

# A Fuzzy Nesterov-Accelerated Nonnegative Latent Factorization of Tensors Model for Efficient Representation to Dynamic Directed Graph Supplementary File

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## I. INTRODUCTION

**T**HIS is the supplementary file for the paper entitled “A Fuzzy Nesterov-Accelerated Nonnegative Latent Factorization of tensors Model for Efficient Representation to Dynamic Directed Graph”. We have put the proof of Lemma 1-2 and Theorem 1-2 in Section II, tables and figures of experimental results in Section IV.

## II. MODEL CONVERGENCE ANALYSIS

The goal of the FNL model is to represent a HDI tensor  $\mathbf{Y}$  via a nonnegative latent factorization. The optimization problem is defined as:

$$\min_{U,W,Z} \varepsilon(U, W, Z) = \sum_{(i,j,k \in \Lambda)} (y_{ijk} - \hat{y}_{ijk})^2 + \lambda^t (\sigma(u_{ir})^2 + \sigma(w_{jr})^2 + \sigma(z_{kr})^2), \quad (S1)$$

where  $\hat{y}_{ijk} = \sum_{r=1}^R \sigma(u_{ir}) \sigma(w_{jr}) \sigma(z_{kr})$  and  $\sigma(*)$  represents Hard-Sigmoid function:

$$\sigma(\theta) = \max(0, \min(1, 0.2\theta + 0.5)), \quad (S2)$$

where  $\Lambda$  and  $\lambda_t$  represent Known set and regularization coefficient on  $t$ -th iteration respectively.

For the convenience of analysis, we alternatively fix the counterpart of the active parameter as constant, i.e., we treat  $w_{jr}$  and  $z_{kr}$  as constant when performing the analyses with  $u_{ir}$ . The gradient of  $u_{ir}$ :

$$\nabla_{u_{ir}} \varepsilon_{i,j,k} = - \left( y_{ijk} - \sum_{r=1}^R \sigma(u_{ir}) \sigma(w_{jr}) \sigma(z_{kr}) \right) \sigma'(u_{ir}) \sigma(w_{jr}) \sigma(z_{kr}) + \lambda^t u_{ir}. \quad (S3)$$

Note that the update of  $u_{ir}$  by NASGD is given as: For the  $t$ -th iteration counts.

$$\begin{aligned} t = 1 : u_{ir}^{t+1} &= u_{ir}^t - \eta^t (1 + \gamma^t) \nabla_{u_{ir}} \varepsilon_{i,j,k} (u_{ir}^t) \\ t \geq 2 : u_{ir}^{t+1} &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{i,j,k} (u_{ir}^t) \\ &\quad + \gamma^t ((u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{i,j,k} (u_{ir}^t)) - (u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{i,j,k} (u_{ir}^{t-1}))). \end{aligned} \quad (S4)$$

It is worth noting that according to the fuzzy reasoning rule table (Table II), we can get:

$$\begin{aligned} \eta^t &\in [\eta_{min}, \eta_{max}], 0 < \eta_{min} \leq \eta^t \leq \eta_{max}, \\ \lambda^t &\in [\lambda_{min}, \lambda_{max}], 0 < \lambda_{min} \leq \lambda^t \leq \lambda_{max}, \\ \gamma^t &\in [\gamma_{min}, \gamma_{max}], 0 < \gamma_{min} \leq \gamma^t \leq \gamma_{max} < 1. \end{aligned} \quad (S5)$$

We define  $w_t$  as:

$$\omega^t = \begin{cases} \frac{\gamma^t}{1-\gamma^t} (u_{ir}^t - u_{ir}^{t-1} + \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) , t \geq 1 \\ 0, t = 0 \end{cases}, \quad (\text{S6})$$

where  $\eta^t, \lambda^t, \gamma^t$  are dynamically adjusted according to the fuzzy reasoning  $I^{(t)} = 0.5(\text{RMSE+MAE})$ , we present the following results.

*Lemma 1:*  $\forall t \geq 0$ , the following equation stands:

$$\begin{aligned} u_{ir}^{t+1} + \omega^{t+1} &= u_{ir}^{t+1} + \frac{\gamma^{t+1}}{1-\gamma^{t+1}} (u_{ir}^{t+1} - u_{ir}^t + \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \gamma^t ((u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)) - (u_{ir}^{t-1} - \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1}))) \\ &\quad + \frac{\gamma^{t+1}}{1-\gamma^{t+1}} (u_{ir}^{t+1} - u_{ir}^t + \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \gamma^t (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \\ &\quad + \frac{\gamma^{t+1}}{1-\gamma^{t+1}} \gamma^t (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \left( \gamma^t + \frac{\gamma^{t+1}\gamma^t}{1-\gamma^{t+1}} \right) (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \gamma^t \left( 1 + \frac{\gamma^{t+1}}{1-\gamma^{t+1}} \right) (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \quad (\text{S7}) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \gamma^t \frac{1 - \gamma^{t+1} + \gamma^{t+1}}{1 - \gamma^{t+1}} (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \frac{\gamma^t}{1 - \gamma^{t+1}} (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \\ &= u_{ir}^t - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \frac{\gamma^t}{1 - \gamma^t} (u_{ir}^t - u_{ir}^{t-1} - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \\ &= u_{ir}^t + \frac{\gamma^t}{1 - \gamma^t} (u_{ir}^t - u_{ir}^{t-1} + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) - \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) - \frac{\gamma^t}{1 - \gamma^t} \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) \\ &= u_{ir}^t + \omega^t - \frac{\gamma^t}{1 - \gamma^t} \eta^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t). \end{aligned}$$

*Lemma 2:* Let  $u_{ir}^{-1} = u_{ir}^0$ , for any  $t \geq 0$ ,  $\exists u_{ir}^*$ :

$$\begin{aligned} &\|u_{ir}^{t+1} + \omega^{t+1} - u_{ir}^*\|^2 \\ &= \left\| u_{ir}^t + \omega^t - \frac{\eta^t}{1 - \gamma^t} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) - u_{ir}^* \right\|^2 \\ &= \left\| (u_{ir}^t + \omega^t - u_{ir}^*) - \frac{\eta^t}{1 - \gamma^t} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) \right\|^2 \\ &= (u_{ir}^t + \omega^t - u_{ir}^*)^2 - 2 \left\langle (u_{ir}^t + \omega^t - u_{ir}^*) \frac{\eta^t}{1 - \gamma^t} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t), \right\rangle + \left( \frac{\eta^t}{1 - \gamma^t} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) \right)^2 \\ &= \|u_{ir}^t + \omega^t - u_{ir}^*\|^2 - 2 \left\langle (u_{ir}^t + \omega^t - u_{ir}^*) \frac{\eta^t}{1 - \gamma^t} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t), \right\rangle + \left( \frac{\eta^t}{1 - \gamma^t} \right)^2 \|\nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)\|^2. \quad (\text{S8}) \end{aligned}$$

Note that (S7) can yield the appearance of  $u_{ir}$  when  $t = 0$ . By setting  $u_{ir}^{-1} = u_{ir}^0$  the above inequality still holds. Hence, Lemma 2 stands.

