

# Adaptive Federated Learning in Resource Constrained Edge Computing Systems

主要分享一下我对文章相关数学证明的想法

## 辅助函数

用 $[k]$ 代表一个训练区间 $[(k-1)\tau, k\tau]$ ，表示第 $k-1$ 次全局更新和第 $k$ 次全局更新之间的训练区间，在这个开区间之中只有局部模型的更新

一个辅助函数如下：

$$v_{[k]}(t) = v_{[k]}(t-1) - \eta \nabla F(v_{[k]}(t-1))$$

这个辅助函数的参数更新代表着与局部模型的更新无关，训练的方法是将所有数据集中在同一个设备上进行梯度的更新（也就是不经过联邦学习的框架直接训练，只是一种理想的状况），由于这样子没有进行联合平均的信息损失，因此往往在一个训练周期内会有更好的训练效果（损失函数的值更小），并且这个辅助函数的值会定期更新，也就是每经过一次全局更新时会被重新设置为全局模型的参数值，如下图所示：

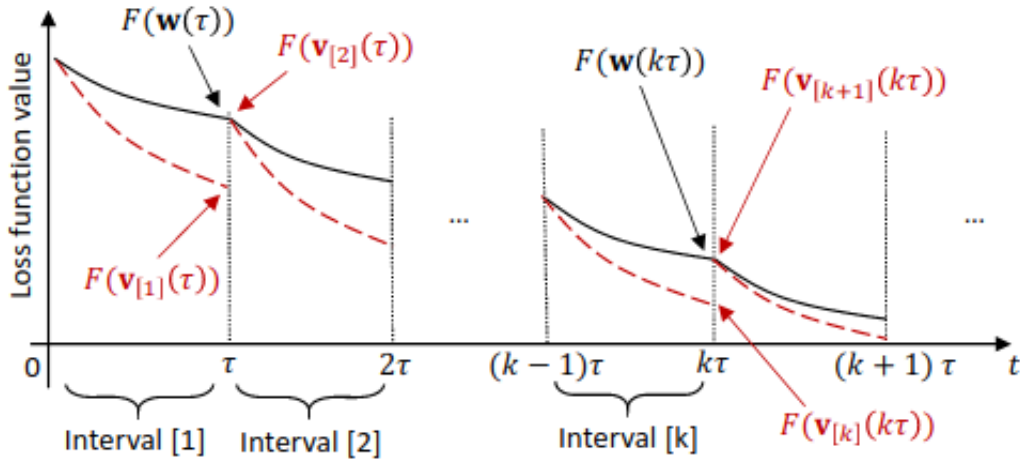


Fig. 3: Illustration of definitions in different intervals.

## 假设1

- $F_i(w)$  is convex
- $F_i(w)$  is  $\rho$ -Lipshitz
- $F_i(w)$  is  $\beta$ -smooth

这里可以轻易得出 $F(w)$ 也是符合上面三个条件的

## 定理1

**Theorem 1.** *For any interval  $[k]$  and  $t \in [k]$ , we have*

$$\|\mathbf{w}(t) - \mathbf{v}_{[k]}(t)\| \leq h(t - (k - 1)\tau) \quad (10)$$

where

$$h(x) \triangleq \frac{\delta}{\beta} ((\eta\beta + 1)^x - 1) - \eta\delta x \quad (11)$$

for any  $x = 0, 1, 2, \dots$

Furthermore, as  $F(\cdot)$  is  $\rho$ -Lipschitz, we have  $F(\mathbf{w}(t)) - F(\mathbf{v}_{[k]}(t)) \leq \rho h(t - (k - 1)\tau)$ .

