جامعة الملك عبدالله للعلوم والتقنية
King Abdullah University of Science and Technology

ARTIFICIAL INTELLIGENCE INITIATIVE

Graph Neural Networks Empowered Origin-Destination Learning for Urban Traffic Prediction

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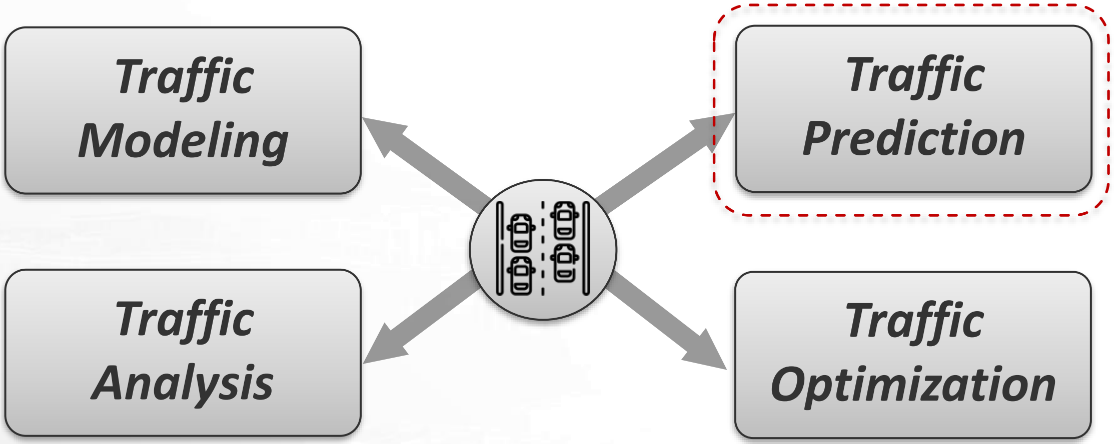
Global Traffic Challenge

Traffic congestion is a **global problem** that impacts all levels of society!

Main reason: **increasing number of vehicles** for a road network with **limited capacity**!

We Need to Understand Traffic

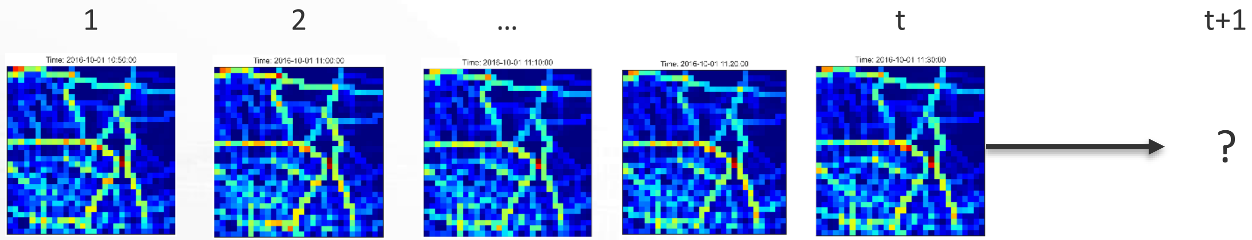
Four Perspectives



Forecasting **real-time** (short-term or long-term) traffic information based on **current** and **historical traffic data**, such as traffic flow, for **every region of a city** (grid-based).