Based on Lemmas 1-2, we present the following important result.

*Theorem 1* (Convergence of NASGD): for any  $t \geq 0$ , let  $\|\nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)\| \leq G$ ,  $|u_{ir}^{t+1} - u_{ir}^t| \leq A$ , where  $G$  and  $A$  are both positive constants, by setting  $B = A + 2\eta_{max}G$  as  $B$  be a positive constant, when  $t \in \{0, \dots, T\}$ , based on Lemma 2, we have:

$$\begin{aligned} \|u_{ir}^{t+1} + \omega^{t+1} - u_{ir}^*\|^2 &= \|u_{ir}^t + \omega^t - u_{ir}^*\|^2 - 2 \left\langle (u_{ir}^t + \omega^t - u_{ir}^*) \frac{\eta^t}{1-\gamma^t} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) \right\rangle \\ &\quad + \left( \frac{\eta^t}{1-\gamma^t} \right)^2 \|\nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)\|^2. \end{aligned} \quad (\text{S9})$$

First of all, function  $\varepsilon_{ijk}(u_{ir})$  is convex, therefore, about  $(u_{ir}^t + \omega^t - u_{ir}^*) \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)$ , we have:

$$\begin{aligned} &(u_{ir}^t + \omega^t - u_{ir}^*) \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) \\ &= (u_{ir}^t - u_{ir}^*) \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) + \omega^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t) \\ &\geq \varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*) + \frac{\gamma^t}{1-\gamma^t} (u_{ir}^t - u_{ir}^{t-1} + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})) \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t). \end{aligned} \quad (\text{S10})$$

Secondly, since  $y_{ijk}$ ,  $\sigma(*)$ ,  $\lambda_t$  are bounded, therefore, setting  $\|\nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)\| \leq G$ , we have:

$$\begin{aligned} &|\omega^t \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^t)| \\ &\leq \frac{\gamma^t}{1-\gamma^t} G |u_{ir}^t - u_{ir}^{t-1} + \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})| \\ &\leq \frac{\gamma^t}{1-\gamma^t} G \gamma^{t-1} |u_{ir}^{t-1} - u_{ir}^{t-2} + \eta^{t-2} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-2}) - \eta^{t-1} \nabla_{u_{ir}} \varepsilon_{ijk}(u_{ir}^{t-1})| \\ &\leq \frac{\gamma_{\max}}{1-\gamma_{\max}} G (A + 2\eta_{\max} G). \end{aligned} \quad (\text{S11})$$

Finally, substitute S(10) and S(11) into S(9) to get:

$$\begin{aligned} \|u_{ir}^{t+1} + \omega^{t+1} - u_{ir}^*\|^2 &\leq \|u_{ir}^t + \omega^t - u_{ir}^*\|^2 - 2 \frac{\eta^t}{1-\gamma^t} (\varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*)) \\ &\quad + 2 \frac{\eta^t}{1-\gamma^t} \frac{\gamma_{\max}}{1-\gamma_{\max}} GB + \left( \frac{\eta^t}{1-\gamma^t} \right)^2 G^2. \end{aligned} \quad (\text{S12})$$

Accumulate from  $t = 0$  to  $T$ :

$$\begin{aligned} \|u_{ir}^{T+1} + \omega^{T+1} - u_{ir}^*\|^2 &\leq \|u_{ir}^0 + \omega^0 - u_{ir}^*\|^2 - 2 \sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} (\varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*)) \right) \\ &\quad + 2 \frac{\gamma_{\max}}{1-\gamma_{\max}} GB \sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} \right) + G^2 \sum_{t=0}^T \left( \left( \frac{\eta^t}{1-\gamma^t} \right)^2 \right). \end{aligned} \quad (\text{S13})$$

According to  $\omega^0 = 0$ ,  $\|u_{ir}^{t+1} + \omega_{ir}^{t+1} - u_{ir}^*\|^2 \geq 0$ :

$$\begin{aligned} &\sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} (\varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*)) \right) \\ &\leq \frac{\|u_{ir}^0 - u_{ir}^*\|^2}{2} + \frac{\gamma_{\max}}{1-\gamma_{\max}} GB \sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} \right) + \frac{1}{2} G^2 \sum_{t=0}^T \left( \left( \frac{\eta^t}{1-\gamma^t} \right)^2 \right) \\ &\leq \frac{\|u_{ir}^0 - u_{ir}^*\|^2}{2} + \frac{\eta_{\max}}{1-\eta_{\max}} \frac{\gamma_{\max}}{1-\gamma_{\max}} GB (T+1) + \frac{1}{2} G^2 \frac{\eta_{\max}}{1-\eta_{\max}} (T+1). \end{aligned} \quad (\text{S14})$$

And then,

$$\begin{aligned}
& \frac{1}{T+1} \sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} (\varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*)) \right) \\
& \leq \frac{\sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} (\varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*)) \right)}{\frac{\eta_{\min}}{1-\gamma_{\max}} (T+1)} \\
& \leq \frac{\|u_{ir}^0 - u_{ir}^*\|^2}{2 \frac{\eta_{\min}}{1-\gamma_{\max}} (T+1)} + \frac{\eta_{\max}}{1-\gamma_{\min}} \frac{\gamma_{\max}}{1-\gamma_{\max}} GB + \frac{1}{2} G^2 \frac{\eta_{\max}}{1-\gamma_{\max}}.
\end{aligned} \tag{S15}$$

Let  $\bar{u}_{ir} = \sum_{t=0}^T u_{ir}^t / (T+1)$ , from the convexity of the function, we can get:

$$\begin{aligned}
& \varepsilon_{ijk}(\bar{u}_{ir}) - \varepsilon_{ijk}(u_{ir}^*) \\
& \leq \frac{1}{T+1} \sum_{t=0}^T \left( \frac{\eta^t}{1-\gamma^t} (\varepsilon_{ijk}(u_{ir}^t) - \varepsilon_{ijk}(u_{ir}^*)) \right) \\
& \leq \frac{\|u_{ir}^0 - u_{ir}^*\|^2}{2 \frac{\eta_{\min}}{1-\gamma_{\max}} (T+1)} + \frac{\eta_{\max}}{1-\gamma_{\min}} \frac{\gamma_{\max}}{1-\gamma_{\max}} GB + \frac{1}{2} G^2 \frac{\eta_{\max}}{1-\gamma_{\max}}.
\end{aligned} \tag{S16}$$

