Deep Traffic Perception:

from Regional Flow to Online OD Prediction

Lingbo Liu

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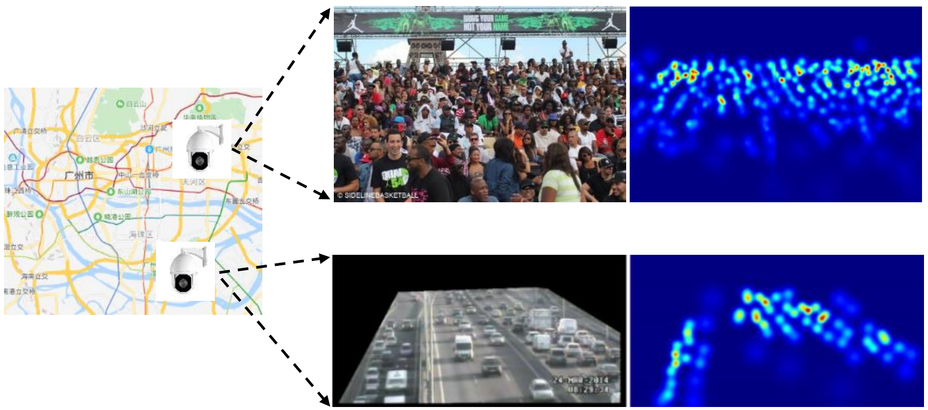
2020/7/2

My Research

Machine Learning + Intelligent Transportation

1 Crowd Counting



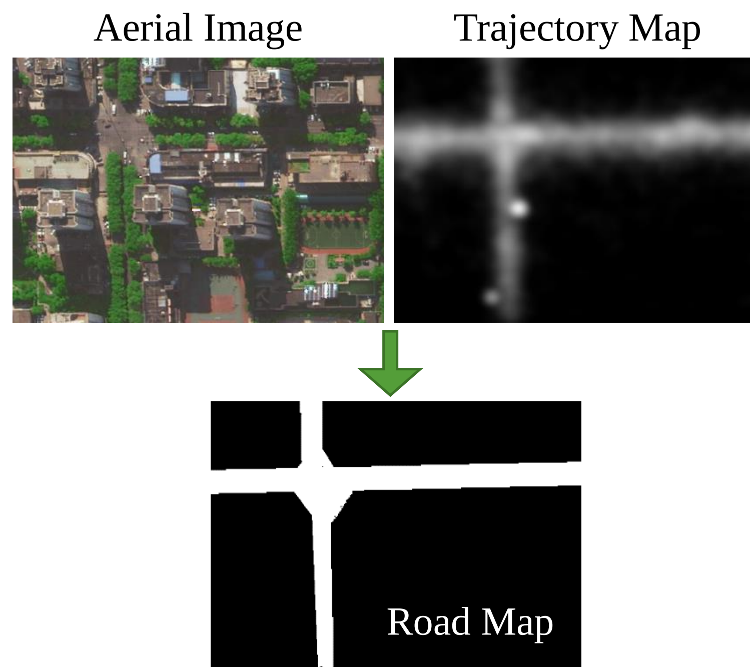
Application

- Security Monitoring, Traffic Management

Papers

- IJCAI 2018: Spatial-Aware Refinement
- ICCV 2019: Structured Learning (Feature, Loss)
- Under Review: KD-based Lightweight Model
- Under Review: Multimodal (RGBT) Alignment

2 Multimodal Road Extraction



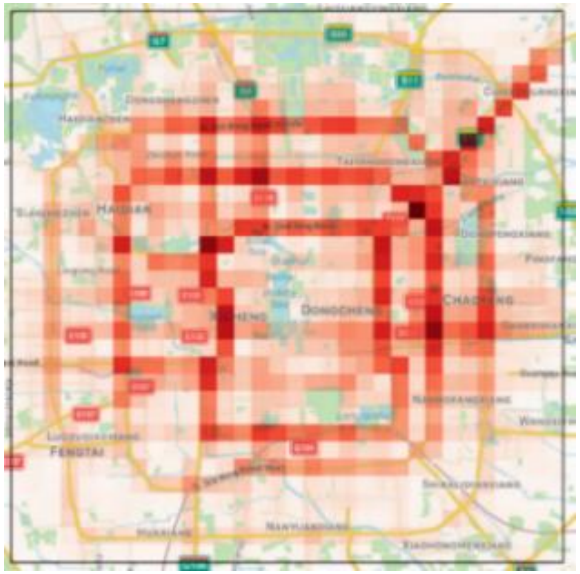
Papers

- Under Review: Cross-modal Dual Refinement
- Under Review: Multimodal (RGBT) Alignment

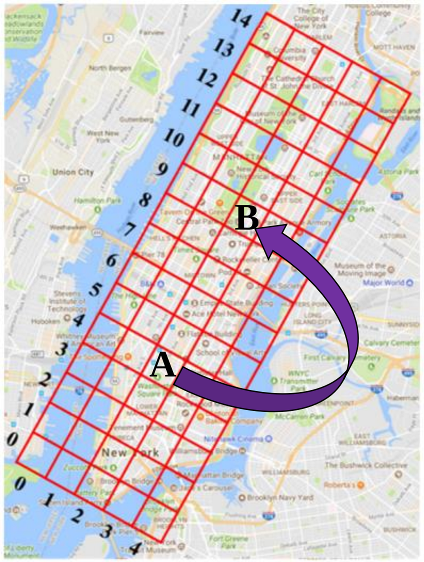
My Research

Machine Learning + Intelligent Transportation

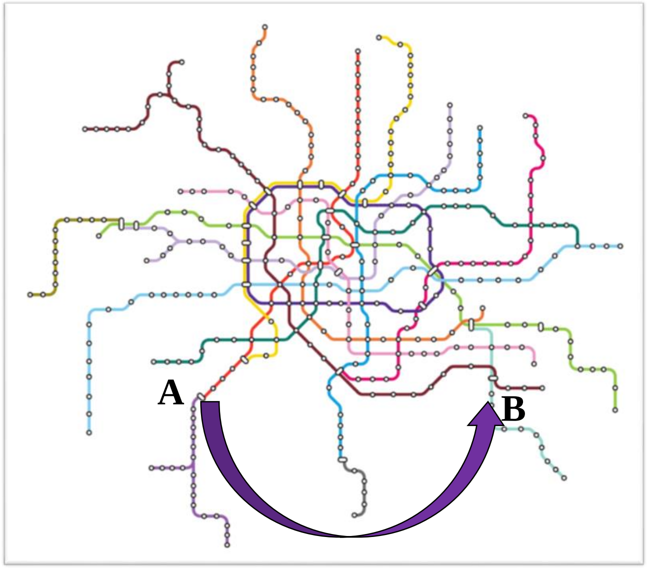
3 Traffic State Prediction



Grid-based Flow



Origin-Destination Demand



Online Origin-Destination Ridership

Papers

- ACM MM 2018: Attentive Crowd Flow Machines
- TITS 2019: Contextualized Spatial-Temporal Network for Taxi Origin-Destination Demand Prediction
- TITS 2020: Dynamic Spatial-Temporal Representation Learning for Traffic Flow Prediction
- Submit to TITS: Physical-Virtual Collaboration Modeling for Intra-and Inter-Station Metro Ridership Prediction

Outline

1. Grid-based Flow Prediction
2. Origin-Destination Demand Prediction
3. Online Origin-Destination Prediction

Outline

1 **Grid-based Flow Prediction**

2 **Origin-Destination Demand Prediction**

3 **Online Origin-Destination Prediction**

Grid-based Flow Prediction

Attentive Crowd Flow Machines

Lingbo Liu, Ruimao Zhang, Jiefeng Peng, Guanbin Li, Bowen Du, Liang Lin

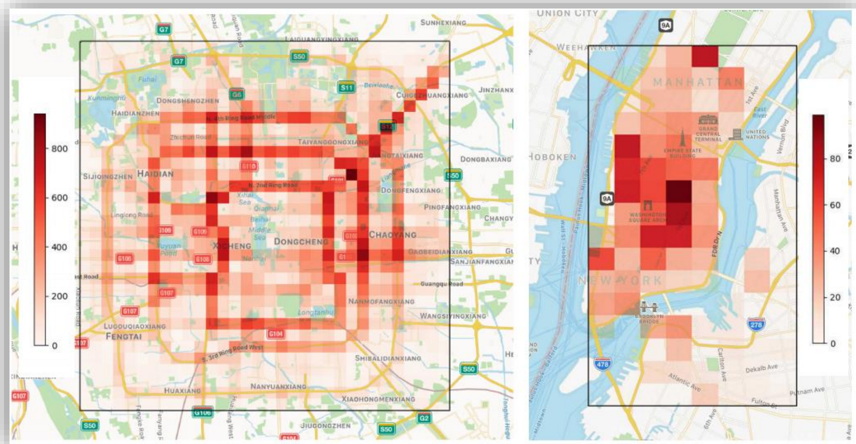
ACM Multimedia 2018

Dynamic Spatial-Temporal Representation Learning for Traffic Flow Prediction

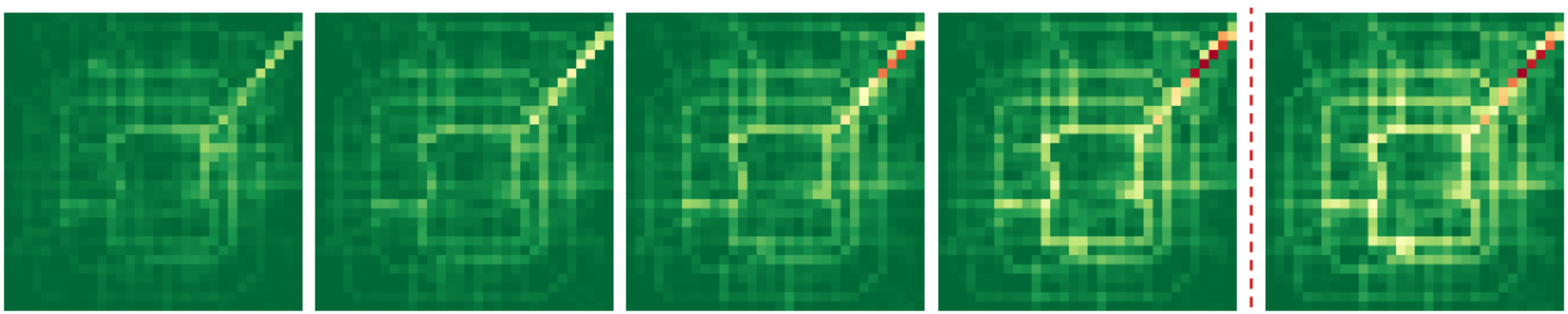
Lingbo Liu, Jiajie Zhen, Guanbin Li,
Geng Zhan, Zhaocheng He, Bowen Du and Liang Lin

