

## Appendix: Supplemental Figures for Experiment

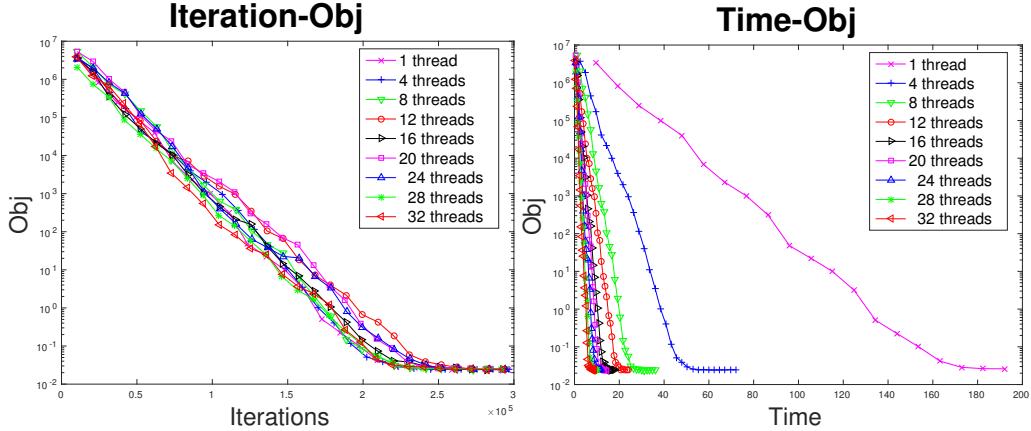


Figure 1: Deep neural network for synthetic data using Algorithm 1. The Algorithm 1 algorithm is run on various numbers of machines from 1 to 32. The curves of the objective loss against the number of iteration and the running time are drawn in the left and the right graphs respectively.

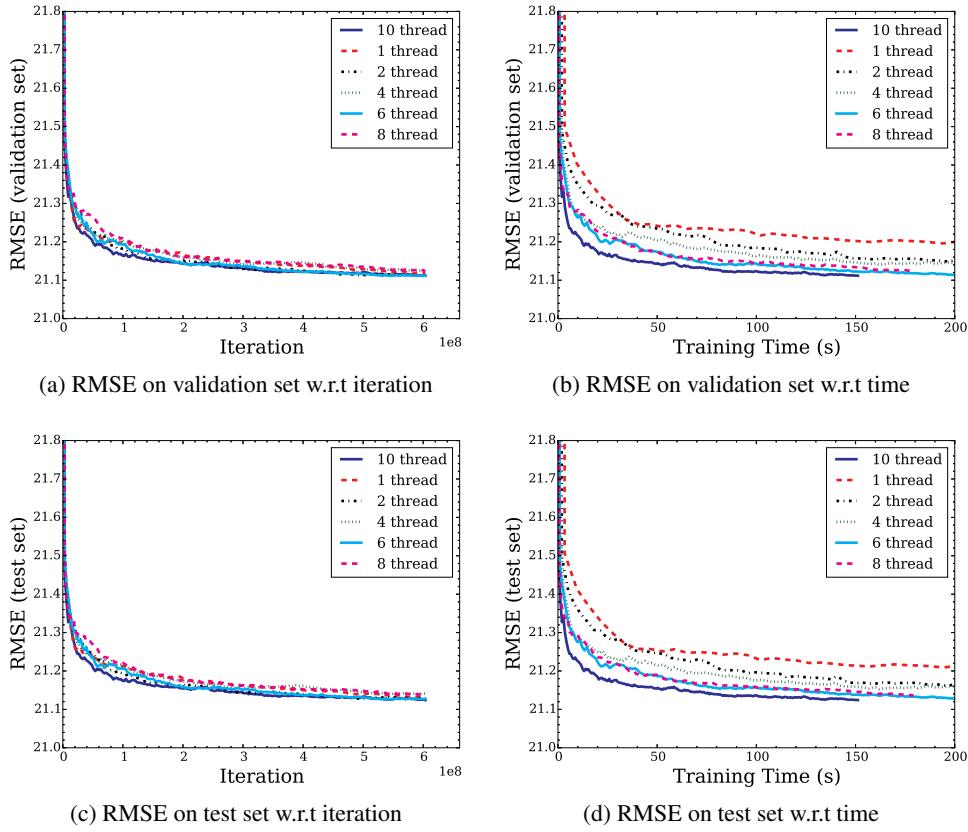


Figure 2: Model blending with Yahoo! Music test data set using ASZD.

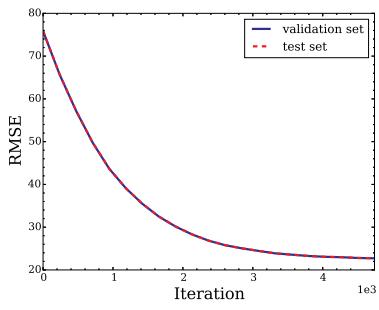


Figure 3: We zoom in for the first a few thousands iterations in Figure 2. Our algorithm quickly approaches to a reasonable RMSE.

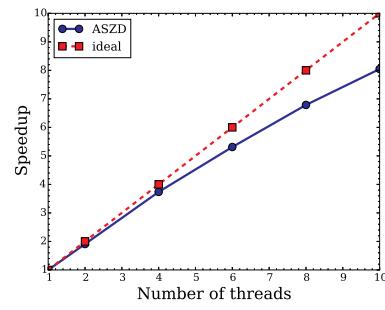


Figure 4: Running time speedup of Algorithm 1 is almost linear. On a 10-core machine we can achieve a 8x speedup.

## Supplemental Materials for Proofs

We first show some preliminary results about the dependence between the zeroth-order gradient and the true gradient, and then prove the convergence property for GASA (Algorithm 1).

### 1 Preliminary results

Given a function  $p(x) : \mathbb{R}^N \rightarrow \mathbb{R}$  and a predefined approximation parameter vector  $(\mu_1, \mu_2, \dots, \mu_N)^\top \in \mathbb{R}_{++}^N$ , we define the smoothing function of  $p(x)$  with respect to the  $i$ th dimension:

$$p_i(x) := \mathbb{E}_{\{v \sim U_{[-\mu_i, \mu_i]}\}}(p(x + ve_i)) = \frac{1}{2\mu_i} \int_{-\mu_i}^{\mu_i} p(x + ve_i) dv = \frac{1}{2} \int_{-1}^1 p(x + v\mu_i e_i) dv. \quad (22)$$

where  $v \sim U_{[-\mu_i, \mu_i]}$  means that  $v$  follows the uniform distribution over the range  $[-\mu_i, \mu_i]$ .  $\nabla_x$  and  $\nabla_v$  denote taking gradient with respect to variable  $x$  and  $v$  respectively.  $\nabla_i$  is short for  $e_i e_i^\top \nabla_x$ .

**Lemma 6** (Zeroth Order Approximation). *Suppose that function  $p(x) : x \in \mathbb{R}^N \rightarrow \mathbb{R}$  has Lipschitzian gradient with parameter  $L$  and  $p(x + ve_i) : v \in \mathbb{R} \rightarrow \mathbb{R}$  has Lipschitzian gradient with parameter  $L_{(i)}$  for all  $x$ . Given an approximation parameter vector  $(\mu_1, \mu_2, \dots, \mu_N)^\top \in \mathbb{R}_{++}^N$ , we have:*

1. *The smoothing function  $p_i$  is differentiable, and also has the Lipschitzian gradient with Lipschitz constant  $L$ .*
2. *For the  $i^{th}$  coordinate,*

$$\nabla_i p_i(x) = \frac{1}{2\mu_i} (p(x + \mu_i e_i) - p(x - \mu_i e_i)) e_i.$$

3. *For any  $x \in \mathbb{R}^N, i \in \{1, \dots, N\}$ , we have*

$$|p_i(x) - p(x)| \leq \frac{L_{(i)}\mu_i^2}{2}, \quad (23)$$

$$\|\nabla_i p_i(x) - \nabla_i p(x)\| \leq \frac{L_{(i)}\mu_i}{2}, \quad (24)$$

$$\mathbb{E}_i \|\nabla_i p_i(x) - \nabla_i p(x)\|^2 \leq \frac{\omega}{4}, \quad (25)$$

where  $\omega$  is defined in (7).