The proof of Theorem 1 can be done by fuzzy reasoning to ensure that  $\eta_t$ ,  $\lambda_t$ ,  $\gamma_t$  are obtained in a limited range. According to the same principle,  $\varepsilon_{i,j,k}(w_{jr})$  converges by training  $w_{jr}$  by fixing  $u_{ir}$  and  $z_{kr}$  as a constant, and  $\varepsilon_{ijk}(Z_{kr})$  converges by training  $z_{kr}$  by fixing  $u_{ir}$  and  $w_{jr}$  as a constant. Therefore, Theorem 1 stands.

### III. EXPERIMENTAL RESULTS

Here are some supplementary tables and figures used in the experiment.

TABLE S1  
THE PERFORMANCE OF FNL WITH MANUALLY-TUNED AND SELF-ADAPTED HYPER-PARAMETERS.

Datasets		Manual-tuning	Self-adaption	Gap
D1	RMSE	$0.3390 \pm 4.32E-04$	<b><math>0.3387 \pm 6.80E-04</math></b>	0.08%
	*Per	$5802.11 \pm 48.73$	<b><math>37.48 \pm 0.66</math></b>	99.35%
	MAE	$0.2452 \pm 2.77E-04$	<b><math>0.2450 \pm 1.81E-04</math></b>	0.08%
	**Per	$8123.96 \pm 29.15$	<b><math>39.82 \pm 0.55</math></b>	99.50%
D2	RMSE	$0.3469 \pm 5.29E-05$	<b><math>0.3466 \pm 1.61E-05</math></b>	0.08%
	*Per	$2613.86 \pm 25.76$	<b><math>22.74 \pm 0.35</math></b>	99.12%
	MAE	$0.2477 \pm 3.64E-05$	<b><math>0.2474 \pm 1.36E-05</math></b>	0.12%
	**Per	$3267.33 \pm 17.63$	<b><math>24.17 \pm 2.35</math></b>	99.26%
D3	RMSE	<b><math>0.3189 \pm 7.19E-05</math></b>	$0.3192 \pm 3.93E-06$	0.09%
	*Per	$1058.04 \pm 34.17$	<b><math>4.99 \pm 0.43</math></b>	99.52%
	MAE	<b><math>0.2184 \pm 3.80E-06</math></b>	$0.2187 \pm 2.12E-06$	0.09%
	**Per	$1143.65 \pm 56.56$	<b><math>3.23 \pm 0.32</math></b>	99.71%
D4	RMSE	$0.3164 \pm 4.51E-06$	<b><math>0.3161 \pm 6.49E-06</math></b>	0.09%
	*Per	$719.59 \pm 9.77$	<b><math>8.03 \pm 0.55</math></b>	98.88%
	MAE	$0.2167 \pm 3.33E-06$	<b><math>0.2166 \pm 2.78E-06</math></b>	0.09%
	**Per	$770.99 \pm 5.61$	<b><math>4.59 \pm 0.66</math></b>	99.41%
D5	RMSE	<b><math>0.2900 \pm 5.29E-04</math></b>	$0.2904 \pm 2.18E-04$	0.13%
	*Per	$1010.39 \pm 11.8$	<b><math>8.88 \pm 0.66</math></b>	99.12%
	MAE	$0.1998 \pm 1.50E-05$	<b><math>0.1996 \pm 1.81E-04</math></b>	0.10%
	**Per	$1309.77 \pm 18.74$	<b><math>9.24 \pm 0.43</math></b>	99.29%
D6	RMSE	$0.3430 \pm 2.14E-04$	<b><math>0.3426 \pm 5.61E-06</math></b>	0.14%
	*Per	$2280.92 \pm 32.15$	<b><math>5.33 \pm 0.04</math></b>	99.76%
	MAE	<b><math>0.2488 \pm 5.37E-04</math></b>	$0.2493 \pm 2.98E-06$	0.16%
	**Per	$2348.05 \pm 18.99$	<b><math>5.33 \pm 0.04</math></b>	99.77%
D7	RMSE	$0.3250 \pm 3.21E-04$	<b><math>0.3245 \pm 2.22E-04</math></b>	0.15%
	*Per	$590361 \pm 3761$	<b><math>4722.89 \pm 129.8</math></b>	99.20%
	MAE	$0.2298 \pm 5.01E-04$	<b><math>0.2294 \pm 3.85E-04</math></b>	0.17%
	**Per	$678780 \pm 1120$	<b><math>5028.77 \pm 425.6</math></b>	99.26%
D8	RMSE	$0.3199 \pm 5.01E-04$	<b><math>0.3117 \pm 4.00E-04</math></b>	0.06%
	*Per	$121296 \pm 407$	<b><math>1083.52 \pm 110</math></b>	99.10%
	MAE	<b><math>0.2162 \pm 3.10E-04</math></b>	$0.2164 \pm 2.98E-04$	0.09%
	**Per	$140988 \pm 356$	<b><math>1137.18 \pm 129</math></b>	99.19%

\*/\*\*Time cost per training in RMSE/MAE (Seconds).

