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FedMetro：

Efficient Metro Passenger Flow Prediction via Federated Graph Learning

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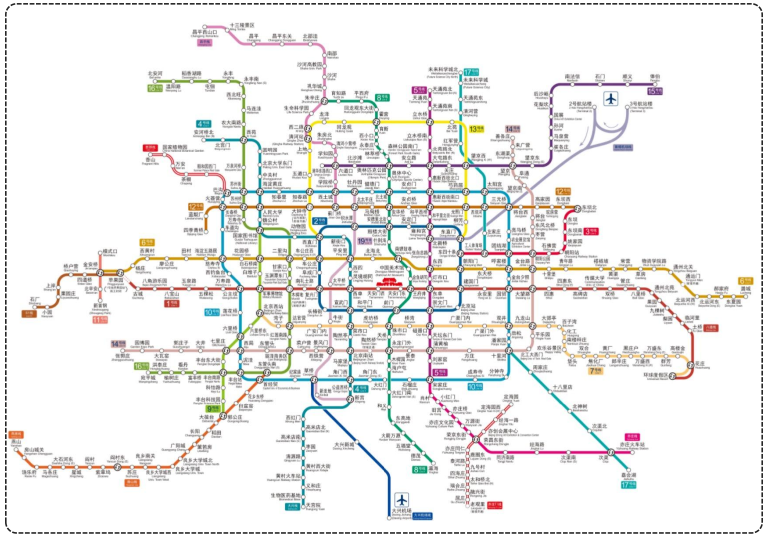
Outline

- Background
- Problem Definition
- Our Solutions
- Experiments

Background

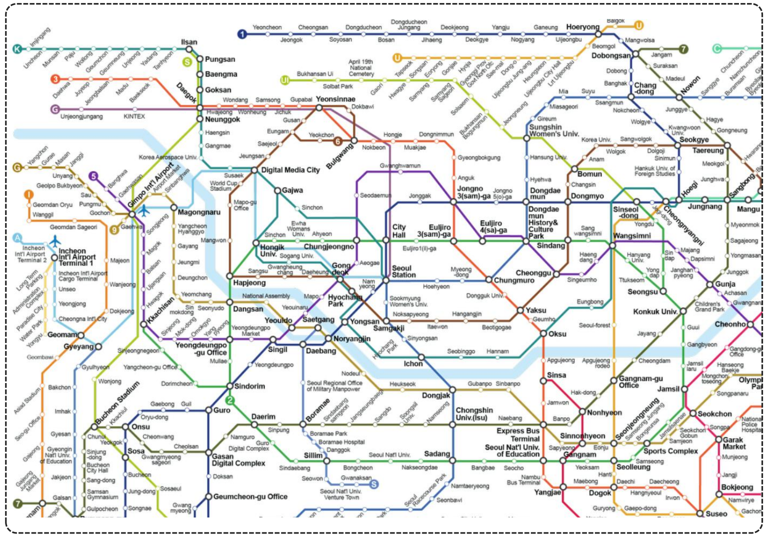
- Metro systems are the main part of urban mobility
- Metro passenger flow prediction is vital for transportation management