TITS 2018

Background



Following ST-ResNet [1], we partition the studied city into a regular grid map and measure the inflow/outflow of each region ➔ $M \in \mathrm{R}^{2*h*w}$



… … M_{d}^{t-1} M_{d}^{t} M_{d}^{t+1} …

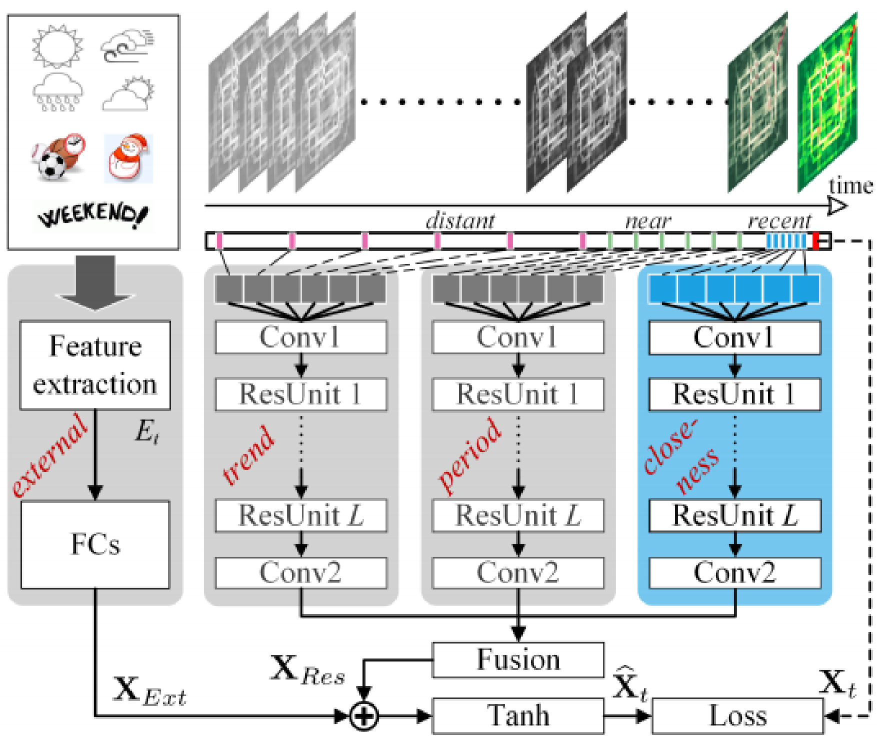
historical flow

future flow

[1] Deep spatio-temporal residual networks for citywide crowd flows prediction, AAAI 2017

Motivation

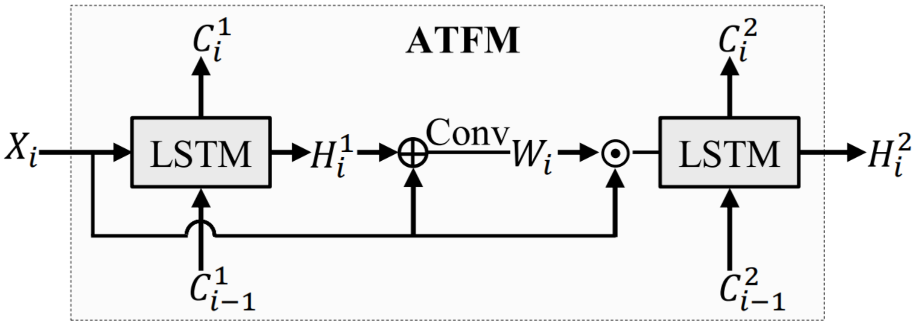
- **Temporal Dynamic**: Traffic flow data can vary greatly in temporal sequences and capturing such dynamic variations is non-trivial.
- **Spatial Dynamic**: The spatial dependencies are not strictly stationary and the relation significance of a specific region may change from time to time.
- **Fusion Dynamic**: Some periodic laws (e.g., rush hours) and external factors (e.g., a precipitate rain) can dynamically affect the situation of traffic flow.



[1] Deep spatio-temporal residual networks for citywide crowd flows prediction, AAAI 2017

Method

- **Spatial Dynamic**
- **Temporal Dynamic**
- **Fusion Dynamic**

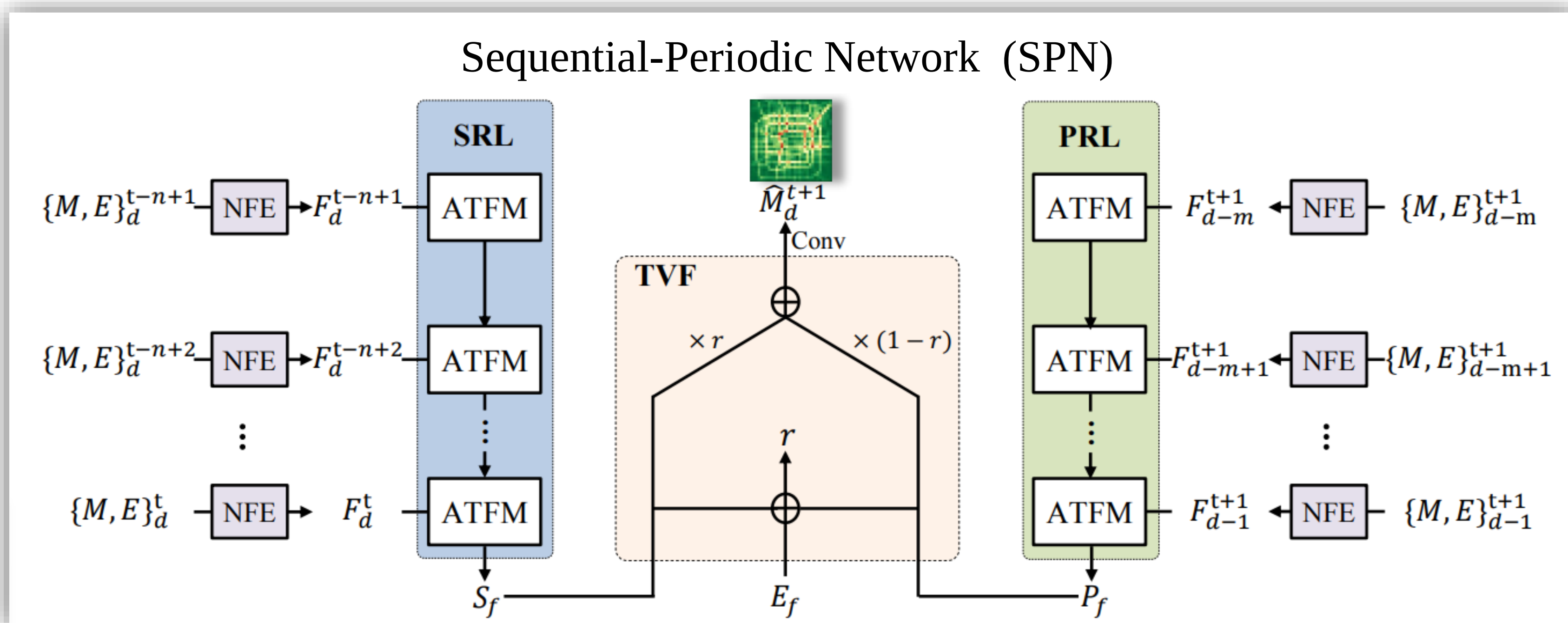


Attentive Traffic Flow Machine (ATFM)

$$H_i^1, C_i^1 = \textbf{ConvLSTM}(H_{i-1}^1, C_{i-1}^1, X_i).$$

$$W_i = \textbf{Conv}_{1\times1}(H_i^1 \oplus X_i, w_a),$$

$$H_i^2, C_i^2 = \textbf{ConvLSTM}(H_{i-1}^2, C_{i-1}^2, X_i \odot W_i)$$

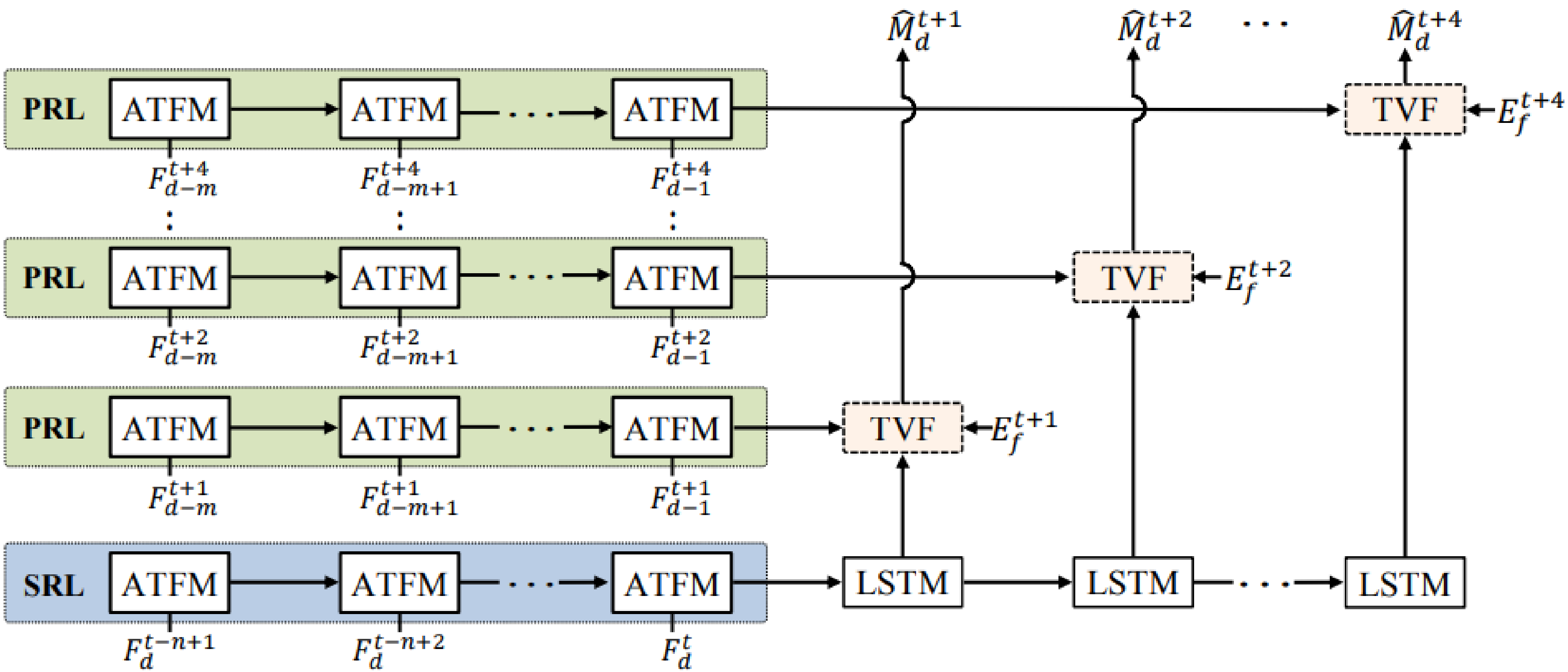


Sequential Representation Learning   Temporally-Varying Fusion   Periodic Representation Learning

