# Parallel Adaptive Stochastic Gradient Descent Algorithms for Latent Factor Analysis of High-Dimensional and Incomplete Industrial Data Supplementary File

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#### I. INTRODUCTION

This is the supplementary file for the paper entitled "Parallel Adaptive Stochastic Gradient Descent Algorithms for Latent Factor Analysis of High-Dimensional and Incomplete Industrial Data". We have put the proof of *Lemma* 1-2 and *Theorem* 1-2 in Section II, and some figures and tables of experimental results in Section III.

II. Proofs for Lemma 1-2, and Theorems 1-2

## A. Proof of Lemma 1

Considering Lemma 1, we have the following inferences:

$$\mathbf{x}_{u}^{\tau+1} + \mathbf{w}^{\tau+1} = \mathbf{x}_{u}^{\tau+1} + \frac{\gamma}{1-\gamma} \left( \mathbf{x}_{u}^{\tau+1} - \mathbf{x}_{u}^{\tau} + \sigma \eta \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau} \right) \right) = \frac{1}{1-\gamma} \mathbf{x}_{u}^{\tau+1} + \frac{\gamma}{1-\gamma} \left( \sigma \eta \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau} \right) - \mathbf{x}_{u}^{\tau} \right) \\
= \frac{1}{1-\gamma} \left( \mathbf{x}_{u}^{\tau} - \eta \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau} \right) + \gamma \left[ \left( \mathbf{x}_{u}^{\tau} - \sigma \eta \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau} \right) \right) - \left( \mathbf{x}_{u}^{\tau-1} - \sigma \eta \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau-1} \right) \right) \right] \right) + \frac{\gamma}{1-\gamma} \left( \sigma \eta \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau} \right) - \mathbf{x}_{u}^{\tau} \right) \quad (S1)$$

$$= \mathbf{x}_{u}^{\tau} + \mathbf{w}^{\tau} - \frac{\eta}{1-\gamma} \nabla_{\mathbf{x}_{u}} \varepsilon_{u,i} \left( \mathbf{x}_{u}^{\tau} \right).$$

Thus, *Lemma* 1 stands.  $\Box$ 

#### B. Proof of Lemma 2

Considering Lemma 2, we have the following inferences:

$$\begin{aligned} \left\| \boldsymbol{x}_{u}^{\tau+1} + \boldsymbol{w}^{\tau+1} - \boldsymbol{x}_{u} \right\|^{2} &= \left\| \boldsymbol{x}_{u}^{r} + \boldsymbol{w}^{r} - \frac{\eta}{1 - \gamma} \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) - \boldsymbol{x}_{u} \right\|^{2} \\ &= \left\| \boldsymbol{x}_{u}^{r} + \boldsymbol{w}^{r} - \boldsymbol{x}_{u} \right\|^{2} - \frac{2\eta}{1 - \gamma} \left\langle \boldsymbol{x}_{u}^{r} + \boldsymbol{w}^{r} - \boldsymbol{x}_{u}, \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\rangle + \left( \frac{\eta}{1 - \gamma} \right)^{2} \left\| \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\|^{2} \\ &= \left\| \boldsymbol{x}_{u}^{r} + \boldsymbol{w}^{r} - \boldsymbol{x}_{u} \right\|^{2} - \frac{2\eta}{1 - \gamma} \left\langle \boldsymbol{x}_{u}^{r} + \frac{\gamma}{1 - \gamma} \left( \boldsymbol{x}_{u}^{r} - \boldsymbol{x}_{u}^{r-1} + \sigma \eta \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r-1} \right) \right) - \boldsymbol{x}_{u}, \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\rangle + \left( \frac{\eta}{1 - \gamma} \right)^{2} \left\| \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\rangle - \frac{2\eta \gamma}{\left( 1 - \gamma \right)^{2}} \left\langle \boldsymbol{x}_{u}^{r} - \boldsymbol{x}_{u}^{r-1}, \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\rangle \\ &- \frac{2\sigma \eta^{2} \gamma}{1 - \gamma} \left\langle \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r-1} \right), \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\rangle + \left( \frac{\eta}{1 - \gamma} \right)^{2} \left\| \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{r} \right) \right\|^{2}. \end{aligned} \tag{S2}$$

According to the properties of a convex function, the following inequality can be achieved:

$$\|\boldsymbol{x}_{u}^{\tau+1} + \boldsymbol{w}^{\tau+1} - \boldsymbol{x}_{u}\|^{2} = \|\boldsymbol{x}_{u}^{\tau} + \boldsymbol{w}^{\tau} - \boldsymbol{x}_{u}\|^{2} - \frac{2\eta}{1-\gamma} \langle \boldsymbol{x}_{u}^{\tau} - \boldsymbol{x}_{u}, \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau}\right) \rangle - \frac{2\eta\gamma}{\left(1-\gamma\right)^{2}} \langle \boldsymbol{x}_{u}^{\tau} - \boldsymbol{x}_{u}^{\tau-1}, \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau}\right) \rangle$$