Beijing, China

Length: 879 km

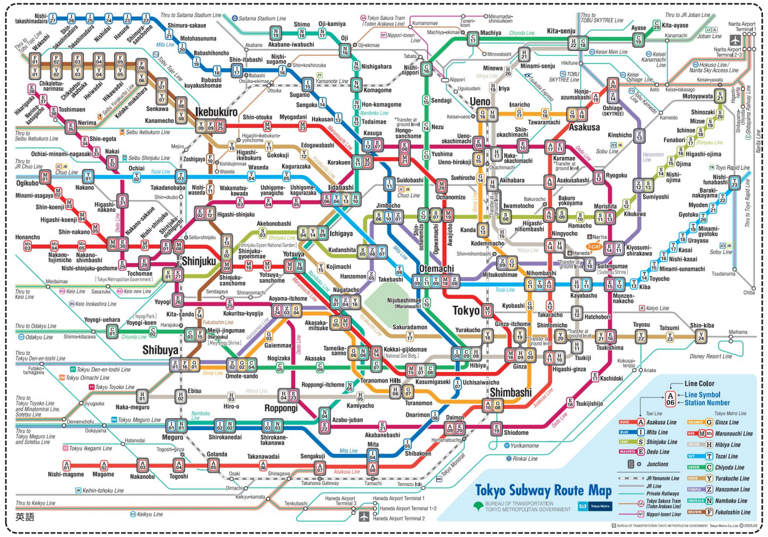
Daily ridership: 99 million



Seoul, South Korea

Length: 385 km

Daily ridership: 90 million



Tokyo, Japan

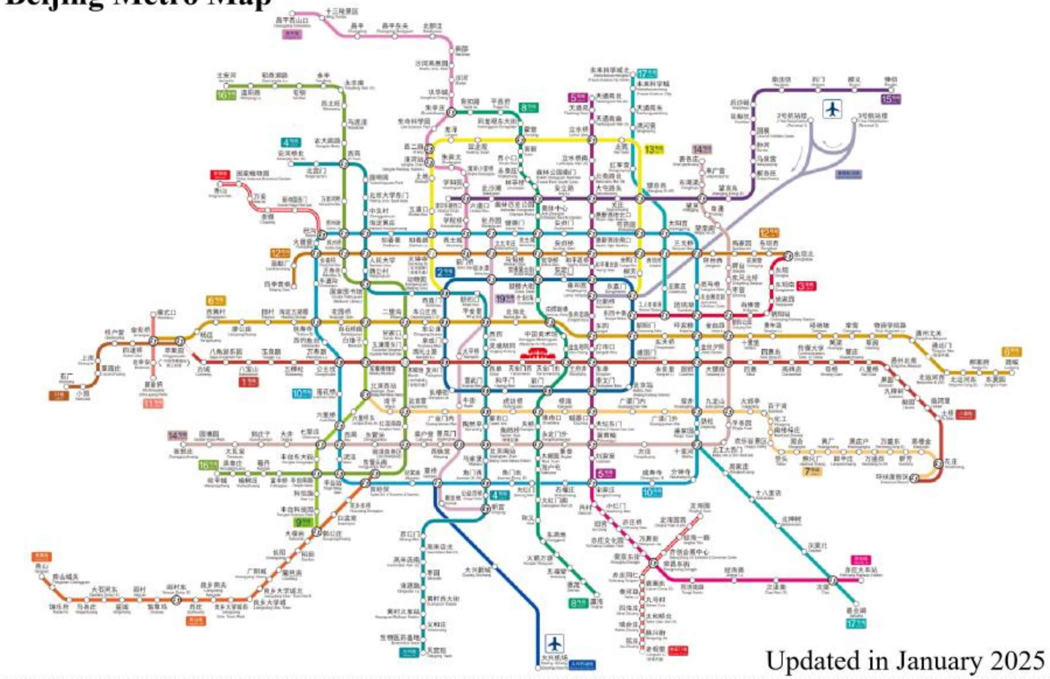
Length: 304 km

Daily ridership: 94 million

Background

- Practical application is hindered by **data silos** within distributed AFC systems

Beijing Metro Map



Updated in January 2025

Automatic Fare Collection Gate

Beijing Metro Lines

Line 1	Line 2	Line 3	Line 4	Line 5	Line 6	Line 7	Line 8
Line 9	Line 10	Line 11	Line 12	Line 13	Line 14	Line 15	Line 16	Line 17	Line 19
Line T1	Line S1	Daxing Line	Xijiao Line	Yanfang Line	Capital Airport Express
Fangshan Line	Yizhuang Line	Changping Line	Batong Line	Daxing Airport Express

Data privacy constraints

Personal Information Protection Law

AFC data silos

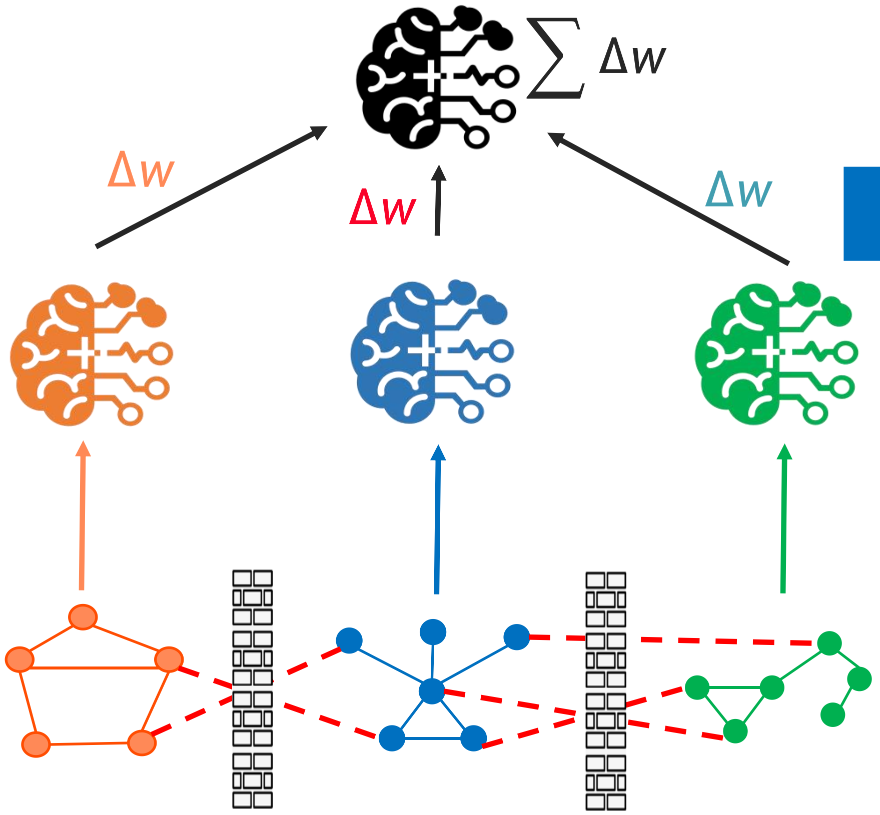
Beijing Metro: **29** Lines

The AFC databases of each metro line are **autonomous**

Background

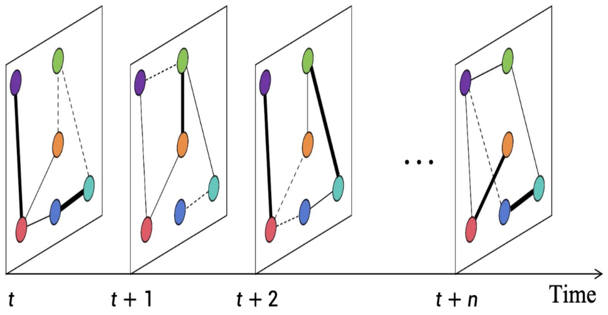
- **Federated graph learning** enables privacy-preserving STGNN training

