Curb-GAN: Conditional Urban Traffic Estimation Through Spatio-Temporal Generative Adversarial Networks

KDD-20 Research Track Paper

Code: github.com/Curb-GAN/Curb-GAN

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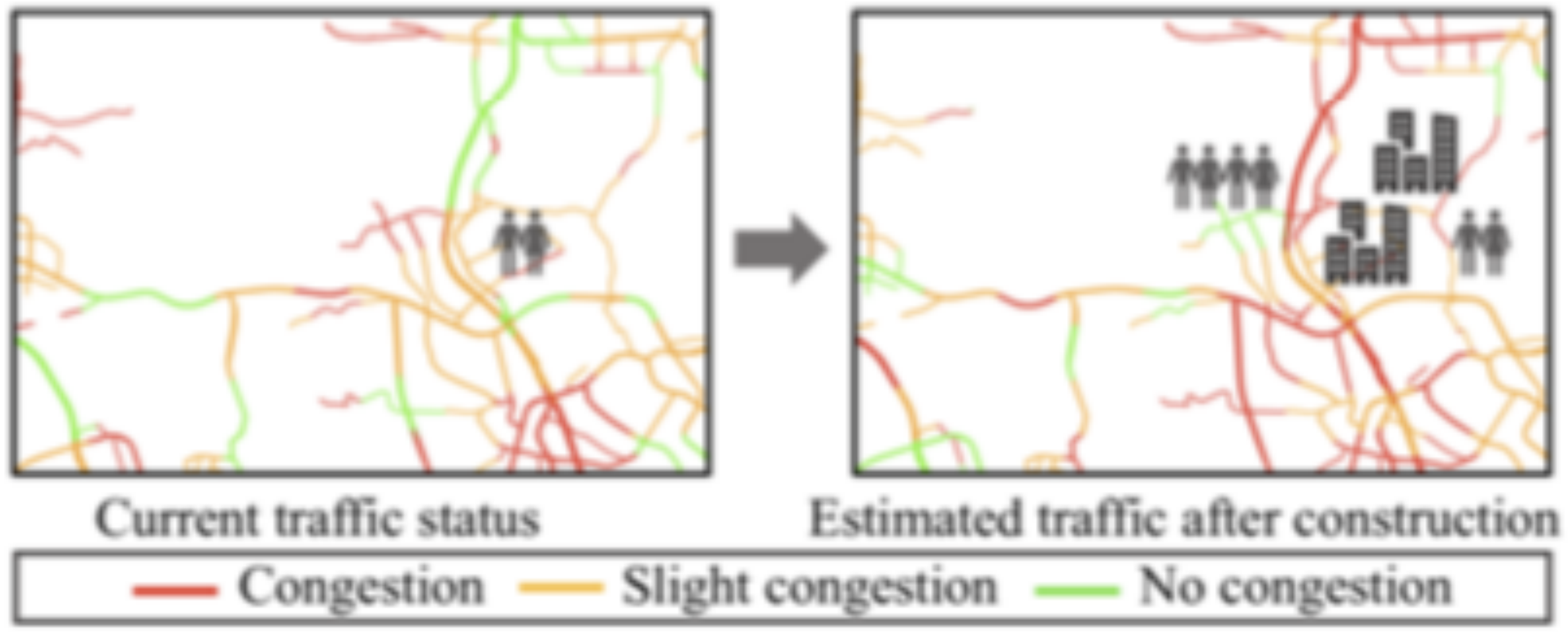
Problem Overview

& Definitions



- Challenges:
- (1) Traffic status heavily depends on travel demand. When travel demand dramatically changes (e.g. big development/construction), data-driven approaches may no longer be effective
- (2) Spatial/Temporal auto-correlations
- Conditional traffic estimation problem:

estimate traffic distribution (on region *R*) sequence based on expected travel demand sequence