$$- \frac{2\sigma\eta^{2}\gamma}{1-\gamma} \langle \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau-1}\right), \nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau}\right) \rangle + \left(\frac{\eta}{1-\gamma}\right)^{2} \|\nabla_{\boldsymbol{x}_{u}} \varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau}\right) \|^{2}$$

$$\leq \|\boldsymbol{x}_{u}^{\tau} + \boldsymbol{w}^{\tau} - \boldsymbol{x}_{u}\|^{2} - \frac{2\eta}{1-\gamma} \left(\varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau}\right) - \varepsilon_{u,i} \left(\boldsymbol{x}_{u}\right)\right) - \frac{2\eta\gamma}{\left(1-\gamma\right)^{2}} \left(\varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau}\right) - \varepsilon_{u,i} \left(\boldsymbol{x}_{u}^{\tau-1}\right)\right) + \left(\frac{\eta}{1-\gamma}\right)^{2} \left(2\sigma\gamma + 1\right).$$
(S3)

Note that (S3) can yield the appearance of  $x_u^{-1}$  when  $\tau = 0$ . Following previous research [57], by setting  $x_u^{-1} = x_u^0$  the above

inequality still holds. Hence, Lemma 2 stands.□

## C.Proof of Theorem 1

**Proof.** We prove the correctness of *Theorem* 1 in the manuscript separately in the following.

When  $\tau \in \{0, ..., T\}$ , the formula (21) is cumulatively summed to get:

$$\frac{2\eta}{1-\gamma} \sum_{\tau=0}^{T} \left( \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{\tau} \right) - \varepsilon_{u,i} \left( \boldsymbol{x}_{u} \right) \right) \leq \frac{2\eta\gamma}{\left(1-\gamma\right)^{2}} \left( \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{0} \right) - \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{T} \right) \right) + \left\| \boldsymbol{x}_{u}^{0} - \boldsymbol{x}_{u} \right\|^{2} + \left( \frac{\eta}{1-\gamma} \right)^{2} \left( 2\sigma\gamma + 1 \right) \left( T + 1 \right) G^{2}. \tag{S4}$$

Since  $x_u = x_u^*$ , and  $\varepsilon_{u,i}(x_u^r) \ge \varepsilon_{u,i}(x_u^*)$ , we get:

$$\sum_{\tau=0}^{T} \left( \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{\tau} \right) - \varepsilon_{u,i} \left( \boldsymbol{x}_{u} \right) \right) \leq \frac{\gamma}{1-\gamma} \left( \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{0} \right) - \varepsilon_{u,i} \left( \boldsymbol{x}_{u}^{0} \right) \right) + \frac{1-\gamma}{2\eta} \left\| \boldsymbol{x}_{u}^{0} - \boldsymbol{x}_{u}^{*} \right\|^{2} + \frac{\eta}{2(1-\gamma)} (2\sigma\gamma + 1)(T+1)G^{2}. \tag{S5}$$

Let  $\overline{x}_u = \sum_{\tau=0}^T x_u^{\tau} / (T+1)$ , for a convex function  $\varepsilon_{u,i}(x_u)$  have

$$\varepsilon_{u,i}\left(\bar{\boldsymbol{x}}_{u}\right) - \varepsilon_{u,i}\left(\boldsymbol{x}_{u}^{*}\right) \leq \frac{\gamma}{(1-\gamma)(T+1)} \left(\varepsilon_{u,i}\left(\boldsymbol{x}_{u}^{0}\right) - \varepsilon_{u,i}\left(\boldsymbol{x}_{u}^{*}\right)\right) + \frac{1-\gamma}{2\eta(T+1)} \left\|\boldsymbol{x}_{u}^{0} - \boldsymbol{x}_{u}^{*}\right\|^{2} + \frac{\eta}{2(1-\gamma)} (2\sigma\gamma + 1)G^{2}. \tag{S6}$$

The proof of **Theorem 1** can be done by plugging in the value of the learning rate  $\eta$ . According to the same principle,  $\varepsilon_{u,i}(y_i)$  converges by training  $y_i$  by fixing  $x_u$  as a constant. Therefore, *Theorem* 1 stands.

## D. Proof of Theorem 2

**Proof.** We prove the correctness of *Theorem* 2 in the manuscript separately in the following.

To facilitate subsequent proof, we transform the update rule (11) of A-ASGD into:

$$\boldsymbol{m}_{u}^{(0)}=0,\boldsymbol{z}_{u}^{(0)}=0,$$

for the  $\tau$ th instance  $r_{u,i} \in \Lambda(u)$  as  $\tau \in [1, 2, ..., |\Lambda(u)|]$ :

$$\boldsymbol{m}_{u}^{(\tau)} = \gamma_{1} \boldsymbol{m}_{u}^{(\tau-1)} + \left(1 - \gamma_{2}\right) \boldsymbol{h}_{u}^{\tau}, \quad \boldsymbol{m}_{u}^{(\tau)} = \frac{\boldsymbol{m}_{u}^{(\tau)}}{\left(1 - \gamma_{1}^{\tau}\right)}, \tag{S7}$$