Federated graph learning

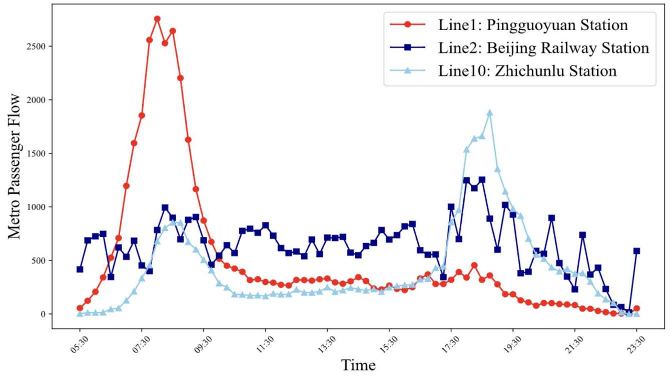


Unique challenges of crossline metro passenger flow prediction

- Time-evolving Spatial Correlations
- Heterogeneous Temporal Correlations
- Communication Bottlenecks



Time-evolving spatial correlations



Heterogeneous temporal correlations

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Problem Definition

Federated Metro Passenger Flow Prediction

- Signal Graph: Naturally partitioned across the metro lines

$$\boldsymbol{X}^{1:T} = \begin{bmatrix} \boldsymbol{X}_1^1 & \cdots & \boldsymbol{X}_1^T \\ \vdots & \ddots & \vdots \\ \boldsymbol{X}_M^1 & \cdots & \boldsymbol{X}_M^T \end{bmatrix}$$

- Problem Definition:

Given a current prediction timestep $t \in \{\tau - T_{in}+1, \ldots, \tau\}$, we aim to learn a predictive function $F(\cdot)$ that maps a sequence of T_{in} historical observations to the next future observations:

$$\hat{\boldsymbol{X}}^{(\tau+1):(\tau+T_{out})} \leftarrow \mathcal{F}(\boldsymbol{X}^{(\tau-T_{in}+1):\tau})$$

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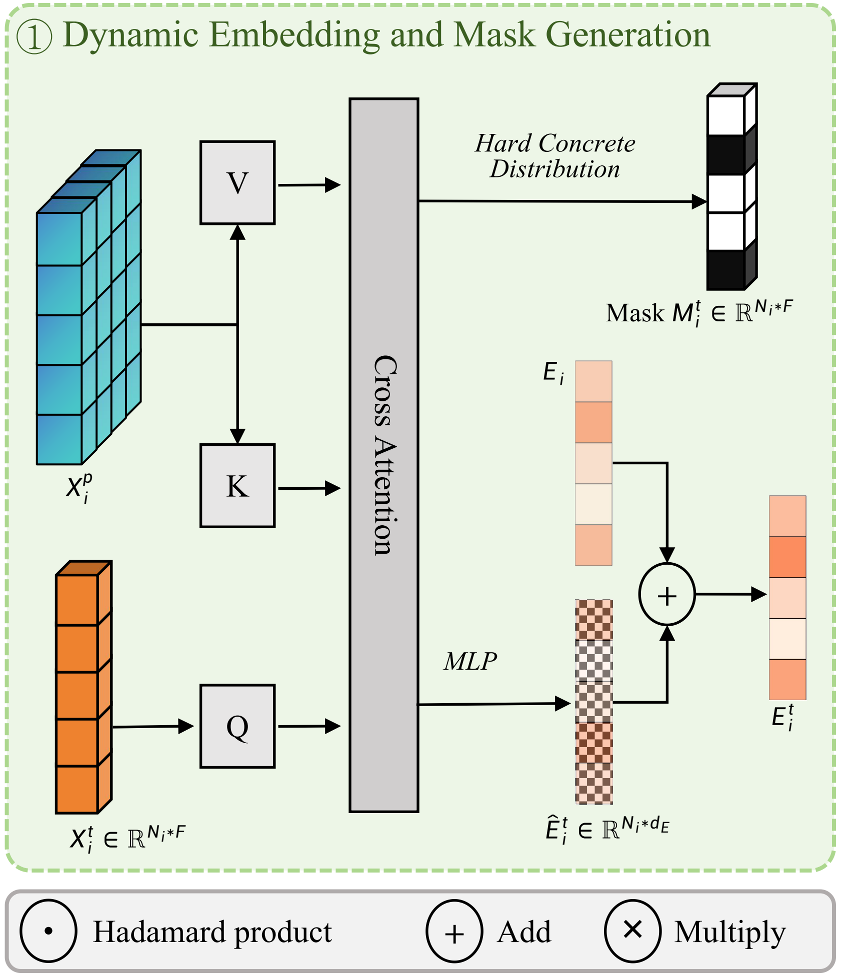
Our Solutions