4. *If  $p$  is convex, then  $p_i$  is also convex.*

*Proof.* To prove the first statement, we note that

$$\nabla p_i(x) = \frac{1}{2} \int_{-1}^1 \nabla_x p(x + \mu_i ve_i) dv.$$

Since function  $p(x)$  has Lipschitzian gradient, we have

$$\begin{aligned} \|\nabla p_i(x) - \nabla p_i(y)\| &= \|\mathbb{E}_{\{v \sim U_{[-1,1]}\}}(\nabla p(x + \mu_i ve_i) - \nabla p(y + \mu_i ve_i))\| \\ &\leq \mathbb{E}_{\{v \sim U_{[-1,1]}\}}(L\|x - y\|) \\ &= L\|x - y\|, \end{aligned}$$

which implies the first statement.

To prove the second statement, we have

$$\begin{aligned} \nabla_i p_i(x) &= \frac{1}{2} \left( \int_{-1}^1 \nabla_i p(x + \mu_i ve_i) dv \right) \\ &= \frac{1}{2\mu_i} \left( \int_{-1}^1 \nabla_v p(x + \mu_i ve_i) dv \right) e_i \\ &= \frac{1}{2\mu_i} (p(x + \mu_i e_i) - p(x - \mu_i e_i)) e_i, \end{aligned}$$

where the last step comes from the Stokes' theorem.

Next we prove the third statement. First (23) can be proved by

$$\begin{aligned}
|p_i(x) - p(x)| &\leq \frac{1}{2} \left| \int_{-1}^1 p(x + \mu_i v e_i) - p(x + 0 \mu_i e_i) dv \right| \\
&= \frac{1}{2} \left| \int_{-1}^1 p(x + \mu_i v e_i) - p(x + 0 \mu_i e_i) - \langle \nabla_v p(x), \mu_i v \rangle dv \right| \\
&\leq \frac{1}{2} \int_{-1}^1 |p(x + \mu_i v e_i) - p(x) - \langle \nabla_v p(x), \mu_i v \rangle| dv \\
&\leq \frac{1}{2} \int_{-1}^1 \frac{L_{(i)} \mu_i^2 v^2}{2} dv \\
&\leq \frac{L_{(i)} \mu_i^2}{2},
\end{aligned}$$

where the second step is based on the observation

$$\int_{-1}^1 \langle \nabla_v p(x), \mu_i v \rangle dv = 0,$$

and the second last step uses the assumption that  $p(x + v e_i)$  has Lipschitzian gradient (with constant  $L_{(i)}$ ) with respect to  $v$ . (24) can be proved from

$$\begin{aligned}
\|\nabla_i p_i(x) - \nabla_i p(x)\| &= \left\| \frac{1}{2\mu_i} (p(x + \mu_i e_i) - p(x - \mu_i e_i)) e_i - \nabla_i p(x) \right\| \\
&= \left\| \frac{1}{2\mu_i} ((p(x + \mu_i e_i) - p(x - \mu_i e_i)) e_i - 2\mu_i \nabla_i p(x)) \right\| \\
&\leq \left\| \frac{1}{2\mu_i} ((p(x + \mu_i e_i) - p(x)) e_i - \mu_i \nabla_i p(x)) \right\| \\
&\quad + \left\| \frac{1}{2\mu_i} ((p(x) - p(x - \mu_i e_i)) e_i - \mu_i \nabla_i p(x)) \right\| \\
&\leq \frac{1}{2\mu_i} L_{(i)} \mu_i^2 = \frac{L_{(i)} \mu_i}{2}.
\end{aligned}$$

(25) can be proved by

$$\mathbb{E}_i \|\nabla_i p_i(x) - \nabla_i p(x)\|^2 \stackrel{(24)}{\leq} \sum_i \frac{L_{(i)}^2 \mu_i^2}{4N} = \frac{\omega}{4}.$$

For the last statement, given any  $\theta \in [0, 1]$ , we have

$$\begin{aligned}
\theta p_i(x) + (1 - \theta) p_i(y) &= \frac{1}{2} \int_{-1}^1 \theta p(x + \mu_i v e_i) + (1 - \theta) p(y + \mu_i v e_i) dv \\
&\geq \frac{1}{2} \int_{-1}^1 p(\theta x + (1 - \theta)y + \mu_i v e_i) dv \\
&= p_i(\theta x + (1 - \theta)y).
\end{aligned}$$

It proves the convexity of  $p_i(x)$ .  $\square$

## .2 Proofs to Theorem 1

We first prove the general convergence property for Algorithm 1 and then apply it to prove Theorem 1.

**Theorem 7** (Convergence). *If the stepsize  $\gamma_k$  in Algorithm 1 is appropriately chosen to satisfy*

$$\Theta_k := \frac{N\gamma_k}{2} - 2\gamma_k^2 \frac{L_Y}{Y} N^2 - 2L_T^2 \frac{N^2}{Y^2} \gamma_k \sum_{\nu=1}^T \gamma_{k+\nu} \left( \gamma_k Y + \frac{Y^{3/2} \sum_{j' \in J(k+\nu) \setminus \{k\}} \gamma_{j'}}{\sqrt{N}} \right) \geq 0, \forall k, \quad (26)$$

we have

$$\begin{aligned} \frac{1}{2} \sum_{k=0}^K \gamma_k \mathbb{E} \|\nabla f(x_k)\|^2 &\leq f(x_0) - f^* + 2N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{k=0}^K \left( \gamma_k \sum_{j \in J(k)} \gamma_j^2 \right) \\ &\quad + \left( \frac{L_Y}{Y} N\sigma^2 + \frac{L_Y}{Y} N^2 \omega \right) \sum_{k=0}^K \gamma_k^2 + \frac{1}{4} N\omega \sum_{k=0}^K \gamma_k. \end{aligned}$$

*Proof.* Besides of (3), we introduce one more notation here to abbreviate the notation:

$$G_i(x; \xi) = \frac{N}{2\mu_i} (F(x + \mu_i e_i; \xi) - F(x - \mu_i e_i; \xi)) e_i.$$

Note that  $G_i(x; \xi) = N \nabla_i F_i(x; \xi)$  for any  $x$  and  $\xi$ , where  $F_i(\cdot; \xi)$  is defined using the same way in (22) for  $p = F(\cdot; \xi)$ . We first highlight a frequently used inequality in the subsequent proof:

$$\|a + b\|^2 \leq 2\|a\|^2 + 2\|b\|^2. \quad (27)$$

We then start from the Lipschitzian property of  $f(\cdot)$ :

$$\begin{aligned} f(x_{k+1}) - f(x_k) &\leq \langle \nabla_{S_k} f(x_k), x_{k+1} - x_k \rangle + \frac{L_Y}{2} \|x_{k+1} - x_k\|^2 \\ &= -\gamma_k \langle \nabla_{S_k} f(x_k), G_{S_k}(\hat{x}_k; \xi_k) \rangle \\ &\quad + \frac{1}{2} \gamma_k^2 L_Y \|G_{S_k}(\hat{x}_k; \xi_k)\|^2 \\ &\stackrel{(27)}{\leq} -\gamma_k \langle \nabla_{S_k} f(x_k), G_{S_k}(\hat{x}_k; \xi_k) \rangle \\ &\quad + \gamma_k^2 L_Y \left\| \frac{N}{Y} \nabla_{S_k} F(\hat{x}_k; \xi_k) \right\|^2 \\ &\quad + \gamma_k^2 L_Y \left\| G_{S_k}(\hat{x}_k; \xi_k) - \frac{N}{Y} \nabla_{S_k} F(\hat{x}_k; \xi_k) \right\|^2. \end{aligned} \quad (28)$$