Method: Long-term Prediction

- **Spatial Dynamic**
- **Temporal Dynamic**
- **Fusion Dynamic**

Long-term Sequential-Periodic Network (SPN-LONG)



Experiments: Compare with State-of-the-art

Dateset: TaxiBJ 、 BikeNYC
Metric： RMSE、MAE

Short-term Prediction

Method	TaxiBJ		BikeNYC	
	RMSE	MAE	RMSE	MAE
HA	57.79	-	21.57	-
SARIMA	26.88	-	10.56	-
VAR	22.88	-	9.92	-
ARIMA	22.78	-	10.07	-
ST-ANN	19.57	-	-	-
DeepST	18.18	-	7.43	-
VPN	16.75	9.62	6.17	3.68
ST-ResNet	16.69	9.52	6.37	2.95
PredNet	16.68	9.67	7.45	3.71
PredRNN	16.34	9.62	5.99	4.89
SPN (Ours)	**15.31**	**9.14**	**5.59**	**2.74**

Long-term Prediction on TaxiBJ

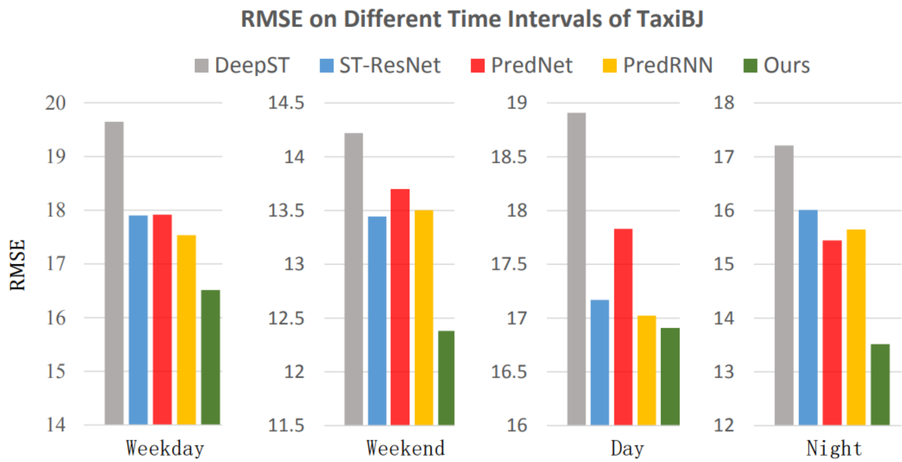
Method	Time Interval			
	1 (0.5 h)	2 (1.0 h)	3 (1.5 h)	4 (2.0 h)
ST-ResNet	16.75	19.56	21.46	22.91
VPN	17.42	20.50	22.58	24.26
PredNet	27.55	254.68	255.54	255.47
PredRNN	16.08	19.51	20.66	22.69
SPN (Ours)	15.31	19.59	23.70	28.61
SPN-LONG (Ours)	**15.42**	**17.63**	**19.08**	**20.83**

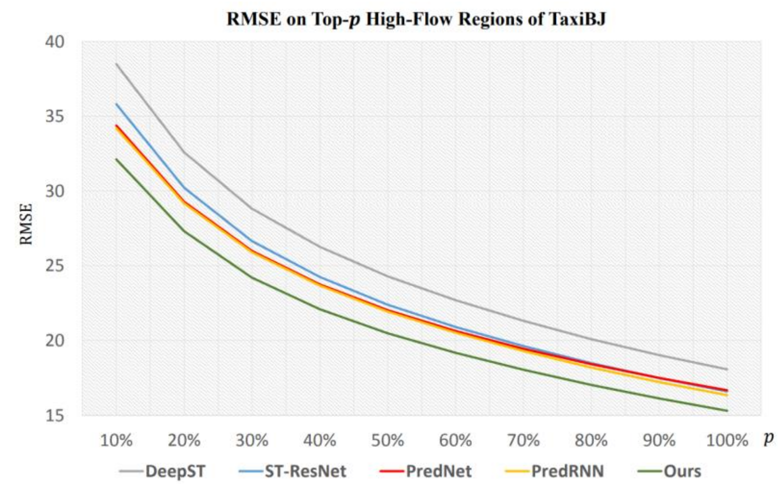
Long-term Prediction on BikeNYC

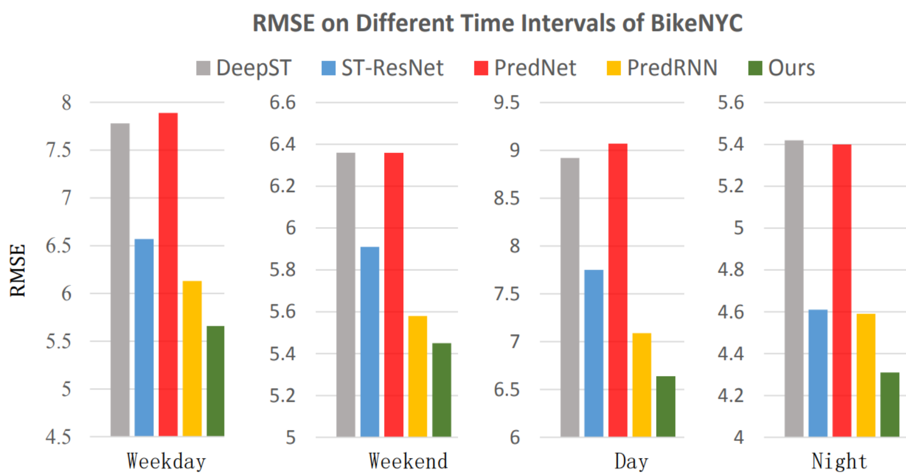
Method	Time Interval			
	1 (1.0 h)	2 (2.0 h)	3 (3.0 h)	4 (4.0 h)
ST-ResNet	6.45	7.47	8.77	10.28
VPN	6.55	8.01	8.86	9.41
PredNet	7.46	8.95	10.08	10.93
PredRNN	5.97	7.37	8.61	9.40
SPN (Ours)	5.59	7.81	11.96	15.74
SPN-LONG (Ours)	**5.81**	**6.80**	**7.54**	**7.90**

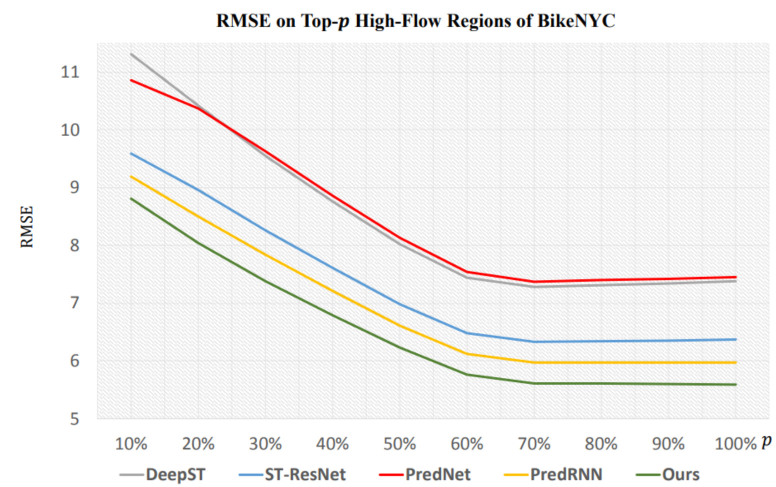
Superiority!

Experiments: Compare with State-of-the-art









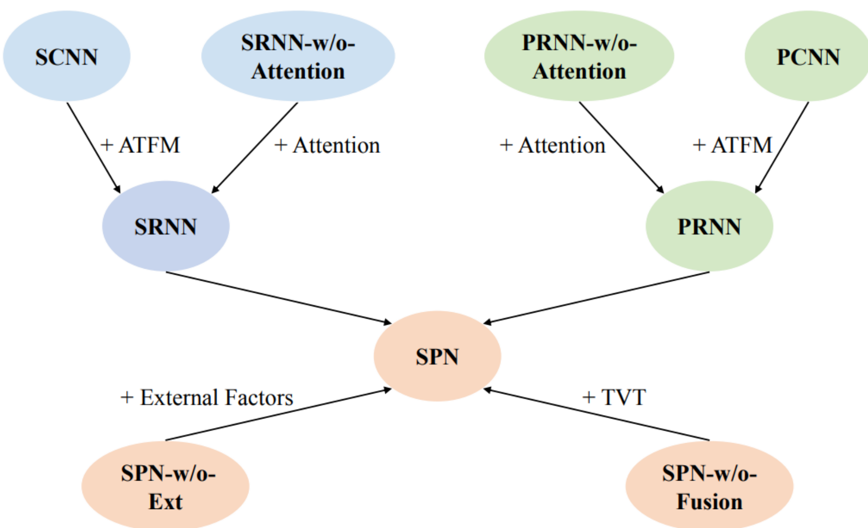
Superiority!

Experiments: Ablation Study

"SRNN-w/o-Attention vs SRNN"
"PRNN-w/o-Attention vs PRNN" → the effectiveness of spatial attention.

"SPN-w/o-Ext vs. SPN" → the effectiveness of external factors

"SPN-w/o-Fusion vs. SPN" → the effectiveness of Temporally-Varying Fusion (TVF)

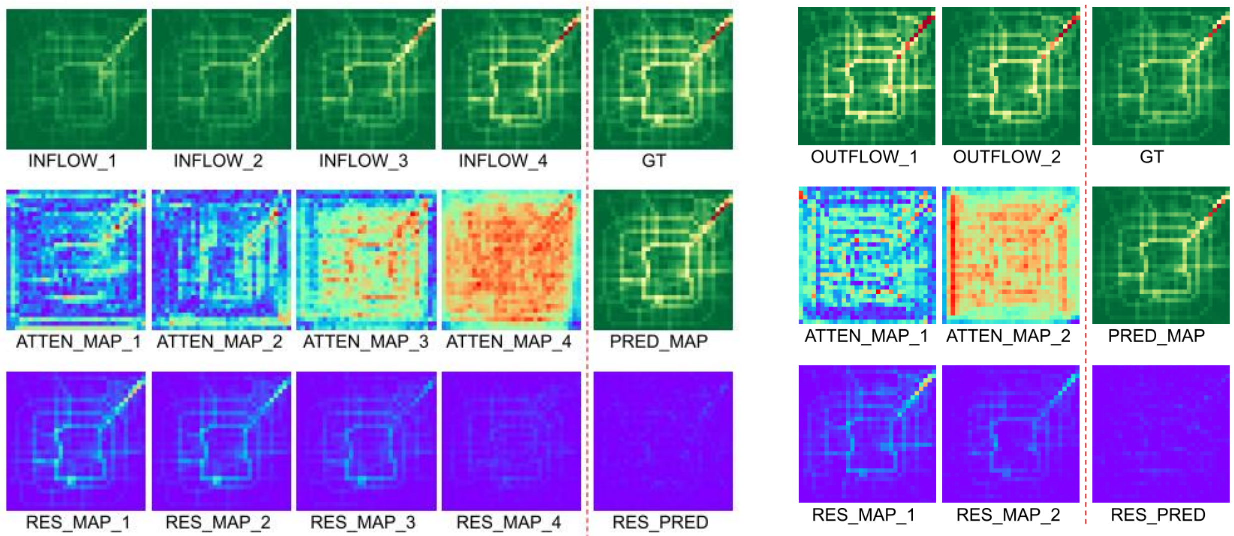


Model	RMSE	MAE
PCNN	33.91	17.16
PRNN-w/o-Attention	33.51	16.70
PRNN	32.89	16.64
SCNN	17.15	9.56
SRNN-w/o-Attention	16.20	9.43
SRNN	15.82	9.34
SPN-w/o-Ext	16.84	9.83
SPN-w/o-Fusion	15.67	9.40
SPN	15.31	9.14

Effectiveness!