$\hat{\mathcal{M}}^R = \{\hat{M}_1^R, \dots, \hat{M}_{N_t}^R\} \in \mathbb{R}^{N_t \times \ell \times \ell}$ $\longleftarrow$ $\hat{\mathcal{D}}^R = \{\hat{d}_1^R, \dots, \hat{d}_{N_t}^R\} \in \mathbb{N}^{N_t}$

- Definitions: traffic status m_t^s on target square region $R_{ij} = \langle s_{ij}, \ell \rangle$ with $N_s = \ell \times \ell$ grid cells

traffic correlation tensor $\mathcal{A}^R = \{A_1^R, \dots, A_{N_t}^R\} \in \mathbb{R}^{N_t \times N_s \times N_s}$

traffic condition tensor $C^R = \{C_1^R, \dots, C_{N_t}^R\} \in \mathbb{R}^{N_t \times N_s \times 4}$, in which $C_t^R = \text{Repeat}(\text{Concat}(i, j, d_t^R, t))$,

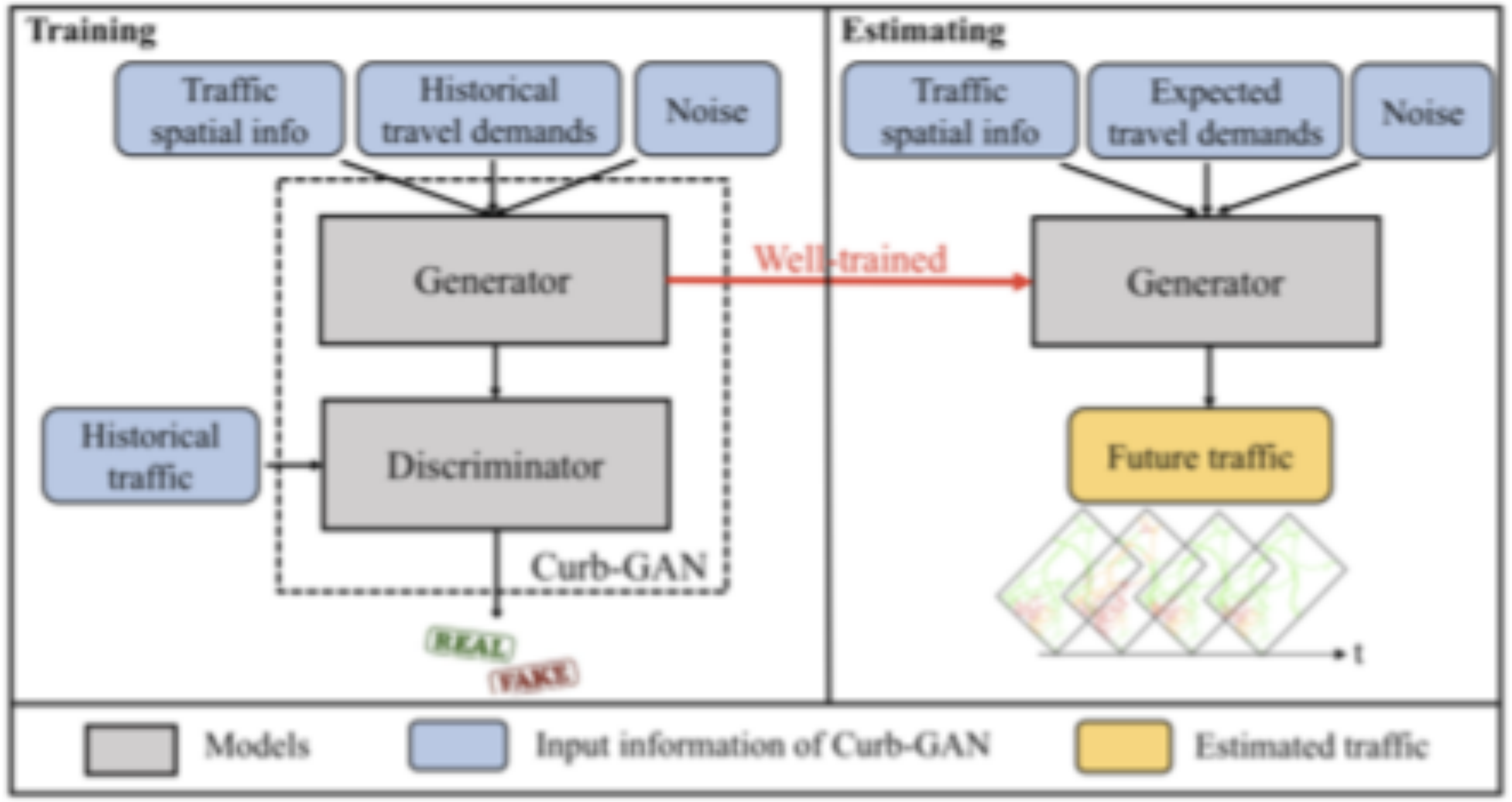
Methodology

Motivations & Model Components

- Formulate Conditional traffic estimation problem as a traffic data generation problem

Solve challenge (1)

- cGAN structure: conditional image sequence generation problem (travel demand as condition)
- Propose Curb-GAN:



Solve challenge (2)

- Spatially, Dynamic GConv. $H_i^R = f\left(H_{i-1}^R, A^R\right) = \sigma\left(A^R H_{i-1}^R W_i\right)$
- Temporally, Self-Attention (Transformer multi-head)

$$\text{MultiHead}(Q, K, V) = \text{Concat}\left(\text{head}_1, \ldots, \text{head}_h\right) W^O$$

