

ST-LoRA: Low-rank Adaptation for Spatio-Temporal Forecasting

Weilin Ruan, Wei Chen, Xilin Dang, Jianxiang Zhou,
Weichuang Li, Xu Liu, Yuxuan Liang*



GitHub



WeChat

Presenter: Weilin RUAN
MPhil @ HKUST(GZ)

Key Points:

- We propose *ST-LoRA*, a plug-and-play framework with Node-Adaptive Low-rank Layers and Node-Specific Predictors for efficient modeling of node heterogeneity.
- Extensive experiments across 6 baselines and 6 real-world traffic datasets show ~7% performance improvement with <1% additional parameters.

Background & Challenges

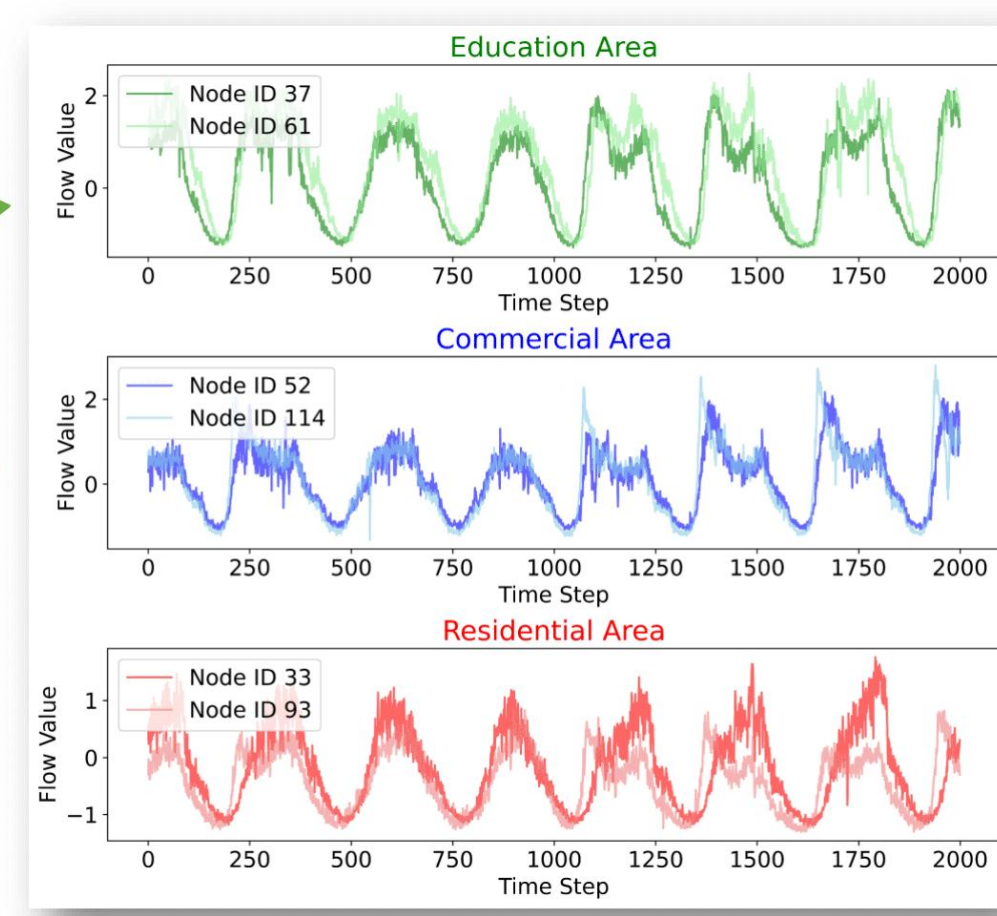
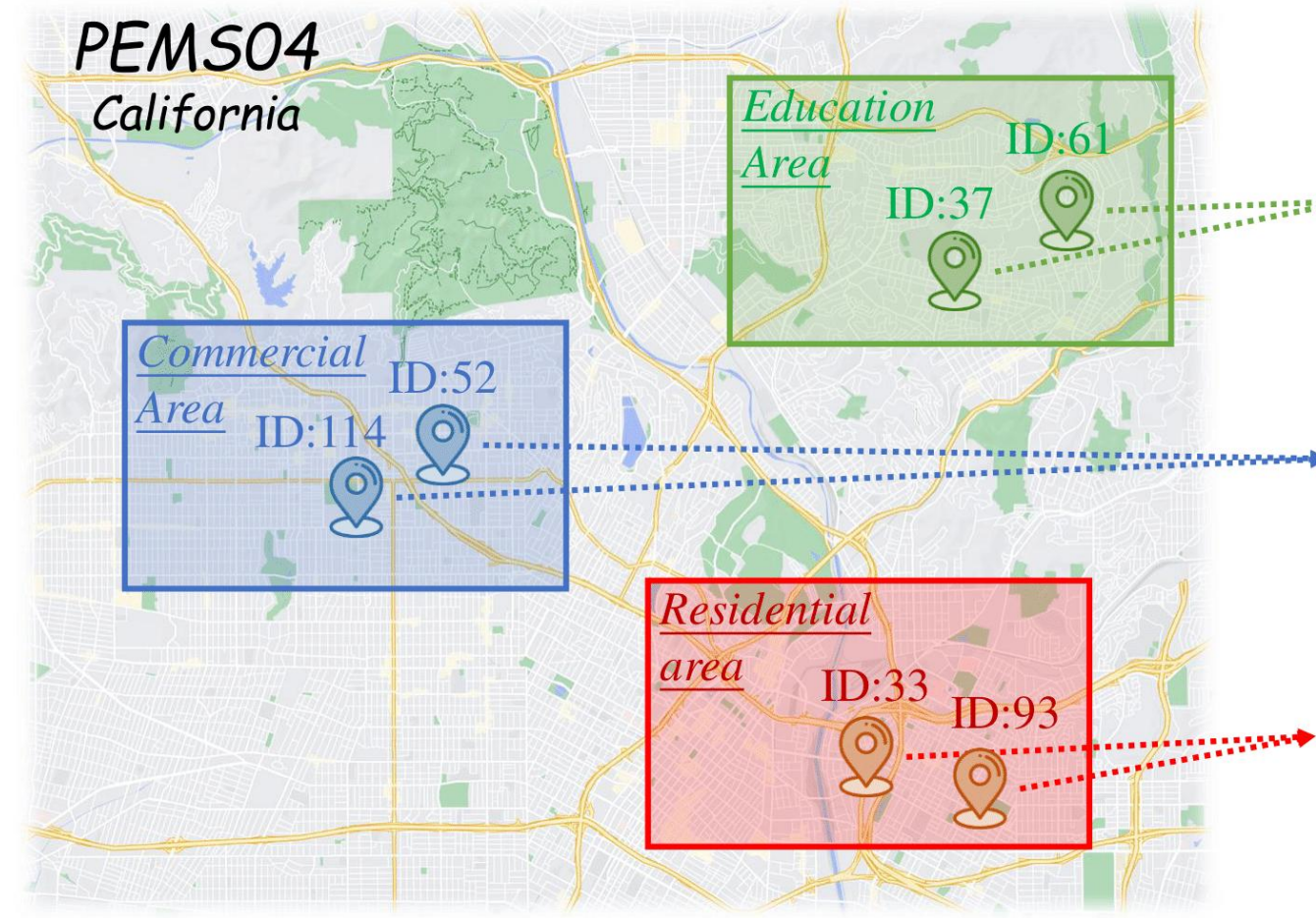
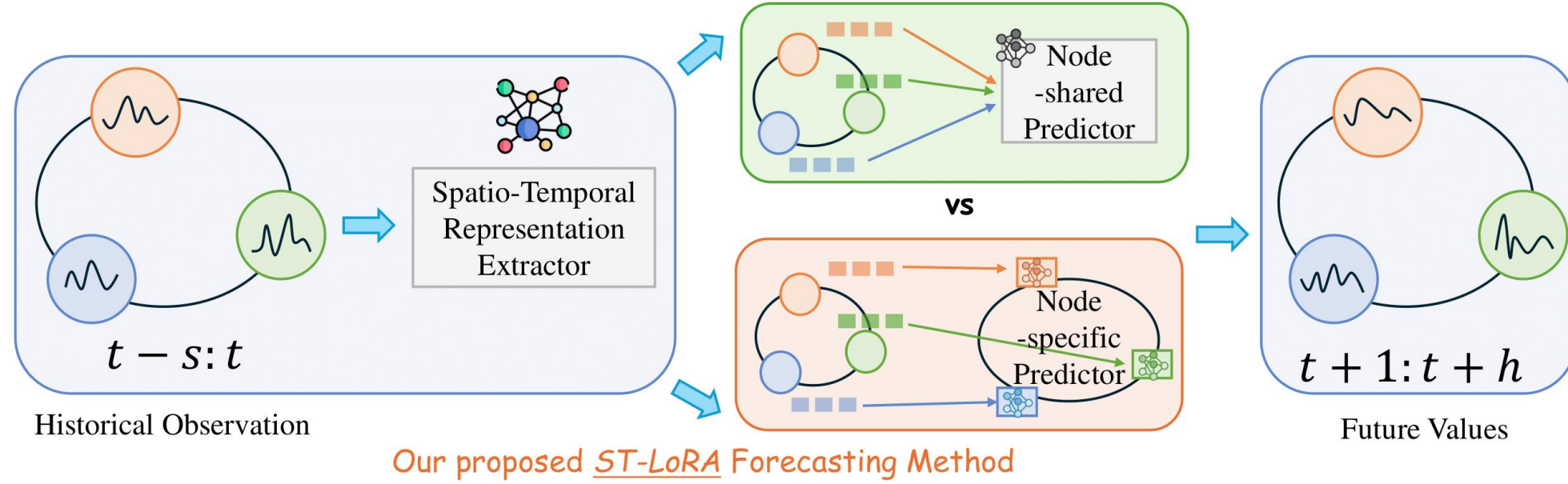
Spatio-temporal Forecasting:

$$[X^{(t-s+1)}, \dots, X^{(t)}; \mathcal{G}] \xrightarrow{\mathcal{F}(\cdot)} [X^{(t+1)}, \dots, X^{(t+h)}].$$

Facing Node heterogeneity & Over-parameterization!

Our Solution

Conventional Spatio-Temporal Forecasting Methods



*Node-shared predictor struggles to address node-level heterogeneity. We need an efficient solution to the trade-off between **heterogeneity** and computational **complexity**.*

Node-Adaptive Low-rank Layer

$$\Delta W_{v_i} = B A_{v_i} \cdot \frac{\alpha}{r}, \quad \hat{y}_i = \sigma(Wx + \Delta W_{v_i}x + b),$$

Decompose each **node-level** parameter weights into two low-rank matrices.

Node-Specific Predictor

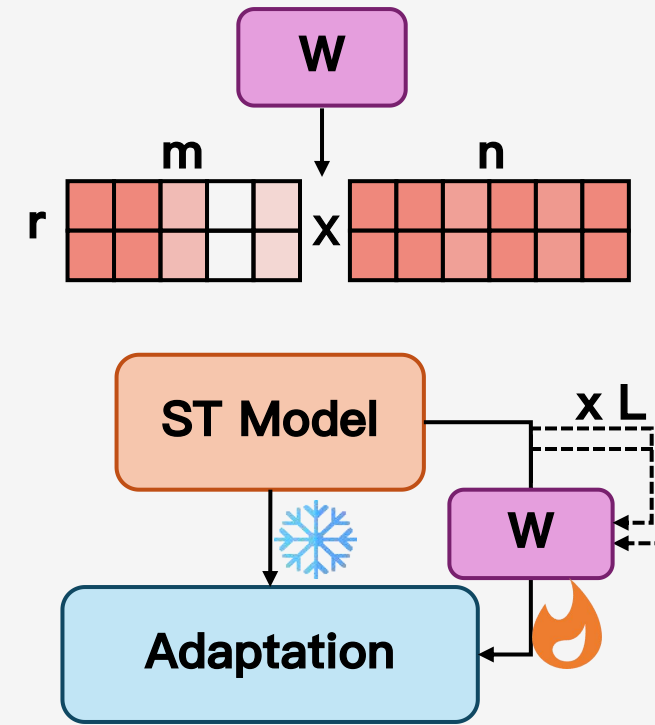
$$H^{(0)} = \text{Conv2D}(X_{t-T:t}),$$

$$H^{(l)} = H^{(l-1)} + \text{NALL}^{(l)}(\sigma(H^{(l-1)})), \quad l = 1, 2, \dots, L$$

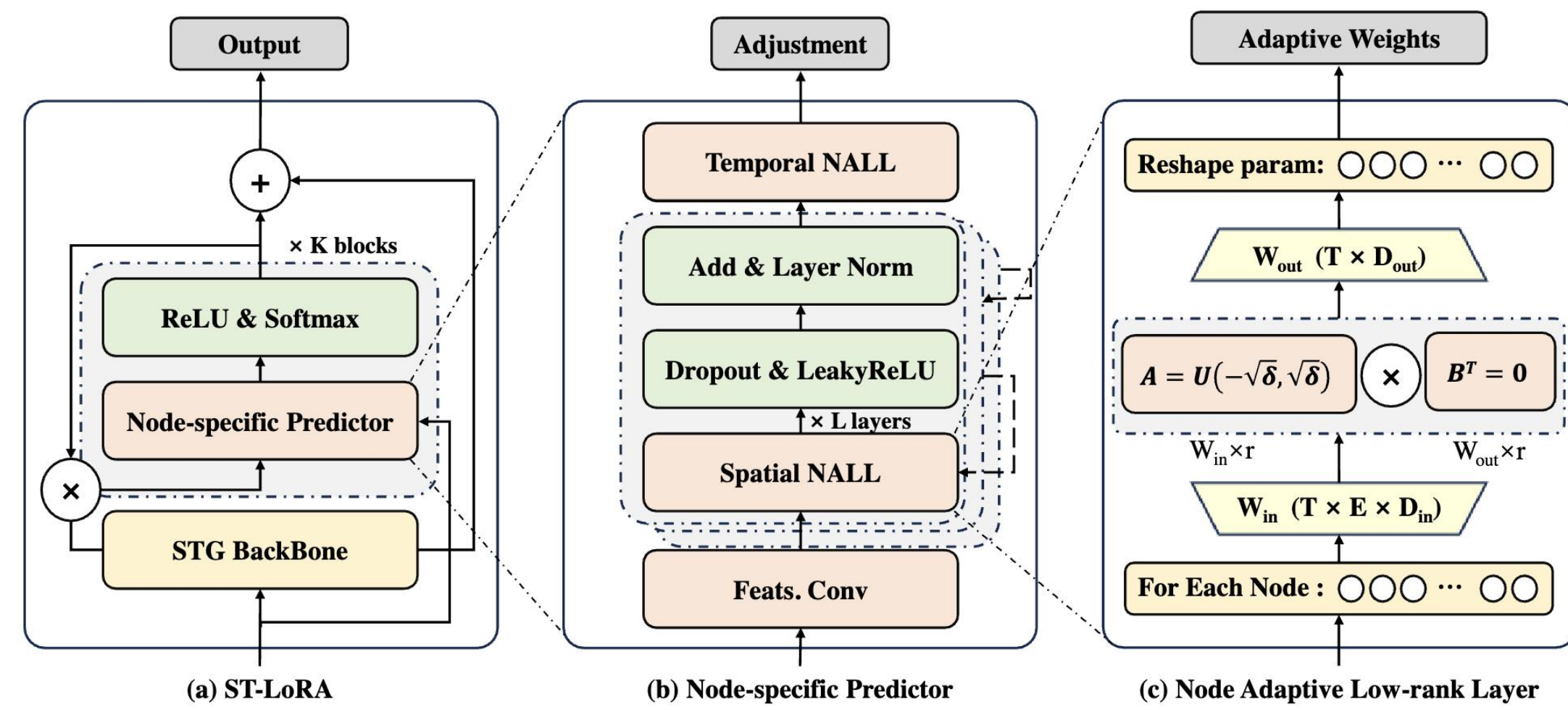
$$\hat{Y}_t = \mathcal{G}_t(H^{(L)}),$$

Node specific predictor that models dynamics without heavy computation.