Experiments: More Discussion

◆ Attention Map Visualization

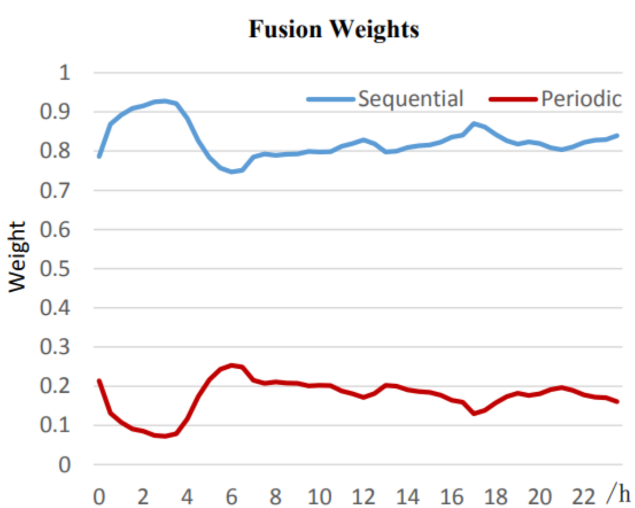


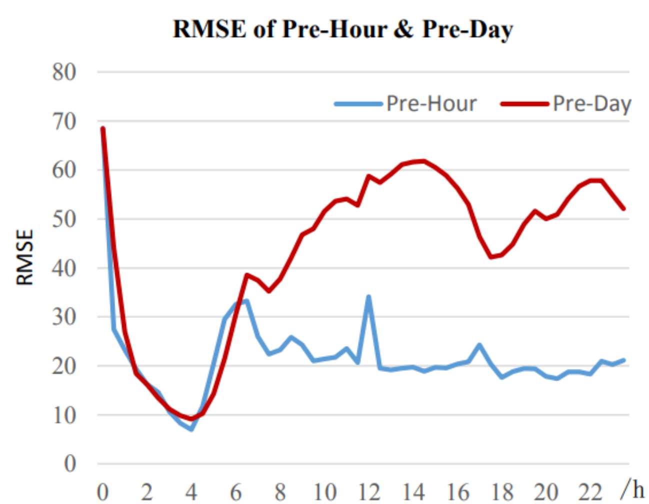
attentional maps

negative correlation to some extent

residual maps

◆ Fusion Weight Visualization





Outline

1 Grid-based Flow Prediction

2 **Origin-Destination Demand Prediction**

3 Online Origin-Destination Prediction

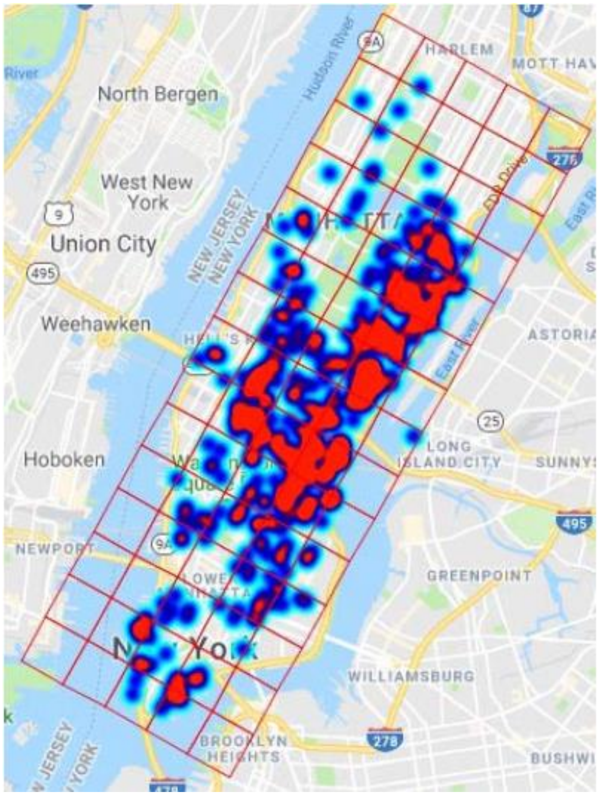
Contextualized Spatial-Temporal Network for Taxi Origin-Destination Demand Prediction

Lingbo Liu, Zhilin Qiu, Guanbin Li,
Qing Wang, Wanli Ouyang, Liang Lin

TITS 2019

Background

2D Tensor



divide a city into a $H \times W$ grid map based on geographical coordinate

Taxi Demand Prediction

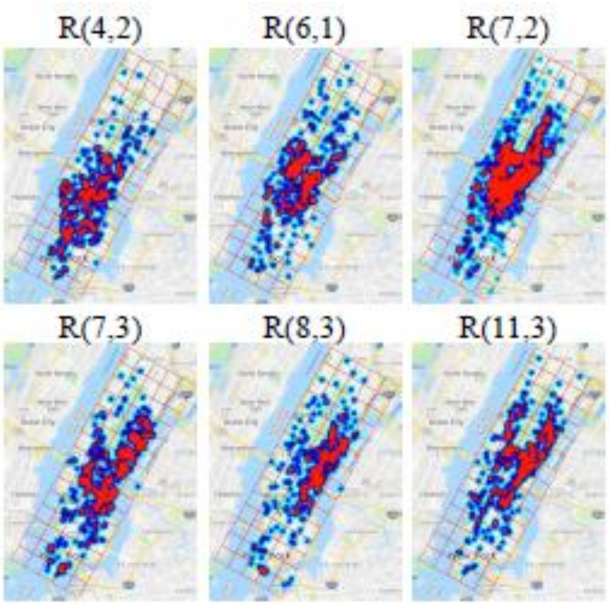
- the taxi demand heat map at each time interval is denoted as a 2D tensor $X_t \in R^{H \times W}$
- predict the taxi demand in each region

Method	Task and Scope	
Zhang et al. [4] Jin et al. [5]	Traffic Inflow and Outflow Prediction in all regions	AAAI 2017 ICCDA 2018
Tong et al. [6] Yao et al. [7]	Taxi Demand Prediction in all regions	KDD 2017 AAAI 2018
Toqu et al. [8] Azzouni et al. [9] Yang et al. [10]	Traffic Flow or Demand Prediction between some well-designed positions (e.g., highway toll booths, subway and bus stations)	ITSC2016 Arxiv 2017 ITSC 2017
Zhou et al. [11]	Passenger Pickup/Dropoff Demand Prediction in all regions	ICWSDM 2018
Ours	Taxi Demand Prediction between all regions	

Background

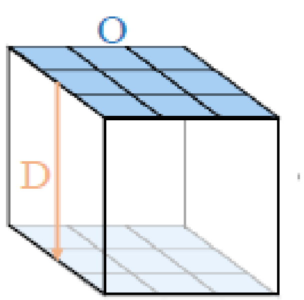
Taxi Demand Prediction

3D Tensor



- the taxi demand heat map at each time interval is denoted as a 2D tensor $X_t \in R^{H \times W}$
- predict the taxi demand in each region

Taxi Origin-Destination Demand Prediction

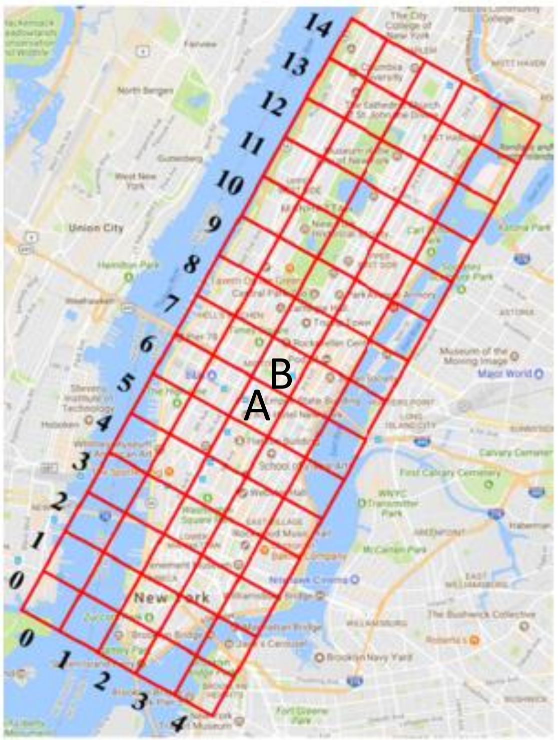


$X_i : N \times H \times W$

- forecast the taxi demand between any two regions
- the taxi demand heat map at each time interval is denoted as a 3D tensor $X_t \in R^{N \times H \times W}$
- each channel of X_t is the demand from all regions to a special region

Challenge

Key Point : how to effectively capture the diverse contextual information to learn the demand patterns



➢ **Local Spatial Context**

Some regions that are spatially adjacent usually have the similar demand patterns.

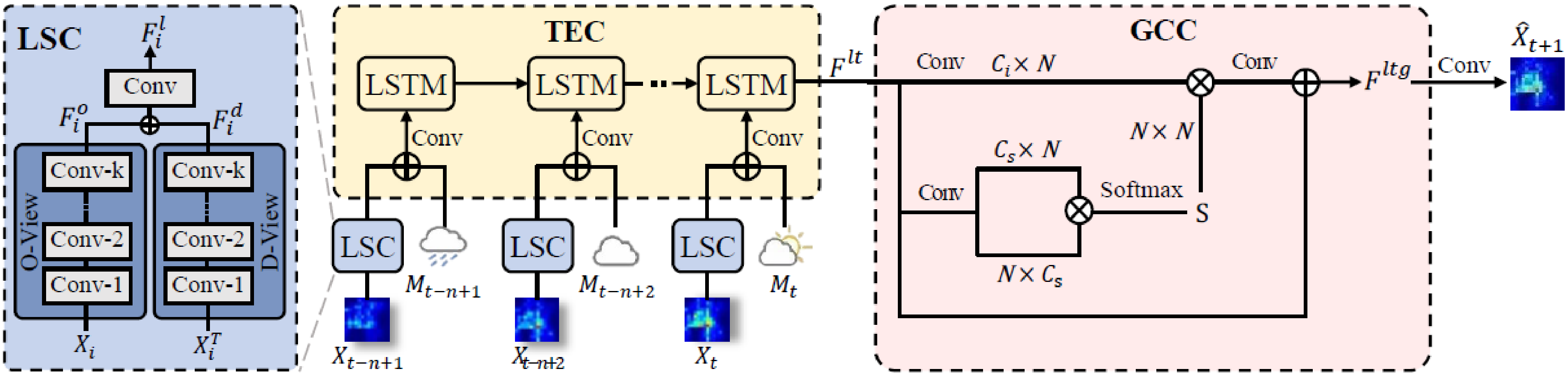
➢ **Global Correlation Context**

Even though two regions are spatially distant, their patterns may still have some correlation, if they share similar functionality.