$$\text{where head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right)$$

Methodology

Basic GAN Framework

- Gaming between generator G and discriminator D

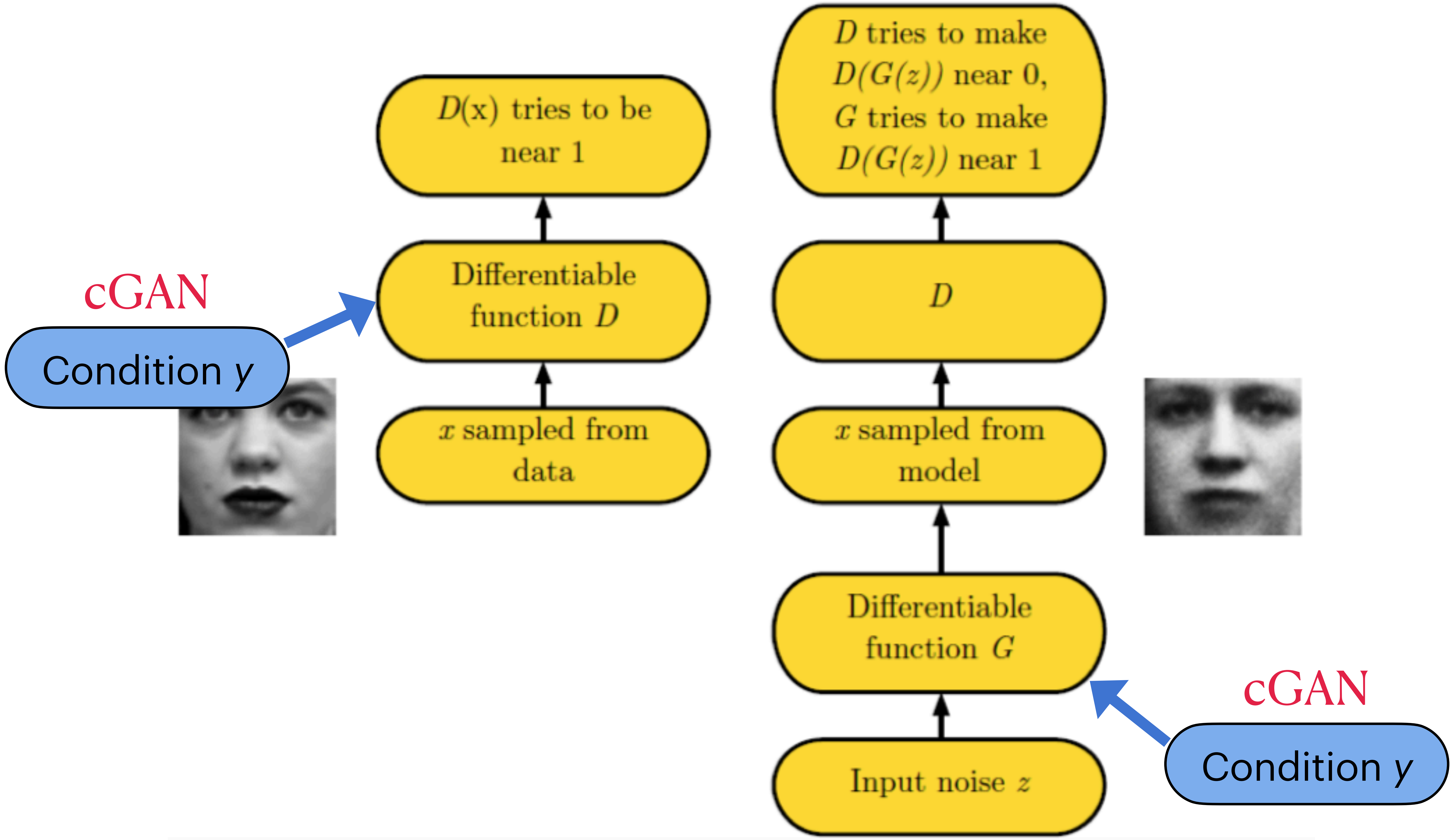
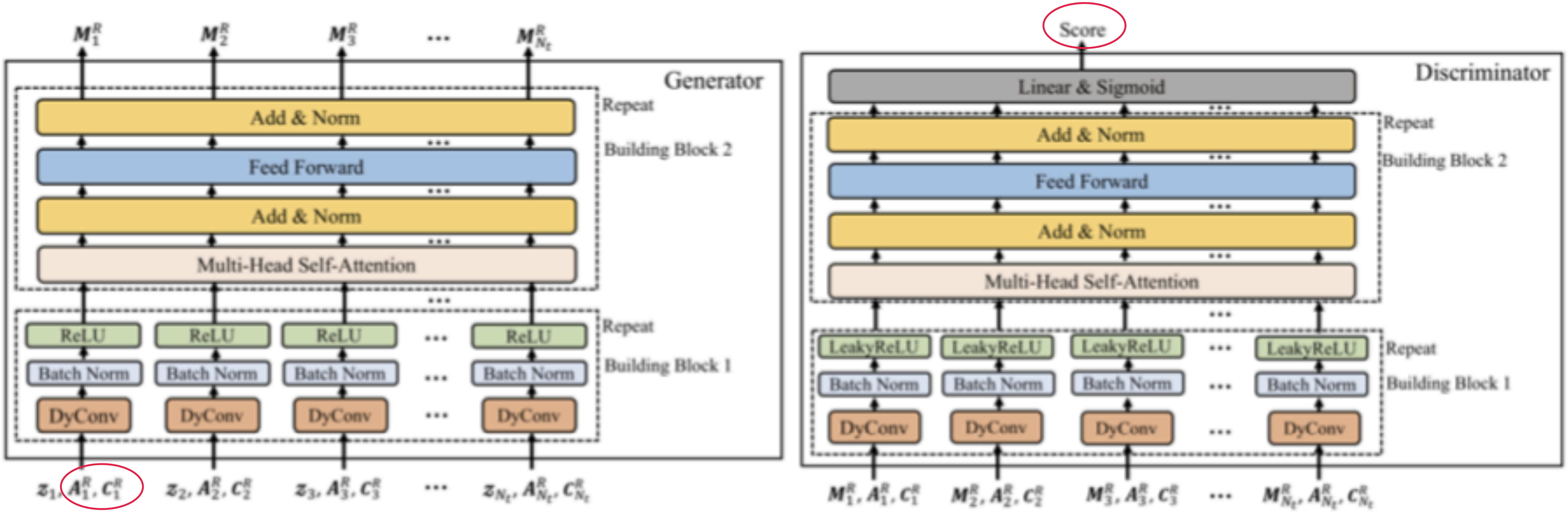