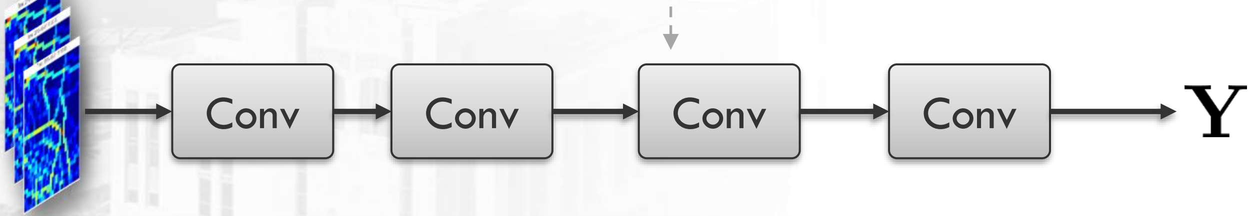
Solutions

General frameworks to traffic prediction problem



$$\hat{\mathbf{X}}_{t+1} = f(\mathcal{X}_t; \mathbf{W})$$

The model is normally a deep neural network



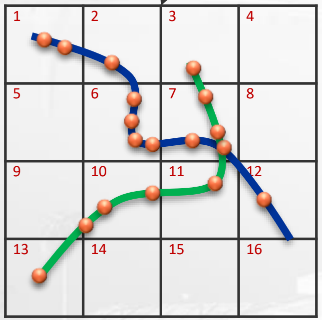
Existing Problems

- The fundamental challenge is how to ***accurately capture the spatial and temporal dependences*** among different regions
- Relying solely on historical traffic data may not capture the **heterogeneity of spatial dependencies** well
- All traffic sequences are time series with characteristics of autocorrelation and periodicity, resulting in **high spatial correlations for any two different regions**.

Our Method: Key Idea

We introduce Origin-Destination (OD) data into traffic prediction, to accurately model the dynamic spatial dependency

$$\hat{\mathbf{X}}_{t+1} = f(\mathcal{X}_t, \mathcal{D}_t; \mathbf{W})$$

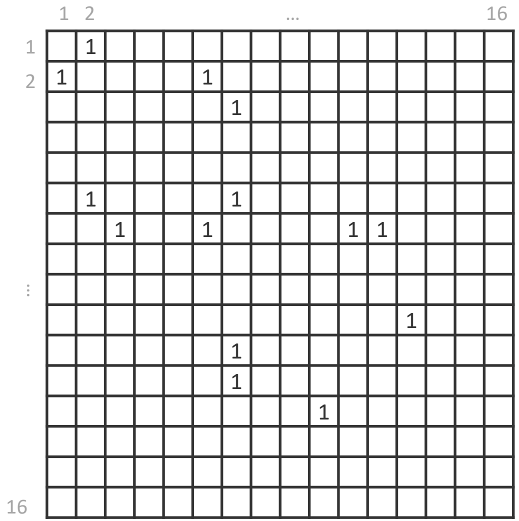


Trajectories

Origin	Destination
1	2
2	6
6	7
7	12
13	10
10	11
11	7
7	3

OD Pair

Two trajectories



OD Matrix (reflects spatial correlations directly and clearly)

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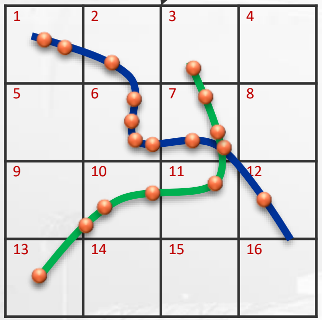