➢ **Temporal Evolution Context**

Taxi OD demand is time-varying and its evolution is related to many factors.

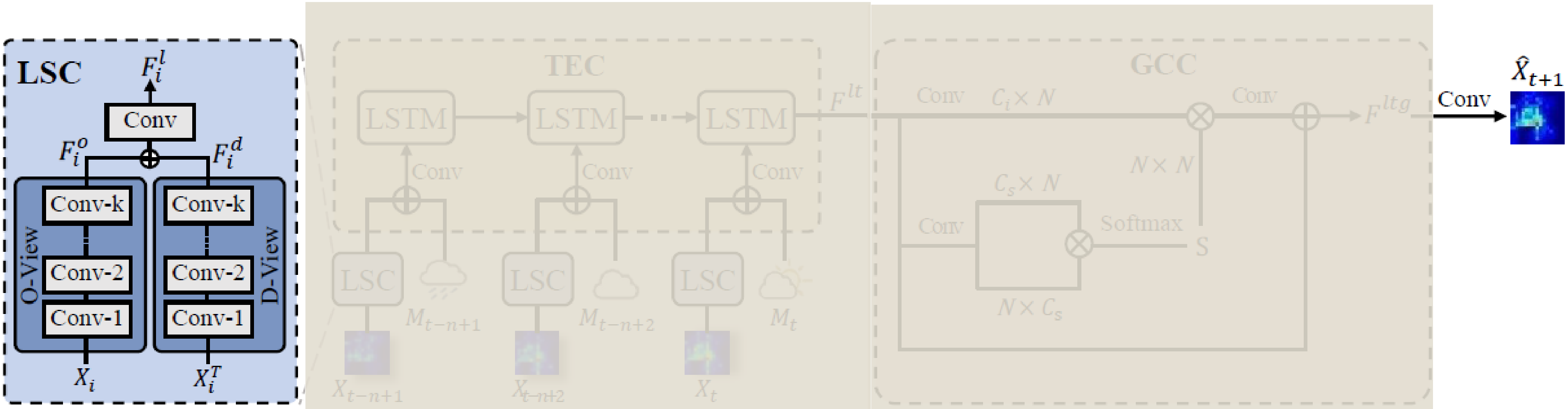
Method: Contextualized Spatial-Temporal Network



Three modules:

- **Local Spatial Context Modeling (LSC)**
- **Temporal Evolution Context Modeling (TEC)**
- **Global Correlation Context Modeling (GCC)**

Method



Local Spatial Context Modeling (LSC)

- Captures the local spatial context of taxi demand from both the origin view and destination view
- Implemented by a Two-View CNN

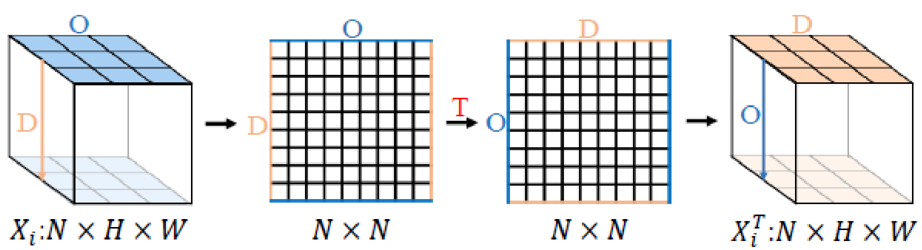
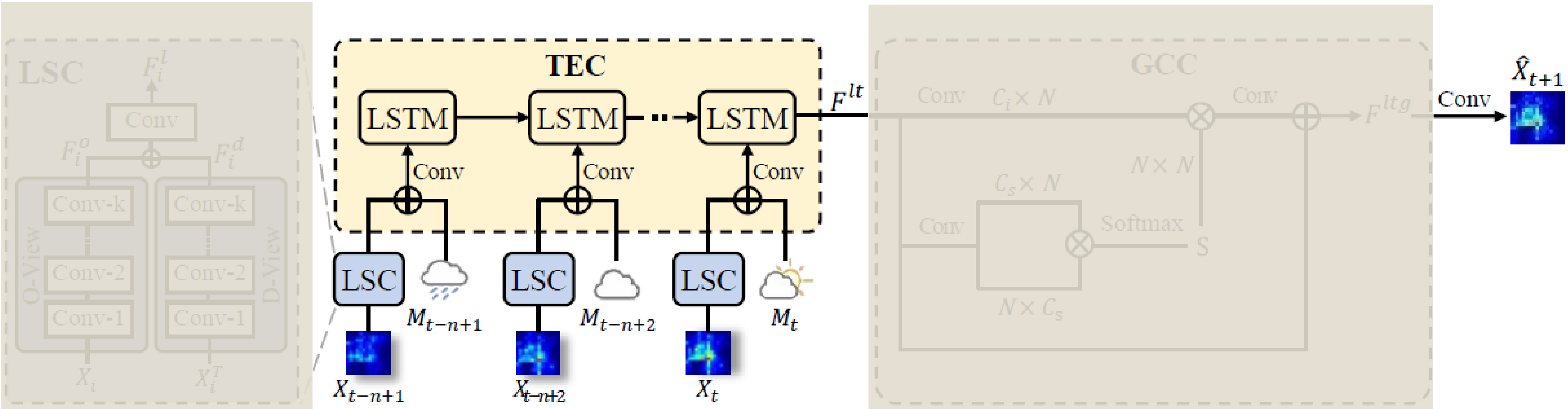


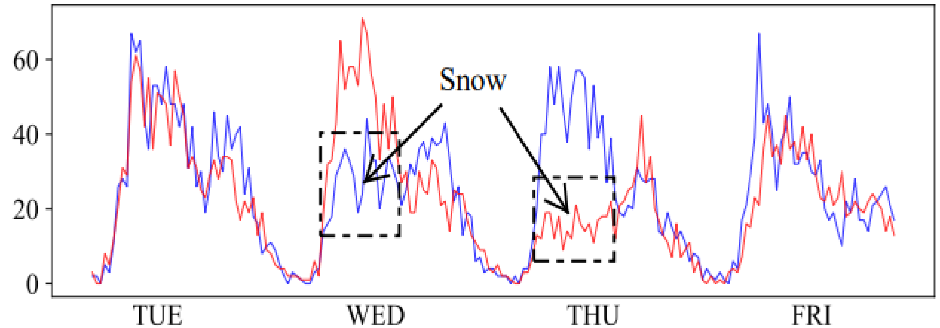
Fig. 3. The generation process of DO matrix from OD matrix. N is equal to $H \cdot W$ and T is a matrix transposition operation.

Method



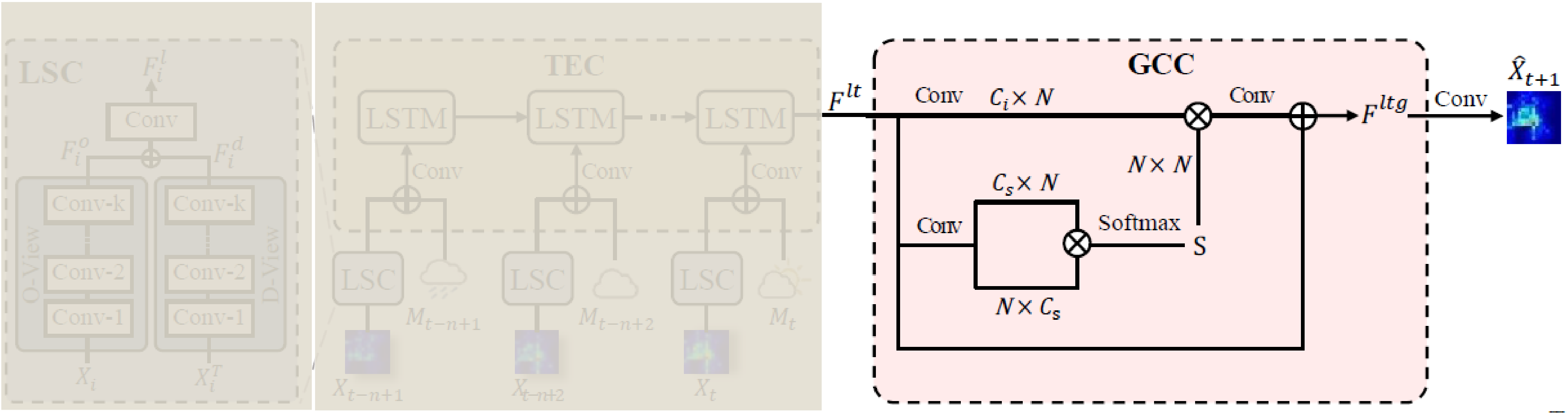
Temporal Evolution Context Modeling (TEC)

- Learn the evolving tendency of taxi demand along the temporal dimension
- Incorporate the historical demand and the ever-changing weather to model TEC with ConvLSTM



Influence of weather conditions on taxi demand

Method



Global Correlation Context Modeling (GCC)

- Model the relationship between any two regions
- Global Feature Fusion

(1) calculate the similarity of region pairs with a dot-product operation

$$S = \textbf{Softmax}(F_s^T \otimes F_s),$$

(2) generate the global correlation feature by combining the features of all regions with the similarity weights

$$F^g = F^{lt} \otimes S,$$

Experiments: Dataset

NYC-TOD： the first benchmark for taxi OD demand prediction

- Choose New York as our studied city
- Collect the taxi demand data of YNC during 2014
  - Train our network with the data of the first ten months
  - Test on the remaining two months

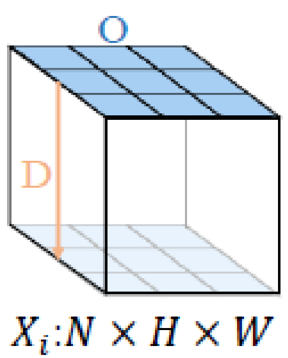
Experiments: Compare with State-of-the-art