TABLE S2  
HYPER-PARAMETER SETTINGS OF ALL MODELS

Datasets		Hyper-parameter Setting					
<b>D1</b>	M2: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.001$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.001$	M4: $R = 10$ , $\lambda = 4 \times 10^{-8}$ , $\gamma = 480$	M5: $R = 10$ , $\lambda_1 = 0.04$ , $\lambda_2 = 0.2$	M6: $R = 10$ , $\lambda_1 = 0.5$ , $\lambda_2 = 0.0625$	M7: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.1$	M8: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.001$
<b>D2</b>	M2: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.001$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.002$	M4: $R = 10$ , $\lambda = 10^{-8}$ , $\gamma = 500$	M5: $R = 10$ , $\lambda_1 = 0.04$ , $\lambda_2 = 0.2$	M6: $R = 10$ , $\lambda_1 = 0.125$ , $\lambda_2 = 0.25$	M7: $R = 10$ , $\eta = 0.2$ , $\lambda = 0.1$	M8: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.0001$
<b>D3</b>	M2: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.001$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.004$	M4: $R = 10$ , $\lambda = 10^{-8}$ , $\gamma = 450$	M5: $R = 10$ , $\lambda_1 = 0.005$ , $\lambda_2 = 0.4$	M6: $R = 10$ , $\lambda_1 = 0.25$ , $\lambda_2 = 0.0625$	M7: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.2$	M8: $R = 10$ , $\eta = 0.2$ , $\lambda = 0.01$
<b>D4</b>	M2: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.002$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.005$	M4: $R = 10$ , $\lambda = 4 \times 10^{-8}$ , $\gamma = 500$	M5: $R = 10$ , $\lambda_1 = 0.007$ , $\lambda_2 = 0.4$	M6: $R = 10$ , $\lambda_1 = 0.5$ , $\lambda_2 = 0.0625$	M7: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.1$	M8: $R = 10$ , $\eta = 0.2$ , $\lambda = 0.001$
<b>D5</b>	M2: $R = 10$ , $\lambda = 10^{-4}$ , $\eta = 0.001$	M3: $R = 10$ , $\lambda = 10^{-4}$ , $\eta = 0.008$	M4: $R = 10$ , $\lambda = 10^{-7}$ , $\gamma = 480$	M5: $R = 10$ , $\lambda_1 = 0.07$ , $\lambda_2 = 0.3$	M6: $R = 10$ , $\lambda_1 = 0.5$ , $\lambda_2 = 0.0625$	M7: $R = 10$ , $\eta = 0.2$ , $\lambda = 0.2$	M8: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.002$
<b>D6</b>	M2: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.001$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.004$	M4: $R = 10$ , $\lambda = 10^{-8}$ , $\gamma = 450$	M5: $R = 10$ , $\lambda_1 = 0.006$ , $\lambda_2 = 0.5$	M6: $R = 10$ , $\lambda_1 = 0.25$ , $\lambda_2 = 0.03125$	M7: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.1$	M8: $R = 10$ , $\eta = 0.2$ , $\lambda = 0.01$
<b>D7</b>	M2: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.01$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.004$	M4: $R = 10$ , $\lambda = 10^{-8}$ , $\gamma = 480$	M5: $R = 10$ , $\lambda_1 = 0.005$ , $\lambda_2 = 0.4$	M6: $R = 10$ , $\lambda_1 = 0.25$ , $\lambda_2 = 0.0625$	M7: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.2$	M8: $R = 10$ , $\eta = 0.2$ , $\lambda = 0.01$
