Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting

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Joint work with
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Introduction

- Traffic congesting is wasteful of time, money and energy
  - Traffic congestion costs Americans $124 billion\(^*\) direct/indirect loss in 2013.
- Accurate traffic forecasting could substantially improve route planning and mitigate traffic congestion.


\(^+\) https://www.forbes.com/sites/federicoguerrini/2014/10/14/traffic-congestion-costs-americans-124-billion-a-year-report-says/
Introduction

Route 1: Best route according to current traffic conditions

Route 2: Let’s see.

Route 1

Route 2

Destination

7:00AM
Introduction

The Problem

- Evolution of traffic over time

Existing Solutions

Predictive vs. Real-Time Path Planning

7:15AM

Route 1

Route 2

Destination
Traffic forecasting enables better route planning.

7:30AM
Traffic Forecasting Problem

- Traffic speed forecasting
  - Input: road network and past T' traffic speed observed at sensors
  - Output: traffic speed for the next T steps

Input: Observations

Output: Predictions

7:00 AM  ...  9:00 AM 9:05AM, 9:10AM, ..., 10:00 AM
Challenges for Traffic Forecasting

- **Complex Spatial Dependency**
- **Non-linear, non-stationary Temporal Dynamic**
Challenges for Traffic Forecasting

- Spatial relationship among traffic flow is **non-Euclidean** and **directed**.
Traffic Forecasting Problem

- Model traffic sensor network as a **directed graph**
  - Graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$
  - Nodes $\mathcal{V}$: sensors
  - Edges $\mathcal{E}$: proximity between sensors based on road network distance

- Graph signal $\mathbf{X}_t \in \mathbb{R}^{|\mathcal{V}| \times P}$: traffic flow observed on $\mathcal{G}$ at time $t$
  - Learn a function $h(\cdot)$ to map $T'$ historical graph signals to future $T$ graph signals

$$[\mathbf{X}_{t-T'+1}, \ldots, \mathbf{X}_t; \mathcal{G}] \xrightarrow{h(\cdot)} [\mathbf{X}_{t+1}, \ldots, \mathbf{X}_{t+T}]$$
Spatial Dependency Modeling

- Convolution Neural Networks* (CNN) learn meaningful *spatial patterns*
  - State-of-the-art results on image related tasks

Spatial Dependency Modeling

- CNN \textit{does not} apply to general graph.
- Model traffic flow as a diffusion process
  - Spatial correlation is dominated by connectivity

Classical Convolution on image

\begin{array}{cccccc}
1_{x_2} & 1_{x_0} & 1_{x_1} & 0 & 0 \\
0_{x_0} & 1_{x_1} & 1_{x_0} & 1 & 0 \\
0_{x_1} & 0_{x_0} & 1_{x_1} & 1 & 1 \\
0 & 0 & 1 & 1 & 0 \\
0 & 1 & 1 & 0 & 0 \\
\end{array}

Diffusion convolution on graph

Weight
Max
Min
Model Spatial Dependency using Convolution on Graph

- **Diffusion convolution filter**: combination of diffusion processes with different steps on the graph.
  - Efficient: $O(K|\mathcal{E}|)$, $|\mathcal{E}|$ number of edges

$$X:.,p \ast_{g} f_{\theta} = \sum_{k=0}^{K-1} \left( \theta_{k,1}(D_{0}^{-1}W)^{k} + \theta_{k,2}(D_{I}^{-1}W^{T})^{k} \right) X:.,p$$

Example diffusion filter on Grid graph

- Transition matrices of the diffusion process
- Diffusion process with 0, 1, 2, and K steps
- Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting

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Challenges for Traffic Forecasting

Complicated Spatial Dependency

Non-linear, non-stationary Temporal Dynamic
Recurrent Neural Network (RNN)
- Non-linear, no stationary auto-regression
- Long-term temporal dependency
- State-of-the-art performance in sequence modeling

Model Temporal Dynamics using Recurrent Neural Network

\[ \text{GRU} + \text{Diffusion Convolution} \rightarrow \text{DCGRU} \]
Model Temporal Dynamics using Recurrent Neural Network

- **Diffusion Convolutional Recurrent Neural Network (DCRNN)**
  - Sequence to sequence learning with *encoder-decoder* framework
  - Improve long term forecasting with *curriculum learning*


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Experimental Settings

**METR-LA:**
- 207 traffic sensors in Los Angeles
- 4 months in 2012
- 6.5M observations

**PEMS-BAY:**
- 345 traffic sensors in Bay Area
- 6 months in 2017
- 17M observations
Experimental Settings

- Baselines:
  - Historical Average (HA)
  - Autoregressive Integrated Moving Average (ARIMA)
  - Support Vector Regression (SVR)
  - Vector Auto-Regression (VAR)
  - Feed forward Neural network (FNN)
  - Fully connected LSTM with Sequence to Sequence framework (FC-LSTM)
Experimental Results

- **DCRNN** achieves the **best performance** for all forecasting horizons for both datasets.

![Graph showing mean absolute error (MAE) for different forecasting models on METR-LA and PEMS-BAY datasets.](image)
Experimental Results

- Effects of Spatiotemporal Dependency Modeling
  - Removing either spatial or temporal modeling results in **significantly worse** results.
Results Visualization

**DCRNN** can generate smooth prediction of the mean when frequent oscillation exists in the traffic signal.
Results Visualization

- **DCRNN** is more likely to accurately *predict abrupt changes* in the traffic speed than baseline methods.
Summary

- Propose *diffusion convolution* to model the spatial dependency of traffic flow.

- Propose *Diffusion Convolutional Recurrent Neural Network* (DCRNN) that captures *both spatial and temporal* dependencies.

- DCRNN obtains *consistent improvement* over state-of-the-art baseline methods.

https://arxiv.org/1707.01926

https://github.com/liyaguang/DCRNN
Thank You!

Q & A