$$\boldsymbol{z}_{u}^{(\tau)} = \gamma_{1} \boldsymbol{z}_{u}^{(\tau-1)} + \left(1 - \gamma_{2}\right) \left(\boldsymbol{h}_{u}^{\tau}\right)^{2}, \quad \boldsymbol{z}_{u}^{(\tau)} = \frac{\boldsymbol{z}_{u}^{(\tau)}}{\left(1 - \gamma_{2}^{\tau}\right)},$$

$$x_u^{(\tau)} \leftarrow x_u^{(\tau-1)} - \frac{\eta \, \boldsymbol{m}_u^{(\tau)}}{\sqrt{\boldsymbol{z}_u^{(\tau)}}},$$

where  $h_u^r = \nabla \varepsilon_{u,i}(x_u^r)$ . According to the iteration formula of x in the (S7), we have

$$\mathbf{m}_{u}^{\tau} = \gamma_{1} \mathbf{m}_{u}^{\tau-1} + (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau} = \gamma_{1}^{2} \mathbf{m}_{u}^{\tau-2} + \gamma_{1} (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau-1} + (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau} 
= \gamma_{1}^{\tau} \mathbf{m}_{u}^{0} + \gamma_{1}^{\tau-1} (1 - \gamma_{1}) \mathbf{h}_{u}^{1} + \dots + \gamma_{1}^{2} (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau-2} + \gamma_{1} (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau-1} + (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau} 
\begin{pmatrix} \mathbf{m}^{(0)} = 0 \\ = \gamma_{1}^{\tau-1} (1 - \gamma_{1}) \mathbf{h}_{u}^{1} + \dots + \gamma_{1}^{2} (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau-2} + \gamma_{1} (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau-1} + (1 - \gamma_{1}) \mathbf{h}_{u}^{\tau} 
= \sum_{p=1}^{\tau} (1 - \gamma_{1}) \gamma_{1}^{\tau-p} \mathbf{h}_{u}^{p} = (1 - \gamma_{1}) \sum_{p=1}^{\tau} \gamma_{1}^{\tau-p} \mathbf{h}_{u}^{p}.$$
(S8)

Note that  $\mathbf{z}_{u}^{\tau} = \sum_{n=1}^{\tau} (1 - \gamma_{2}) \gamma_{2}^{\tau-p} \left(\mathbf{h}_{u}^{p}\right)^{2} = (1 - \gamma_{2}) \sum_{n=1}^{\tau} \gamma_{2}^{\tau-p} \left(\mathbf{h}_{u}^{p}\right)^{2}$ . So we observe  $\mathbf{E}\left[\mathbf{m}_{u}^{\tau}\right]$ ,  $\mathbf{E}\left[\mathbf{z}_{u}^{\tau}\right]$ :

$$\mathbf{E}\left[\boldsymbol{m}_{u}^{\tau}\right] = (1 - \gamma_{1}) \sum_{p=1}^{\tau} \gamma_{1}^{\tau-p} \mathbf{E}\left[\boldsymbol{h}_{u}^{p}\right] = \mathbf{E}\left[\boldsymbol{h}_{u}^{p}\right] (1 - \gamma_{1}^{\tau}), \quad \mathbf{E}\left[\boldsymbol{z}_{u}^{\tau}\right] = (1 - \gamma_{2}) \sum_{p=1}^{\tau} \gamma_{2}^{\tau-p} \mathbf{E}\left[\left(\boldsymbol{h}_{u}^{p}\right)^{2}\right] = \mathbf{E}\left[\left(\boldsymbol{h}_{u}^{p}\right)^{2}\right] (1 - \gamma_{2}^{\tau}). \tag{S9}$$

To make  $\mathrm{E}\left[\boldsymbol{m}_{u}^{\tau}\right] = \mathrm{E}\left[\boldsymbol{h}_{u}^{p}\right]$ ,  $\mathrm{E}\left[\boldsymbol{z}_{u}^{\tau}\right] = \mathrm{E}\left[\left(\boldsymbol{h}_{u}^{p}\right)^{2}\right]$ , we have  $\boldsymbol{m}_{u}^{\tau} \to \widehat{\boldsymbol{m}}_{u}^{\tau} = \frac{\boldsymbol{m}_{u}^{\tau}}{\left(1 - \gamma_{1}^{\tau}\right)}$ ,  $\boldsymbol{z}_{u}^{\tau} \to \widehat{\boldsymbol{z}}_{u}^{\tau} = \frac{\boldsymbol{z}_{u}^{\tau}}{\left(1 - \gamma_{2}^{\tau}\right)}$ . The weight assigned by

A-ASGD decreases as  $\tau$  increases. By making  $\forall p$ :  $\left\| \left( \boldsymbol{h}_{u}^{p} \right)^{2} \right\|_{2} \leq I$  as I be a positive consant, then we ahve

$$\left\|\boldsymbol{z}_{\boldsymbol{u}}^{\tau}\right\|_{2} = \sum_{p=1}^{\tau} \left(1 - \gamma_{2}\right) \gamma_{2}^{\tau-p} \left\|\left(\boldsymbol{h}_{\boldsymbol{u}}^{p}\right)^{2}\right\|_{2} \leq I \ .$$