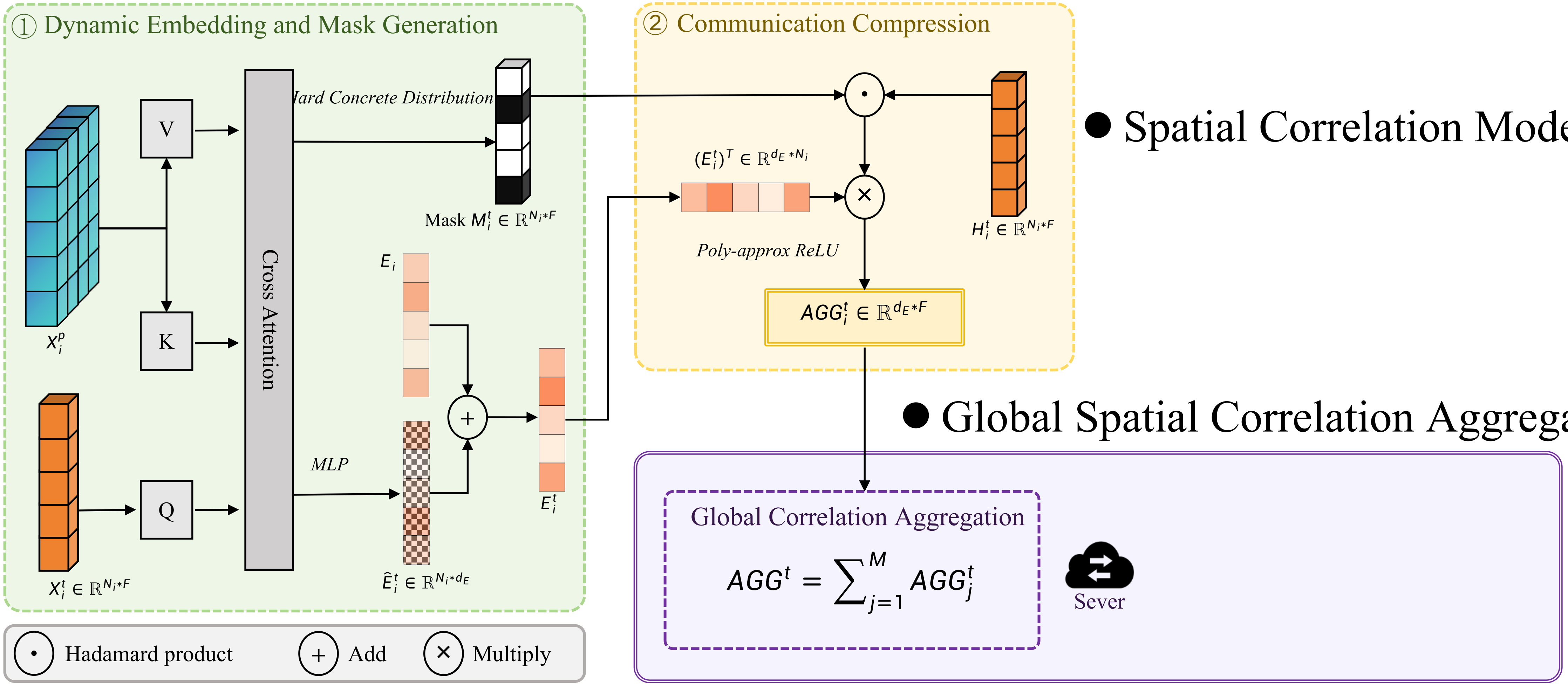
Dynamic Embedding and Mask Generation



- Historical Pattern Mining
- **Dynamic** Embedding Generation
- **Dynamic** Mask Generation