Next we consider the expectation of three items of the right hand side of (28). Let  $\{i_k\}_{k=0}^K$  be independent random variables uniformly distributed over  $\{1, \dots, N\}$ . Note that  $i_k$  is just a dummy random variable independent of all  $S_k$ 's. Let  $\Omega_k$  be the set consisting of all possible  $S_k$ 's. With this new variable, we can rewrite  $\mathbb{E}_{S_k} \langle \nabla_{S_k} f(x_k), G_{S_k}(\hat{x}_k; \xi_k) \rangle$  by

$$\begin{aligned} &\mathbb{E}_{S_k} \langle \nabla_{S_k} f(x_k), G_{S_k}(\hat{x}_k; \xi_k) \rangle \\ &= \frac{1}{Y} \mathbb{E}_{S_k} \sum_{m \in S_k} \langle \nabla_m f(x_k), G_m(\hat{x}_k; \xi_k) \rangle \\ &= \frac{1}{Y |\Omega_k|} \sum_{S \in \Omega_k} \sum_{m \in S} \langle \nabla_m f(x_k), G_m(\hat{x}_k; \xi_k) \rangle \\ &= \frac{1}{Y |\Omega_k|} \frac{|\Omega_k| Y}{N} \left\langle \nabla f(x_k), \sum_{n \in [N]} G_n(\hat{x}_k; \xi_k) \right\rangle \\ &= \frac{1}{Y} Y \mathbb{E}_{i_k} \langle \nabla_{i_k} f(x_k), G_{i_k}(\hat{x}_k; \xi_k) \rangle \\ &= \mathbb{E}_{i_k} \langle \nabla_{i_k} f(x_k), G_{i_k}(\hat{x}_k; \xi_k) \rangle, \end{aligned} \quad (29)$$

where the second last step is due to the fact that  $S_k$  is selected uniformly randomly. Following similar derivation yields:

$$\begin{aligned} \mathbb{E}_{S_k} \left\| \frac{N}{Y} \nabla_{S_k} F(\hat{x}_k; \xi_k) \right\|^2 &= \frac{N^2}{Y^2} \mathbb{E}_{S_k} \sum_{m \in S_k} \|\nabla_m F(\hat{x}_k; \xi_k)\|^2 \\ &= \frac{N^2}{Y^2} Y \mathbb{E}_{i_k} \|\nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2 \end{aligned}$$

$$\begin{aligned}
&= \frac{N^2}{Y} \mathbb{E}_{i_k} \|\nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2 \\
&= \frac{1}{Y} \mathbb{E}_{i_k} \|N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2,
\end{aligned} \tag{30}$$

and

$$\begin{aligned}
&\mathbb{E}_{S_k} \left\| G_{S_k}(\hat{x}_k; \xi_k) - \frac{N}{Y} \nabla_{S_k} F(\hat{x}_k; \xi_k) \right\|^2 \\
&= \mathbb{E}_{S_k} \sum_{m \in S_k} \left\| \frac{1}{Y} G_m(\hat{x}_k; \xi_k) - \frac{N}{Y} \nabla_m F(\hat{x}_k; \xi_k) \right\|^2 \\
&= \frac{1}{Y^2} \mathbb{E}_{S_k} \sum_{m \in S_k} \|G_m(\hat{x}_k; \xi_k) - N \nabla_m F(\hat{x}_k; \xi_k)\|^2 \\
&= \frac{1}{Y^2} Y \mathbb{E}_{i_k} \|G_{i_k}(\hat{x}_k; \xi_k) - N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2 \\
&= \frac{1}{Y} \mathbb{E}_{i_k} \|G_{i_k}(\hat{x}_k; \xi_k) - N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2.
\end{aligned} \tag{31}$$

We give two more equalities which will be used soon in the following:

$$\begin{aligned}
\mathbb{E}_{\xi_k} \|\nabla F(\hat{x}_k; \xi_k)\|^2 &= \mathbb{E}_{\xi_k} (\|\nabla F(\hat{x}_k; \xi_k) - \nabla f(\hat{x}_k) + \nabla f(\hat{x}_k)\|^2) \\
&= \mathbb{E}_{\xi_k} (\|\nabla F(\hat{x}_k; \xi_k) - \nabla f(\hat{x}_k)\|^2 + \|\nabla f(\hat{x}_k)\|^2) \\
&\quad + 2 \mathbb{E}_{\xi_k} \langle \nabla F(\hat{x}_k; \xi_k) - \nabla f(\hat{x}_k), \nabla f(\hat{x}_k) \rangle \\
&= \mathbb{E}_{\xi_k} (\|\nabla F(\hat{x}_k; \xi_k) - \nabla f(\hat{x}_k)\|^2 + \|\nabla f(\hat{x}_k)\|^2) \\
&\quad + 2 \langle \nabla f(\hat{x}_k) - \nabla f(\hat{x}_k), \nabla f(\hat{x}_k) \rangle \\
&= \mathbb{E}_{\xi_k} (\|\nabla F(\hat{x}_k; \xi_k) - \nabla f(\hat{x}_k)\|^2 + \|\nabla f(\hat{x}_k)\|^2),
\end{aligned} \tag{32}$$

and

$$\begin{aligned}
&-2 \langle \nabla_{i_k} f(x_k), \nabla_{i_k} f_{i_k}(\hat{x}_k) \rangle \\
&= \|\nabla_{i_k} f(x_k) - \nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 - \|\nabla_{i_k} f(x_k)\|^2 - \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2.
\end{aligned} \tag{33}$$

We then put (29), (30), (31) into (28):

$$\begin{aligned}
\mathbb{E}_{\xi_k, S_k} (f(x_{k+1}) - f(x_k)) &\leq -\gamma_k \mathbb{E}_{\xi_k, i_k} \langle \nabla_{i_k} f(x_k), G_{i_k}(\hat{x}_k; \xi_k) \rangle \\
&\quad + \gamma_k^2 \frac{L_Y}{Y} \mathbb{E}_{\xi_k, i_k} \|N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2 \\
&\quad + \gamma_k^2 \frac{L_Y}{Y} \mathbb{E}_{\xi_k, i_k} \|G_{i_k}(\hat{x}_k; \xi_k) - N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2 \\
&= -\gamma_k \mathbb{E}_{i_k} \langle \nabla_{i_k} f(x_k), N \nabla_{i_k} f_{i_k}(\hat{x}_k) \rangle \\
&\quad + \gamma_k^2 \frac{L_Y}{Y} N \mathbb{E}_{\xi_k} \|\nabla F(\hat{x}_k; \xi_k)\|^2 \\
&\quad + \gamma_k^2 \frac{L_Y}{Y} \mathbb{E}_{\xi_k, i_k} \|G_{i_k}(\hat{x}_k; \xi_k) - N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2 \\
&\stackrel{(32)}{=} -\gamma_k N \mathbb{E}_{i_k} \langle \nabla_{i_k} f(x_k), \nabla_{i_k} f_{i_k}(\hat{x}_k) \rangle \\
&\quad + \gamma_k^2 \frac{L_Y}{Y} N \underbrace{(\mathbb{E}_{\xi_k} \|\nabla F(\hat{x}_k; \xi_k) - \nabla f(\hat{x}_k)\|^2 + \|\nabla f(\hat{x}_k)\|^2)}_{\leq \sigma^2} \\
&\quad + \gamma_k^2 \frac{L_Y}{Y} \underbrace{\mathbb{E}_{\xi_k, i_k} \|G_{i_k}(\hat{x}_k; \xi_k) - N \nabla_{i_k} F(\hat{x}_k; \xi_k)\|^2}_{\leq N^2 \omega / 4 \text{ from (25)}} \\
&\stackrel{(33)}{\leq} -\frac{\gamma_k}{2} \left( \|\nabla f(x_k)\|^2 + N \mathbb{E}_{i_k} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \right) \\
&\quad + \frac{\gamma_k}{2} N \underbrace{\mathbb{E}_{i_k} \|\nabla_{i_k} f(x_k) - \nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2}_{=: T_1}
\end{aligned}$$

$$\begin{aligned}
& + \gamma_k^2 \frac{L_Y}{Y} N(\sigma^2 + \|\nabla f(\hat{x}_k)\|^2) \\
& + \gamma_k^2 \frac{L_Y}{Y} N^2 \frac{\omega}{4}.
\end{aligned} \tag{34}$$

