

# Supplemental Material of Paper “Adaptive Proximal Average based Variance Reducing Stochastic Methods for Optimization with Composite Regularization”

## 1 Proof of Lemma 2.

In this section, we give the proof of Lemma 2. In the  $s$ -th outer loop, we denote  $\hat{x}_s^*$  as the minimum of the approximated function  $\hat{F}$ ,  $x_s^l$  as  $x$  in the  $l$ -th inner loop. Besides, we adopt  $\gamma_s = \rho^s/3L$  and  $c_s = \frac{3L}{2(1-\mu\gamma_s)n}$  as stated in the main body.

**Lemma 2.** Suppose that Assumptions 1, 2 and 3 hold and the radius of the iterate set  $\{x^k\}_{k=0,1,2,\dots}$  defined by

$$R := \sup_{k=0,1,2,\dots} \|x^k - x^*\|$$

is bounded, that is,  $R < +\infty$ . Then the following inequality holds

$$T_{s+1}^0 \leq T_s^m + \rho^{s/2} \cdot D_1 + \rho^s \cdot D_2, \quad (1)$$

where  $D_1 = 2RL(1 + \frac{9L}{(3L-\mu)n})\sqrt{\frac{\bar{L}^2}{\mu}}$ ,  $D_2 = 4L(1 + \frac{9L}{2(3L-\mu)n})\frac{\bar{L}^2}{\mu}$ .

*Proof.* By the definition of  $T_s^k$ , we have

$$T_s^m = \frac{1}{n} \sum_{i=1}^n f_i(x_i^k) - f(\hat{x}_s^*) - \frac{1}{n} \sum_{i=1}^n \langle \nabla f_i(\hat{x}_s^*), x_i^k - \hat{x}_s^* \rangle + c_s \|x_s^m - \hat{x}_s^*\|^2, \quad (2)$$

and

$$T_{s+1}^0 = \frac{1}{n} \sum_{i=1}^n f_i(x_i^0) - f(\hat{x}_{s+1}^*) - \frac{1}{n} \sum_{i=1}^n \langle \nabla f_i(\hat{x}_{s+1}^*), x_i^0 - \hat{x}_{s+1}^* \rangle + c_{s+1} \|x_{s+1}^0 - \hat{x}_{s+1}^*\|^2. \quad (3)$$

Since  $x_s^m = x_{s+1}^0$  and  $x_i^k$  in (2) is the same value as  $x_i^0$  in (3), it holds that

$$\begin{aligned} T_{s+1}^0 - T_s^m &= f(\hat{x}_s^*) - f(\hat{x}_{s+1}^*) + \frac{1}{n} \sum_{i=1}^n \langle \nabla f_i(\hat{x}_s^*), x_i - \hat{x}_s^* \rangle \\ &\quad - \frac{1}{n} \sum_{i=1}^n \langle \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_{s+1}^* \rangle + c_{s+1} \|x_{s+1}^0 - \hat{x}_{s+1}^*\|^2 - c_s \|x_s^m - \hat{x}_s^*\|^2. \end{aligned} \quad (4)$$

We combine the two inner product terms on the right side:

$$\begin{aligned} &\langle \nabla f_i(\hat{x}_s^*), x_i - \hat{x}_s^* \rangle - \langle \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_{s+1}^* \rangle \\ &= \langle \nabla f_i(\hat{x}_s^*) - \nabla f_i(\hat{x}_{s+1}^*) + \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_s^* \rangle - \langle \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_{s+1}^* \rangle \\ &= \langle \nabla f_i(\hat{x}_s^*) - \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_s^* \rangle + \langle \nabla f_i(\hat{x}_{s+1}^*), \hat{x}_{s+1}^* - \hat{x}_s^* \rangle, \end{aligned} \quad (5)$$

where  $\langle \nabla f_i(\hat{x}_s^*) - \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_s^* \rangle$  can be bounded by

$$\begin{aligned}
& \langle \nabla f_i(\hat{x}_s^*) - \nabla f_i(\hat{x}_{s+1}^*), x_i - \hat{x}_s^* \rangle \\
& \leq \|\nabla f_i(\hat{x}_s^*) - \nabla f_i(\hat{x}_{s+1}^*)\| \cdot \|x_i - \hat{x}_s^*\| \\
& \leq \|\nabla f_i(\hat{x}_s^*) - \nabla f_i(\hat{x}_{s+1}^*)\| \cdot (\|x_i - x^*\| + \|\hat{x}_s^* - x^*\|) \\
& \leq L\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \cdot (R + \|\hat{x}_s^* - x^*\|),
\end{aligned} \tag{6}$$

