Labs

Optimization for Machine Learning
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#### **Saarland University**

CISPA Helmholtz Center for Information Security **Sebastian Stich** 

TAs: Yuan Gao & Xiaowen Jiang https://cms.cispa.saarland/optml24/

# Problem Set 7 — Solutions (Local SGD)

### 1 Local SGD on Heterogeneous Functions

Consider the (generalized) example from the lecture, with  $f \colon \mathbb{R} \to \mathbb{R}$  defined as:

$$f_1(x) = \frac{1}{2}x^2$$
  $f_2(x) = a(x-1)^2$   $f(x) = \frac{1}{2}(f_1(x) + f_2(x))$ ,

for  $a \geq 0$ . Verify that the optimal solution  $x^* := \operatorname{argmin} f(x)$  is given as  $x^* = \frac{2a}{1+2a}$ .

#### 1.1 The optimal solution is not a fix point of Local SGD

Consider local SGD with stepsize  $\gamma>0$ , and  $\tau=2$  local steps. Prove that when we start local SGD at  $x_0=x^\star$  we end up at

$$x_2 = x^* + \frac{(a - 2a^2)\gamma^2}{1 + 2a}$$

after the first averaging round.

#### 1.2 Similarity

Based the previous observation, can you derive conditions under which  $x_2 = x^*$ , i.e. the optimal solution is a fixed point? Do these conditions also hold for  $\tau > 2$  local steps?

*Proof.* By setting the gradient to zero,  $0 = \nabla f_1(x^*) + \nabla f_2(x^*) = x^* + 2a(x^*-1)$  we deduce  $x^* = \frac{2a}{1+2a}$ .

Compute first the local iterates after two steps of local SGD, but before averaging. In the lecture we denoted these iterates as  $x_2^{(i)'}$ , for  $i \in \{1,2\}$ . We obtain:

$$x_2^{(1)'} = (1 - \gamma)^2 x_0 = (1 - \gamma)^2 \frac{2a}{1 + 2a}$$
$$x_2^{(2)'} = 1 + (1 - a\gamma)^2 (x_0 - 1) = 1 - \frac{(1 - a\gamma)^2}{1 + 2a}$$

and finally

$$x_2 = \frac{1}{2} \left( x_2^{(1)'} + x_2^{(2)'} \right) = \frac{2a}{1+2a} + \frac{(a-2a^2)\gamma^2}{1+2a} = x^* \left( 1 + \frac{(1-2a)\gamma^2}{2} \right).$$

From this we see that when  $a=\frac{1}{2}$ , then  $x^*$  is a fix point.

## 2 Verify the proof of the Local SGD Theorem (general case):

In the lecture, we left out two steps:

• Plugging the (Difference) lemma into the (Decrease) lemma, and rearranging the terms to obtain

$$\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E} \left\| \nabla f(\bar{\mathbf{x}}_t) \right\|^2 = \mathcal{O} \left( \frac{\Delta}{\gamma T} + \gamma L \frac{\sigma^2}{n} + \gamma^2 L^2 (\tau^2 \zeta^2 + \tau \sigma^2) \right)$$

• And the tuning of the stepsize (with respect to the constraint  $\gamma \leq \frac{1}{10L\tau}$ ).

Proof. Recall the (Decrease) lemma

$$\mathbb{E}[f(\bar{\mathbf{x}}_{t+1})] \leq \mathbb{E}[f(\bar{\mathbf{x}}_{t})] - \frac{\gamma}{4} \mathbb{E}[||\nabla f(\bar{\mathbf{x}}_{t})||^{2}] + \gamma^{2} L \frac{\sigma^{2}}{n} + \gamma \frac{L^{2}}{n} \sum_{i=1}^{n} \mathbb{E}[||\mathbf{x}_{t}^{(i)} - \bar{\mathbf{x}}_{t}||^{2}]$$

and the (Difference) lemma

$$\mathbb{E}\left[\frac{1}{n}\sum_{i=1}^{n}||\mathbf{x}_{t}^{(i)} - \bar{\mathbf{x}}_{t}||^{2}\right] \leq \frac{1}{10L^{2}\tau}\sum_{j=(t-1)-k}^{t-1}\mathbb{E}[||\nabla f(\bar{\mathbf{x}}_{j})||^{2}] + 5\gamma^{2}\sigma^{2}\tau + 40\gamma^{2}\tau^{2}\zeta^{2}$$

Plug (Difference) into (Decrease), rearrange and divide by  $\gamma$ 

$$\frac{1}{4}\mathbb{E}[||\nabla f(\bar{\mathbf{x}}_t)||^2] \leq \frac{1}{\gamma}(\mathbb{E}[f(\bar{\mathbf{x}}_t)] - \mathbb{E}[f(\bar{\mathbf{x}}_{t+1})]) + \gamma L \frac{\sigma^2}{n} + \frac{1}{10\tau} \sum_{j=(t-1)-k}^{t-1} \mathbb{E}[||\nabla f(\bar{\mathbf{x}}_j)||^2] + 5\gamma^2 L^2 \sigma^2 \tau + 40\gamma^2 L^2 \tau^2 \zeta^2$$

Divide by T and sum over t = 0, ..., T - 1

$$\frac{1}{4T} \sum_{t=0}^{T-1} \mathbb{E}[||\nabla f(\bar{\mathbf{x}}_t)||^2] \leq \frac{f(\mathbf{x}_0) - f^*}{\gamma T} + \frac{1}{10T} \sum_{t=0}^{T-1} \mathbb{E}[||\nabla f(\bar{\mathbf{x}}_t)||^2] + \gamma L \frac{\sigma^2}{n} + 5\gamma^2 L^2 \sigma^2 \tau + 40\gamma^2 L^2 \tau^2 \zeta^2$$

Use  $\frac{1}{4T} - \frac{1}{10T} \geq \frac{1}{8T}$  and rearrange

$$\frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[||\nabla f(\bar{\mathbf{x}}_t)||^2] \leq 8 \frac{f(\mathbf{x}_0) - f^*}{\gamma T} + 8\gamma L \frac{\sigma^2}{n} + 40\gamma^2 L^2 \sigma^2 \tau + 320\gamma^2 L^2 \tau^2 \zeta^2$$

$$= \mathcal{O}\left(\frac{\Delta}{\gamma T} + \gamma L \frac{\sigma^2}{n} + \gamma^2 L^2 (\tau^2 \zeta^2 + \tau \sigma^2)\right)$$

Use Exercise 8.1 with  $A=\Delta$ ,  $B=\frac{L\sigma^2}{n}$ ,  $C=L^2(\tau^2\zeta^2+\tau\sigma^2)$  and  $D=L\tau$  gives

$$\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[||\nabla f(\bar{\mathbf{x}}_t)||^2] \leq \mathcal{O}\left(\frac{\Delta L \tau}{T} + \left(\frac{L\Delta(\tau\zeta + \sqrt{\tau}\sigma)}{T}\right)^{\frac{2}{3}} + \frac{\sqrt{L\Delta\sigma^2}}{\sqrt{Tn}}\right)$$