Image from: https://filebox.ece.vt.edu/~jbhuang/teaching/ece6554/sp17/lectures/cGAN-topic.pdf

Methodology

Curb-GAN Modules

Scalar [0, 1]



Conditions

(a) Generator of Curb-GAN

(b) Discriminator of Curb-GAN

Methodology

Model optimization

$\mathcal{P} = \{(C^1, \mathcal{A}^1, \mathcal{M}^1), \cdots, (C^n, \mathcal{A}^n, \mathcal{M}^n)\}$

sample m

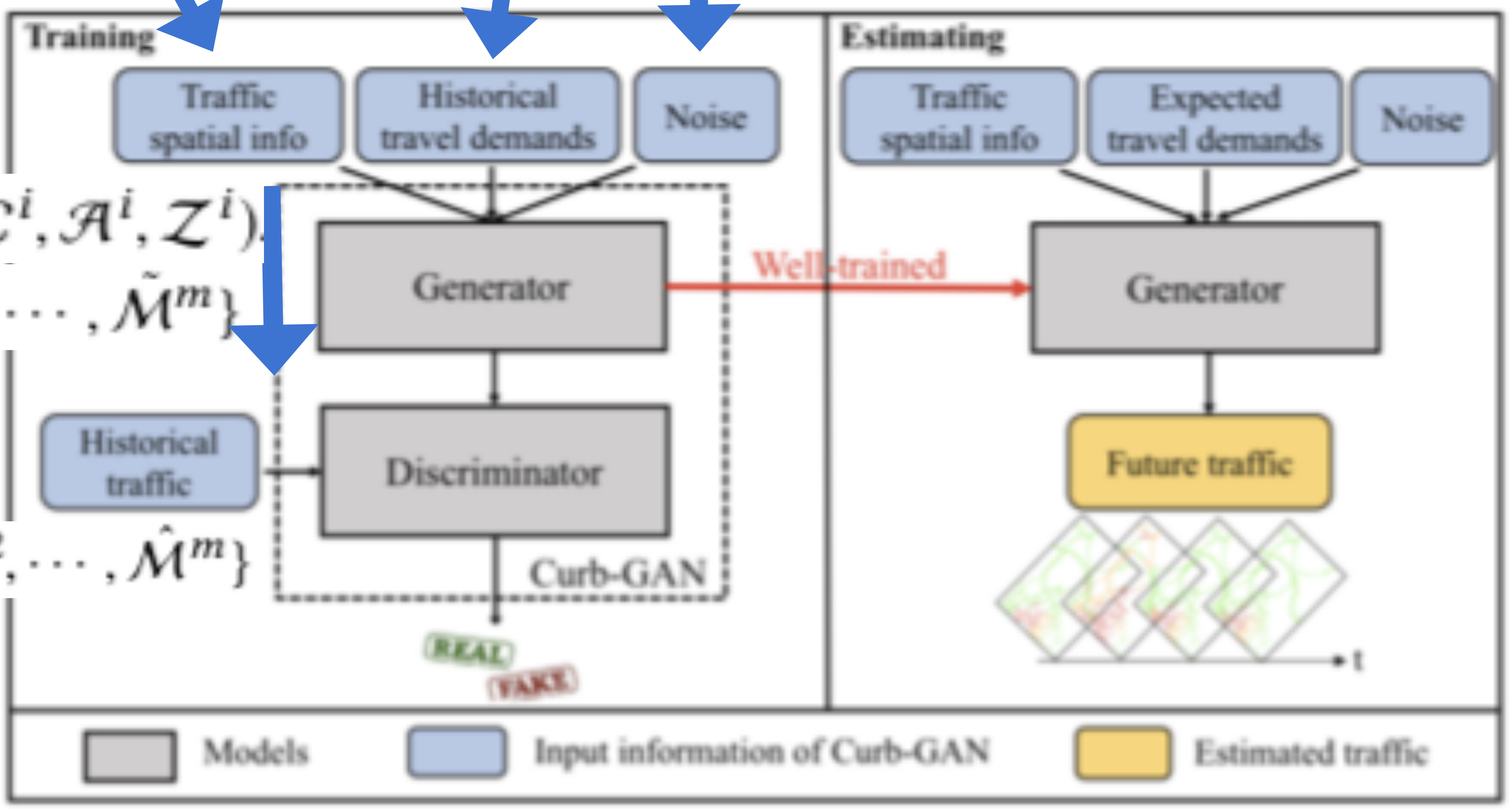
Conditions

$\mathcal{A}^R$ $[C_t^R \in \mathbb{R}^{N_t \times N_s \times 4}, \mathcal{Z}] = \{z_1, \ldots, z_{N_t}\} \in \mathbb{R}^{N_t \times N_s \times N_s}$

$\tilde{\mathcal{M}}^i = G(C^i, \mathcal{A}^i, \mathcal{Z}^i)$

$\tilde{O} = \{\tilde{\mathcal{M}}^1, \cdots, \tilde{\mathcal{M}}^m\}$

$\hat{O} = \{\hat{\mathcal{M}}^1, \hat{\mathcal{M}}^2, \cdots, \hat{\mathcal{M}}^m\}$



A decision rule for minimizing the worst case (maximum) loss

- Loss function: (two-player minimax game)

$$\min_G \max_D V(D, G) = E_{\mathcal{M} \sim p_{data}(\mathcal{M})}[\log D(C, \mathcal{A}, \mathcal{M})] + E_{\mathcal{Z} \sim p_{\mathcal{Z}}(\mathcal{Z})}[\log(1 - D(G(C, \mathcal{A}, \mathcal{Z})))].$$

(resembles Jensen-Shannon divergence: measuring 两个概率分布的相似性)