证明过程:

- 对于每一个设备i:

**Lemma 3.** *For any interval  $[k]$ , and  $t \in [(k - 1)\tau, k\tau)$ , we have*

$$\|\tilde{\mathbf{w}}_i(t) - \mathbf{v}_{[k]}(t)\| \leq g_i(t - (k - 1)\tau)$$

where we define the function  $g_i(x)$  as

$$g_i(x) \triangleq \frac{\delta_i}{\beta} ((\eta\beta + 1)^x - 1)$$

- 再利用联合平均的等式将每个 $g_i(x)$ 关联起来, 证明

$$\begin{aligned} & \|\mathbf{w}(t) - \mathbf{v}_{[k]}(t)\| - \|\mathbf{w}(t - 1) - \mathbf{v}_{[k]}(t - 1)\| \\ & \leq \eta\delta \left( (\eta\beta + 1)^{t-1-(k-1)\tau} - 1 \right) \end{aligned} \quad (24)$$

- 最后利用加和消项计算出 $\|\mathbf{w}(t) - \mathbf{v}_{[k]}(t)\| =$

$$\begin{aligned}
&= \sum_{y=(k-1)\tau+1}^t \left\| \mathbf{w}(y) - \mathbf{v}_{[k]}(y) \right\| - \left\| \mathbf{w}(y-1) - \mathbf{v}_{[k]}(y-1) \right\| \\
&\leq \eta\delta \sum_{y=(k-1)\tau+1}^t \left( (\eta\beta + 1)^{y-1-(k-1)\tau} - 1 \right) \\
&= \eta\delta \sum_{z=1}^{t-(k-1)\tau} \left( (\eta\beta + 1)^{z-1} - 1 \right) \\
&= \eta\delta \sum_{z=1}^{t-(k-1)\tau} (\eta\beta + 1)^{z-1} - \eta\delta(t - (k-1)\tau) \\
&= \eta\delta \frac{(1 - (\eta\beta + 1)^{t-(k-1)\tau})}{-\eta\beta} - \eta\delta(t - (k-1)\tau) \\
&= \eta\delta \frac{(\eta\beta + 1)^{t-(k-1)\tau} - 1}{\eta\beta} - \eta\delta(t - (k-1)\tau) \\
&= \frac{\delta}{\beta} \left( (\eta\beta + 1)^{t-(k-1)\tau} - 1 \right) - \eta\delta(t - (k-1)\tau) \\
&= h(t - (k-1)\tau)
\end{aligned}$$

问题：如何得出 $g_i(x)$ 这个函数？

解：先用训练时间间隔作为自变量，将 $g_i(x)$ 代入归纳证明的框架中，一直到以下这一步：

$$\begin{aligned}
&\quad \quad \quad \text{(from the } \beta\text{-smoothness of } F_i(\cdot) \text{ and (9))} \\
&\leq (\eta\beta + 1)g_i(t - 1 - (k-1)\tau) + \eta\delta_i \\
&\quad \quad \quad \text{(from the induction assumption in (22))} \\
&= (\eta\beta + 1) \left( \frac{\delta_i}{\beta} \left( (\eta\beta + 1)^{t-1-(k-1)\tau} - 1 \right) \right) + \eta\delta_i
\end{aligned}$$

在这里将 $g_i(t - 1 - (k-1)\tau)$ 凑出来，让展开之后化简的表达式可以表示为 $g_i(t - (k-1)\tau)$

## 引理2

---

**Lemma 2.** When all the following conditions are satisfied:

- 1)  $\eta \leq \frac{1}{\beta}$
- 2)  $\eta\varphi - \frac{\rho h(\tau)}{\tau\varepsilon^2} > 0$
- 3)  $F(\mathbf{v}_{[k]}(k\tau)) - F(\mathbf{w}^*) \geq \varepsilon$  for all  $k$
- 4)  $F(\mathbf{w}(T)) - F(\mathbf{w}^*) \geq \varepsilon$

for some  $\varepsilon > 0$ , where we define  $\varphi \triangleq \omega \left(1 - \frac{\beta\eta}{2}\right)$  and  $\omega \triangleq \frac{1}{\min_k \|\mathbf{v}_{[k]}((k-1)\tau) - \mathbf{w}^*\|^2}$ , then the convergence upper bound of Algorithm [1](#) after  $T$  iterations is given by

$$F(\mathbf{w}(T)) - F(\mathbf{w}^*) \leq \frac{1}{T \left( \eta\varphi - \frac{\rho h(\tau)}{\tau\varepsilon^2} \right)}. \quad (12)$$

为了证明这个引理，提出了一个辅助定义引理4-6来辅助证明

## 定义2

**Definition 2.** For an interval  $[k]$ , we define  $\theta_{[k]}(t) = F(\mathbf{v}_{[k]}(t)) - F(\mathbf{w}^*)$ , for a fixed  $k$ ,  $t$  is defined between  $(k-1)\tau \leq t \leq k\tau$ .