Our Solutions

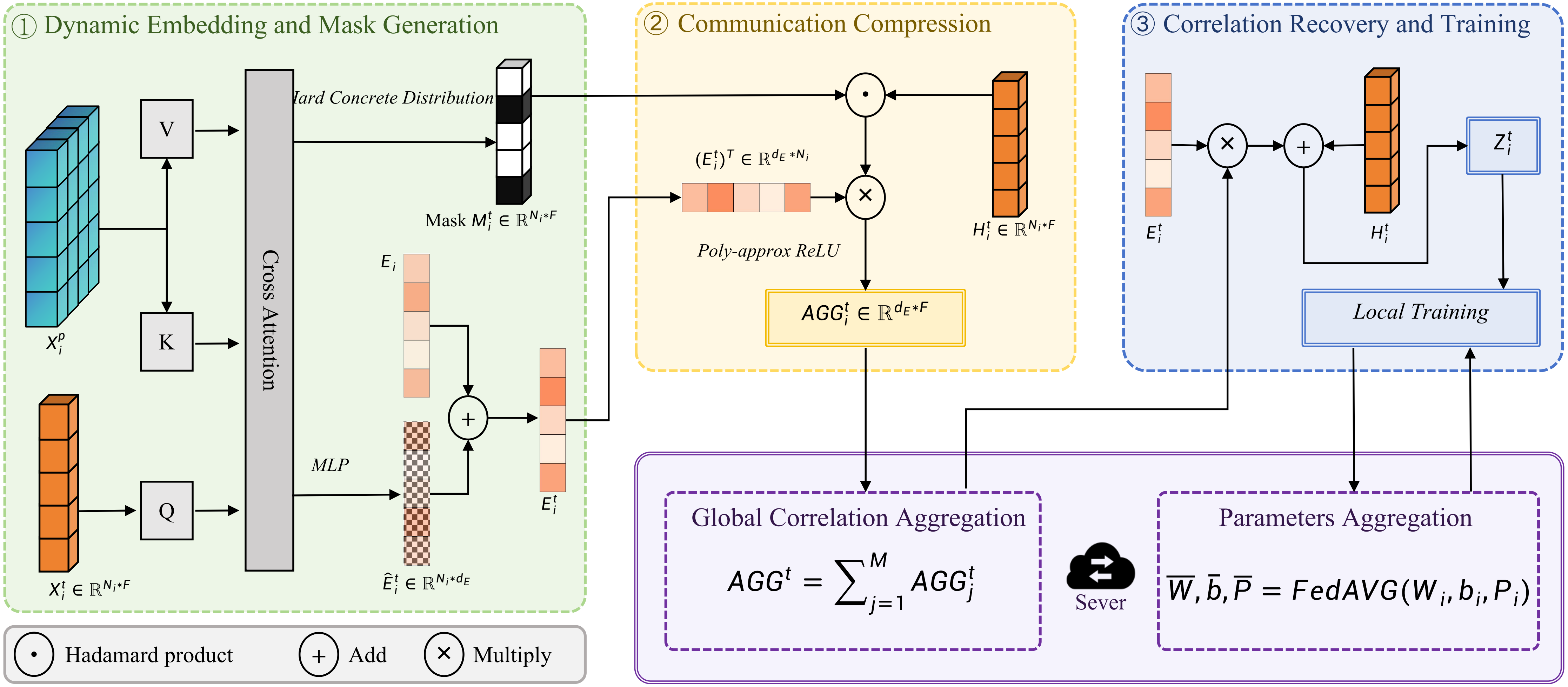
Global Spatial Correlations Learning



- Spatial Correlation Modeling
- Global Spatial Correlation Aggregation

Our Solutions

Federated Training and Inference



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Experiments

Datasets

	BJMetro	SHMetro	HZMetro
City	Beijing, China	Shanghai, China	Hangzhou, China
Lines	15	14	3
Stations	276	288	80
Edges	906	958	248
Period	2016/02/29–2016/04/02	2016/07/01–2016/09/30	2019/01/01–2019/01/25