Algorithm 1 Curb-GAN Training Process

Input: Training iteration k, a training set $\mathcal{P}$, initialized G and D.
Output: Well trained G and D.

1: In each training iteration $iter$:
2: **repeat**
3: Sample $\mathcal{P}_0$ from training set $\mathcal{P}$.
4: Sample $\mathcal{B}$ from Gaussian distribution.
5: Generate $\tilde{O}$ with G.
6: Sample $\hat{O}$ from training set $\mathcal{Z}$.
7: Update D with Eq. 6 to maximize Eq. 5.
8: Update G with Eq. 8 to maximize Eq. 7.
9: **until** $iter > k$.

Aim: increase error rate of *D*!

generated

sampled true

$$\tilde{V}_D = \frac{1}{m}\sum_{i=1}^{m}\Big(\log(1 - D(C^i, \mathcal{A}^i, \underline{\tilde{\mathcal{M}}^i})) + \log D(C^i, \mathcal{A}^i, \underline{\mathcal{M}^i}) + \log(1 - D(C^i, \mathcal{A}^i, \underline{\hat{\mathcal{M}}^i}))\Big), \quad (5)$$

$$\theta_D = \theta_D + \eta_D \nabla \tilde{V}_{\theta_D}(\theta_D). \quad (6)$$

sampled wrong

Heuristic, non-saturating game

$$\tilde{V}_G = \frac{1}{m}\sum_{i=1}^{m} \underline{\log D(G(C^i, \mathcal{A}^i, \mathcal{Z}^i))}, \quad (7)$$

$$\theta_G = \theta_G + \eta_G \nabla \tilde{V}_{\theta_G}(\theta_G). \quad (8)$$