Since  $\varepsilon_{u,i}(\mathbf{x}_u)$  is convex when  $y_i$  is fixed [55], we have  $R(T) = \sum_{\tau=1}^{T} \left( \varepsilon_{u,i} \left( \mathbf{x}_u^{(\tau)} \right) - \varepsilon_{u,i} \left( \mathbf{x}_u^* \right) \right) \le \sum_{\tau=1}^{T} \mathbf{h}_u^{\tau} \left( \mathbf{x}_u^{(\tau)} - \mathbf{x}_u^* \right)$ . According to the update scheme of A-ASGD, we have:

$$\boldsymbol{x}_{u}^{(\tau+1)} = \boldsymbol{x}_{u}^{(\tau)} - \eta \frac{\widehat{\boldsymbol{m}}_{u}^{(\tau)}}{\sqrt{\widehat{\boldsymbol{z}}_{u}^{(\tau)}}} = \boldsymbol{x}_{u}^{(\tau)} - \eta \frac{1}{\left(1 - \boldsymbol{\gamma}_{\perp}^{\tau}\right)} \frac{\boldsymbol{m}_{u}^{(\tau)}}{\sqrt{\widehat{\boldsymbol{z}}_{u}^{(\tau)}}} = \boldsymbol{x}_{u}^{(\tau)} - \eta \frac{1}{\left(1 - \boldsymbol{\gamma}_{\perp}^{\tau}\right)} \frac{\boldsymbol{\gamma}_{1} \boldsymbol{m}_{u}^{(\tau-1)} + \left(1 - \boldsymbol{\gamma}_{1}\right) \boldsymbol{h}_{u}^{(\tau)}}{\sqrt{\widehat{\boldsymbol{z}}_{u}^{(\tau)}}}.$$
(S10)

Let  $\gamma_1 = \gamma_1, \tau$ , then  $\gamma_1$  varies with iteraions and will not increase monotonically, i.e., we have  $\gamma_1, 1 \ge \gamma_1, 2 \ge ... \ge \gamma_1, \tau$ ... Hene, the momentum will gradually disappear. By making  $m_u \rightarrow h_u$  [59], we have:

$$\mathbf{x}_{u}^{(\tau+1)} = \mathbf{x}_{u}^{(\tau)} - \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \frac{\gamma_{1,\tau} \mathbf{m}_{u}^{(\tau-1)} + (1 - \gamma_{1,\tau}) \mathbf{h}_{u}^{(\tau)}}{\sqrt{\bar{\mathbf{z}}_{u}^{(\tau+1)}}}.$$
 (S11)

 $\text{Let } \alpha_{\tau} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \text{, then } \boldsymbol{x}_{u}^{(\tau+1)} = \boldsymbol{x}_{u}^{(\tau)} - \alpha_{\tau} \frac{\gamma_{1,\tau} \boldsymbol{m}_{u}^{(\tau-1)} + \left(1 - \gamma_{1,\tau}\right) \boldsymbol{h}_{u}^{(\tau)}}{\sqrt{\boldsymbol{z}_{u}^{(\tau)}}} \text{. So we separate } \boldsymbol{h}_{u}^{\tau} \left(\boldsymbol{x}_{u}^{(\tau)} - \boldsymbol{x}_{u}^{*}\right) \text{ as: } \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} \cdot \boldsymbol{r} = \eta \frac{1}{1 - \prod_{p=1}^{\tau} \gamma_{1,p}} \boldsymbol{r} = \eta \frac{1}{$ 

$$\mathbf{x}_{u}^{(\tau+1)} = \mathbf{x}_{u}^{(\tau)} - \alpha_{\tau} \frac{\mathbf{y}_{1,\tau} \mathbf{m}_{u}^{(\tau-1)} + (1 - \mathbf{y}_{1,\tau}) \mathbf{h}_{u}^{(\tau)}}{\sqrt{\widehat{\mathbf{z}}_{u}^{(\tau)}}} 
\Rightarrow \left(\mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*}\right)^{2} = \left[\left(\mathbf{x}_{u}^{(\tau)} - \mathbf{x}_{u}^{*}\right) - \alpha_{\tau} \frac{\mathbf{y}_{1,\tau} \mathbf{m}_{u}^{(\tau-1)} + (1 - \mathbf{y}_{1,\tau}) \mathbf{h}_{u}^{(\tau)}}{\sqrt{\widehat{\mathbf{z}}_{u}^{(\tau)}}}\right]^{2} 
\Rightarrow 2\alpha_{\tau} \frac{\mathbf{y}_{1,\tau} \mathbf{m}_{u}^{(\tau-1)} + (1 - \mathbf{y}_{1,\tau}) \mathbf{h}_{u}^{(\tau)}}{\sqrt{\widehat{\mathbf{z}}_{u}^{(\tau)}}} \left(\mathbf{x}_{u}^{(\tau)} - \mathbf{x}_{u}^{*}\right) = \left(\mathbf{x}_{u}^{(\tau)} - \mathbf{x}_{u}^{*}\right)^{2} - \left(\mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*}\right)^{2} + \alpha_{\tau}^{2} \frac{\left[\mathbf{y}_{1,\tau} \mathbf{m}_{u}^{(\tau-1)} + (1 - \mathbf{y}_{1,\tau}) \mathbf{h}_{u}^{(\tau)}\right]^{2}}{\widehat{\mathbf{z}}_{u}^{(\tau)}}.$$
(S12)