the last inequality holds since  $f_i$  is  $L$ -smooth, and  $\langle \nabla f_i(\hat{x}_{s+1}^*), \hat{x}_{s+1}^* - \hat{x}_s^* \rangle$  can be bounded by

$$\langle \nabla f_i(\hat{x}_{s+1}^*), \hat{x}_{s+1}^* - \hat{x}_s^* \rangle \leq -f_i(\hat{x}_s^*) + f_i(\hat{x}_{s+1}^*) + \frac{L}{2}\|\hat{x}_s^* - \hat{x}_{s+1}^*\|^2, \tag{7}$$

which is also due to the property that  $f_i$  is  $L$ -smooth. Meanwhile, we have

$$\begin{aligned}
& c_{s+1}\|x_{s+1}^0 - \hat{x}_{s+1}^*\|^2 - c_s\|x_s^m - \hat{x}_s^*\|^2 \\
& \leq c_s\|x_{s+1}^0 - \hat{x}_{s+1}^*\|^2 - c_s\|x_s^m - \hat{x}_s^*\|^2 \\
& = c_s\langle \hat{x}_s^* - \hat{x}_{s+1}^*, x_{s+1}^0 + x_s^m - \hat{x}_{s+1}^* - \hat{x}_s^* \rangle \\
& \leq c_s\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \cdot \|x_{s+1}^0 + x_s^m - \hat{x}_{s+1}^* - \hat{x}_s^*\| \\
& \leq c_s\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \cdot (\|x_{s+1}^0 - x^*\| + \|\hat{x}_{s+1}^* - x^*\| + \|x_s^m - x^*\| + \|\hat{x}_s^* - x^*\|) \\
& \leq c_s\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \cdot (2R + \|\hat{x}_{s+1}^* - x^*\| + \|\hat{x}_s^* - x^*\|),
\end{aligned} \tag{8}$$

the last inequality holds due to the assumption that  $\|x^k - x^*\|_{k=0,1,2,\dots}$  is not greater than  $R$  and  $R < +\infty$ . Plugging (5), (6), (7) and (8) into (4) yields

$$\begin{aligned}
T_{s+1}^0 - T_s^m & \leq L\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \cdot (R + \|\hat{x}_s^* - x^*\|) + \frac{L}{2}\|\hat{x}_s^* - \hat{x}_{s+1}^*\|^2 \\
& \quad + c_s\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \cdot (2R + \|\hat{x}_{s+1}^* - x^*\| + \|\hat{x}_s^* - x^*\|).
\end{aligned} \tag{9}$$

We further bound  $\|\hat{x}_s^* - x^*\|^2$  by

$$\|\hat{x}_s^* - x^*\|^2 \leq \frac{2}{\mu}(F(\hat{x}_s^*) - F(x^*)) \leq \frac{2}{\mu}(F(\hat{x}_s^*) - \hat{F}(\hat{x}_s^*)) \leq \frac{\bar{L}^2}{\mu}\gamma_s, \tag{10}$$

where the three inequalities are due to the strong convexity of  $F$ , the fact that  $F(x^*) \geq \hat{F}(x^*) \geq \hat{F}(\hat{x}_s^*)$ , and Lemma 1 respectively. Bounding  $\|\hat{x}_{s+1}^* - x^*\|^2$  in the same way as (10), we get

$$\|\hat{x}_{s+1}^* - x^*\|^2 \leq \frac{\bar{L}^2}{\mu}\gamma_{s+1}, \tag{11}$$

Note that  $\|\hat{x}_s^* - \hat{x}_{s+1}^*\| \leq \|\hat{x}_s^* - x^*\| + \|\hat{x}_{s+1}^* - x^*\|$ ,  $\|\hat{x}_s^* - \hat{x}_{s+1}^*\|^2 \leq 2\|\hat{x}_s^* - x^*\|^2 + 2\|\hat{x}_{s+1}^* - x^*\|^2$  and  $\gamma_{s+1} \leq \gamma_s$ . Plugging the above three inequalities, (10) and (11) into (9), we get