<b>D8</b>	M2: $R = 10$ , $\lambda = 10^{-4}$ , $\eta = 0.01$	M3: $R = 10$ , $\lambda = 10^{-5}$ , $\eta = 0.004$	M4: $R = 10$ , $\lambda = 10^{-8}$ , $\gamma = 500$	M5: $R = 10$ , $\lambda_1 = 0.004$ , $\lambda_2 = 0.5$	M6: $R = 10$ , $\lambda_1 = 0.5$ , $\lambda_2 = 0.03125$	M7: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.2$	M8: $R = 10$ , $\eta = 0.1$ , $\lambda = 0.01$

TABLE S3  
RMSE, MAE, WIN/LOSS COUNTS OF M1-8 ON D1-8.

Datasets	M1	M2	M3	M4	M5	M6	M7	M8
<b>D1</b>	<b>RMSE</b> $0.3387 \pm 6.8E-4$ <b>MAE</b> $0.2450 \pm 1.8E-4$	$0.3605 \pm 8.3E-4$ $0.2498 \pm 6.3E-4$	$0.3431 \pm 3.5E-4$ $0.2492 \pm 2.1E-4$	$0.3647 \pm 7.1E-4$ $0.2557 \pm 4.8E-4$	$0.3498 \pm 4.8E-5$ $0.2512 \pm 7.4E-5$	$0.3531 \pm 4.5E-5$ $0.2508 \pm 4.5E-5$	$0.5871 \pm 6.1E-5$ $0.4126 \pm 7.6E-5$	$0.5869 \pm 4.2E-6$ $0.4111 \pm 2.7E-6$
<b>D2</b>	<b>RMSE</b> $0.3466 \pm 1.6E-5$ <b>MAE</b> $0.2474 \pm 1.3E-5$	$0.3697 \pm 1.0E-3$ $0.2951 \pm 6.4E-2$	$0.3485 \pm 5.2E-4$ $0.2552 \pm 3.6E-4$	$0.3675 \pm 4.5E-4$ $0.2619 \pm 4.5E-3$	$0.3535 \pm 7.4E-5$ $0.2556 \pm 5.8E-5$	$0.3534 \pm 8.1E-5$ $0.2560 \pm 4.9E-5$	$0.6027 \pm 1.4E-5$ $0.4259 \pm 1.7E-5$	$0.6024 \pm 8.6E-6$ $0.4246 \pm 1.1E-5$
<b>D3</b>	<b>RMSE</b> $0.3192 \pm 3.9E-6$ <b>MAE</b> $0.2187 \pm 2.1E-6$	$0.3296 \pm 2.2E-4$ $0.2234 \pm 3.1E-4$	$0.3252 \pm 2.1E-0$ $0.2273 \pm 2.0E-4$	$0.3671 \pm 2.4E-0$ $0.2471 \pm 1.3E-3$	$0.3344 \pm 2.7E-5$ $0.2219 \pm 8.1E-5$	$0.3325 \pm 1.8E-4$ $0.2282 \pm 1.2E-4$	$0.4758 \pm 1.9E-6$ $0.3125 \pm 4.3E-6$	$0.4759 \pm 3.9E-6$ $0.3123 \pm 1.4E-6$
<b>D4</b>	<b>RMSE</b> $0.3161 \pm 6.4E-6$ <b>MAE</b> $0.2166 \pm 2.7E-6$	$0.3359 \pm 2.7E-4$ $0.2216 \pm 5.6E-4$	$0.3172 \pm 1.0E-4$ $0.2186 \pm 3.7E-5$	$0.3855 \pm 5.3E-4$ $0.2770 \pm 3.2E-4$	$0.3425 \pm 7.5E-5$ $0.2314 \pm 7.8E-5$	$0.3489 \pm 8.6E-5$ $0.2377 \pm 1.6E-5$	$0.4856 \pm 9.0E-7$ $0.3242 \pm 5.6E-6$	$0.4857 \pm 3.8E-6$ $0.3239 \pm 1.5E-6$
<b>D5</b>	<b>RMSE</b> $0.2904 \pm 2.1E-4$ <b>MAE</b> $0.1996 \pm 1.8E-4$	$0.3021 \pm 5.5E-4$ $0.2033 \pm 1.0E-3$	$0.2939 \pm 3.4E-4$ $0.2039 \pm 2.8E-3$	$0.2962 \pm 8.5E-3$ $0.2029 \pm 8.9E-3$	$0.2985 \pm 6.1E-5$ $0.2089 \pm 2.0E-4$	$0.3050 \pm 9.6E-5$ $0.2161 \pm 1.2E-5$	$0.4794 \pm 1.6E-6$ $0.3353 \pm 4.7E-5$	$0.4793 \pm 1.8E-7$ $0.3336 \pm 3.1E-6$
<b>D6</b>	<b>RMSE</b> $0.3426 \pm 5.6E-6$ <b>MAE</b> $0.2493 \pm 2.9E-6$	$0.3717 \pm 7.0E-4$ $0.2570 \pm 2.4E-4$	$0.3477 \pm 2.6E-4$ $0.2555 \pm 1.1E-4$	$0.3489 \pm 3.3E-4$ $0.2583 \pm 2.1E-5$	$0.3436 \pm 5.4E-2$ $0.2599 \pm 3.9E-4$	$0.3440 \pm 1.0E-5$ $0.2593 \pm 5.1E-5$	$0.5881 \pm 5.0E-6$ $0.4295 \pm 2.6E-5$	$0.5880 \pm 3.5E-6$ $0.4287 \pm 7.0E-6$
<b>D7</b>	<b>RMSE</b> $0.3245 \pm 2.2E-4$ <b>MAE</b> $0.2294 \pm 3.8E-4$	$0.3440 \pm 8.3E-4$ $0.2420 \pm 6.8E-4$	$0.3294 \pm 3.6E-4$ $0.2351 \pm 4.4E-4$	$0.3488 \pm 7.3E-4$ $0.2478 \pm 6.6E-4$	$0.3359 \pm 5.1E-5$ $0.2386 \pm 5.8E-5$	$0.3375 \pm 6.4E-5$ $0.2397 \pm 6.1E-5$	-	-
<b>D8</b>	<b>RMSE</b> $0.3117 \pm 4.0E-4$ <b>MAE</b> $0.2164 \pm 3.0E-4$	$0.3304 \pm 7.8E-4$ $0.2283 \pm 6.0E-4$	$0.3164 \pm 4.2E-4$ $0.2283 \pm 5.9E-4$	$0.3251 \pm 8.0E-4$ $0.2337 \pm 6.2E-4$	$0.3226 \pm 6.2E-5$ $0.2251 \pm 5.4E-5$	$0.3242 \pm 6.9E-5$ $0.2261 \pm 5.6E-5$	-	-
Win/Loss	-	16/0	16/0	16/0	16/0	16/0	16/0	16/0
F-rank	1.00	4.28	2.59	4.88	3.63	4.31	7.75	7.31