Then we study the upper bound for  $T_1$ :

$$\begin{aligned}
T_1 &= \mathbb{E}_{i_k} \|\nabla_{i_k} f(x_k) - \nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\
&= \mathbb{E}_{i_k} \|\nabla_{i_k} f(x_k) - \nabla_{i_k} f(\hat{x}_k) + \nabla_{i_k} f(\hat{x}_k) - \nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\
&\stackrel{(27)}{\leq} 2\mathbb{E}_{i_k} \left( \|\nabla_{i_k} f(x_k) - \nabla_{i_k} f(\hat{x}_k)\|^2 + \|\nabla_{i_k} f(\hat{x}_k) - \nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \right) \\
&\stackrel{(25)}{\leq} 2\mathbb{E}_{i_k} \|\nabla_{i_k} f(x_k) - \nabla_{i_k} f(\hat{x}_k)\|^2 + \frac{\omega}{2} \\
&\leq \frac{2}{N} L_T^2 \|x_k - \hat{x}_k\|^2 + \frac{\omega}{2} \\
&= \frac{2}{N} L_T^2 \underbrace{\left\| \sum_{j \in J(k)} (x_{j+1} - x_j) \right\|^2}_{=: T_2} + \frac{\omega}{2}.
\end{aligned} \tag{35}$$

We then bound  $T_2$  by

$$\begin{aligned}
\mathbb{E}(T_2) &= \mathbb{E} \left\| \sum_{j \in J(k)} (x_{j+1} - x_j) \right\|^2 \\
&= \mathbb{E} \left\| \sum_{j \in J(k)} \gamma_j G_{S_j}(\hat{x}_j; \xi_j) \right\|^2 \\
&= \mathbb{E} \left\| \sum_{j \in J(k)} \left( \gamma_j \left( G_{S_j}(\hat{x}_j; \xi_j) - \frac{N}{Y} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right) + \frac{N}{Y} \sum_{m \in S_j} \gamma_j \nabla_m f_m(\hat{x}_j) \right) \right\|^2 \\
&\stackrel{(27)}{\leq} 2\mathbb{E} \underbrace{\left\| \sum_{j \in J(k)} \gamma_j \left( G_{S_j}(\hat{x}_j; \xi_j) - \frac{N}{Y} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right) \right\|^2}_{=: T_3} \\
&\quad + 2 \frac{N^2}{Y^2} \mathbb{E} \underbrace{\left\| \sum_{j \in J(k)} \gamma_j \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right\|^2}_{=: T_4}.
\end{aligned} \tag{36}$$

Next we show the upper bounds for  $\mathbb{E}(T_4)$  and  $\mathbb{E}(T_3)$  respectively:

$$\begin{aligned}
& \mathbb{E}(T_4) \\
&= \mathbb{E} \left\| \sum_{j \in J(k)} \gamma_j \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right\|^2 \\
&= \mathbb{E} \left( \sum_{j \in J(k)} \gamma_j^2 \left\| \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right\|^2 \right) \\
&\quad + 2\mathbb{E} \left( \sum_{j, j' \in J(k), j > j'} \gamma_j \gamma_{j'} \left( \left\langle \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j), \sum_{m' \in S_{j'}} \nabla_{m'} f_{m'}(\hat{x}_{j'}) \right\rangle \right) \right)
\end{aligned}$$

$$\begin{aligned}
&= \mathbb{E} \left( \sum_{j \in J(k)} \gamma_j^2 Y \mathbb{E}_{i_j} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 \right) \\
&\quad + 2 \mathbb{E} \left( \sum_{j, j' \in J(k), j > j'} \gamma_j \gamma_{j'} \left\langle \mathbb{E}_{S_j} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j), \sum_{m' \in S_{j'}} \nabla_{m'} f_{m'}(\hat{x}_{j'}) \right\rangle \right) \\
&\leq \sum_{j \in J(k)} \gamma_j^2 Y \mathbb{E} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 \\
&\quad + \mathbb{E} \left( \sum_{j, j' \in J(k), j > j'} \gamma_j \gamma_{j'} \left( \frac{1}{\alpha} \left\| \mathbb{E}_{S_j} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right\|^2 + \alpha \mathbb{E}_{S_{j'}} \left\| \sum_{m' \in S_{j'}} \nabla_{m'} f_{m'}(\hat{x}_{j'}) \right\|^2 \right) \right) \\
&\leq \sum_{j \in J(k)} \gamma_j^2 Y \mathbb{E} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 \\
&\quad + \mathbb{E} \left( \sum_{j, j' \in J(k), j > j'} \gamma_j \gamma_{j'} \left( \frac{1}{\alpha} \| Y \mathbb{E}_{i_j} \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 + \alpha \mathbb{E}_{S_{j'}} \left\| \sum_{m' \in S_{j'}} \nabla_{m'} f_{m'}(\hat{x}_{j'}) \right\|^2 \right) \right) \\
&\leq \sum_{j \in J(k)} \gamma_j^2 Y \mathbb{E} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 \\
&\quad + \mathbb{E} \left( \sum_{j, j' \in J(k), j > j'} \gamma_j \gamma_{j'} \left( \frac{Y^2}{\alpha N} \mathbb{E}_{i_j} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 + \alpha Y \mathbb{E}_{i_{j'}} \| \nabla_{i_{j'}} f_{\mu_{i_{j'}, i_{j'}}}(\hat{x}_{j'}) \|^2 \right) \right) \\
&= \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \alpha Y \sum_{j' > j, j' \in J(k)} \gamma_{j'} + \frac{Y^2 \sum_{j' < j, j' \in J(k)} \gamma_{j'}}{\alpha N} \right) \mathbb{E} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 \\
&= \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \| \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2,
\end{aligned}$$

where we set  $\alpha = \sqrt{Y/N}$  in the last step. We next consider  $\mathbb{E}(T_3)$

$$\begin{aligned}
\mathbb{E}(T_3) &= \mathbb{E} \left( \left\| \sum_{j \in J(k)} \gamma_j \left( G_{S_j}(\hat{x}_j; \xi_j) - \frac{N}{Y} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right) \right\|^2 \right) \\
&= \mathbb{E} \left( \sum_{j \in J(k)} \gamma_j^2 \left\| G_{S_j}(\hat{x}_j; \xi_j) - \frac{N}{Y} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right\|^2 \right) \\
&= \mathbb{E} \left( \sum_{j \in J(k)} \frac{\gamma_j^2}{Y^2} \left\| Y G_{S_j}(\hat{x}_j; \xi_j) - N \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \right\|^2 \right) \\
&= \mathbb{E} \left( \sum_{j \in J(k)} \frac{\gamma_j^2}{Y} \| G_{i_j}(\hat{x}_j; \xi_j) - N \nabla_{i_j} f_{i_j}(\hat{x}_j) \|^2 \right), \tag{37}
\end{aligned}$$

where the last equality is due to the same reason of (31) and the second last equality is from

$$2 \mathbb{E} \left( \sum_{j > j'; j, j' \in J(k)} \gamma_j \gamma_{j'} \langle \Gamma_j, \Gamma_{j'} \rangle \right)$$

$$\begin{aligned}
&= 2\mathbb{E} \left( \sum_{j>j'; j, j' \in J(k)} \gamma_j \gamma_{j'} \left\langle \mathbb{E}_{\xi_j} G_{S_j}(\hat{x}_j; \xi_j) - \frac{N}{Y} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j), \Gamma_{j'} \right\rangle \right) \\
&= 0,
\end{aligned}$$

where

$$\begin{aligned}
\Gamma_j &:= G_{S_j}(\hat{x}_j; \xi_j) - \frac{N}{Y} \sum_{m \in S_j} \nabla_m f_m(\hat{x}_j) \\
\Gamma_{j'} &:= G_{S_{j'}}(\hat{x}_{j'}; \xi_{j'}) - \frac{N}{Y} \sum_{m' \in S_{j'}} \nabla_{m'} f_{m'}(\hat{x}_{j'}).
\end{aligned}$$