Since  $\boldsymbol{m}_{u}^{(\tau)} = \gamma_{1,\tau} \boldsymbol{m}_{u}^{(\tau-1)} + (1 - \gamma_{1,\tau}) \boldsymbol{h}_{u}^{(\tau)}$ ,

$$\boldsymbol{h}_{u}^{r}\left(\boldsymbol{x}_{u}^{r}-\boldsymbol{x}_{u}^{*}\right) = \underbrace{\frac{\sqrt{\widehat{\boldsymbol{z}}_{u}^{r}}\left[\left(\boldsymbol{x}_{u}^{r}-\boldsymbol{x}_{u}^{*}\right)^{2}-\left(\boldsymbol{x}_{u}^{(r+1)}-\boldsymbol{x}_{u}^{*}\right)^{2}\right]}{2\alpha_{r}\left(1-\gamma_{1,r}\right)}}_{(1)} - \underbrace{\frac{\gamma_{1,r}\boldsymbol{m}_{u}^{(r-1)}}{\left(1-\gamma_{1,r}\right)}\left(\boldsymbol{x}_{u}^{r}-\boldsymbol{x}_{u}^{*}\right)}_{(2)} + \underbrace{\frac{\alpha_{r}}{2\left(1-\gamma_{1,r}\right)}\frac{\left(\boldsymbol{m}_{u}^{r}\right)^{2}}{\sqrt{\widehat{\boldsymbol{z}}_{u}^{r}}}}_{(3)}.$$
(S13)

Summing and scaling each item of the upper bound of R(T), we have:

$$\sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{\tau}} \left[ \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right]}{2\alpha_{\tau} \left( 1 - \gamma_{1,\tau} \right)} = \sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u,i}^{\tau}} \left[ \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right]}{2\eta \frac{1}{1 - \prod_{p=1}^{\tau} \beta_{1,p}} \left( 1 - \gamma_{1,\tau} \right)}$$

$$= \sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{\tau}} \left[ \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right] \left( 1 - \prod_{p=1}^{\tau} \gamma_{1,p} \right)}{2\eta \left( 1 - \gamma_{1,\tau} \right)}$$

$$\leq \sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{\tau}} \left[ \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right]}{2\eta \left( 1 - \gamma_{1,1} \right)}.$$
(S14)

And the dislocation recombination summation is given as:

$$\sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{\tau}} \left[ \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right]}{2\alpha_{\tau} \left( 1 - \gamma_{1,\tau} \right)} \leq \sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{\tau}} \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\widehat{z}_{u}^{\tau}} \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2}}{2\eta \left( 1 - \gamma_{1,1} \right)} \\
= \frac{\sqrt{\widehat{z}_{u}^{1}} \left( \mathbf{x}_{u}^{1} - \mathbf{x}_{u}^{*} \right)^{2}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\widehat{z}_{u}^{T}} \left( \mathbf{x}_{u}^{(T+1)} - \mathbf{x}_{u}^{*} \right)^{2}}{2\eta \left( 1 - \gamma_{1,1} \right)} + \sum_{\tau=2}^{T} \left( \mathbf{x}_{u}^{\tau} - \mathbf{x}_{u}^{*} \right)^{2} \cdot \left[ \frac{\sqrt{\widehat{z}_{u}^{\tau}}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\widehat{z}_{u}^{(\tau-1)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} \right]. \tag{S15}$$

Note that the above inferences adopt the condition of  $\frac{\sqrt{\widehat{z}_u^{(\tau)}}}{\eta} \ge \frac{\sqrt{\widehat{z}_u^{(\tau-1)}}}{\eta}$ , which holds according to (8). Thus, we further have:

$$\sum_{r=2}^{T} \left( \boldsymbol{x}_{u}^{r} - \boldsymbol{x}_{u}^{*} \right)^{2} \cdot \left[ \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(r)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(r-1)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} \right] \leq \sum_{r=1}^{T} D^{2} \cdot \left[ \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(r)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(r-1)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} \right] = D^{2} \cdot \left[ \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(r)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(1)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\hat{\boldsymbol{z}}_{u}^{(1)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} \right], \tag{S16}$$

where the final scaling is organized as:

$$\sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{(\tau)}} \left[ \left( \mathbf{x}_{u}^{(\tau)} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right]}{2\alpha_{\tau} \left( 1 - \gamma_{1,\tau} \right)} \leq \frac{\sqrt{\widehat{z}_{u}^{(1)}} D^{2}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{\sqrt{\widehat{z}_{u}^{(\tau)}} \left( \mathbf{x}_{u,i}^{(T+1)} - \mathbf{x}_{u,i}^{*} \right)^{2}}{2\eta \left( 1 - \gamma_{1,1} \right)} + \left[ \frac{D^{2} \sqrt{\widehat{z}_{u}^{(T)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} - \frac{D^{2} \sqrt{\widehat{z}_{u}^{(1)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} \right] \leq \frac{D^{2} \sqrt{\widehat{z}_{u}^{(T)}}}{2\eta \left( 1 - \gamma_{1,1} \right)}. \quad (S17)$$