TABLE S4  
SINGLE TRAINING TIME COST IN RMSE/MAE(SECONDS), WIN/LOSS COUNTS OF M1-8 ON D1-8

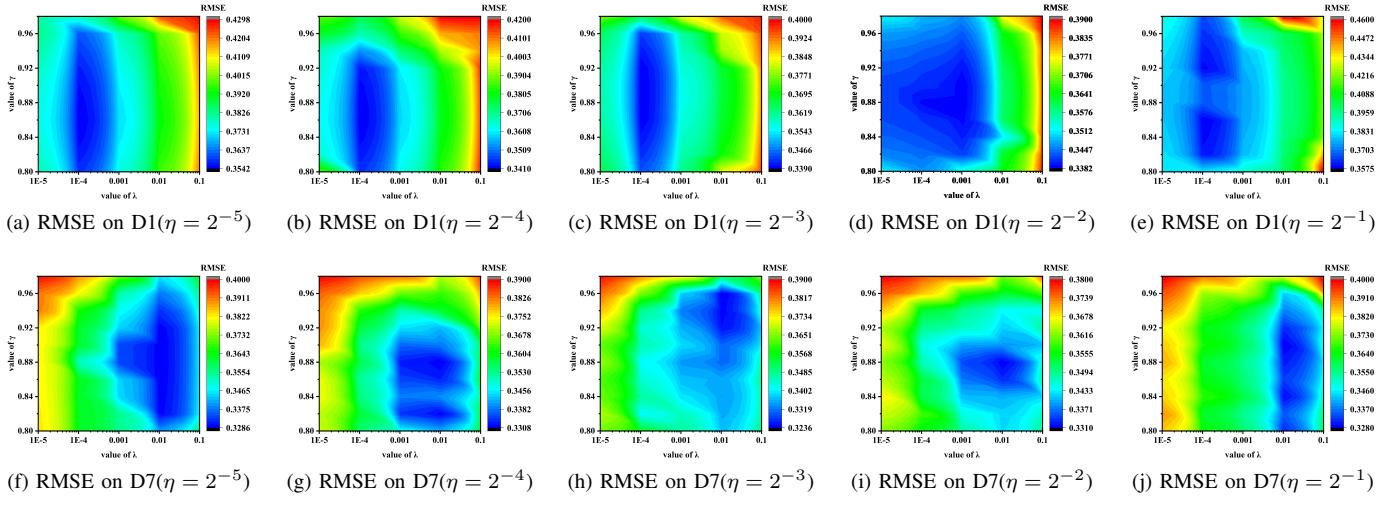
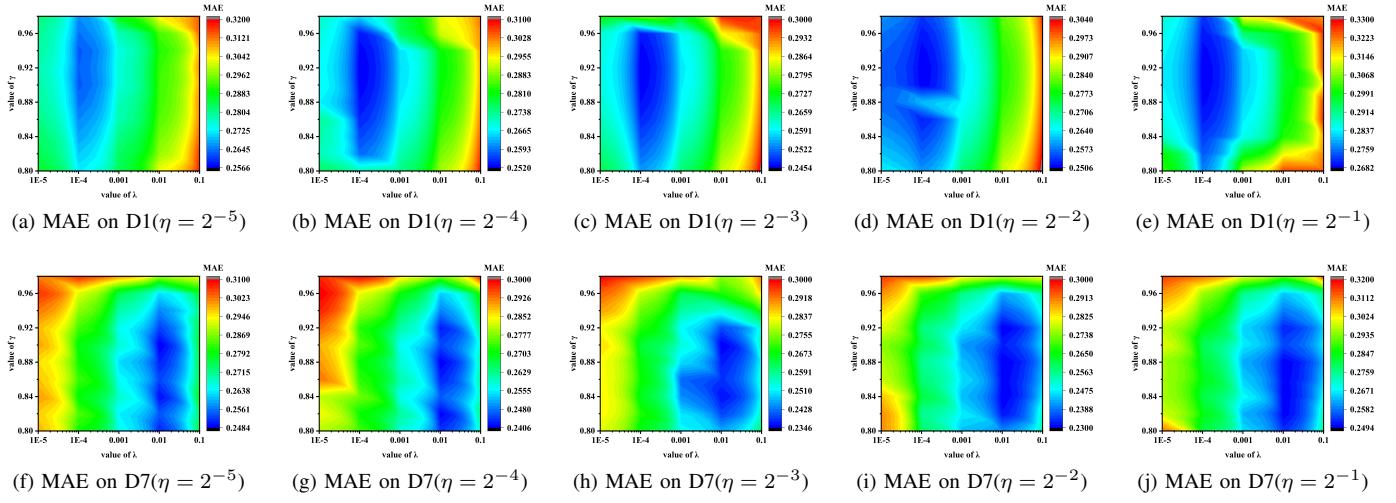
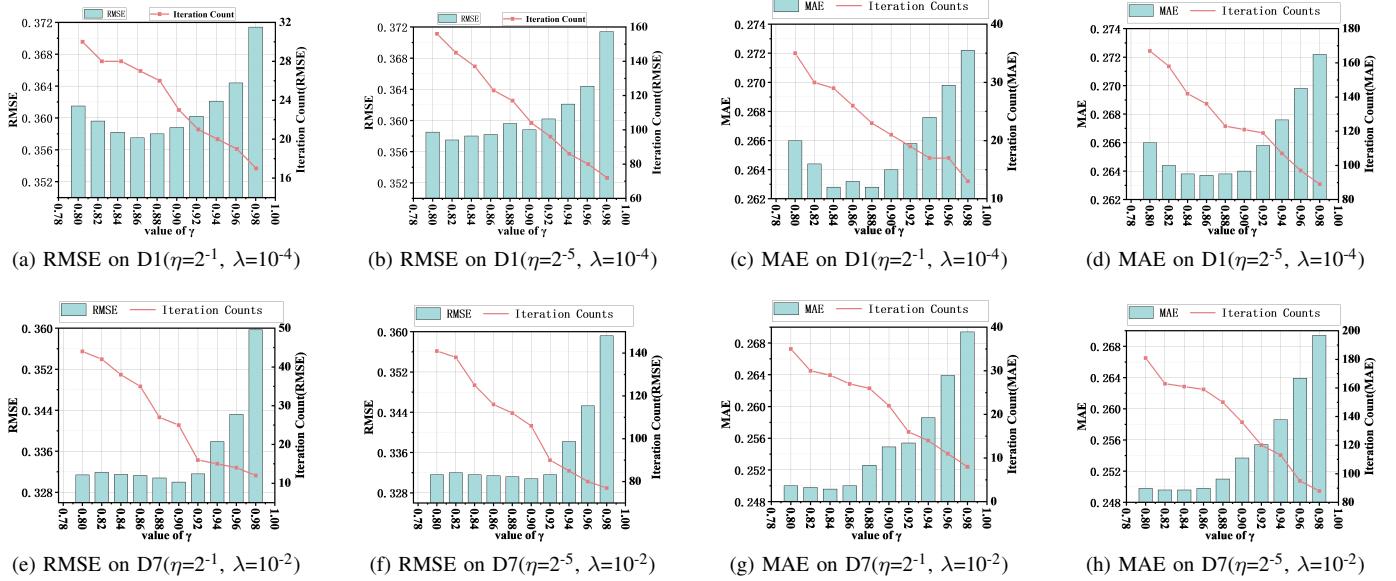
Datasets	M1	M2	M3	M4	M5	M6	M7	M8
<b>D1</b>	<b>RMSE</b> <b>37.48<math>\pm</math>0.66</b>	1222.25 $\pm$ 2428.2	1358.66 $\pm$ 61.69	57.01 $\pm$ 5.65	180.48 $\pm$ 7.25	358.29 $\pm$ 6.03	1419.7 $\pm$ 113.98	522.58 $\pm$ 10.01
	<b>MAE</b> <b>39.82<math>\pm</math>0.55</b>	1318.37 $\pm$ 468.16	1357.62 $\pm$ 61.76	55.97 $\pm$ 3.42	92.55 $\pm$ 0.77	206.14 $\pm$ 2.85	1812.03 $\pm$ 132.77	1097.77 $\pm$ 54.89
<b>D2</b>	<b>RMSE</b> <b>22.74<math>\pm</math>0.35</b>	693.79 $\pm$ 40.64	700.9 $\pm$ 51.93	38.83 $\pm$ 2.82	79.12 $\pm$ 5.57	96.65 $\pm$ 3.98	986.4 $\pm$ 119.81	378.21 $\pm$ 3.17
	<b>MAE</b> <b>24.17<math>\pm</math>2.35</b>	740.65 $\pm$ 41.59	689.27 $\pm$ 44.32	38.83 $\pm$ 1.73	61.89 $\pm$ 3.34	54.67 $\pm$ 3.91	1222.48 $\pm$ 132.77	857.7 $\pm$ 2.31
<b>D3</b>	<b>RMSE</b> <b>4.99<math>\pm</math>0.43</b>	270.32 $\pm$ 95.46	122.41 $\pm$ 3.54	31.32 $\pm$ 3.03	25.05 $\pm$ 0.98	61.74 $\pm$ 4.18	394.79 $\pm$ 11.95	175.21 $\pm$ 2.63
	<b>MAE</b> <b>3.23<math>\pm</math>0.32</b>	272.08 $\pm$ 96.06	119.19 $\pm$ 4.27	30.5 $\pm$ 4.79	15.03 $\pm$ 1.11	51.38 $\pm$ 2.95	482.28 $\pm$ 7.46	342.87 $\pm$ 6.23
<b>D4</b>	<b>RMSE</b> <b>8.03<math>\pm</math>0.55</b>	171.97 $\pm$ 60.97	129.93 $\pm$ 0.28	22.63 $\pm$ 0.65	17.02 $\pm$ 0.63	34.27 $\pm$ 1.92	219.58 $\pm$ 5.08	158.55 $\pm$ 51.02