Trajectories

Origin	Destination
1	*2*
2	*6*
6	*7*
7	*12*
13	*10*
10	*11*
11	*7*
7	*3*

OD Pair

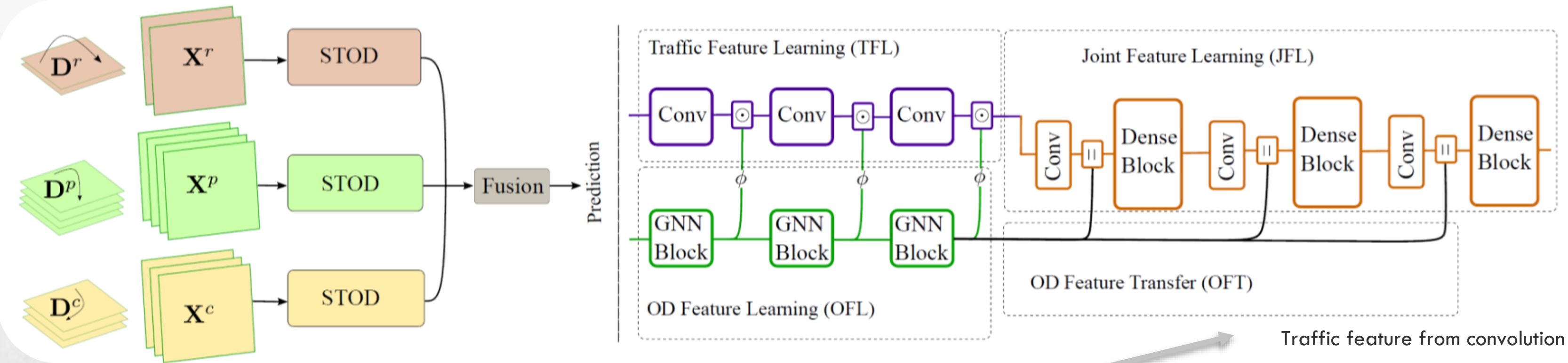
If more trajectories →

	1	2							...							16
1		1														
2	1					2			3							
							1					4		7		
					1											
				1								1			1	
		2					1									
			1			1					1	1			1	
									7							
⋮		3						7			3					
													1			
							1		3							1
			4		1		1									
										1				5		
			7										5			1
					1		1									
16											1			1		

OD Matrix (reflects spatial correlations directly and clearly)

Our Method: Framework

We adopt graph neural networks (GNNs) to model the OD data and propose a **S**patial-**T**emporal **O**rigin-**D**estination enhanced deep **Net**work framework (STOD-Net) for urban traffic prediction



OD data

Traffic volume

- **Closeness** dependence
- **Periodicity** dependence
- **Trend** dependence

Key operation

Traffic feature from convolution

$$\mathbf{X}_t^{(l+1)} = \sigma(\mathbf{W}_{\mathrm{TFL}}^{(l+1)} * \mathbf{X}_t^{(l)}) \odot \mathbf{G}_t^{(l+1)}$$

Gating mechanism from OD feature

$$\mathbf{G}_t^{(l+1)} = \beta\phi(\mathbf{H}_t^{(l+1)}) + (1-\beta)\phi(\mathbf{H}^{(l+1)})$$

Dynamic OD feature learning

Weight parameter

Static OD feature learning

Experimental Results (1/2)

Data	Method	In Traffic			Out Traffic		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE
NYC-Taxi	HA	71.02	41.10	38.06%	59.90	32.55	36.23%
	Naive	36.96	22.72	22.94%	31.78	18.32	22.96%
	ARIMA	34.92	21.97	24.85%	29.99	18.12	25.26%
	LR	30.55	18.93	19.83%	25.66	15.12	19.66%
	MLP	30.09 ± 0.21	18.57 ± 0.13	$19.97 \pm 0.18\%$	24.69 ± 0.24	14.31 ± 0.12	$19.06 \pm 0.16\%$
	ST-ResNet	23.89 ± 0.16	15.25 ± 0.07	$17.16 \pm 0.07\%$	19.47 ± 0.09	12.14 ± 0.06	$16.67 \pm 0.07\%$
	STDN	22.32 ± 0.22	14.09 ± 0.18	$16.15 \pm 0.62\%$	18.08 ± 0.27	11.38 ± 0.20	$16.13 \pm 0.52\%$
	STOD-Net	$\mathbf{21.30 \pm 0.09}$	$\mathbf{13.30 \pm 0.06}$	$\mathbf{15.07 \pm 0.07\%}$	$\mathbf{17.37 \pm 0.09}$	$\mathbf{10.78 \pm 0.05}$	$\mathbf{15.10 \pm 0.06\%}$
NYC-Bike	HA	17.46	11.02	37.31%	16.72	10.69	35.54%
	Naive	14.03	9.48	31.25%	13.43	9.28	30.62%
	ARIMA	12.92	8.81	28.59%	12.38	8.60	27.84%
	LR	11.89	8.07	26.76%	11.21	7.74	25.69%
	MLP	9.41 ± 0.04	6.54 ± 0.02	$23.05 \pm 0.10\%$	8.54 ± 0.06	6.12 ± 0.03	$21.71 \pm 0.15\%$
	ST-ResNet	8.96 ± 0.03	6.46 ± 0.02	$22.72 \pm 0.06\%$	8.19 ± 0.04	6.08 ± 0.03	$21.49 \pm 0.09\%$
	STDN	8.61 ± 0.18	6.14 ± 0.13	$21.42 \pm 0.22\%$	7.78 ± 0.18	5.73 ± 0.12	$20.15 \pm 0.31\%$
	STOD-Net	$\mathbf{8.22 \pm 0.02}$	$\mathbf{5.91 \pm 0.02}$	$\mathbf{20.63 \pm 0.06\%}$	$\mathbf{7.51 \pm 0.02}$	$\mathbf{5.54 \pm 0.01}$	$\mathbf{19.30 \pm 0.06\%}$