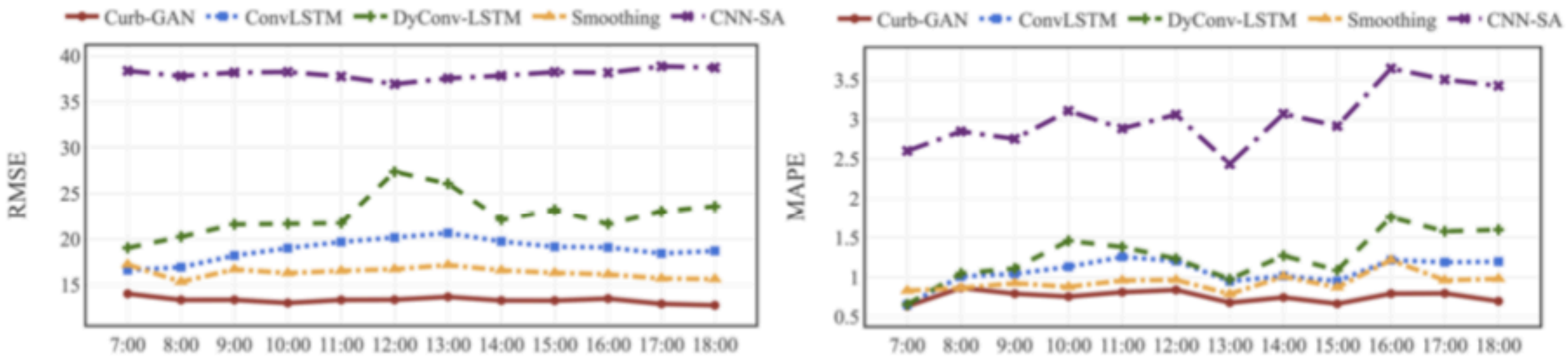
Experiment

on (16下半年) Shenzhen Traffic speed and taxi inflow data

- Partition: 40×50 grid → Region: 10×10 (N_s=100)
- Time interval: 1 hour; 7AM-7PM (N_t=12)

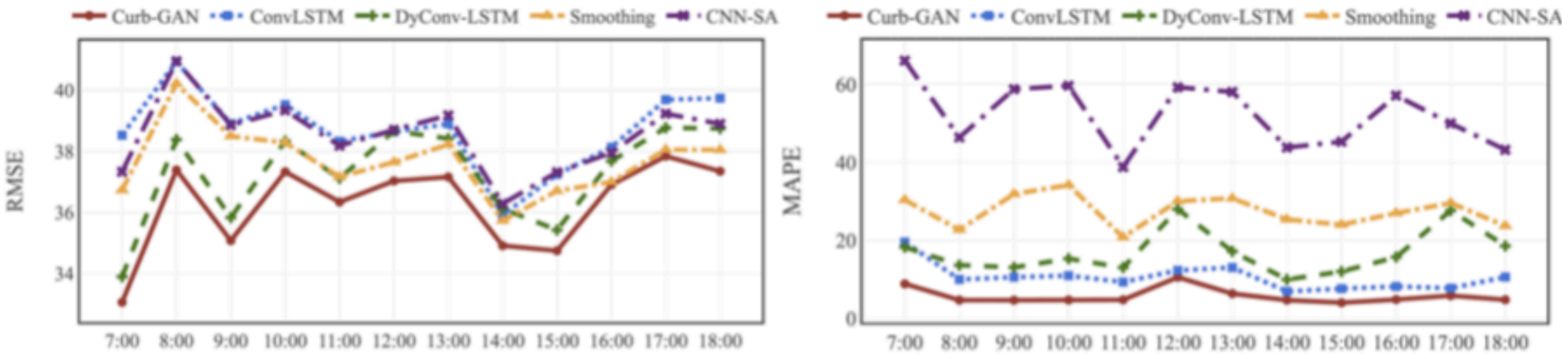
$$\mathrm{MAPE} = \frac{1}{N_s N_t} \sum_{s=1}^{N_s} \sum_{t=1}^{N_t} \left| y_{s,t} - \hat{y}_{s,t} \right| / y_{s,t}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_s N_t} \sum_{s=1}^{N_s} \sum_{t=1}^{N_t} \left(y_{s,t} - \hat{y}_{s,t} \right)^2}$$