By scaling  $\hat{z}_u^{(T)}$  with the previously mentioned expected approximation and bounded gradient, we finally scaling the term of (S13)-(1) as:

$$\sum_{\tau=1}^{T} \frac{\sqrt{\widehat{z}_{u}^{(\tau)}} \left[ \left( \mathbf{x}_{u}^{(\tau)} - \mathbf{x}_{u}^{*} \right)^{2} - \left( \mathbf{x}_{u}^{(\tau+1)} - \mathbf{x}_{u}^{*} \right)^{2} \right]}{2\alpha_{\tau} \left( 1 - \gamma_{1,\tau} \right)} \leq \frac{D^{2} \sqrt{\widehat{z}_{u}^{(T)}}}{2\eta \left( 1 - \gamma_{1,1} \right)} \leq \frac{D^{2} G}{2\eta \left( 1 - \gamma_{1,1} \right)}. \tag{S18}$$

Considering the term of (S13)-(2), we have

$$\sum_{\tau=1}^{T} - \frac{\gamma_{1,\tau} \boldsymbol{m}_{u}^{(\tau-1)}}{\left(1 - \gamma_{1,\tau}\right)} \left(\boldsymbol{x}_{u}^{(\tau)} - \boldsymbol{x}_{u}^{*}\right) = \sum_{\tau=1}^{T} \frac{\gamma_{1,\tau}}{\left(1 - \gamma_{1,\tau}\right)} \boldsymbol{m}_{u}^{(\tau-1)} \left[ -\left(\boldsymbol{x}_{u}^{(\tau)} - \boldsymbol{x}_{u}^{*}\right) \right] \leq \sum_{\tau=1}^{T} \frac{\gamma_{1,\tau}}{\left(1 - \gamma_{1,\tau}\right)} \left| \boldsymbol{m}_{u}^{(\tau-1)} \right| D^{2}.$$
(S19)

According to the following inference,

$$\begin{aligned}
\mathbf{m}_{u}^{(\tau)} &= \gamma_{1,\tau} \mathbf{m}_{u}^{(\tau-1)} + \left(1 - \gamma_{1,\tau}\right) \mathbf{h}_{u}^{(\tau)} &= \gamma_{1,\tau} \gamma_{1,\tau-1} \mathbf{m}_{u}^{(\tau-2)} + \gamma_{1,\tau} \left(1 - \gamma_{1,\tau-1}\right) \mathbf{h}_{u}^{(\tau-1)} + \left(1 - \gamma_{1,\tau}\right) \mathbf{h}_{u}^{(\tau)} \\
&= \sum_{p=1}^{\tau} \left(1 - \gamma_{1,p}\right) \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right) \mathbf{h}_{u}^{(p)}, \\
\left|\mathbf{m}_{u}^{(\tau)}\right| &\leq \sum_{p=1}^{\tau} \left(1 - \gamma_{1,p}\right) \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right) \left|\mathbf{h}_{u}^{(p)}\right| &\leq \sum_{p=1}^{\tau} \left(1 - \gamma_{1,p}\right) \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right) G^{2} \leq G^{2}.
\end{aligned}$$
(S20)

we formulate the term (S13)-(2) as:

$$\sum_{\tau=1}^{T} - \frac{\gamma_{1,\tau} \boldsymbol{m}_{u}^{(\tau-1)}}{\left(1 - \gamma_{1,\tau}\right)} \left(\boldsymbol{x}_{u}^{(\tau)} - \boldsymbol{x}_{u}^{*}\right) \leq \sum_{\tau=1}^{T} \frac{\gamma_{1,\tau}}{\left(1 - \gamma_{1,\tau}\right)} G^{2} D^{2} = G^{2} D^{2} \sum_{\tau=1}^{T} \frac{\gamma_{1,\tau}}{\left(1 - \gamma_{1,\tau}\right)}.$$
 (S21)

Regarding (S13)-(3), we focus on the following formula:

$$\frac{\left(\boldsymbol{m}_{u}^{(r)}\right)^{2}}{\sqrt{\widehat{\boldsymbol{z}}_{u}^{(r)}}} = \left(1 - \gamma_{2}^{r}\right) \frac{\left(\boldsymbol{m}_{u}^{(r)}\right)^{2}}{\sqrt{\boldsymbol{z}_{u}^{(r)}}} \leq \frac{\left(\boldsymbol{m}_{u}^{(r)}\right)^{2}}{\sqrt{\boldsymbol{z}_{u}^{(r)}}}.$$
(S22)

Then considering the closed solution formula of numerator and denominator, we have

$$\boldsymbol{m}_{u}^{(r)} = \sum_{p=1}^{r} \left(1 - \gamma_{1,p}\right) \left(\prod_{k=p+1}^{r} \gamma_{1,k}\right) h_{u}^{(p)}, \quad \boldsymbol{z}_{u}^{(r)} = \left(1 - \gamma_{2}\right) \sum_{p=1}^{r} \gamma_{2}^{r-p} \left(h_{u}^{(p)}\right)^{2},$$

$$\left(\boldsymbol{m}_{u}^{(r)}\right)^{2} = \left(\sum_{p=1}^{r} \frac{\left(1 - \gamma_{1,p}\right) \left(\prod_{k=p+1}^{r} \gamma_{1,k}\right)}{\sqrt{\left(1 - \gamma_{2}\right) \gamma_{2,p}^{r-p}}} \sqrt{\left(1 - \gamma_{2}\right) \gamma_{2,p}^{r-p}} \boldsymbol{h}_{u}^{(p)}\right)^{2}.$$
(S23)