	<b>MAE</b> <b>4.59<math>\pm</math>0.66</b>	182.39 $\pm$ 69.95	128.18 $\pm$ 1.32	23.18 $\pm$ 0.62	12.07 $\pm$ 1.68	40.09 $\pm$ 1.72	275.74 $\pm$ 10.48	296.24 $\pm$ 96.35
<b>D5</b>	<b>RMSE</b> <b>8.88<math>\pm</math>0.66</b>	138.95 $\pm$ 9.59	128.5 $\pm$ 3.71	11.71 $\pm$ 0.94	26.98 $\pm$ 0.41	42.2 $\pm$ 3.53	390.7 $\pm$ 14.97	272 $\pm$ 16.51
	<b>MAE</b> <b>9.24<math>\pm</math>0.43</b>	141.5 $\pm$ 8.23	127.79 $\pm$ 4.95	12.66 $\pm$ 0.52	14.68 $\pm$ 0.61	59.06 $\pm$ 2.34	509.75 $\pm$ 23.17	901.16 $\pm$ 11.82
<b>D6</b>	<b>RMSE</b> <b>5.33<math>\pm</math>0.04</b>	214.96 $\pm$ 3.58	258.28 $\pm$ 4.71	19.57 $\pm$ 2.82	35.77 $\pm$ 1.1	65.38 $\pm$ 1.91	799.05 $\pm$ 9.98	146.72 $\pm$ 26.42
	<b>MAE</b> <b>5.33<math>\pm</math>0.04</b>	192.14 $\pm$ 4.36	220.03 $\pm$ 7.75	6.34 $\pm$ 0.93	8.82 $\pm$ 0.65	116.52 $\pm$ 3.96	1125.55 $\pm$ 5.81	575.61 $\pm$ 93.9
<b>D7</b>	<b>RMSE</b> <b>4722.89<math>\pm</math>129.8</b>	153965 $\pm$ 13366	171167 $\pm$ 3378	7175 $\pm$ 311	22549 $\pm$ 398	44765 $\pm$ 671	-	-
	<b>MAE</b> <b>5028.77<math>\pm</math>425.6</b>	171479 $\pm$ 23392	171614 $\pm$ 11662	7040 $\pm$ 233	14130 $\pm$ 926.34	25803 $\pm$ 2207	-	-
<b>D8</b>	<b>RMSE</b> <b>2083.52<math>\pm</math>110</b>	135316 $\pm$ 11325.60	139236 $\pm$ 2862	4646 $\pm$ 263	15175 $\pm$ 337	210273 $\pm$ 568	-	-
	<b>MAE</b> <b>3137.18<math>\pm</math>129</b>	135923 $\pm$ 13284	140292 $\pm$ 3358	5592 $\pm$ 308	13190 $\pm$ 395	25836 $\pm$ 667	-	-
Win/Loss	-	16/0	16/0	16/0	16/0	16/0	16/0	16/0
F-rank	1.00	6.00	5.38	2.25	2.81	3.94	7.75	6.25