Overview



ST-LoRA Framework



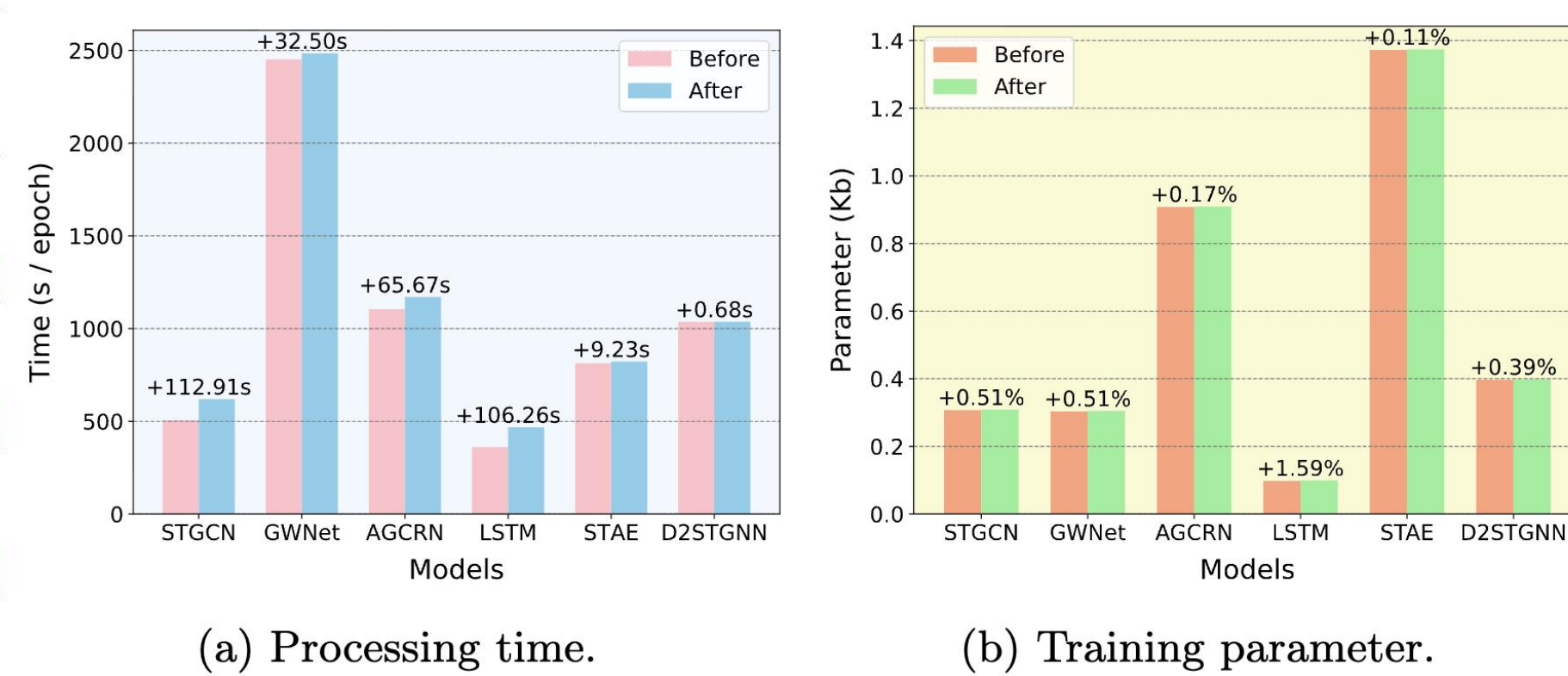
Experiment Results

Model	15min			30min			60min			Average		
	MAE ↓	RMSE ↓	MAPE% ↓	MAE ↓	RMSE ↓	MAPE% ↓	MAE ↓	RMSE ↓	MAPE% ↓	MAE ↓	RMSE ↓	MAPE% ↓
HA	28.92±1.25	42.69±1.82	20.31±0.89	33.73±1.28	49.37±1.85	24.01±0.91	46.97±1.31	67.43±1.89	35.11±0.92	38.03±1.28	59.24±1.85	27.88±0.91
VAR	21.94±0.62	34.30±1.02	16.42±0.48	23.72±0.71	36.58±1.08	18.02±0.52	26.76±0.82	40.28±1.23	20.94±0.64	23.51±0.72	36.39±1.11	17.85±0.55
SVR	22.52±0.68	35.30±1.12	14.71±0.45	27.63±0.78	42.23±1.25	18.29±0.49	37.86±1.15	56.01±1.70	26.72±0.82	28.66±0.87	44.59±1.36	19.15±0.59
LSTM	21.94±0.59	33.37±0.93	15.32±0.40	25.83±0.66	39.10±1.04	20.35±0.43	36.41±0.82	50.73±1.28	29.92±0.56	27.14±0.69	41.59±1.08	18.20±0.46
LSTM+	18.89±0.58	29.96±0.91	13.02±0.30	21.31±0.65	34.22±1.04	13.96±0.43	26.34±0.80	41.30±1.26	18.26±0.56	22.18±0.68	35.16±1.07	15.08±0.46
Δ	-3.05±0.18	-3.41±0.20	-2.30±0.14	-4.52±0.27	-4.88±0.29	-6.39±0.38	-10.07±0.60	-9.43±0.57	-11.66±0.70	-4.96±0.30	-6.43±0.39	-3.12±0.19
STGCN	19.45±0.59	30.12±0.92	14.21±0.43	21.85±0.62	34.43±0.97	14.13±0.44	26.97±0.68	41.11±1.06	16.84±0.48	22.70±0.63	35.55±0.98	14.59±0.45
STGCN+	19.12±0.58	29.72±0.91	13.89±0.42	19.92±0.61	31.63±0.96	13.77±0.42	22.07±0.67	34.47±1.05	15.42±0.47	20.37±0.62	31.94±0.97	14.36±0.44
Δ	-0.33±0.02	-0.40±0.02	-0.32±0.02	-1.93±0.12	-2.80±0.17	-0.36±0.02	-4.90±0.29	-6.64±0.40	-1.42±0.09	-2.33±0.14	-3.61±0.22	-0.23±0.01
GWNNet	18.65±0.57	29.24±0.89	13.82±0.42	19.57±0.60	30.62±0.92	13.28±0.39	23.07±0.70	35.35±1.08	17.34±0.53	25.45±0.62	39.70±0.97	17.29±0.45
