1}{HM}\sum_{c=1}^M\sum_{h=0}^{H-1}\mathbb{E}\left[\|\nabla f_c(\theta_r) - \nabla f_c(\theta_{r,h}^c)\|_2^2|\theta_r\right] \\ &\leq \frac{L^2}{HM}\sum_{c=1}^M\sum_{h=0}^{H-1}\mathbb{E}\left[\|\theta_r - \theta_{r,h}^c\|_2^2|\theta_r\right]. \quad (37) \end{aligned}$$

Using Lemma F.1, we obtain

$$\left\|\nabla F(\theta_r) - \beta^2\mathbb{E}[\theta_r - \theta_{r+1}|\theta_r]\right\|_2^2 \leq 4\eta^2(H-1)^2L^2\|\nabla F(\theta_r)\|_2^2 + 4\eta^2(H-1)^2L^2\zeta^2 + 4\eta^2(H-1)L^2\sigma^2. \quad (38)$$

Multiplying by $1/(2\beta^2) = \eta H/2$, we obtain the following bound on (A)

$$(\mathbf{A}) \leq 2\eta^3H(H-1)^2L^2\|\nabla F(\theta_r)\|_2^2 + 2\eta^3H(H-1)^2L^2\zeta^2 + 2\eta^3H(H-1)L^2\sigma^2.$$

Bounding (B). To bound this second term, we use the following decomposition

$$\begin{aligned} & \frac{L}{2} \mathbb{E} [\|\theta_{r+1} - \theta_r\|_2^2 | \theta_r] - \frac{\beta^2}{2} \|\mathbb{E} [\theta_{r+1} - \theta_r | \theta_r]\|_2^2 \\ &= \frac{L}{2} \mathbb{E} [\|\mathbb{E} [\theta_{r+1} | \theta_r] - \theta_{r+1}\|^2 | \theta_r] + \frac{L}{2} \|\mathbb{E} [\theta_{r+1} - \theta_r | \theta_r]\|_2^2 - \frac{\beta^2}{2} \|\mathbb{E} [\theta_{r+1} - \theta_r | \theta_r]\|_2^2 \\ &= \frac{L}{2} \mathbb{E} [\|\mathbb{E} [\theta_{r+1} | \theta_r] - \theta_{r+1}\|^2 | \theta_r] + \left(\frac{L}{2} - \frac{\beta^2}{2} \right) \|\mathbb{E} [\theta_{r+1} - \theta_r | \theta_r]\|_2^2 . \end{aligned}$$

Since $\eta HL \leq 1$, we have $\frac{L}{2} - \frac{\beta^2}{2} = \frac{L}{2} - \frac{1}{2\eta H} \leq 0$, and the second term is negative. To bound the first term, we write

$$\begin{aligned} & \mathbb{E} [\|\mathbb{E} [\theta_{r+1} | \theta_r] - \theta_{r+1}\|^2 | \theta_r] = \mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) - \mathbb{E} [\nabla f_c(\theta_{r,h}^c) | \theta_r] \right\|^2 \middle| \theta_r \right] \\ &= \mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) - \nabla f_c(\theta_r) + \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c(\theta_r) - \mathbb{E} [\nabla f_c(\theta_{r,h}^c) | \theta_r] \right\|^2 \middle| \theta_r \right] \\ &\leq 2\mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) - \nabla f_c(\theta_r) \right\|^2 \middle| \theta_r \right] + 2\mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c(\theta_r) - \mathbb{E} [\nabla f_c(\theta_{r,h}^c) | \theta_r] \right\|^2 \middle| \theta_r \right] \\ &\leq 4\mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) - \nabla f_c(\theta_r) \right\|^2 \middle| \theta_r \right] , \end{aligned}$$

where we used Young's and Jensen's inequalities. Now, using Young's inequality again, we obtain

$$\begin{aligned} & \mathbb{E} [\|\mathbb{E} [\theta_{r+1} | \theta_r] - \theta_{r+1}\|^2 | \theta_r] \\ &\leq 4\mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) - \nabla f_c(\theta_{r,h}^c) + \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c(\theta_{r,h}^c) - \nabla f_c(\theta_r) \right\|^2 \middle| \theta_r \right] \\ &\leq 8\mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c^{Z_{r,h}^c}(\theta_{r,h}^c) - \nabla f_c(\theta_{r,h}^c) \right\|^2 \middle| \theta_r \right] + 8\mathbb{E} \left[\left\| \frac{\eta}{M} \sum_{c=1}^M \sum_{h=1}^H \nabla f_c(\theta_{r,h}^c) - \nabla f_c(\theta_r) \right\|^2 \middle| \theta_r \right] . \end{aligned}$$

The first term is a variance term, that we bound using the fact that the $\theta_{r,h}^c$ are independent from the future noise draws $Z_{r,h'}^c$ for $h' \geq h$, and the fact that the $Z_{r,h}^c$ are independent from an agent to another, and bounding each gradient variance using **FL-4**. We bound the second term by decomposing it using Jensen's inequality and the smoothness of the f_c . This gives

$$\mathbb{E} [\|\mathbb{E} [\theta_{r+1} | \theta_r] - \theta_{r+1}\|^2 | \theta_r] \leq \frac{8\eta^2 H}{M} \sigma^2 + \frac{8\eta^2 L^2 H}{M} \sum_{c=1}^M \sum_{h=1}^H \mathbb{E} [\|\theta_{r,h}^c - \theta_r\|^2 | \theta_r] .$$