) According to the convergence lower bound of gradient descent given in [\[39\]](#), Theorem 3.14], we always have

$$\theta_{[k]}(t) > 0 \quad (25)$$

) for any finite  $t$  and  $k$ .

## 引理4

**Lemma 4.** When  $\eta \leq \frac{1}{\beta}$ , for any  $k$ , and  $t \in [(k-1)\tau, k\tau]$ , we have that  $\|\mathbf{v}_{[k]}(t) - \mathbf{w}^*\|$  does not increase with  $t$ , where  $\mathbf{w}^*$  is the optimal parameter defined in [\(3\)](#).

## 引理5

**Lemma 5.** For any  $k$ , when  $\eta \leq \frac{1}{\beta}$  and  $t \in [(k-1)\tau, k\tau)$ , we have

$$F(\mathbf{v}_{[k]}(t+1)) - F(\mathbf{v}_{[k]}(t)) \leq -\eta \left(1 - \frac{\beta\eta}{2}\right) \|\nabla F(\mathbf{v}_{[k]}(t))\|^2 \quad (26)$$

## 引理6

**Lemma 6.** For any  $k$ , when  $\eta \leq \frac{1}{\beta}$  and  $t \in [(k-1)\tau, k\tau)$ , we have

$$\frac{1}{\theta_{[k]}(t+1)} - \frac{1}{\theta_{[k]}(t)} \geq \omega\eta \left(1 - \frac{\beta\eta}{2}\right) \quad (27)$$

where  $\omega = \min_k \frac{1}{\|\mathbf{v}_{[k]}((k-1)\tau) - \mathbf{w}^*\|^2}$

然后开始证明引理2:

同样, 先用加和消项:

$$\begin{aligned} \frac{1}{\theta_{[k]}(k\tau)} - \frac{1}{\theta_{[k]}((k-1)\tau)} &= \sum_{z=(k-1)\tau}^{k\tau-1} \left( \frac{1}{\theta_{[k]}(t+1)} - \frac{1}{\theta_{[k]}(t)} \right) \\ &\geq \tau\omega\eta \left(1 - \frac{\beta\eta}{2}\right) \end{aligned}$$

进一步:

$$\begin{aligned} \sum_{k=1}^K \left( \frac{1}{\theta_{[k]}(k\tau)} - \frac{1}{\theta_{[k]}((k-1)\tau)} \right) &\geq \sum_{k=1}^K \tau\omega\eta \left(1 - \frac{\beta\eta}{2}\right) \\ &= K\tau\omega\eta \left(1 - \frac{\beta\eta}{2}\right) \end{aligned}$$

将等式的加和式左边重写, 用 $T$ 替换 $k\tau$ :

$$\begin{aligned} & \frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)} - \sum_{k=1}^{K-1} \left( \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} \right) \\ & \geq T\omega\eta \left( 1 - \frac{\beta\eta}{2} \right) \end{aligned}$$

移项：

$$\begin{aligned} & \frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)} \\ & \geq T\omega\eta \left( 1 - \frac{\beta\eta}{2} \right) + \sum_{k=1}^{K-1} \left( \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} \right) \quad (30) \end{aligned}$$

将右边的项化简：

$$\begin{aligned} \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} &= \frac{\theta_{[k]}(k\tau) - \theta_{[k+1]}(k\tau)}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \\ &= \frac{F(\mathbf{v}_{[k]}(k\tau)) - F(\mathbf{v}_{[k+1]}(k\tau))}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \\ &\geq \frac{-\rho h(\tau)}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \quad (31) \end{aligned}$$

根据引理5,有

$$\begin{aligned} & \frac{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)}{-1} \geq -\frac{1}{\varepsilon^2} \quad (32) \end{aligned}$$

然后就可以缩放了：

$$\begin{aligned} \sum_{k=1}^{K-1} \left( \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} \right) &\geq - \sum_{k=1}^{K-1} \frac{\rho h(\tau)}{\varepsilon^2} \\ &= -(K-1) \frac{\rho h(\tau)}{\varepsilon^2} \end{aligned}$$