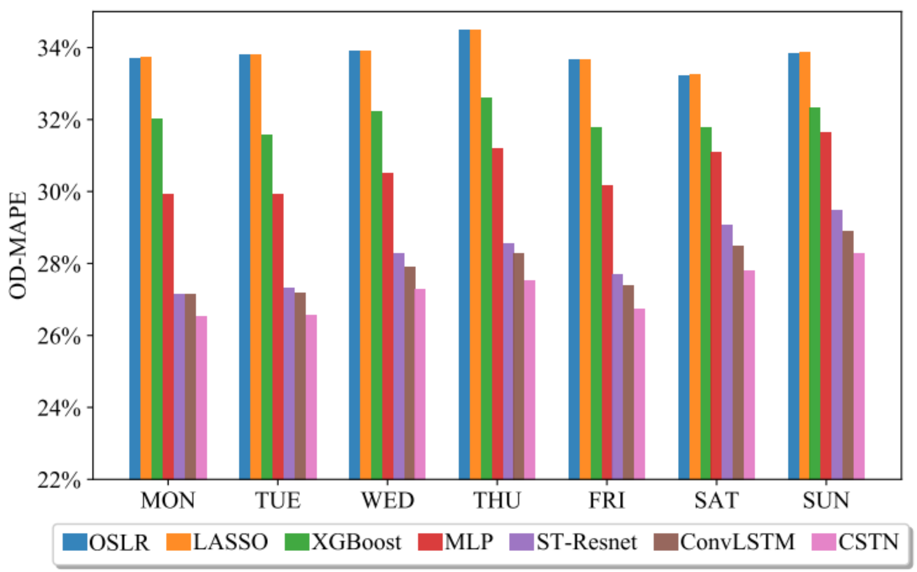
On whole test set

Method	OD-MAPE	OD-RMSE	O-MAPE	O-RMSE
HA-All	37.71%	1.93	45.04%	52.44
HA-Rec	35.46%	1.89	47.59%	54.33
Lasso	33.85%	1.65	34.89%	33.00
OLSR	33.86%	1.65	33.09%	32.68
XGBoost	32.04%	1.54	37.78%	31.23
MLP	30.70%	1.49	25.24%	25.60
ST-ResNet	28.53%	1.38	24.16%	22.43
ConvLSTM	27.99%	1.36	19.89%	21.02
CSTN	**27.37%**	**1.32**	**18.48%**	**19.85**

On high-demand region

Method	OD-MAPE	OD-RMSE	O-MAPE	O-RMSE
HA-All	36.96%	5.69	46.47%	93.38
HA-Rec	35.65%	5.67	49.62%	97.16
Lasso	31.51%	4.59	24.88%	57.32
OLSR	31.55%	4.58	24.28%	56.80
XGBoost	29.63%	4.28	34.30%	53.20
MLP	27.81%	4.01	17.18%	42.15
ST-ResNet	25.98%	3.71	16.13%	37.09
ConvLSTM	25.81%	3.65	13.80%	35.33
CSTN	**24.93%**	**3.58**	**12.92%**	**33.73**





On different days of the week

Our CSTN outperforms other methods on two tasks

(1) taxi OD demand prediction (2) taxi demand prediction

Experiments: Ablation Study

Effectiveness of the Two-View ConvNet in LSC

Method	OD-MAPE	O-MAPE
Origin View	28.94%	23.03%
Origin View + Destination view	28.54%	20.80%

Effectiveness of Different Context

Method	LSC	LSC+TEC	LSC+TEC+GCC
OD-MAPE	28.54%	27.80%	27.27%
O-MAPE	20.80%	19.41%	18.48%

The performance can be gradually improved with more context.

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Physical-Virtual Collaboration Modeling for Intra-and Inter-Station Metro Ridership Prediction

Lingbo Liu, Jingwen Chen, Hefeng Wu,
Jiajie Zhen, Guanbin Li, Liang Lin

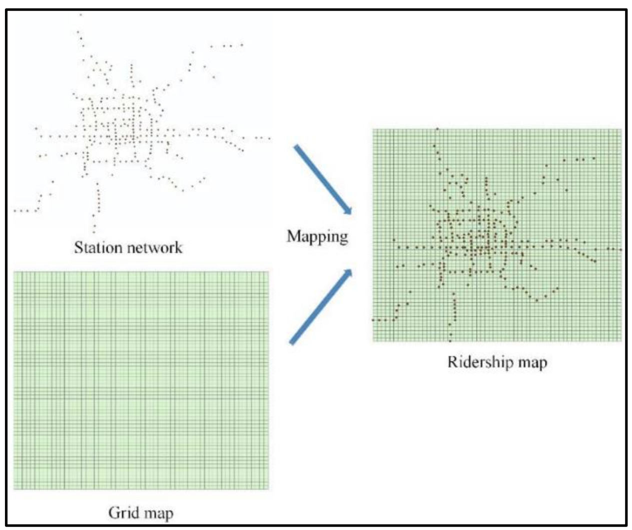
Submit to TITS (major revision)

Background

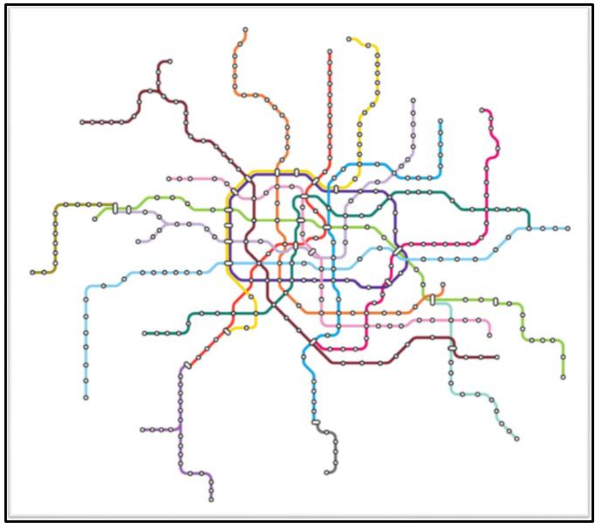
Urban Metro

- an efficient and economical travel mode
- plays an important role in the daily life of residents
  - ✓ Beijing ： 10.54 million (2018 daily avg)
  - ✓ Shanghai： 10.16 million (2018 daily avg)

	Inflow	Outflow
Station 1	137	99
Station 2	59	74
Station 3	99	85
	…	…
Station N	106	121



This image is quoted from [1]

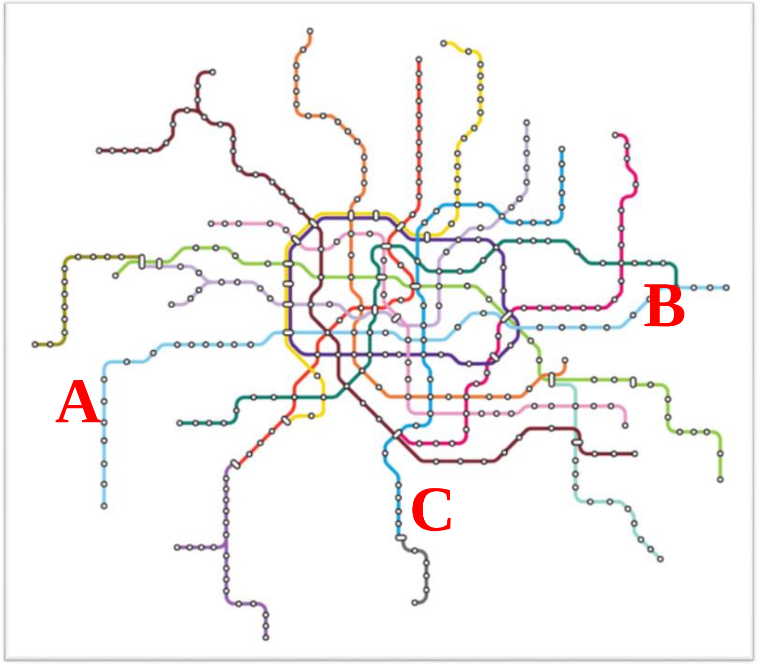


[1] Parallel Architecture of Convolutional Bi-Directional LSTM Neural Networks for Network-Wide Metro Ridership Prediction, TITS 2019

Motivation

How to construct the graph of metro system?

- **Physical Topology**
- **Inter-station Flow Similarity**
  - Two metro stations in different regions may have similar evolution patterns of passenger flow
- **Inter-station Flow Correlation**
  - The ridership between every two stations is not uniform and the direction of passenger flow implicitly represents the correlation of two stations.



Physical-Virtual Collaboration Graph Network

➢ Station-level Metro Ridership Prediction

$$\boldsymbol{X}_t = (\boldsymbol{X}_t^1, \boldsymbol{X}_t^2, ..., \boldsymbol{X}_t^N) \quad \boldsymbol{X}_t^i \in \mathbb{R}^2,$$

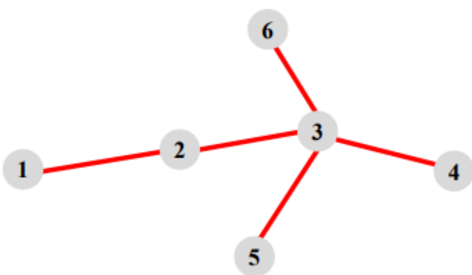
$$\hat{\boldsymbol{X}}_{t+1}, \hat{\boldsymbol{X}}_{t+2}, ..., \hat{\boldsymbol{X}}_{t+m} = \mathrm{PVCGN}(\boldsymbol{X}_{t-n+1}, \boldsymbol{X}_{t-n+2}, ..., \boldsymbol{X}_t)$$

➢ Online Origin-Destination Ridership Prediction

Defined Later

Physical-Virtual Collaboration Graph Network

$$\mathcal{G}_p = (\mathcal{V}, \mathcal{E}_p, W_p) \qquad \mathcal{G}_s = (\mathcal{V}, \mathcal{E}_s, W_s) \qquad \mathcal{G}_c = (\mathcal{V}, \mathcal{E}_c, W_c)$$



(a) Physical Graph

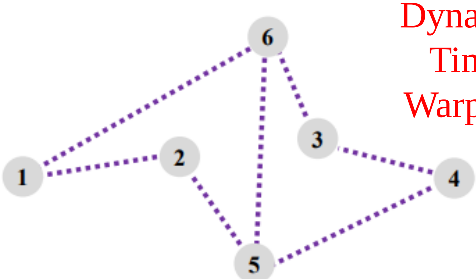
	1				
1		1			
	1		1	1	1
		1			
		1			
		1			

(b) Physical Connection Matrix

Row-Norm

	1.00				
0.50		0.50			
	0.25		0.25	0.25	0.25
		1.00			
		1.00			
		1.00			

(c) Physical Edge Weight



(d) Similarity Graph

Dynamic Time Warping

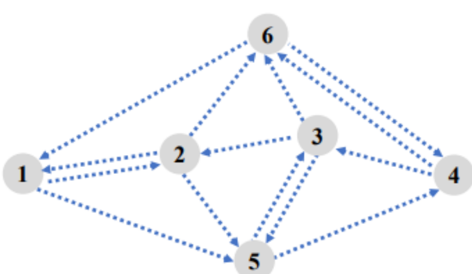
	0.71	0.02	0.05	0.08	0.54
0.71		0.07	0.04	0.45	0.06
0.02	0.07		0.38	0.01	0.51
0.05	0.04	0.38		0.44	0.05
0.08	0.45	0.01	0.44		0.48
0.54	0.06	0.51	0.05	0.48	