Using Lemma F.1, we obtain

$$\begin{aligned} (\mathbf{B}) &\leq \frac{4\eta^2 HL}{M} \sigma^2 + 4\eta^2 H^2 L^3 (4\eta^2 (H-1)^2 \|\nabla F(\theta_r)\|_2^2 + 4\eta^2 (H-1)^2 \zeta^2 + 4\eta^2 (H-1) \sigma^2) \\ &= 16\eta^4 H^2 (H-1)^2 L^3 \|\nabla F(\theta_r)\|_2^2 + 16\eta^4 H^2 (H-1)^2 L^3 \zeta + \left(\frac{4\eta^2 HL}{M} + 16\eta^4 H^2 (H-1) L^3 \right) \sigma^2 . \end{aligned}$$

Bound on (36). Plugging in the bounds on (A) and (B) in (36) yields

$$\begin{aligned} & \mathbb{E} [F(\theta_{r+1}) | \theta_r] - F(\theta_r) \\ &= \left(2\eta^3 H (H-1)^2 L^2 + 16\eta^4 H^2 (H-1)^2 L^3 - \frac{\eta H}{2} \right) \|\nabla F(\theta_r)\|_2^2 + (2\eta^3 H (H-1)^2 L^2 + 16\eta^4 H^2 (H-1)^2 L^3) \zeta^2 \\ &+ \left(\frac{4\eta^2 HL}{M} + 2\eta^3 H (H-1) L^2 + 16\eta^4 H^2 (H-1) L^3 \right) \sigma^2 . \end{aligned}$$

Using that $\eta HL \leq 1/18$, it holds that

$$\mathbb{E} [F(\theta_{r+1})|\theta_r] \leq F(\theta_r) - \frac{\eta H}{4} \|\nabla F(\theta_r)\|_2^2 + \eta H \zeta^2 + \frac{4\eta^2 HL}{M} \sigma^2 + 3\eta^3 H(H-1)L^2 \sigma^2 . \quad (39)$$

Applying (19), we get

$$\mathbb{E} [F(\theta_{r+1})|\theta_r] - F^* \leq F(\theta_r) - F^* - \frac{\eta H \mu}{4} (F(\theta_r) - F^*) + 2\eta H \zeta^2 + \frac{4\eta^2 HL}{M} \sigma^2 + 3\eta^3 H(H-1)L^2 \sigma^2 .$$

The result follows from taking the expectation and unrolling the recursion.

F.2. Convergence of FedAVG for general $1 < \alpha \leq 2$

Lemma F.3. Assume **FL-1**, **FL-2** with $\alpha > 1$, **FL-3** and **FL-4**. For any $\eta > 0$ that satisfies $\eta \leq 1/L$, the following inequality holds on the last iterate provided by FedAVG with $H = 1$

$$\mathbb{E}[F(\theta_R)] - F^* \leq \frac{F(\theta_0) - F^*}{(\eta \mu R(\alpha - 1)(F(\theta_0) - F^*)^{\alpha-1}/4 + 1)^{1/(\alpha-1)}} + 2 \left(\frac{\zeta^2}{\mu} \right)^{1/\alpha} + 2 \left(\frac{(2L\eta\sigma^2)}{M\mu} \right)^{1/\alpha} ,$$

where $F^* = \frac{1}{M} \sum_{c=1}^M f_c^*$ and where $(f_c^*)_{c \in [M]}$ are defined in **FL-2**.

Proof. Starting from (35), we have

$$\mathbb{E} [F(\theta_{r+1})|\theta_r] \leq F(\theta_r) - \eta(1 - L\eta) \|\nabla F(\theta_r)\|_2^2 + \frac{L\eta^2 \sigma^2}{M} .$$

Now, using (19), subtracting F^* from both sides of the inequality yields, and using that $\eta \leq 1/L$, we have,

$$\mathbb{E} [F(\theta_{r+1})|\theta_r] - F^* \leq F(\theta_r) - F^* - \frac{\eta \mu}{2} (F(\theta_r) - F^*)^\alpha + \frac{\eta}{2} \zeta^2 + \frac{L\eta^2 \sigma^2}{M} . \quad (40)$$

Taking the expectation with respect to all the stochasticity and applying Jensen's inequality gives

$$\mathbb{E}[F(\theta_{r+1})] - F^* \leq \mathbb{E}[F(\theta_r)] - F^* - \frac{\eta \mu}{2} (\mathbb{E}[F(\theta_r)] - F^*)^\alpha + \frac{\eta}{2} \zeta^2 + \frac{L\eta^2 \sigma^2}{M}$$