TABLE S5  
WILCOXON SIGNED-RANKS TEST FOR TABLE S3

Comparison	R+	R-	p-value
M1 vs M2	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M3	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M4	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M5	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M6	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M7	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M8	136	0	1.53 $\times$ 10 $^{-5}$

TABLE S6  
WILCOXON SIGNED-RANKS TEST FOR TABLE S4

Comparison	R+	R-	p-value
M1 vs M2	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M3	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M4	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M5	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M6	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M7	136	0	1.53 $\times$ 10 $^{-5}$
M1 vs M8	136	0	1.53 $\times$ 10 $^{-5}$

Fig. S1. RMSE of FNL as  $\eta$ ,  $\lambda$  and  $\gamma$  varies on D1 and D7.Fig. S2. MAE of FNL as  $\eta$ ,  $\lambda$  and  $\gamma$  varies on D1 and D7.Fig. S3. RMSE/MAE and Iteration of FNL as  $\eta$ ,  $\lambda$  and  $\gamma$  varies on D1 and D7.

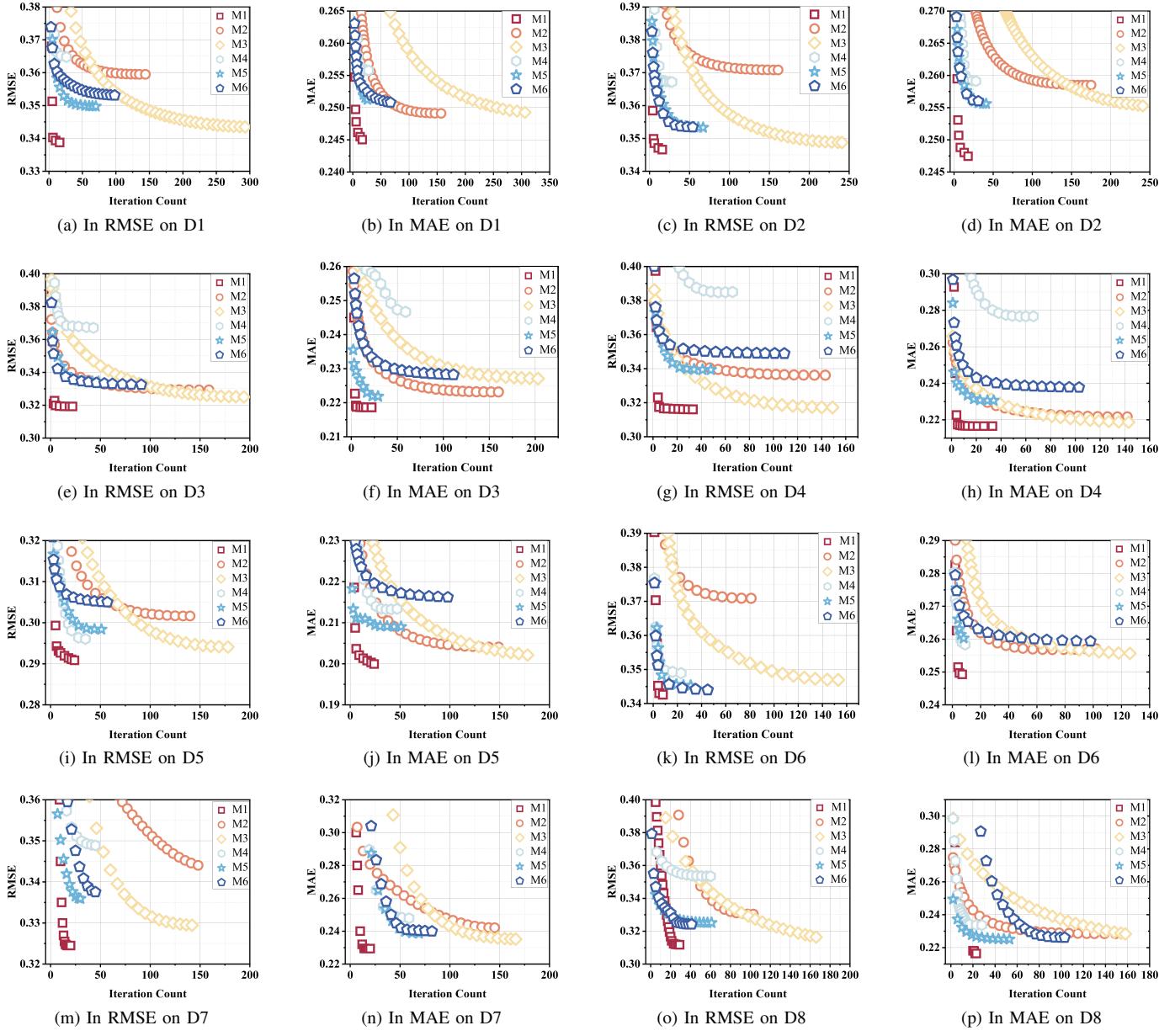


Fig. S4. Training curves of M1-6 in RMSE and MAE on D1-8.

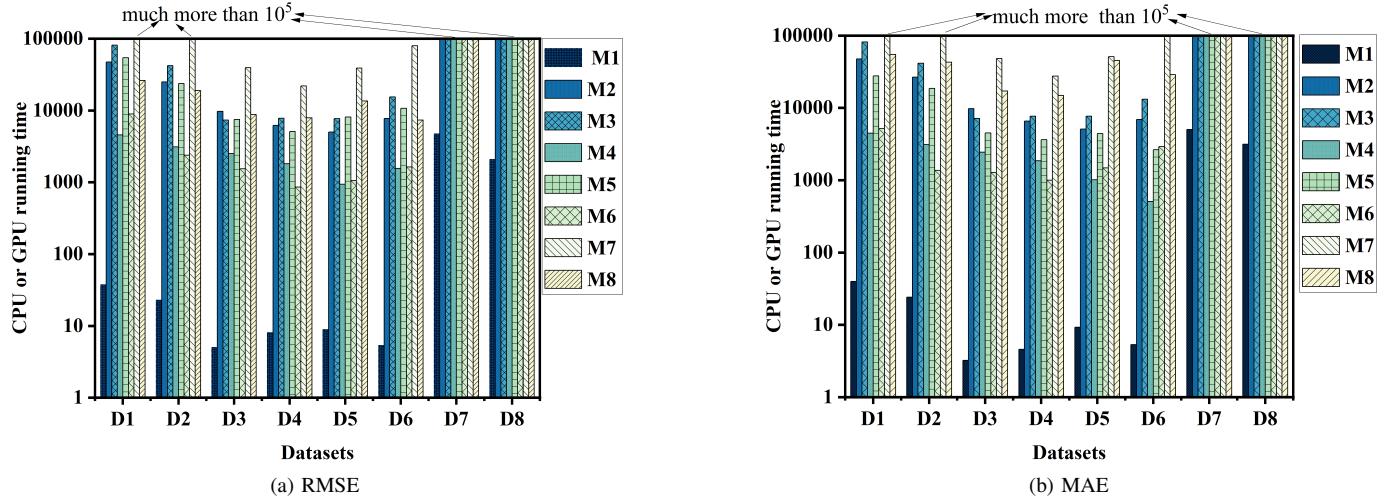


Fig. S5. The total time cost of M1-8 for obtaining the lowest RMSE and MAE on D1-8.

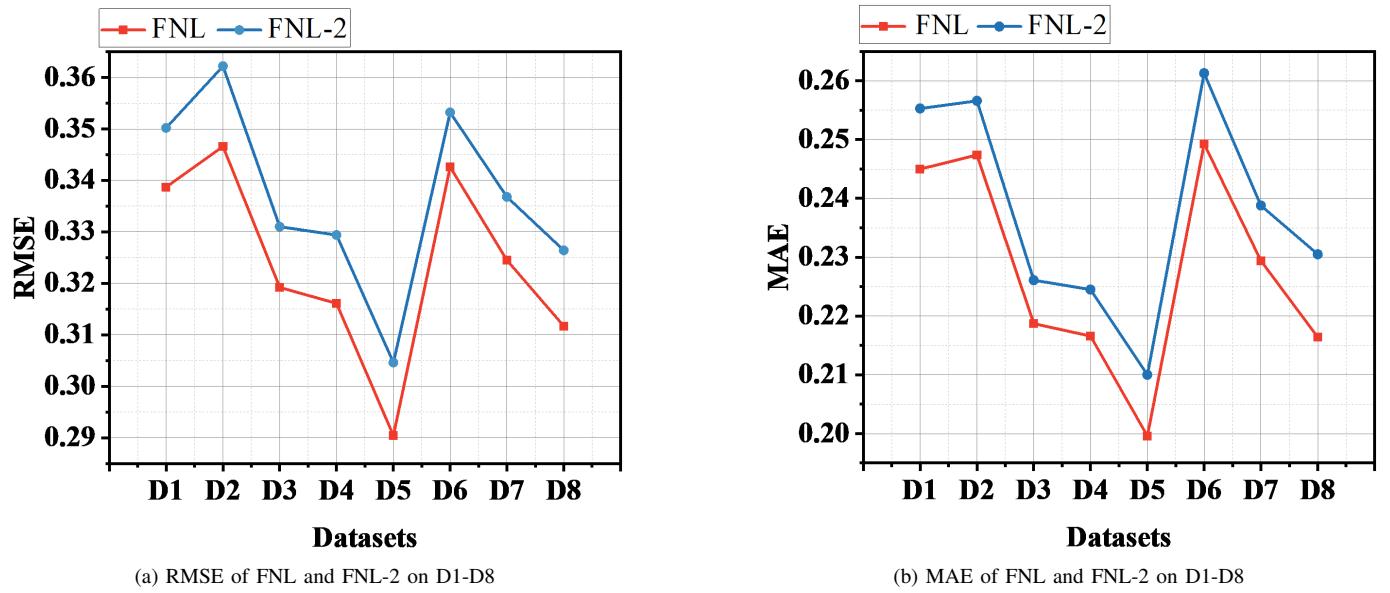


Fig. S6. Ablation study with nonlinear activation function on D1-D8.