根据假设  $F(W(T)) - F(w^*) \geq \epsilon$ , 有：

$$\frac{-1}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \geq -\frac{1}{\varepsilon^2} \quad (34)$$

则：

$$\begin{aligned}
 \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} - \frac{1}{\theta_{[K]}(T)} &= \frac{\theta_{[K]}(T) - (F(\mathbf{w}(T)) - F(\mathbf{w}^*))}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \\
 &= \frac{F(\mathbf{v}_{[K]}(T)) - F(\mathbf{w}(T))}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \\
 &\geq \frac{-\rho h(\tau)}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \\
 &\geq -\frac{\rho h(\tau)}{\varepsilon^2} \quad (35)
 \end{aligned}$$

然后综合上式：

$$\begin{aligned}
 \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} - \frac{1}{\theta_{[1]}(0)} &\geq T\omega\eta \left(1 - \frac{\beta\eta}{2}\right) - K\frac{\rho h(\tau)}{\varepsilon^2} \\
 &= T\omega\eta \left(1 - \frac{\beta\eta}{2}\right) - T\frac{\rho h(\tau)}{\tau\varepsilon^2} \\
 &= T \left( \omega\eta \left(1 - \frac{\beta\eta}{2}\right) - \frac{\rho h(\tau)}{\tau\varepsilon^2} \right)
 \end{aligned}$$

显然：

$$\begin{aligned}
 \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} &\geq \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} - \frac{1}{\theta_{[1]}(0)} \\
 &\geq T \left( \omega\eta \left(1 - \frac{\beta\eta}{2}\right) - \frac{\rho h(\tau)}{\tau\varepsilon^2} \right) > 0
 \end{aligned}$$

倒一下项：

$$\begin{aligned}
 F(\mathbf{w}(T)) - F(\mathbf{w}^*) &\leq \frac{1}{T \left( \omega\eta \left(1 - \frac{\beta\eta}{2}\right) - \frac{\rho h(\tau)}{\tau\varepsilon^2} \right)} \\
 &= \frac{1}{T \left( \eta\varphi - \frac{\rho h(\tau)}{\tau\varepsilon^2} \right)}
 \end{aligned}$$

得证

如果倒着看呢？

我们要求解  $F(w(T)) - F(w^*)$  的上界，可以直接用加和消项来求解，但作者应该是试过了这种方法却发现有些地方很难处理，因此通过求解  $\frac{1}{F(w(T)) - F(w^*)}$  的下界来求解  $F(w(T)) - F(w^*)$  的上界，这两者是等价的

$$\begin{aligned} \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} &\geq \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} - \frac{1}{\theta_{[1]}(0)} \\ &\geq T \left( \omega\eta \left( 1 - \frac{\beta\eta}{2} \right) - \frac{\rho h(\tau)}{\tau\epsilon^2} \right) > 0 \end{aligned}$$

然后我们看如何得到右边这个式子的，左边放缩之前的式子可以改写为

$$\frac{1}{F(w(T)) - F(w^*)} - \frac{1}{\theta_{[K]}(T)} + \frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)}$$

然后就分别求解  $\frac{1}{F(w(T)) - F(w^*)} - \frac{1}{\theta_{[K]}(T)}$  和  $\frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)}$ ，后面这项很明显可以用加和消项来处理，首先算出一个训练周期内的差值，再算出从训练开始到训练结束 ( $t = T$ ) 的差值

$$\begin{aligned} \frac{1}{\theta_{[k]}(k\tau)} - \frac{1}{\theta_{[k]}((k-1)\tau)} &= \sum_{z=(k-1)\tau}^{k\tau-1} \left( \frac{1}{\theta_{[k]}(t+1)} - \frac{1}{\theta_{[k]}(t)} \right) \\ &\geq \tau\omega\eta \left( 1 - \frac{\beta\eta}{2} \right) \end{aligned}$$

Summing up the above for all  $k = 1, 2, \dots, K$  yields

$$\begin{aligned} \sum_{k=1}^K \left( \frac{1}{\theta_{[k]}(k\tau)} - \frac{1}{\theta_{[k]}((k-1)\tau)} \right) &\geq \sum_{k=1}^K \tau\omega\eta \left( 1 - \frac{\beta\eta}{2} \right) \\ &= K\tau\omega\eta \left( 1 - \frac{\beta\eta}{2} \right) \end{aligned}$$