Defining $s_r = \mathbb{E}[F(\theta_r)] - F^*$, the precedent expression can be rewritten as

$$s_{r+1} \leq s_r - \frac{\eta \mu}{2} s_r^\alpha + \frac{\eta}{2} \zeta^2 + \frac{L\eta^2 \sigma^2}{M} .$$

This expression can be interpreted as a difference inequality corresponding to an Euler discretization of Bernoulli's differential equation. To solve it, we first homogenize the recursive relation by introducing the sequence $v_r = s_r - C$, where $C = ((\zeta^2)/\mu)^{1/\alpha} + ((2L\eta\sigma^2)/(M\mu))^{1/\alpha}$. The sequence v_r then satisfies the following recursive relation:

$$v_{r+1} \leq v_r - \frac{\eta \mu}{2} (v_r + C)^\alpha + \eta \zeta^2 . \quad (41)$$

We now consider the case where $s_r \geq C$ for all $r \in [R]$ which implies $v_r \geq 0$ for all $r \in [R]$. Since for $\alpha \geq 1$, and $a, b \geq 0$, $(a + b)^\alpha \geq a^\alpha + b^\alpha$, we get

$$v_{r+1} \leq v_r - \frac{\eta \mu}{2} v_r^\alpha - \frac{\eta \mu C^\alpha}{2} + \eta \zeta^2 = v_r - \kappa v_r^\alpha ,$$

with $\kappa = \frac{\eta \mu}{2}$. Dividing this inequality by v_r^α yields

$$\frac{v_{r+1} - v_r}{v_r^\alpha} \leq -\kappa . \quad (42)$$

For $x > 0$, define $g(x) = x^{-(\alpha-1)}$. By convexity of g on \mathbb{R}_+^* , we have $g(v_{r+1}) \geq g(v_r) + (v_{r+1} - v_r)g'(v_r)$ which can be rewritten as

$$v_{r+1}^{-(\alpha-1)} \geq v_r^{-(\alpha-1)} + (v_{r+1} - v_r) \frac{1-\alpha}{v_r^\alpha} ,$$

and which implies, after dividing by $1 - \alpha < 0$, and using (42)

$$\frac{v_{r+1}^{-(\alpha-1)} - v_r^{-(\alpha-1)}}{1 - \alpha} \leq \frac{v_{r+1} - v_r}{v_r^\alpha} \leq -\kappa .$$

Summing up both sides over $r = 0 \dots R - 1$ and rearranging the terms yields

$$(s_R - C)^{-(\alpha-1)} \geq \kappa R(\alpha - 1) + s_0^{-(\alpha-1)} .$$

Finally, we get

$$s_R \leq C + \left\{ \kappa R(\alpha - 1) + s_0^{-(\alpha-1)} \right\}^{-1/(\alpha-1)} = C + \frac{s_0}{(\kappa R(\alpha - 1)s_0^{\alpha-1} + 1)^{1/(\alpha-1)}} .$$

Now in the case where there exists s_r such that $s_r \leq C$ it is straightforward to see the sequence s_r will stay smaller than $2C$. \square

Theorem F.4. Assume **FL-1**, **FL-2** with $\alpha > 1$, and **FL-3**. Then, for any $\eta > 0$ that satisfies $\eta \leq \frac{1}{18MLH}$, the iterates θ_R of Algorithm *FedAVG* satisfies:

$$\mathbb{E}[F(\theta_R)] - F^* \leq \frac{F(\theta_0) - F^*}{1 + R^{1/(\alpha-1)} \cdot (F(\theta_0) - F^*) \cdot (\eta H \mu (\alpha - 1)/4)^{1/(\alpha-1)}} + 2 \left(\frac{8\zeta^2}{\mu} \right)^{1/\alpha} + 2 \left(\frac{16L\eta\sigma^2}{M\mu} \right)^{1/\alpha} ,$$

where $F^* = \frac{1}{M} \sum_{c=1}^M f_c^*$ and where $(f_c^*)_{c \in [M]}$ are defined in **FL-2**.

Proof. Let us follow the first steps of the proof of Theorem F.2. Starting from (39) and applying (19) yields

$$\mathbb{E}[F(\theta_{r+1})|\theta_r] \leq F(\theta_r) - \frac{\eta H}{4} (F(\theta_r) - F^*) \|\nabla F(\theta_r)\|_2^2 + 2\eta H \zeta^2 + \frac{4\eta^2 H L}{M} \sigma^2 + 3\eta^3 H (H - 1) L^2 \sigma^2 .$$

We recognise the same type of recursion as in (40) of Lemma F.3. Similarly, setting $C = (8\zeta^2/\mu)^{1/\alpha} + (16L\eta\sigma^2/M\mu)^{1/\alpha}$ and $\kappa = \eta H \mu / 4$, we obtain

$$\mathbb{E}[F(\theta_{r+1})|\theta_r] - F^* \leq C + \frac{F(\theta_0) - F^*}{(\kappa R(\alpha - 1)(F(\theta_0) - F^*)^{\alpha-1} + 1)^{1/(\alpha-1)}} .$$

Finally using that for $\alpha \geq 1$, and $a, b \geq 0$, $(a + b)^\alpha \geq a^\alpha + b^\alpha$ concludes the proof. \square