(a) RMSE of selected models from 7:00 to 19:00 (b) MAPE of selected models from 7:00 to 19:00

Figure 7: Comparisons of selected models in consecutive time slots in traffic speed estimation.

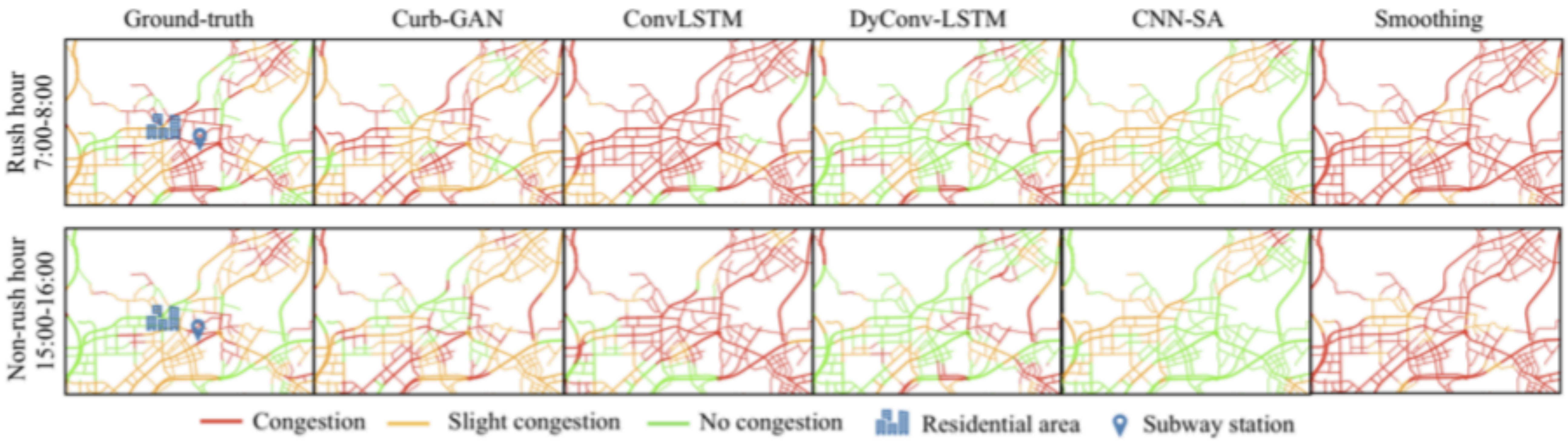


(a) RMSE of selected models from 7:00 to 19:00 (b) MAPE of selected models from 7:00 to 19:00

Figure 8: Comparisons of selected models in consecutive time slots in taxi inflow estimation.

Table 2: Performance results on traffic speed estimation and taxi inflow estimation.

Methods		Smoothing	ConvLSTM	FC-SA	CNN-SA	FC-LSTM	CNN-LSTM	DyConv-LSTM	**Curb-GAN**
Traffic speed	RMSE	16.37	18.90	44.30	38.06	128.03	30.15	22.72	**13.34**
	MAPE	0.94	1.07	3.44	3.02	3.70	2.27	1.26	**0.76**
Taxi inflow	RMSE	37.71	38.73	40.30	38.54	41.11	38.20	37.33	**36.29**
	MAPE	27.56	10.43	79.75	52.25	36.92	62.02	16.88	**5.88**



Thanks for your listening!

Discussion Time 🙋‍♂️