Rewriting the left-hand side and noting that  $T = K\tau$  yields

$$\begin{aligned} \frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)} - \sum_{k=1}^{K-1} \left( \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} \right) \\ \geq T\omega\eta \left( 1 - \frac{\beta\eta}{2} \right) \end{aligned}$$

which is equivalent to

$$\frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)}$$



$$\geq T\omega\eta \left(1 - \frac{\beta\eta}{2}\right) + \sum_{k=1}^{K-1} \left( \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} \right) \quad (30)$$

Each term in the sum in right-hand side of (30) can be further expressed as

$$\begin{aligned} \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} &= \frac{\theta_{[k]}(k\tau) - \theta_{[k+1]}(k\tau)}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \\ &= \frac{F(\mathbf{v}_{[k]}(k\tau)) - F(\mathbf{v}_{[k+1]}(k\tau))}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \\ &\geq \frac{-\rho h(\tau)}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \end{aligned} \quad (31)$$

where the last inequality is obtained using Theorem 1 and noting that, according to the definition,  $\mathbf{v}_{[k+1]}(k\tau) = \mathbf{w}(k\tau)$ , thus  $F(\mathbf{v}_{[k+1]}(k\tau)) = F(\mathbf{w}(k\tau))$ .

It is assumed that  $F(\mathbf{v}_{[k]}(k\tau)) - F(\mathbf{w}^*) \geq \varepsilon$  for all  $k$ . According to Lemma 5,  $F(\mathbf{v}_{[k]}(t)) \geq F(\mathbf{v}_{[k]}(t+1))$  for any  $t \in [(k-1)\tau, k\tau)$ . Therefore, we have  $\theta_{[k]}(t) = F(\mathbf{v}_{[k]}(t)) - F(\mathbf{w}^*) \geq \varepsilon$  for all  $t$  and  $k$  for which  $\mathbf{v}_{[k]}(t)$  is defined. Consequently,

$$\begin{aligned} \theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau) &\geq \varepsilon^2 \\ \frac{-1}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} &\geq -\frac{1}{\varepsilon^2} \end{aligned} \quad (32)$$

Combining (32) with (31), the sum in the right-hand side of (30) can be bounded by

$$\begin{aligned} \sum_{k=1}^{K-1} \left( \frac{1}{\theta_{[k+1]}(k\tau)} - \frac{1}{\theta_{[k]}(k\tau)} \right) &\geq - \sum_{k=1}^{K-1} \frac{\rho h(\tau)}{\varepsilon^2} \\ &= -(K-1) \frac{\rho h(\tau)}{\varepsilon^2} \end{aligned}$$

Substituting the above into (30), we get

$$\frac{1}{\theta_{[K]}(T)} - \frac{1}{\theta_{[1]}(0)} \geq T\omega\eta \left(1 - \frac{\beta\eta}{2}\right) - (K-1) \frac{\rho h(\tau)}{\varepsilon^2} \quad (33)$$

前面这一项可以从已证的下式中变换而来：

$$\frac{-1}{\theta_{[k]}(k\tau)\theta_{[k+1]}(k\tau)} \geq -\frac{1}{\varepsilon^2}$$

我们继续有

$$\begin{aligned} \frac{1}{F(\mathbf{w}(T)) - F(\mathbf{w}^*)} - \frac{1}{\theta_{[K]}(T)} &= \frac{\theta_{[K]}(T) - (F(\mathbf{w}(T)) - F(\mathbf{w}^*))}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \\ &= \frac{F(\mathbf{v}_{[K]}(T)) - F(\mathbf{w}(T))}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \\ &\geq \frac{-\rho h(\tau)}{(F(\mathbf{w}(T)) - F(\mathbf{w}^*)) \theta_{[K]}(T)} \\ &\geq -\frac{\rho h(\tau)}{\varepsilon^2} \end{aligned} \quad (35)$$

还是那个问题，如何得到这个上界的？（论文只给出了证明，并没有讲如何求解）

顺着推，就能求得这个上界（逆着推就是证明）