(e) Similarity Score Matrix

Selection
Row-Norm

	0.57				0.43
0.61				0.39	
			0.43		0.57
		0.46		0.54	
	0.33		0.32		0.35
0.35		0.34		0.31	

(f) Similarity Edge Weight



(g) Correlation Graph

0.01	0.56	0.02	0.04	0.03	0.34
0.48	0.02	0.40	0.05	0.03	0.02
0.04	0.03	0.01	0.35	0.54	0.03
0.05	0.02	0.03	0.03	0.45	0.42
0.31	0.25	0.34	0.04	0.01	0.05
0.04	0.36	0.29	0.26	0.04	0.01

(h) Correlation Ratio Matrix

Selection
Row-Norm

	0.62				0.38
0.55		0.45			
			0.39	0.61	
				0.52	0.48
0.34	0.28	0.38			
	0.40	0.32	0.28		

(i) Correlation Edge Weight

Physical-Virtual Collaboration Graph Network

➢ Graph Convolution Gated Recurrent Unit

$$
\begin{aligned}
f(I_t^i) = \Theta_l I_t^i &+ \boxed{\sum_{j \in \mathcal{N}_p(i)} W_p(i,j) \odot \Theta_p I_t^j} \rightarrow \text{Physical Graph} \\
&+ \boxed{\sum_{j \in \mathcal{N}_s(i)} W_s(i,j) \odot \Theta_s I_t^j} \rightarrow \text{Similarity Graph} \\
&+ \boxed{\sum_{j \in \mathcal{N}_c(i)} W_c(i,j) \odot \Theta_c I_t^j,} \rightarrow \text{Correlation Graph}
\end{aligned}
$$

$$H_t = \text{GC-GRU}(I_t, \widetilde{H}_{t-1})$$

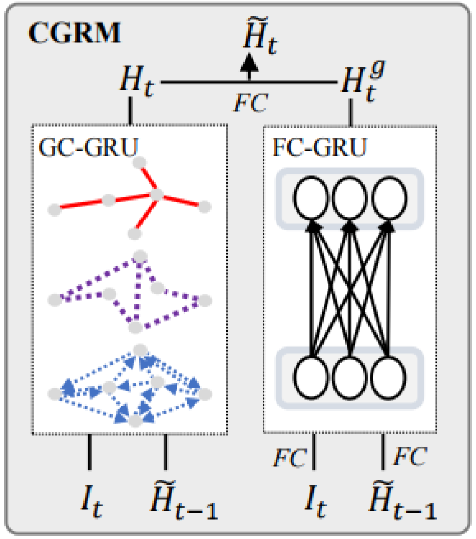
local context

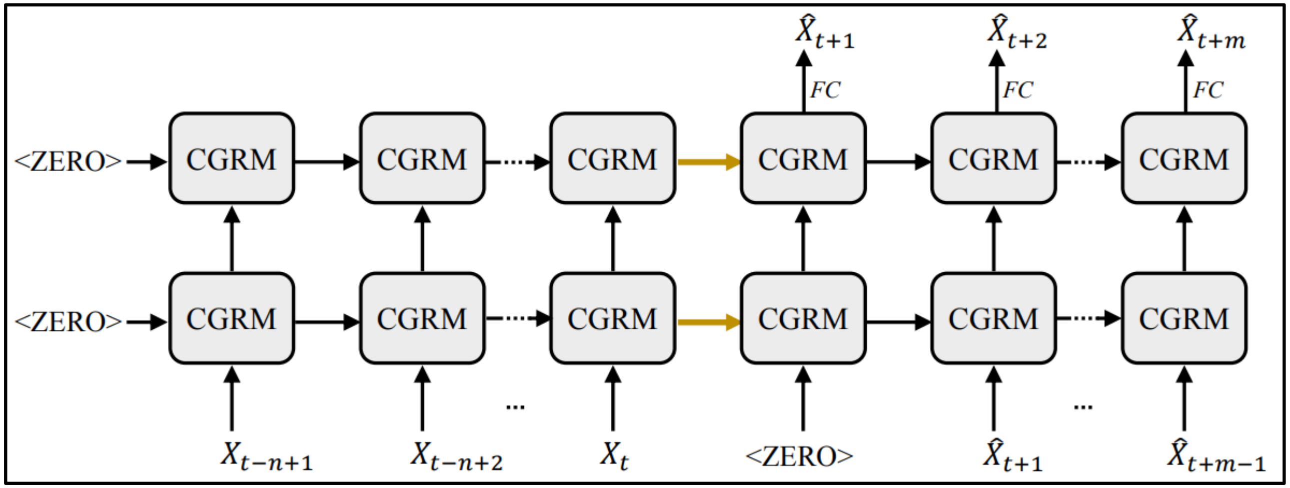
➢ Full-connection Gated Recurrent Unit

$$I_t^e = \text{FC}(I_t), \quad H_{t-1}^e = \text{FC}(\widetilde{H}_{t-1}),$$
$$H_t^g = \text{FC-GRU}(I_t^e, H_{t-1}^e),$$

global context

Collaborative Gated Recurrent Module



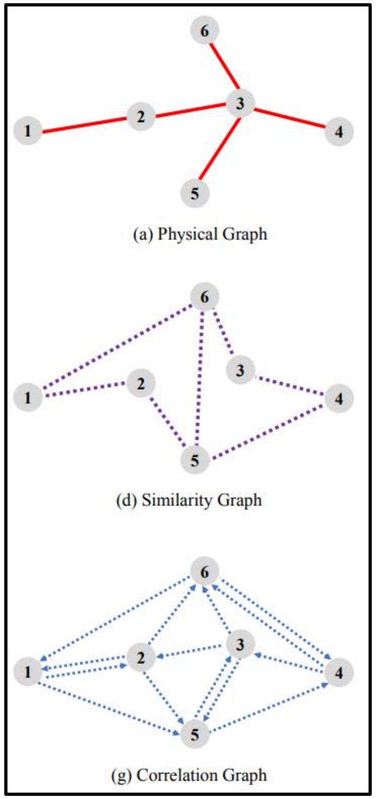


Physical-Virtual Collaboration Graph Network

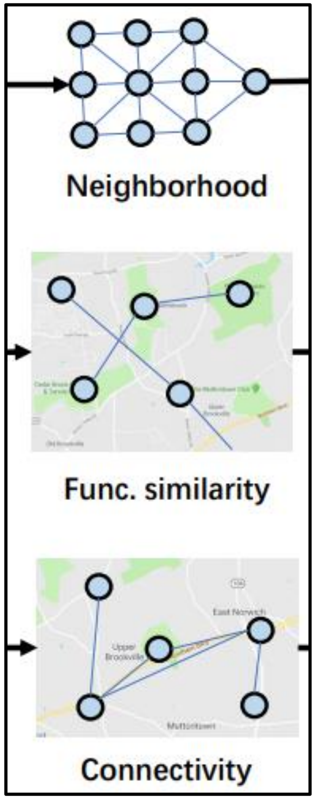
more flexible/universal

more comprehensive

PVCGN



ST-MGCN [1]



Point of Interests (POI)

Road Networks

[1] Spatiotemporal Multi-Graph Convolution Network for Ride-Hailing Demand Forecasting, AAAI 2019

Experiments: Setting

two benchmarks， three evaluation metrics

Dataset	SHMetro	HZMetro
City	Shanghai, China	Hangzhou, China
# Station	288	80
# Physical Edge	958	248
Ridership/Day	8.82 M	2.35 M
Time Interval	15 min	15 min
Training Timespan	7/01/2016 - 8/31/2016	1/01/2019 - 1/18/2019
Validation Timespan	9/01/2016 - 9/09/2016	1/19/2019 - 1/20/2019
Testing Timespan	9/10/2016 - 9/30/2016	1/21/2019 - 1/25/2019

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2},$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{X}_i - X_i|,$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{X}_i - X_i|}{X_i}$$

Experiments: Station-level Metro Ridership Prediction

SHMetro Dataset

Time	Metric	HA	RF	GBDT	MLP	LSTM	GRU	DCRNN	GCRNN	Graph-WaveNet	PVCGN (Ours)
15 min	*RMSE*	136.97	66.63	62.59	48.71	55.53	52.04	46.02	46.09	46.98	44.97
	MAE	48.26	34.37	32.72	25.16	26.68	25.91	24.04	24.26	24.91	23.29
	MAPE	31.55%	24.09%	23.40%	19.44%	18.76%	18.87%	17.82%	18.06%	20.05%	16.83%
30 min	*RMSE*	136.81	88.03	82.32	51.80	57.37	54.02	49.90	50.12	51.64	47.83
	MAE	47.88	41.37	39.50	26.15	27.25	26.39	25.23	25.42	26.53	24.16
	MAPE	31.49%	28.89%	28.17%	20.38%	19.04%	19.20%	18.35%	18.73%	20.38%	17.23%
45 min	*RMSE*	136.45	118.65	113.95	57.06	60.45	56.97	54.92	54.87	58.50	52.02
	MAE	47.26	50.91	49.14	27.91	28.08	27.17	26.76	26.92	28.78	25.33
	MAPE	31.27%	41.34%	40.76%	22.20%	19.61%	19.84%	19.30%	19.81%	21.99%	17.92%
60 min	*RMSE*	135.72	143.5	137.5	63.33	63.41	59.91	58.83	58.67	65.08	55.27
	MAE	46.40	59.15	57.31	29.92	28.94	28.08	28.01	28.18	30.90	26.29
	MAPE	30.80%	52.91%	52.60%	23.96%	20.59%	21.03%	20.44%	21.07%	24.36%	18.69%

HZMetro Dataset

Time	Metric	HA	RF	GBDT	MLP	LSTM	GRU	DCRNN	GCRNN	Graph-WaveNet	PVCGN (Ours)
15 min	*RMSE*	64.19	53.52	51.50	46.55	45.30	45.10	40.39	40.24	40.78	37.76
	MAE	36.37	32.19	30.88	26.57	25.76	25.69	23.76	23.84	24.07	22.68
	MAPE	19.14%	18.34%	17.60%	16.26%	14.91%	15.13%	14.00%	14.08%	14.27%	13.70%
30 min	*RMSE*	64.10	64.54	61.94	47.96	45.52	45.26	42.57	41.95	42.80	39.34
	MAE	36.37	38.00	36.48	27.44	26.01	25.93	25.22	25.14	25.48	23.33
	MAPE	19.31%	21.46%	20.49%	17.10%	15.10%	15.35%	14.99%	14.86%	15.23%	13.81%
45 min	*RMSE*	63.92	80.06	76.70	50.66	46.30	46.13	46.26	45.53	45.84	40.95
	MAE	36.23	45.78	44.12	28.79	26.38	26.36	26.97	26.82	27.15	24.22
	MAPE	19.57%	26.51%	25.75%	19.01%	15.40%	15.79%	16.19%	16.05%	17.34%	14.45%
60 min	*RMSE*	63.72	94.29	91.21	54.62	47.53	47.69	49.35	50.28	49.89	42.61
	MAE	35.99	52.95	51.10	30.52	26.76	26.98	28.47	28.75	29.14	24.93
	MAPE	20.01%	37.12%	38.10%	22.56%	16.34%	17.20%	18.16%	17.89%	19.37%	15.49%