Note that we have the following inequality

$$\begin{aligned}
&\mathbb{E}_{\xi, i} \|G_i(x; \xi) - N\nabla_i f_i(x)\|^2 \\
&= \mathbb{E}_{\xi, i} \|G_i(x; \xi) - N\nabla_i F(x; \xi) + N\nabla_i F(x; \xi) - N\nabla_i f(x) + N\nabla_i f(x) - N\nabla_i f_i(x)\|^2 \\
&\leq 3\mathbb{E}_{\xi, i} (\|G_i(x; \xi) - N\nabla_i F(x; \xi)\|^2 + N^2 \|\nabla_i F(x; \xi) - \nabla_i f(x)\|^2 + N^2 \|\nabla_i f(x) - \nabla_i f_i(x)\|^2) \\
&\leq 3\mathbb{E}_{\xi} \left( \frac{N^2 \omega}{2} + N \|\nabla F(x; \xi) - \nabla f(x)\|^2 \right) \\
&\stackrel{(25)}{\leq} \frac{3N^2 \omega}{2} + 3N\sigma^2,
\end{aligned}$$

where the first step uses  $\|a + b + c\|^2 \leq 3(\|a\|^2 + \|b\|^2 + \|c\|^2)$ . Applying it into (37) yields:

$$\mathbb{E}(T_3) \leq \left( \frac{3N^2 \omega}{2Y} + \frac{3N\sigma^2}{Y} \right) \sum_{j \in J(k)} \gamma_j^2,$$

Applying the upper bounds of  $\mathbb{E}(T_3)$  and  $\mathbb{E}(T_4)$  to (36) we obtain

$$\begin{aligned}
\mathbb{E}(T_2) &\leq 2\mathbb{E}(T_3) + 2\frac{N^2}{Y^2} \mathbb{E}(T_4) \\
&\leq 2 \left( \frac{3N^2 \omega}{2Y} + \frac{3N\sigma^2}{Y} \right) \sum_{j \in J(k)} \gamma_j^2 \\
&\quad + 2\frac{N^2}{Y^2} \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \|\nabla_{i_j} f_{i_j}(\hat{x}_j)\|^2.
\end{aligned}$$

We apply the upper bound of  $\mathbb{E}(T_2)$  to (35):

$$\begin{aligned}
\mathbb{E}(T_1) &\leq \frac{2}{N} L_T^2 \mathbb{E}(T_2) + \frac{\omega}{2} \\
&\leq \frac{4L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{j \in J(k)} \gamma_j^2 + \frac{\omega}{2} \\
&\quad + 4L_T^2 \frac{N}{Y^2} \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \|\nabla_{i_j} f_{i_j}(\hat{x}_j)\|^2.
\end{aligned}$$

Substitute the upper bound of  $\mathbb{E}(T_1)$  into (34)

$$\begin{aligned}
&\mathbb{E}(f(x_{k+1}) - f(x_k)) \\
&\leq -\frac{\gamma_k}{2} \left( \mathbb{E} \|\nabla f(x_k)\|^2 + N \mathbb{E} |\nabla_{i_k} f_{i_k}(\hat{x}_k)|^2 \right) \\
&\quad + \frac{\gamma_k}{2} N \mathbb{E}(T_1) + \gamma_k^2 \frac{L_Y}{Y} N (\sigma^2 + \mathbb{E} \|\nabla f(\hat{x}_k)\|^2) + \gamma_k^2 \frac{L_Y}{Y} N^2 \frac{\omega}{4} \\
&\leq -\frac{\gamma_k}{2} \left( \mathbb{E} \|\nabla f(x_k)\|^2 + N \mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \right)
\end{aligned}$$

$$\begin{aligned}
& + \frac{\gamma_k}{2} N \left( 4L_T^2 \frac{(\frac{3N\omega}{2} + 3\sigma^2)}{Y} \sum_{j \in J(k)} \gamma_j^2 + \frac{\omega}{2} \right) \\
& + 2\gamma_k \left( L_T^2 \frac{N^2}{Y^2} \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \|\nabla_{i_j} f_{i_j}(\hat{x}_j)\|^2 \right) \\
& + \gamma_k^2 \frac{L_Y}{Y} N (\sigma^2 + \mathbb{E} \|\nabla f(\hat{x}_k)\|^2) + \gamma_k^2 \frac{L_Y}{Y} N^2 \frac{\omega}{4} \\
& \stackrel{\text{rearrange}}{=} - \frac{\gamma_k}{2} \mathbb{E} \|\nabla f(x_k)\|^2 + \gamma_k^2 \frac{L_Y}{Y} N^2 \underbrace{\frac{1}{N} \mathbb{E} \|\nabla f(\hat{x}_k)\|^2}_{=: T_5} \\
& - \left( \frac{\gamma_k N}{2} \right) \mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\
& + 2\gamma_k \left( L_T^2 \frac{N^2}{Y^2} \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \|\nabla_{i_j} f_{i_j}(\hat{x}_j)\|^2 \right) \\
& + \frac{\gamma_k}{2} N \left( \frac{4L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{j \in J(k)} \gamma_j^2 + \frac{\omega}{2} \right) \\
& + \gamma_k^2 \frac{L_Y}{Y} N \sigma^2 + \gamma_k^2 \frac{L_Y}{Y} N^2 \frac{\omega}{4}. \tag{38}
\end{aligned}$$

Note that

$$\begin{aligned}
T_5 &= \frac{1}{N} \mathbb{E} \|\nabla f(\hat{x}_k)\|^2 \\
&= \mathbb{E} \|\nabla_{i_k} f(\hat{x}_k)\|^2 \\
&\stackrel{(27)}{\leq} 2\mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 + 2\mathbb{E} \|\nabla_{i_k} f(\hat{x}_k) - \nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\
&\stackrel{(25)}{\leq} 2\mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 + \frac{\omega}{2}.
\end{aligned}$$

Substitute this upper bound of  $T_5$  into (38):

$$\begin{aligned}
& \mathbb{E}(f(x_{k+1}) - f(x_k)) \\
& \leq - \frac{\gamma_k}{2} \mathbb{E} \|\nabla f(x_k)\|^2 + \gamma_k^2 \frac{L_Y}{2Y} N^2 \omega \\
& \quad - \left( \frac{\gamma_k N}{2} - 2\gamma_k^2 \frac{L_Y}{Y} N^2 \right) \mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\
& \quad + 2\gamma_k \left( L_T^2 \frac{N^2}{Y^2} \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \|\nabla_{i_j} f_{i_j}(\hat{x}_j)\|^2 \right) \\
& \quad + \frac{\gamma_k}{2} N \left( \frac{4L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{j \in J(k)} \gamma_j^2 + \frac{\omega}{2} \right) \\
& \quad + \gamma_k^2 \frac{L_Y}{Y} N \sigma^2 + \gamma_k^2 \frac{L_Y}{Y} N^2 \frac{\omega}{4} \\
& \leq - \frac{\gamma_k}{2} \mathbb{E} \|\nabla f(x_k)\|^2 - \left( \frac{\gamma_k N}{2} - 2\gamma_k^2 \frac{L_Y}{Y} N^2 \right) \mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\
& \quad + 2\gamma_k \left( L_T^2 \frac{N^2}{Y^2} \sum_{j \in J(k)} \gamma_j \left( \gamma_j Y + \frac{Y^{3/2} \sum_{j' \in J(k) \setminus \{j\}} \gamma_{j'}}{\sqrt{N}} \right) \mathbb{E} \|\nabla_{i_j} f_{i_j}(\hat{x}_j)\|^2 \right) \\
& \quad + 2\gamma_k N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{j \in J(k)} \gamma_j^2
\end{aligned}$$

$$+ \gamma_k^2 \frac{L_Y}{Y} N \sigma^2 + \gamma_k^2 \frac{L_Y}{Y} N^2 \omega + \frac{\gamma_k}{4} N \omega. \quad (39)$$

Summarizing (39) from  $k = 0$  to  $k = K$  (note that  $\Theta_k$  is defined in (26)) yields:

$$\begin{aligned} & \frac{1}{2} \sum_{k=0}^K \gamma_k \mathbb{E} \|\nabla f(x_k)\|^2 \\ \leq & f(x_0) - f(x_{K+1}) - \sum_{k=0}^K \Theta_k \mathbb{E} \|\nabla_{i_k} f_{i_k}(\hat{x}_k)\|^2 \\ & + 2N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{k=0}^K \left( \gamma_k \sum_{j \in J(k)} \gamma_j^2 \right) \\ & + \left( \frac{L_Y}{Y} N \sigma^2 + \frac{L_Y}{Y} N^2 \omega \right) \sum_{k=0}^K \gamma_k^2 + \frac{1}{4} N \omega \sum_{k=0}^K \gamma_k \\ \stackrel{\Theta_k \geq 0}{\leqslant} & f(x_0) - f^* + 2N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{k=0}^K \left( \gamma_k \sum_{j \in J(k)} \gamma_j^2 \right) \\ & + \left( \frac{L_Y}{Y} N \sigma^2 + \frac{L_Y}{Y} N^2 \omega \right) \sum_{k=0}^K \gamma_k^2 + \frac{1}{4} N \omega \sum_{k=0}^K \gamma_k. \end{aligned}$$