$$\begin{aligned}
T_{s+1}^0 - T_s^m & \leq L \cdot 2\sqrt{\frac{\bar{L}^2}{\mu}\gamma_s} \cdot (R + \sqrt{\frac{\bar{L}^2}{\mu}\gamma_s}) + \frac{L}{2} \cdot 4\frac{\bar{L}^2}{\mu}\gamma_s \\
& \quad + c_s \cdot 2\sqrt{\frac{\bar{L}^2}{\mu}\gamma_s} \cdot (2R + 2\sqrt{\frac{\bar{L}^2}{\mu}\gamma_s}) \\
& = (2LR + 4Rc_s)\sqrt{\frac{\bar{L}^2}{\mu}\gamma_s} + 4(L + c_s)\frac{\bar{L}^2}{\mu}\gamma_s \\
& \leq 2RL(1 + \frac{9L}{(3L - \mu)n})\sqrt{\frac{\bar{L}^2}{\mu}\rho^{s/2}} + 4L(1 + \frac{9L}{2(3L - \mu)n})\frac{\bar{L}^2}{\mu}\rho^s.
\end{aligned}$$

□

## 2 Proof of Theorem 2.

**Theorem 2** (APA-SAGA). *Under the same assumptions of Lemma 2, the following inequality holds*

$$\begin{aligned} & \mathbb{E}\|x_s - x^*\|^2 \\ & \leq \frac{4n}{3L}T_0^0 \cdot \theta^{s+1} + \frac{\bar{L}^2}{\mu} \frac{2}{3L}\rho^s + \theta \frac{\theta^s - \rho^{s/2}}{\theta - \rho^{1/2}} \cdot \frac{4n}{3L}D_1 + \theta \frac{\theta^s - \rho^s}{\theta - \rho} \cdot \frac{4n}{3L}D_2. \end{aligned} \quad (12)$$

*Proof.* By Young's inequality, it holds that

$$\|x_s - x^*\|^2 \leq 2\|x_s - \hat{x}_s^*\|^2 + 2\|\hat{x}_s^* - x^*\|^2, \quad (13)$$

we bound the two terms on the right side respectively. The first term can be bounded by

$$\|\hat{x}_s^* - x^*\|^2 \leq \frac{2}{\mu}(F(\hat{x}_s^*) - F(x^*)) \leq \frac{2}{\mu}(F(\hat{x}_s^*) - \hat{F}(\hat{x}_s^*)) \leq \frac{\bar{L}^2}{\mu}\gamma_s, \quad (14)$$

where the three inequalities are due to the strong convexity of  $F$ , the fact that  $F(x^*) \geq \hat{F}(x^*) \geq \hat{F}(\hat{x}_s^*)$ , and Lemma 1 respectively.

Meanwhile, according to Lemma 2, we have

$$\mathbb{E}T_s^m \leq \theta \cdot \mathbb{E}T_s^0 \leq \theta \cdot \mathbb{E}(T_{s-1}^m + \rho^{(s-1)/2}D_1 + \rho^{s-1}D_2).$$

Summing the above inequality over  $0, 1, \dots, s$ , we get

$$\begin{aligned} \mathbb{E}T_s^m & \leq \theta^s \cdot \mathbb{E}T_0^m + (\theta\rho^{s-1} + \theta^2\rho^{s-2} + \dots + \theta^s) \cdot D_2 \\ & \quad + (\theta\rho^{(s-1)/2} + \theta^2\rho^{(s-2)/2} + \dots + \theta^s) \cdot D_1 \\ & \leq \theta^{s+1} \cdot T_0^0 + D_2 \cdot \theta \frac{\theta^s - \rho^s}{\theta - \rho} + D_1 \cdot \theta \frac{\theta^s - \rho^{s/2}}{\theta - \rho^{1/2}}. \end{aligned} \quad (15)$$

Note that  $c\|x_s - \hat{x}_s^*\| \leq T_s^m$  and  $c \geq \frac{3L}{2n}$ , we can further deduce from (15) that

$$\mathbb{E}\|x_s - \hat{x}_s^*\|^2 \leq \frac{2n}{3L}T_0^0 \cdot \theta^{s+1} + \theta \frac{\theta^s - \rho^{s/2}}{\theta - \rho^{1/2}} \cdot \frac{2n}{3L}D_1 + \theta \frac{\theta^s - \rho^s}{\theta - \rho} \cdot \frac{2n}{3L}D_2. \quad (16)$$

Plugging (14) and (16) into (13) with taking expectation on each term leads to the result and completes the proof.  $\square$