Experiments: Station-level Metro Ridership Prediction

Effectiveness of Different Graphs

Time	Metric	SHMetro					HZMetro				
		P	P+S	P+C	S+C	P+S+C	P	P+S	P+C	S+C	P+S+C
15 min	*RMSE*	50.45	47.38	46.18	46.52	44.97	41.80	38.89	39.46	39.92	37.73
	MAE	25.89	24.16	23.88	23.74	23.29	24.81	23.23	23.34	23.84	22.69
	MAPE	19.04%	17.13%	17.12%	16.94%	16.83%	14.84%	13.93%	14.08%	14.38%	13.72%
30 min	*RMSE*	58.09	50.86	50.29	50.18	47.83	45.31	40.63	41.26	41.59	39.38
	MAE	28.13	25.28	25.13	24.74	24.16	26.63	24.22	24.22	24.59	23.35
	MAPE	20.19%	17.72%	17.73%	17.32%	17.23%	15.50%	14.49%	14.36%	14.60%	13.83%
45 min	*RMSE*	65.81	55.98	55.54	54.45	52.02	50.26	42.63	43.96	44.81	40.88
	MAE	30.51	26.90	26.68	26.01	25.33	29.02	25.31	25.42	25.91	24.23
	MAPE	21.65%	18.66%	18.44%	18.03%	17.92%	16.76%	15.35%	15.26%	15.23%	14.48%
60 min	*RMSE*	73.06	60.08	60.59	58.93	55.27	56.32	44.46	44.93	45.49	42.51
	MAE	32.55	27.92	27.94	27.14	26.29	31.41	26.16	26.13	26.54	24.90
	MAPE	23.43%	19.56%	19.30%	18.87%	18.69%	18.33%	16.31%	16.32%	16.69%	15.48%

Influences of Local and Global Context

Time	Metric	SHMetro		HZMetro	
		Local	Local + Global	Local	Local + Global
15 min	*RMSE*	45.64	44.97	38.46	37.76
	MAE	23.51	23.29	23.00	22.68
	MAPE	17.23%	16.83%	13.86%	13.70%
30 min	*RMSE*	48.79	47.83	39.65	39.34
	MAE	24.48	24.16	23.78	23.33
	MAPE	17.59%	17.23%	14.30%	13.81%
45 min	*RMSE*	52.70	52.02	41.45	40.95
	MAE	25.58	25.33	24.60	24.22
	MAPE	18.16%	17.92%	14.88%	14.45%
60 min	*RMSE*	56.56	55.27	43.11	42.61
	MAE	26.50	26.29	25.36	24.93
	MAPE	18.64%	18.69%	16.06%	15.49%

Experiments: Online Origin-Destination Prediction

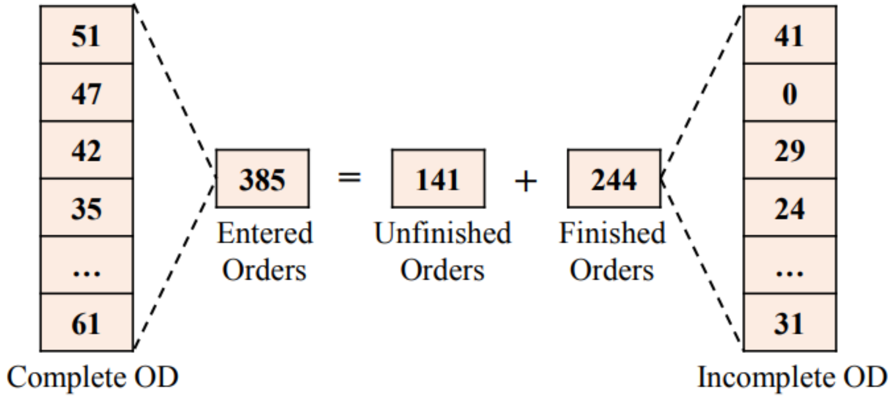


Fig. 4. Illustration of the incomplete origin-destination (OD) distribution. In online metro systems, the complete OD distribution can not be obtained immediately. Suppose there were 385 passengers entered at the i-th station in the past 15 minutes and 244 of them have arrived at their destinations by now. The destinations of remaining passengers are unaware. In this case, we can only construct an incomplete OD vector from the finished orders.

Incomplete OD: $\boldsymbol{X}_t^I = (\boldsymbol{X}_t^{I\_1}, \boldsymbol{X}_t^{I\_2}, \ldots, \boldsymbol{X}_t^{I\_N})$ $\quad \boldsymbol{X}_t^{I\_i} \in \mathbb{R}^{11}$

Complete OD: $\boldsymbol{X}_{t+1}^C = (\boldsymbol{X}_{t+1}^{C\_1}, \boldsymbol{X}_{t+1}^{C\_2}, \ldots, \boldsymbol{X}_{t+1}^{C\_N})$

$$\hat{\boldsymbol{X}}_{t+1}^C, \hat{\boldsymbol{X}}_{t+2}^C, \ldots, \hat{\boldsymbol{X}}_{t+m}^C = \mathrm{PVCGN}(\boldsymbol{X}_{t-n+1}^I, \boldsymbol{X}_{t-n+2}^I, \ldots, \boldsymbol{X}_t^I)$$

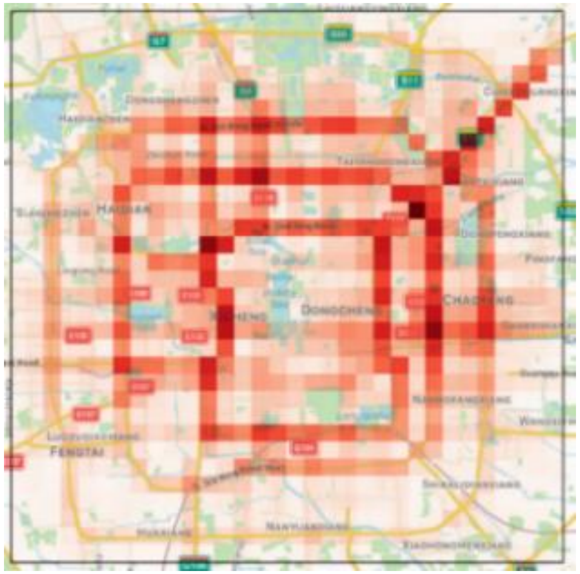
Online OD Prediction

Experiments: Online Origin-Destination Prediction

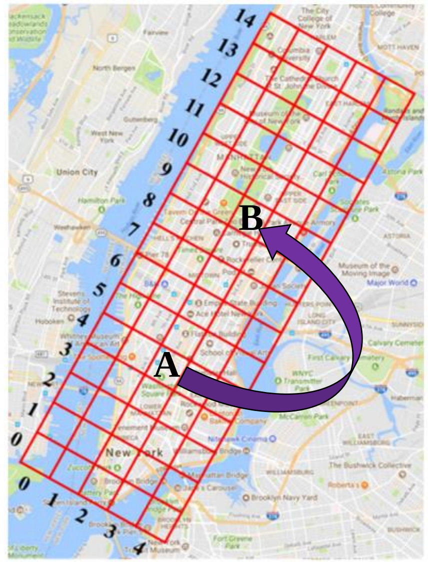
Online origin-destination ridership on the SHMetro dataset

Time	Metric	**HA**	**LSTM**	**GRU**	**DCRNN**	**GCRNN**	**PVCGN (Ours)**
15 min	*RMSE*	29.17	24.67	23.06	16.26	16.29	15.54
	MAE	5.76	5.47	5.30	4.69	4.69	4.54
	MAPE	34.63%	25.50%	25.37%	24.56%	24.56%	23.63%
30 min	*RMSE*	29.1	24.49	23.44	17.88	17.66	16.51
	MAE	5.68	5.47	5.37	4.83	4.79	4.63
	MAPE	34.57%	25.57%	25.54%	24.88%	24.78%	23.87%
45 min	*RMSE*	28.98	24.53	23.66	19.26	19.08	17.7
	MAE	5.59	5.47	5.42	4.93	4.91	4.77
	MAPE	34.48%	25.55%	25.71%	25.28%	25.13%	24.20%
60 min	*RMSE*	28.75	24.71	23.75	20.88	20.6	18.61
	MAE	5.48	5.49	5.42	5.10	5.08	4.87
	MAPE	34.40%	25.57%	25.67%	25.78%	25.66%	24.52%

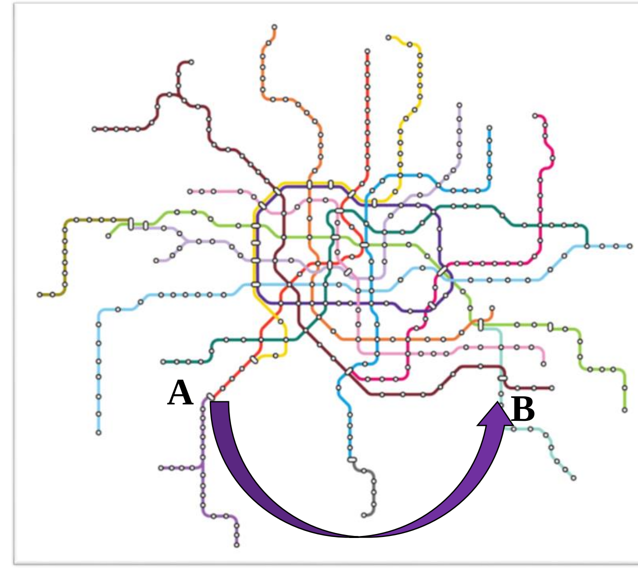
Conclusion



Grid-based Flow



Origin-Destination Demand



Online Origin-Destination Ridership

Attentive Crowd Flow Machines, **ACM MM 2018**
Dynamic Spatial-Temporal Representation Learning for Traffic Flow Prediction, **TITS 2020**
https://github.com/liulingbo918/ATFM

Contextualized Spatial-Temporal Network for Taxi Origin-Destination Demand Prediction,, **TITS 2020**
https://github.com/liulingbo918/CSTN

Physical-Virtual Collaboration Modeling for Intra-and Inter-Station Metro Ridership Prediction, **submit to TITS**
https://github.com/liulingbo918/PVCGN

Thank