Baselines

Local GCN-based methods

- Graph WaveNet
- PVCGN
- STDGRL

Federated graph learning-based methods

- MFVSTGNN
- FedGTP

Experiments

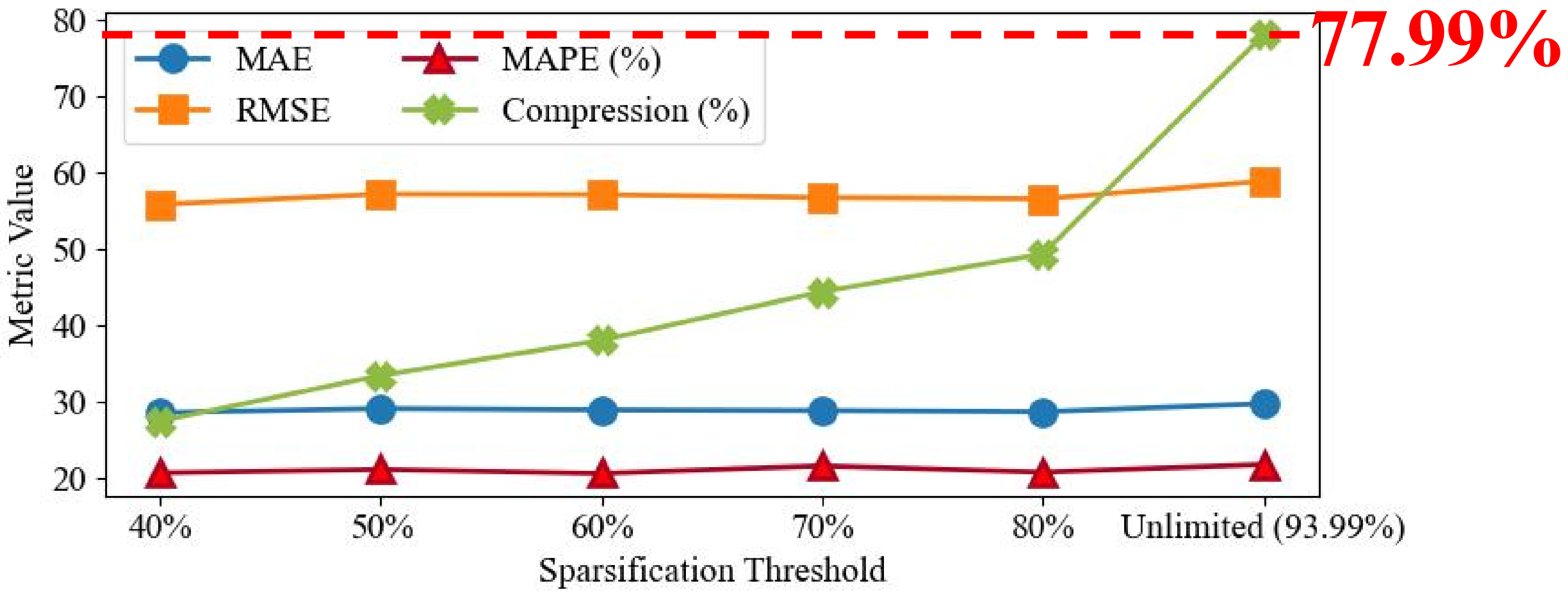
Performance Comparison with Baselines

Method	BJMetro						SHMetro						HZMetro					
	Inflow			Outflow			Inflow			Outflow			Inflow			Outflow		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Graph-WaveNet	46.73	89.35	41.58%	45.16	82.61	59.93%	34.02	84.90	51.79%	33.07	86.03	49.38%	33.79	70.34	37.85%	31.66	68.15	44.51%
PVCGN	55.16	120.97	29.50%	56.87	137.75	29.36%	30.44	67.88	38.68%	30.02	77.32	34.61%	33.10	65.29	36.17%	30.23	65.66	29.41%
STDGRL	37.98	75.89	28.22%	39.34	73.17	27.66%	30.10	62.43	25.44%	30.88	75.88	28.30%	31.76	57.92	22.54%	33.33	71.40	25.21%
MFVSTGNN	39.04	82.77	36.54%	38.60	104.49	74.17%	28.55	60.47	29.66%	29.19	80.93	42.79%	28.22	47.44	40.50%	29.34	60.39	40.59%
FedGTP	31.87	62.11	25.38%	36.31	83.55	27.69%	32.16	67.32	26.59%	31.98	74.15	28.77%	28.02	49.80	20.41%	28.41	56.39	24.51%
FedMetro (Ours)	**29.70**	**58.84**	**21.73%**	**30.11**	**65.59**	**23.15%**	**27.97**	**56.15**	**23.75%**	**29.13**	**68.56**	**26.82%**	**26.21**	**46.53**	**19.46%**	**27.36**	**54.42**	**22.67%**
Improvement	6.81%	5.26%	14.38%	17.08%	10.36%	16.31%	2.03%	7.14%	6.64%	0.21%	7.54%	5.23%	6.46%	1.92%	4.65%	3.70%	3.49%	7.51%

FedMetro outperforms all baselines, with prediction accuracy improving by up to **17.08%**