It completes the proof.  $\square$

**Corollary 8.** Set all steplength  $\gamma_k$  to be a constant  $\gamma$  in Algorithm I

$$\gamma = \frac{Y}{N} \frac{1}{2L_Y \chi}, \quad (40)$$

where  $\chi$  satisfies

$$\chi \geq \sqrt{1 + \frac{L_T^2}{L_Y^2} \left( \frac{Y}{N} + \frac{Y^{3/2} T}{N^{3/2}} \right) T} + 1. \quad (41)$$

It ensures the following convergence rate

$$\frac{1}{2K} \sum_{k=0}^K \mathbb{E} \|\nabla f(x_k)\|^2 \leq \frac{2(f(x_0) - f^*) L_Y N}{K Y} \chi + \frac{N \omega + \sigma^2}{\chi} \left( 1 + \frac{2L_T^2 Y T}{L_Y^2 N} \frac{1}{\chi} \right) + N \omega.$$

*Proof.* To apply Theorem 7, we first verify that the choice of  $\gamma$  in (40) satisfies the prerequisite (26). Letting  $\gamma_k = \gamma$ , the prerequisite (26) in Theorem 7 reduces to

$$\frac{N\gamma}{2} - 2\gamma^2 \frac{L_Y}{Y} N^2 - 2L_T^2 \frac{N^2}{Y^2} \gamma \left( \gamma Y + \frac{Y^{3/2} T \gamma}{\sqrt{N}} \right) T \gamma \geq 0, \forall k,$$

or equivalently

$$\underbrace{\frac{L_T^2}{Y^2} \gamma^2 \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T}_{=:l} + \gamma \frac{L_Y}{Y} - \frac{1}{4N} \leq 0, \forall k.$$

Here we denote  $\left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T$  by  $l$  for short here.

To satisfy the above inequality, it suffices to show

$$\begin{aligned} \gamma &\leq \frac{-L_Y/Y + \sqrt{L_Y^2/Y^2 + (L_T^2/Y^2)l/N}}{2L_T^2 l/Y^2} \\ &= Y \frac{-L_Y + \sqrt{L_Y^2 + L_T^2 l/N}}{2L_T^2 l} \end{aligned}$$

$$\begin{aligned}
&= Y \frac{L_Y}{2L_T^2 l} \left( \sqrt{1 + \frac{L_T^2 l}{L_Y^2 N}} - 1 \right) \\
&= Y \frac{1}{2L_Y N} \frac{\sqrt{1 + \chi'} - 1}{\chi'} \\
&= Y \frac{1}{2L_Y N} \frac{1}{\chi_0},
\end{aligned}$$

where

$$\begin{aligned}
\chi' &:= \frac{L_T^2 l}{L_Y^2 N} = \frac{L_T^2 \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T}{L_Y^2 N}, \\
\chi_0 &:= \sqrt{1 + \chi'} + 1 = \sqrt{1 + \frac{L_T^2 \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T}{L_Y^2 N}} + 1.
\end{aligned}$$

Due to  $\chi \geq \chi_0$ , the choice of  $\gamma$  in (26) satisfies the prerequisite (26).

Now by applying Theorem 7

$$\begin{aligned}
\frac{1}{2} \sum_{k=0}^K \gamma_k \mathbb{E} \|\nabla f(x_k)\|^2 &\leq f(x_0) - f^* + 2N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \sum_{k=0}^K \left( \gamma_k \sum_{j \in J(k)} \gamma_j^2 \right) \\
&\quad + \left( \frac{L_Y}{Y} N\sigma^2 + \frac{L_Y}{Y} N^2 \omega \right) \sum_{k=0}^K \gamma_k^2 + \frac{1}{4} N\omega \sum_{k=0}^K \gamma_k.
\end{aligned}$$

and letting  $\gamma_k = \gamma$  and dividing both sides by  $K\gamma$ , we obtain

$$\begin{aligned}
\frac{1}{2K} \sum_{k=0}^K \mathbb{E} \|\nabla f(x_k)\|^2 &\leq \frac{f(x_0) - f^*}{K\gamma} + 2N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) T\gamma^2 \\
&\quad + \left( \frac{L_Y}{Y} N\sigma^2 + \frac{L_Y}{Y} N^2 \omega \right) \gamma + \frac{1}{4} N\omega. \tag{42}
\end{aligned}$$

Substituting  $\gamma$  into (42), we have

$$\begin{aligned}
\frac{1}{2K} \sum_{k=0}^K \mathbb{E} \|\nabla f(x_k)\|^2 &\leq \frac{f(x_0) - f^*}{K\gamma} + 2N \frac{L_T^2}{Y} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) T\gamma^2 \\
&\quad + \left( \frac{L_Y}{Y} N\sigma^2 + \frac{L_Y}{Y} N^2 \omega \right) \gamma + \frac{1}{4} N\omega \\
&= \frac{2(f(x_0) - f^*) L_Y N}{K Y} \chi \\
&\quad + \frac{L_T^2 Y T}{2L_Y^2 N} \left( \frac{3N\omega}{2} + 3\sigma^2 \right) \frac{1}{\chi^2} + (\sigma^2 + N\omega) \frac{1}{2\chi} + \frac{1}{4} N\omega \\
&\leq \frac{2(f(x_0) - f^*) L_Y N}{K Y} \chi \\
&\quad + \frac{2L_T^2 Y T}{L_Y^2 N} (N\omega + \sigma^2) \frac{1}{\chi^2} + (\sigma^2 + N\omega) \frac{1}{\chi} + N\omega \\
&= \frac{2(f(x_0) - f^*) L_Y N}{K Y} \chi + \frac{N\omega + \sigma^2}{\chi} \left( 1 + \frac{2L_T^2 Y T}{L_Y^2 N} \frac{1}{\chi} \right) + N\omega,
\end{aligned}$$

which completing the proof.  $\square$

**Theorem 9.** Set all steplength  $\gamma_k$  to be a constant  $\gamma$  in Algorithm 1

$$\gamma = \frac{Y}{N} \frac{1}{2L_Y \chi},$$

where

$$\chi = \sqrt{\frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1} + \sqrt{K(N\omega + \sigma^2)\alpha_2}}. \quad (43)$$

It ensures the following convergence rate

$$\frac{\sum_{k=0}^K \mathbb{E}\|\nabla f(x_k)\|^2}{2K} \leq \frac{2\alpha_1}{K\alpha_2\sqrt{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + N\omega.$$

*Proof.* In order to apply Corollary 8, we first verify that the choice of  $\chi$  in (43) satisfies the requirement in (41). (43) suggests that

$$\chi^2 \geq \frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1} + K(N\omega + \sigma^2)\alpha_2 \geq \alpha_1.$$

where the second inequality is due to that  $K = 0$  minimize the second part. Also note that

$$\begin{aligned} \alpha_1 &= 4 \left( 1 + \frac{L_T^2 \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T}{L_Y^2 N} \right) \\ &= \left( 2 \sqrt{1 + \frac{L_T^2}{L_Y^2} \left( \frac{Y}{N} + \frac{Y^{3/2} T}{N^{3/2}} \right) T} \right)^2 \\ &\geq \left( \sqrt{1 + \frac{L_T^2}{L_Y^2} \left( \frac{Y}{N} + \frac{Y^{3/2} T}{N^{3/2}} \right) T} + 1 \right)^2. \end{aligned}$$