GWNNet+	17.89±0.55	28.52±0.87	12.64±0.39	18.88±0.58	29.38±0.89	13.06±0.40	20.89±0.64	32.96±1.00	14.92±0.46	19.22±0.59	30.62±0.93	13.54±0.41
Δ	-0.76±0.05	-0.72±0.04	-1.18±0.07	-0.69±0.04	-1.24±0.07	-0.22±0.01	-2.18±0.13	-2.39±0.14	-2.42±0.15	-6.23±0.37	-9.08±0.54	-3.75±0.23
AGCRN	18.12±0.55	29.45±0.90	12.85±0.39	18.77±0.57	30.08±0.92	12.97±0.40	20.41±0.62	32.87±1.00	14.38±0.44	19.83±0.58	32.26±0.94	13.40±0.41
AGCRN+	17.83±0.54	29.16±0.89	12.55±0.38	18.63±0.57	29.99±0.91	12.82±0.39	19.97±0.61	32.37±0.99	13.78±0.42	18.81±0.57	30.51±0.93	13.05±0.40
Δ	-0.29±0.02	-0.29±0.02	-0.30±0.02	-0.14±0.01	-0.09±0.01	-0.15±0.01	-0.44±0.03	-0.50±0.03	-0.60±0.04	-1.02±0.06	-1.75±0.11	-0.35±0.02
STAE	17.95±0.55	29.12±0.89	12.65±0.39	18.92±0.58	30.09±0.92	13.35±0.41	21.06±0.64	33.37±1.02	15.55±0.47	19.31±0.59	30.86±0.94	13.85±0.42
STAE+	17.65±0.54	28.73±0.88	12.45±0.38	18.62±0.57	29.55±0.90	13.29±0.41	20.40±0.62	32.38±0.99	15.00±0.46	18.89±0.58	30.22±0.92	13.58±0.41
Δ	-0.30±0.02	-0.39±0.02	-0.20±0.01	-0.30±0.02	-0.54±0.03	-0.06±0.01	-0.66±0.04	-0.99±0.06	-0.55±0.03	-0.42±0.03	-0.64±0.04	-0.27±0.02
D2STGNN	18.95±0.58	29.85±0.91	14.82±0.45	19.96±0.61	31.34±0.95	15.52±0.47	23.34±0.71	35.89±1.09	17.39±0.53	20.75±0.63	32.36±0.99	15.91±0.49
D2STGNN+	18.25±0.56	28.92±0.88	14.12±0.43	19.21±0.59	30.50±0.93	13.46±0.41	21.73±0.66	33.73±1.03	17.00±0.52	19.73±0.60	31.05±0.95	14.86±0.45
Δ	-0.70±0.04	-0.93±0.06	-0.70±0.04	-0.75±0.05	-0.84±0.05	-2.06±0.12	-1.61±0.10	-2.16±0.13	-0.39±0.02	-1.02±0.06	-1.31±0.08	-1.05±0.06