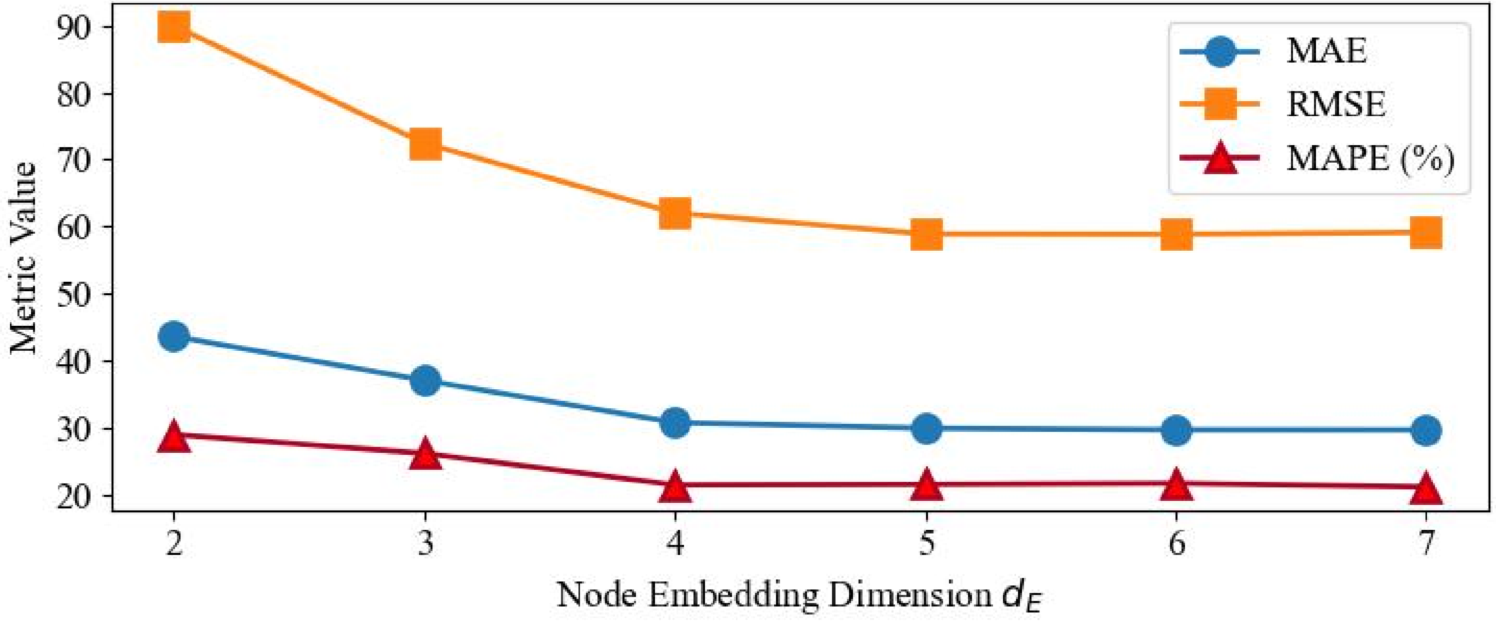
Experiments

Communication Compression Study



Experiments

Node Embedding Dimension Study



Experiments

Ablation Study

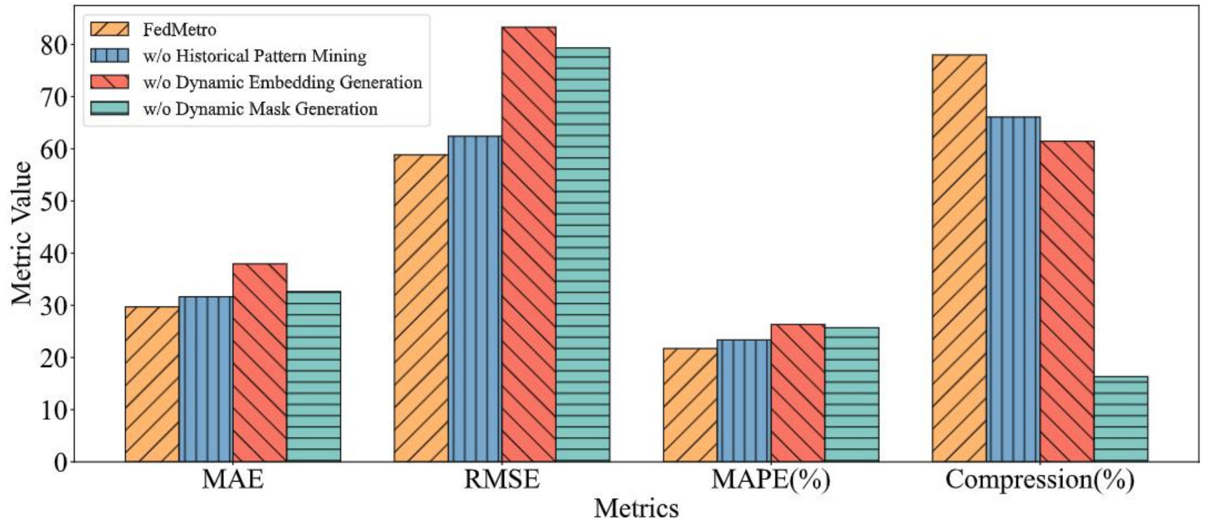


Figure 7: Ablation study on BJMetro.