Therefore the choice of  $\chi$  in (43) satisfies the condition in (41) required by Corollary 8. Applying Corollary 8 yields the following convergence rate

$$\begin{aligned} &\frac{1}{2K} \sum_{k=0}^K \mathbb{E}\|\nabla f(x_k)\|^2 \\ &\leq \frac{2(f(x_0) - f^*)L_Y N}{KY} \chi + \frac{N\omega + \sigma^2}{\chi} \left( 1 + \frac{2L_T^2 YT}{L_Y^2 N} \frac{1}{\chi} \right) + N\omega \\ &\stackrel{(43)}{=} \frac{2(f(x_0) - f^*)L_Y N}{KY} \sqrt{\frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} \\ &\quad + \frac{2(f(x_0) - f^*)L_Y N}{\sqrt{KY}} \sqrt{(N\omega + \sigma^2)\alpha_2} \\ &\quad + \underbrace{\frac{N\omega + \sigma^2}{\sqrt{\frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1} + \sqrt{K(N\omega + \sigma^2)\alpha_2}}}}_{\text{discard}} \\ &\quad + \frac{2L_T^2 YT}{L_Y^2 N} \frac{N\omega + \sigma^2}{\left( \underbrace{\sqrt{\frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}}}_{\text{discard}} + \sqrt{K(N\omega + \sigma^2)\alpha_2} \right)^2} \\ &\quad + N\omega \\ &\leq \frac{2(f(x_0) - f^*)L_Y N\alpha_1}{KY \sqrt{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} \\ &\quad + \frac{2(f(x_0) - f^*)L_Y N \sqrt{(N\omega + \sigma^2)\alpha_2}}{\sqrt{KY}} \end{aligned}$$

$$\begin{aligned}
& + \frac{\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + N\omega \\
= & \frac{2\alpha_1}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + N\omega.
\end{aligned}$$

It completes the proof.  $\square$

### Proof to Theorem 1

*Proof.* Note that in Theorem 1 we have the same steplength as in Theorem 9, so we can safely apply Theorem 9 to obtain

$$\begin{aligned}
& \frac{\sum_{k=0}^K \mathbb{E}\|\nabla f(x_k)\|^2}{2K} \\
\leq & \frac{2\alpha_1}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + N\omega \\
\stackrel{(7)}{=} & \frac{8 \left( 1 + \frac{L_T^2 T}{L_Y^2 N} \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) \right)}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + 4 + \underbrace{\frac{4L_T^2 T}{L_Y^2 N} \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right)}_{\text{discard}}} \\
& + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + N\omega \\
\leq & \frac{8}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}} + \frac{8 \frac{L_T^2 T}{L_Y^2 N} \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right)}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}} \\
& + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + N\omega. \tag{44}
\end{aligned}$$

Next from the condition of  $T$  in Theorem 1 and the definition of  $\alpha_3$ , we can obtain

$$\frac{L_T^2 \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T}{L_Y^2 N} \leq K(N\omega + \sigma^2)\alpha_2 + 4 = \alpha_3 \frac{L_T^2}{L_Y^2}. \tag{45}$$

To see why it is true, it suffices to show that

$$\begin{aligned}
T & \leq \frac{-Y\sqrt{N} + \sqrt{NY^2 + 4Y^{3/2}N^{3/2}\alpha_3}}{2Y^{3/2}} \\
& = \frac{-\sqrt{N} + \sqrt{N + 4Y^{-1/2}N^{3/2}\alpha_3}}{2Y^{1/2}} \\
& = \frac{\sqrt{N}}{2Y^{1/2}} \left( \sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1 \right), \tag{46}
\end{aligned}$$

which is implied by the prerequisite for  $T$  in Theorem 1.

Then we apply (45) to (44) and obtain

$$\begin{aligned}
& \frac{\sum_{k=0}^K \mathbb{E}\|\nabla f(x_k)\|^2}{2K} \\
\leq & \frac{8}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}} + \frac{8 \frac{L_T^2 \left( Y + \frac{Y^{3/2} T}{\sqrt{N}} \right) T}{L_Y^2 N}}{K\alpha_2 \sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}} \\
& + \frac{2L_T^2 YT}{L_Y^2 NK\alpha_2} + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega
\end{aligned}$$

$$\begin{aligned}
&\stackrel{(46)}{\leqslant} \frac{8}{K\alpha_2\sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}} + \frac{8\sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}}{K\alpha_2} \\
&\quad + \frac{L_T^2\sqrt{N\bar{Y}}\left(\sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1\right)}{L_Y^2NK\alpha_2} + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega \\
&\leqslant \frac{8}{K\alpha_2\sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}} + \frac{8\sqrt{K(N\omega + \sigma^2)\alpha_2}}{K\alpha_2} + \frac{16}{K\alpha_2} + \frac{3\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega \\
&\quad + \frac{1}{K\alpha_2}\frac{L_T^2\sqrt{\bar{Y}}\left(\sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1\right)}{L_Y^2\sqrt{N}} \\
&= \frac{1}{K\alpha_2}\left(16 + \frac{L_T^2}{L_Y^2}\frac{\sqrt{\bar{Y}}\left(\sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1\right)}{\sqrt{N}} + \frac{\overbrace{\frac{8}{\sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}}}^{\leqslant 4}}{\sqrt{K(N\omega + \sigma^2)\alpha_2 + 4}}\right) \\
&\quad + \frac{11\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega \\
&\leqslant \frac{1}{K\alpha_2}\left(20 + \frac{L_T^2}{L_Y^2}\frac{\sqrt{\bar{Y}}\left(\sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1\right)}{\sqrt{N}}\right) + \frac{11\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega \\
&= \frac{20}{K\alpha_2} + \frac{1}{K\alpha_2}\left(\frac{L_T^2}{L_Y^2}\frac{\sqrt{\bar{Y}}\left(\sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1\right)}{\sqrt{N}} + 11\sqrt{N\omega + \sigma^2}\sqrt{K\alpha_2}\right) + N\omega.
\end{aligned}$$

It completes the proof.  $\square$

### .3 Proofs to Corollaries

We prove all corollaries using Theorem 1 in this subsection.

#### Proof to Corollary 2

*Proof.* For ASCD, letting  $\sigma = 0$ ,  $\omega = 0$ , and  $Y = 1$  in Thereon 1, we have

$$\begin{aligned}
\gamma^{-1} &= 2L_{\max}N\left(\sqrt{\frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} + \sqrt{K(N\omega + \sigma^2)\alpha_2}\right) \\
&= 2L_{\max}N\sqrt{\alpha_1},
\end{aligned}$$

and the prerequisite becomes

$$\begin{aligned}
T &\leqslant \frac{\sqrt{N}}{2}\left(\sqrt{1 + 4\alpha_3N^{1/2}} - 1\right) \\
&= \frac{\sqrt{N}}{2}\left(\sqrt{1 + 4\frac{L_Y^2}{L_T^2}(K(N\omega + \sigma^2)\alpha_2 + 4)N^{1/2}} - 1\right) \\
&= \frac{\sqrt{N}}{2}\left(\sqrt{1 + 16\frac{L_{\max}^2}{L_T^2}N^{1/2}} - 1\right). \\
&= O(N^{3/4})
\end{aligned}$$

The convergence rate turns out to be

$$\begin{aligned}
&\frac{\sum_{k=0}^K \mathbb{E}\|\nabla f(x_k)\|^2}{2K} \\
&\leqslant \frac{1}{K\alpha_2}\left(20 + \frac{L_T^2}{L_{\max}^2}\frac{\sqrt{1 + 16N^{1/2}\frac{L_{\max}^2}{L_T^2}} - 1}{\sqrt{N}}\right)
\end{aligned}$$

$$= \frac{(f(x_0) - f^*)L_{\max}N}{K} \left( 20 + \frac{L_T^2}{L_{\max}^2} \frac{\sqrt{1 + 16N^{1/2} \frac{L_{\max}^2}{L_T^2}} - 1}{\sqrt{N}} \right).$$

It completes the proof.  $\square$

### Proof to Corollary 3

*Proof.* For ASGD in (11), letting  $\omega = 0$  and  $Y = N$  in  $\alpha_1, \alpha_2$ , and  $\alpha_3$  in (7), we have

$$\begin{aligned}\alpha_1 &= 4 \left( 1 + \frac{L_T^2(1+T)T}{L^2} \right), \\ \alpha_2 &= \frac{1}{(f(x_0) - f^*)L}, \\ \alpha_3 &= \frac{L^2}{L_T^2}(K\sigma^2\alpha_2 + 4).\end{aligned}$$