Dataset	15min			30min			60min			Average		
	MAE	RMSE	MAPE%	MAE	RMSE	MAPE%	MAE	RMSE	MAPE%	MAE	RMSE	MAPE%
PEMS04	-0.33±0.02	-0.40±0.03	-0.07±0.01	-1.45±0.09	-2.50±0.15	-0.10±0.01	-4.94±0.30	-6.61±0.40	-1.28±0.08	-2.24±0.14	-3.17±0.19	-0.48±0.03
PEMS08	-0.20±0.01	-1.09±0.07	-0.57±0.03	-1.37±0.08	-1.79±0.11	-0.30±0.02	-7.63±0.46	-5.86±0.35	-1.28±0.08	-3.07±0.18	-2.91±0.17	-0.72±0.04
PEMS03	-0.31±0.02	-0.51±0.03	-0.72±0.04	-0.22±0.01	-0.23±0.01	-0.60±0.04	-0.45±0.03	-0.35±0.02	-1.25±0.08	-0.33±0.02	-0.36±0.02	-0.86±0.05
PEMS07	-0.26±0.02	-0.29±0.02	-0.16±0.01	-0.38±0.02	-0.35±0.02	-0.31±0.02	-0.59±0.04	-0.59±0.04	-0.32±0.02	-0.41±0.03	-0.41±0.03	-0.26±0.02
METR-LA	-0.10±0.01	-0.36±0.02	-0.03±0.00	-0.33±0.02	-0.83±0.05	-0.80±0.05	-1.05±0.06	-1.97±0.12	-2.30±0.14	-0.49±0.03	-1.05±0.06	-1.04±0.06
PEMSBAY	-0.04±0.00	-0.06±0.00	-0.11±0.01	-0.10±0.01	-0.45±0.03	-0.23±0.01	-0.50±0.03	-1.14±0.07	-1.02±0.06	-0.21±0.01	-0.55±0.03	-0.45±0.03

Extensive Experiments across Multiple Models and Datasets.

Comprehensive Efficiency Study



(a) Processing time.

(b) Training parameter.

Conclusion

Our paper highlights the potential of **low-rank adaptation** techniques to improve spatio-temporal forecasting in real-world scenarios, achieving consistent enhanced performance across multiple datasets and models.

Future Work

Develop a **unified, scalable framework** for flexible LoRA variants, and benchmark across diverse spatio-temporal models and datasets.