Two benchmark datasets

Traditional time series forecasting methods

Shallow machine learning methods

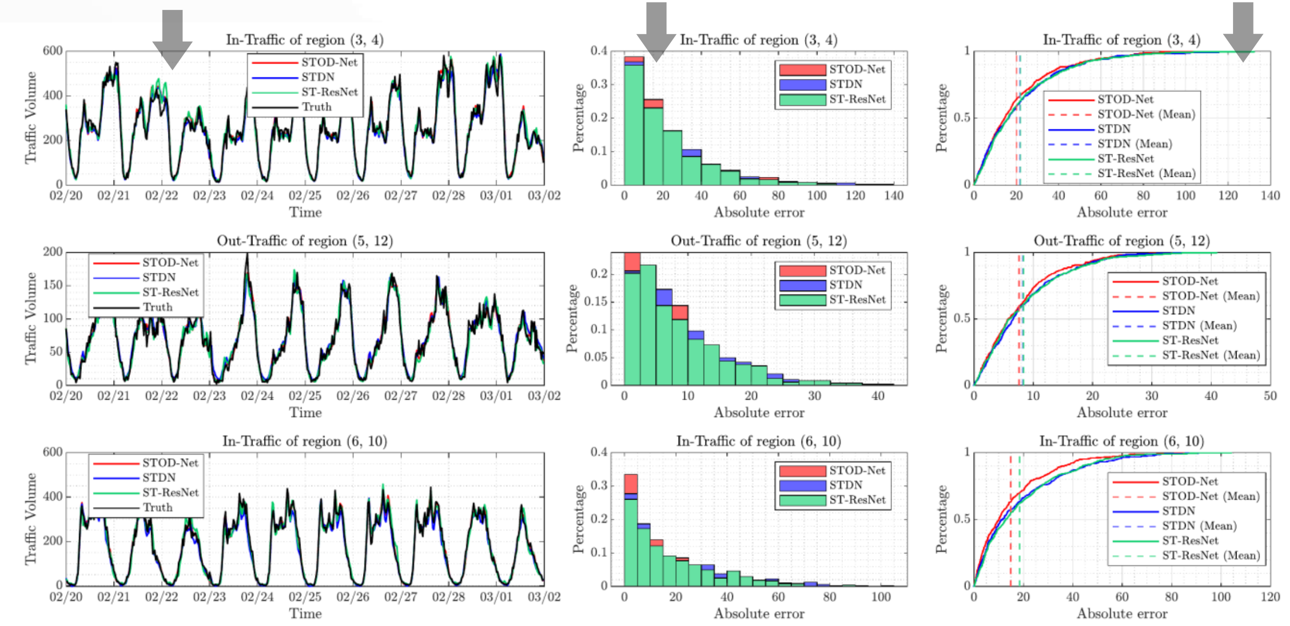
Deep CNN-based methods

ST-ResNet, *AAAI'17*
STDN, *AAAI'19*

Our proposed STOD-Net **outperforms all baselines** and achieves **more stable results** (lower standard deviation)

Experimental Results (2/2)

Predictions vs ground truth, error distribution, and CDF of absolute prediction error



Our proposed STOD-Net **predicts the traffic values accurately** and has **lower prediction errors** compared to state-of-the-art algorithms

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Thanks!

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