Next letting  $\omega = 0$  and  $Y = N$  in Theorem 1, the prerequisite for  $T$  becomes

$$\begin{aligned}T &\leq \frac{\sqrt{N}}{2\sqrt{N}} \left( \sqrt{1 + 4N^{-1/2}N^{1/2}\alpha_3} - 1 \right) \\ &= \frac{1}{2} (\sqrt{1 + 4\alpha_3} - 1) \\ &= \frac{1}{2} \left( \sqrt{1 + 4 \frac{L^2}{L_T^2} \left( \frac{K\sigma^2}{(f(x_0) - f^*)L} + 4 \right)} - 1 \right) \\ &= O(\sqrt{K\sigma^2 + 1}).\end{aligned}$$

We finally obtain the following convergence rate

$$\begin{aligned}&\frac{\sum_{k=0}^K \mathbb{E} \|\nabla f(x_k)\|^2}{2K} \\ &\leq \frac{1}{K\alpha_2} \left( 20 + \frac{L_T^2}{L_Y^2} \frac{\sqrt{Y} \left( \sqrt{1 + 4Y^{-1/2}N^{1/2}\alpha_3} - 1 \right)}{\sqrt{N}} \right) \\ &\quad + \frac{11\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega \\ &= \frac{1}{K\alpha_2} \left( 20 + \frac{L_T^2}{L^2} \sqrt{1 + 4\alpha_3} - 1 \right) + \frac{11\sigma}{\sqrt{K\alpha_2}} \\ &\leq \frac{1}{K\alpha_2} \left( 20 + \frac{L_T^2}{L^2} \sqrt{5\alpha_3} \right) + \frac{11\sigma}{\sqrt{K\alpha_2}} \\ &\leq \frac{1}{K\alpha_2} \left( 20 + \frac{L_T^2}{L^2} \sqrt{5\alpha_3} \right) + \frac{11\sigma}{\sqrt{K\alpha_2}} \\ &= \frac{1}{K\alpha_2} \left( 20 + \frac{L_T^2}{L^2} \sqrt{5 \frac{L^2}{L_T^2} (K\sigma^2\alpha_2 + 4)} \right) + \frac{11\sigma}{\sqrt{K\alpha_2}} \\ &= \frac{1}{K\alpha_2} \left( 20 + \frac{L_T\sqrt{5}}{L} \sqrt{K\sigma^2\alpha_2 + 4} \right) + \frac{11\sigma}{\sqrt{K\alpha_2}} \\ &\leq \frac{1}{K\alpha_2} \left( 20 + \frac{L_T\sqrt{5}}{L} \left( \sqrt{K\sigma^2\alpha_2} + 2 \right) \right) + \frac{11\sigma}{\sqrt{K\alpha_2}} \\ &= O\left(\frac{1}{K} + \frac{\sigma}{\sqrt{K}}\right),\end{aligned}$$

It completes the proof.  $\square$

### Proof to Corollary 4 and Corollary 5

*Proof.* Corollary 4 can be considered a special case of Corollary 5 with  $\omega = 0$ . We only prove Corollary 5 here, which automatically implies Corollary 4. Letting  $Y = 1$  in (7) and Theorem 1, we obtain

$$\gamma^{-1} = 2L_{\max}N \left( \sqrt{\frac{\alpha_1^2}{K(N\omega + \sigma^2)\alpha_2 + \alpha_1}} + \sqrt{K(N\omega + \sigma^2)\alpha_2} \right),$$

and

$$\begin{aligned}\alpha_1 &= 4 \left( 1 + \frac{L_T^2 \left( 1 + \frac{T}{\sqrt{N}} \right) T}{L_{\max}^2 N} \right), \\ \alpha_2 &= \frac{1}{(f(x_0) - f^*)L_{\max}N}, \\ \alpha_3 &= \frac{L_{\max}^2}{L_T^2} (K(N\omega + \sigma^2)\alpha_2 + 4), \\ \omega &= \frac{\sum_{i=1}^N L_{(i)}^2 \mu_i^2}{N}.\end{aligned}$$

The prerequisite for  $T$  in Theorem 1 becomes

$$\begin{aligned}T &\leq \frac{\sqrt{N}}{2} \left( \sqrt{1 + 4\alpha_3 N^{1/2}} - 1 \right) \\ &= \frac{\sqrt{N}}{2} \left( \sqrt{1 + 4 \frac{L_{\max}^2}{L_T^2} (K(N\omega + \sigma^2)\alpha_2 + 4) N^{1/2}} - 1 \right) \\ &= O \left( N^{3/4} \sqrt{K \left( \omega + \frac{\sigma^2}{N} \right) + 1} \right) \\ &= O \left( \sqrt{N^{3/2} + K N^{1/2} \sigma^2} \right).\end{aligned}\tag{47}$$

The convergence rate becomes

$$\begin{aligned}&\frac{\sum_{k=0}^K \mathbb{E} \|\nabla f(x_k)\|^2}{2K} \\ &\leq \frac{1}{K\alpha_2} \left( 20 + \frac{L_T^2}{L_{\max}^2} \frac{\sqrt{1 + 4N^{1/2}\alpha_3} - 1}{\sqrt{N}} \right) + \frac{11\sqrt{N\omega + \sigma^2}}{\sqrt{K\alpha_2}} + N\omega \\ &= O \left( \frac{N}{K} + \frac{N^{3/4}}{\sqrt{K}} \sqrt{\omega + \frac{\sigma^2}{N} + \frac{1}{K}} + \frac{N\sqrt{\omega + \frac{\sigma^2}{N}}}{\sqrt{K}} + N\omega \right) \\ &\leq O \left( \frac{N}{K} + \frac{N^{3/4}}{\sqrt{K}} \left( \sqrt{\omega + \frac{\sigma^2}{N}} + \frac{1}{\sqrt{K}} \right) + \frac{N\sqrt{\omega + \frac{\sigma^2}{N}}}{\sqrt{K}} + N\omega \right) \\ &= O \left( \frac{N}{K} + \frac{\sqrt{N}\sqrt{N\omega + \sigma^2}}{\sqrt{K}} + N\omega \right) \\ &\leq O \left( \frac{N}{K} + \frac{\sqrt{N}\sigma}{\sqrt{K}} + \frac{N\sqrt{\omega}}{\sqrt{K}} + N\omega \right).\end{aligned}$$

Since  $\omega = \frac{\sum_{i=1}^N L_{(i)}^2 \mu_i^2}{N}$ , if we use a constant  $\mu$  for all  $\mu_i$ , and if we let  $N\omega \leq O(N/K)$ ,  $\frac{N\sqrt{\omega}}{\sqrt{K}} \leq O(N/K)$ , we need

$$\mu \leq \sqrt{\frac{N}{K \sum_{i=1}^N L_{(i)}^2}} = O \left( \frac{1}{\sqrt{K}} \right).\tag{48}$$

If let  $N\omega \leq O(\frac{\sqrt{N}\sigma}{\sqrt{K}})$ ,  $\frac{N\sqrt{\omega}}{\sqrt{K}} \leq O(\frac{\sqrt{N}\sigma}{\sqrt{K}})$ , it suffices that

$$\mu \leq O\left(\min\left\{\frac{\sqrt{\sigma}}{(K)^{1/4}(N)^{1/4}}, \sigma/\sqrt{N}\right\}\right). \quad (49)$$

Since (18) satisfies either (48) or (49), we obtain a convergence rate of

$$\frac{\sum_{k=0}^K \mathbb{E}\|\nabla f(x_k)\|^2}{2K} \leq O\left(\frac{N}{K} + \frac{\sqrt{N}\sigma}{\sqrt{K}}\right).$$

The prerequisite (47) becomes

$$\begin{aligned} T &\leq O\left(N^{3/4}\sqrt{K\left(\omega + \frac{\sigma^2}{N}\right) + 1}\right) \\ &\leq O\left(N^{3/4}\sqrt{1 + \frac{K\sigma^2}{N}}\right), \end{aligned}$$

which completing the proof.  $\square$