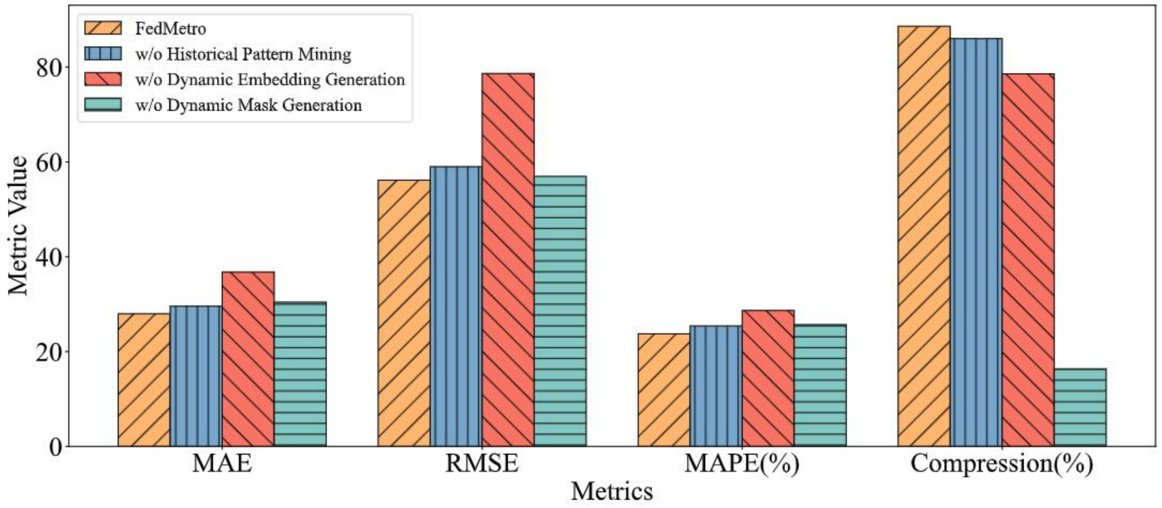


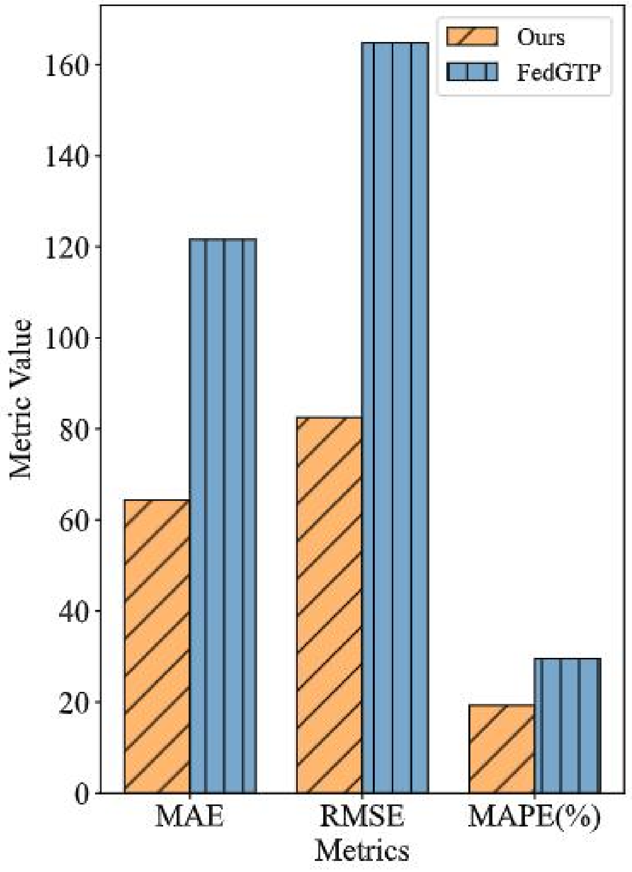
Figure 8: Ablation study on SHMetro.

Deployment

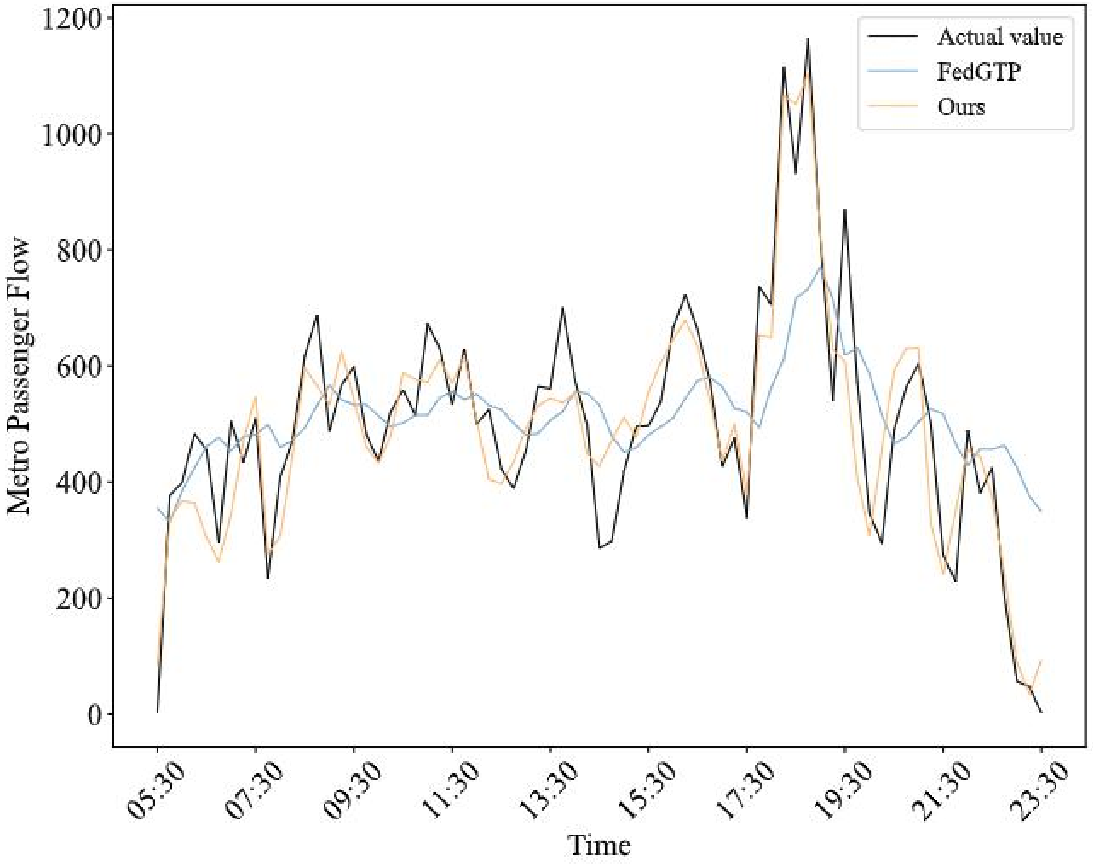
- Visualization of Beijing metro passenger flow prediction results

Deployment

- Comparison of deployment performance at Beijingzhan Station



(a) Comparison of metric value



(b) Comparison of predicted and actual value

THANK YOU