With the Cauchy's inequality, (S23) yields:

$$\left(\boldsymbol{m}_{u}^{(r)}\right)^{2} = \left(\sum_{p=1}^{r} \frac{\left(1-\gamma_{1,p}\right)\left(\prod_{k=p+1}^{r} \gamma_{1,k}\right)}{\sqrt{\left(1-\gamma_{2}\right)\gamma_{2,p}^{r-p}}} \sqrt{\left(1-\gamma_{2}\right)\gamma_{2,p}^{r-p}} \boldsymbol{h}_{u}^{(p)}\right)^{2} \leq \sum_{p=1}^{t} \left(\frac{\left(1-\gamma_{1,p}\right)\left(\prod_{k=p+1}^{r} \gamma_{1,k}\right)}{\sqrt{\left(1-\gamma_{2}\right)\gamma_{2,p}^{r-p}}} \right)^{2} \sum_{p=1}^{r} \left(\sqrt{\left(1-\gamma_{2}\right)\gamma_{2,p}^{r-p}} \boldsymbol{h}_{u}^{(p)}\right)^{2} \\
= \sum_{p=1}^{r} \frac{\left(1-\gamma_{1,p}\right)^{2} \left(\prod_{k=p+1}^{r} \gamma_{1,k}\right)^{2}}{\left(1-\gamma_{2}\right)\gamma_{2,p}^{r-p}} \sum_{p=1}^{r} \left(\left(1-\gamma_{2}\right)\gamma_{2,p}^{r-p} \left(\boldsymbol{h}_{u}^{(p)}\right)^{2}\right). \tag{S24}$$

Then the term of (S13)-(3) is reformulated as:

$$\begin{split} &\sum_{\tau=1}^{T} \frac{\alpha_{\tau}}{2\left(1-\gamma_{1,\tau}\right)} \frac{\left(\boldsymbol{m}_{u}^{(\tau)}\right)^{2}}{\sqrt{\hat{\boldsymbol{z}}_{u}^{(\tau)}}} \leq &\sum_{t=1}^{T} \frac{\alpha_{\tau}}{2\left(1-\beta_{1,t}\right)} \sum_{p=1}^{\tau} \frac{\left(1-\gamma_{1,p}\right)^{2} \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right)^{2}}{\left(1-\gamma_{2}\right) \gamma_{2,p}^{\tau-p}} \frac{\sum_{p=1}^{\tau} \left(\left(1-\gamma_{2}\right) \gamma_{2,p}^{t-p} \left(\boldsymbol{h}_{u}^{(p)}\right)^{2}\right)}{\sqrt{\sum_{p=1}^{\tau} \left(\left(1-\gamma_{2}\right) \gamma_{2,p}^{t-p} \left(\boldsymbol{h}_{u}^{(p)}\right)^{2}\right)}} \\ &= &\sum_{\tau=1}^{T} \frac{\alpha_{\tau}}{2\left(1-\gamma_{1,\tau}\right)^{2}} \sum_{s=1}^{\tau} \frac{\left(1-\gamma_{1,p}\right)^{2} \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right)^{2}}{\left(1-\gamma_{2}\right) \gamma_{2,p}^{\tau-p}} \sqrt{\boldsymbol{z}_{i}^{(t)}} \leq &\sum_{\tau=1}^{T} \frac{\alpha_{\tau}}{2\left(1-\gamma_{1,t}\right)} \sum_{p=1}^{\tau} \frac{\left(1-\gamma_{1,p}\right)^{2} \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right)^{2}}{\left(1-\gamma_{2}\right) \gamma_{2,p}^{\tau-p}} G^{2}. \end{split} \tag{S25}$$

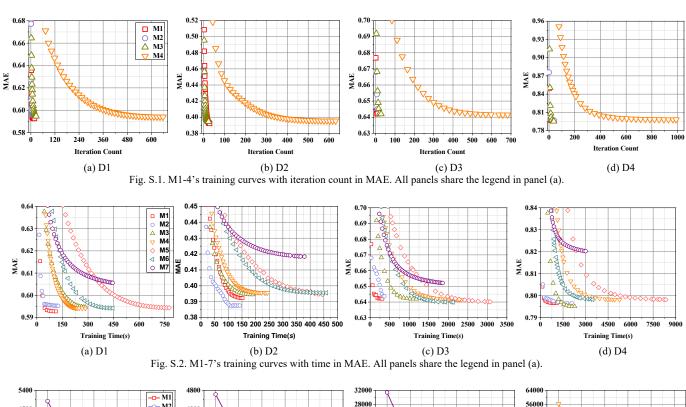
By integrating the scaling of (S13)-(1) and (S13)-(3), we have:

$$R(T) \leq \frac{D^2 G}{2\eta (1 - \gamma_{1,1})} + G D \sum_{\tau=1}^{T} \frac{\gamma_{1,\tau}}{(1 - \gamma_{1,\tau})} + G \sum_{\tau=1}^{T} \frac{\alpha_{\tau}}{2(1 - \gamma_{1,\tau})} \sum_{p=1}^{\tau} \frac{(1 - \gamma_{1,p})^2 \left(\prod_{k=p+1}^{\tau} \gamma_{1,k}\right)^2}{(1 - \gamma_2) \gamma_{2,p}^{\tau-p}}.$$
(S26)
and the average value  $R(T)/T \rightarrow 0$  of  $R(T)$ , the algorithm converges. According to the same principle,  $\varepsilon_{tr}(v)$ 

Hence, where  $T \rightarrow \infty$ , and the average value  $R(T)/T \rightarrow 0$  of R(T), the algorithm converges. According to the same principle,  $\varepsilon_{u,i}(\mathbf{y}_i)$  converges by training  $\mathbf{y}_i$  by fixing  $\mathbf{x}_u$  as a constant. Therefore, *Thereom* 2 stands.

#### III. SOME FIGURES AND TABLES OF EXPERIMENTAL RESULTS

Some experimental results are shown in this section.



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Fig. S.3. M1-7's training time in MAE as thread count increases. Both panels share the legend in panel (a).

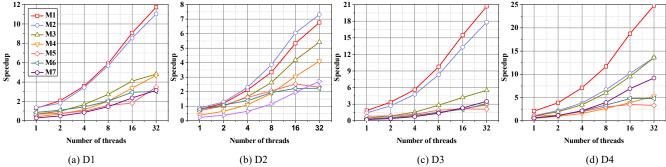


Fig.S.4. M1-7's speedup with MAE as thread count increases. Both panels share the legend in panel (a).

TABLE S.I. M1-4's converging iteration count in MAE.

N	Iteration count								
No. –	D1	D2	D3	D4					
M1	18±3.2	28±4.8	10±3	26±1.5					
M2	17±1.2	18±3.5	12±1.2	41±7					
M3	25±1.7	23±1.5	29±5.2	38±4.1					
M4	659±7.9	634 <sub>±12</sub>	669±1.4	990±3.7					

TABLE S.II. Comparison results on Speedup with 32 threads, including win/loss counts and Friedman test (●, ○ and ● indicates M1-3

has a higher computational efficiency than its peers, respectively).									
NO.	CASE	M1●	M2O	M3 <b>O</b>	M4	M5	M6	M7	
D1	RMSE-Speedup	11.54	11.53	5.34	4.62	1.64	3.04	2.88	
	KWISE-Speedup				●○0		ullet	●○❸	
DΙ	MAE-Speedup	11.73	11.03	4.82	4.69	3.48	3.03	1.56	
	MAE-Speedup				●○❸	●○0	ullet	●○②	
D2	RMSE-Speedup	5.06	5.20	3.30	3.14	1.64	1.78	1.46	
					●○❸	ullet	ullet	ullet	
DZ	MAE-Speedup	6.77	7.32	5.41	4.11	2.31	2.24	2.71	
					●○❸		$\bullet \circ \circ$	ullet	
	RMSE-Speedup	12.48	9.50	5.42	2.85	1.77	2.98	2.88	
D3					●○❸	●○0	ullet	●○❸	
DS	MAE-Speedup	20.68	17.81	5.50	2.85	2.09	3.05	3.50	
	MAE-Speedup				●○❸	●○○	ullet		
	RMSE-Speedup	24.81	16.43	10.14	5.39	3.38	7.90	8.14	
D4					●○0	●○≎	●○○	●○0	
D4	MAE-Speedup	24.79	13.58	13.58	5.26	3.33	4.78	9.20	
					●○0	●○≎	●○0	●○≎	
	●Win/Loss				8/0	8/0	8/0	8/0	
	○Win/Loss				8/0	8/0	8/0	8/0	
	<b>⊘</b> Win/Loss				8/0	8/0	8/0	8/0	
Friedman Rank		1.22	1.83	2.94	4.78	6.56	5.44	5.22	

<sup>\*</sup> A lower F-rank value indicates a higher computational efficiency

TABLE S.III. Results of the Wilcoxon signed-ranks test on Speedup with the different thread of Figs. 7 and S.4.

Vs.	M4				M5 N			M	16 M7			
VS.	R+	R-	<i>p</i> -value*	R+	R-	<i>p</i> -value*	R+	R-	<i>p</i> -value*	R+	R-	p-value*
M1	1176	0	8.42E-10	1162	14	2.03E-09	1173	3	1.02E-09	1176	0	8.42E-10
M2	1176	0	8.42E-10	1156	0	2.93E-09	1174	2	9.55E-10	1176	0	8.42E-10
M3	1176	10	8.42E-10	1069	107	4.15E-07	1117	59	2.97E-08	1176	0	8.42E-10
		4 004				1 12		20.4				

<sup>\*</sup> The accepted hypotheses with a significance level of 0.1 are highlighted.