

Spatio-Temporal-Graph-Convolutional-Networks-A-Deep-Learning-Framework-for-Traffic-Forecasting

reference

- <https://www.zhihu.com/question/54504471>
- https://en.wikipedia.org/wiki/Laplacian_matrix
- <https://tkipf.github.io/graph-convolutional-networks/>
- <https://www.inference.vc/how-powerful-are-graph-convolutions-review-of-kipf-welling-2016-2/>
- <http://cs229.stanford.edu/section/cs229-moregaussians.pdf>

abstract

- Spatio-Temporal Graph Convolutional Network
- tackle the time series prediction problem in traffic domain
- complete convolutional structures.

introduction

- linear regression perform well on short interval forecast instead of long terms
- this is a data-driven and using spatio-temporal information method.
- fully utilize spatio-information instead of treating it as discrete units

- $\hat{v}_{t+1}, \dots, \hat{v}_{t+H} = \operatorname{argmax}_{\log_{10}} P(v_{t+1}, \dots, v_{t+H} | v_{t-M}, \dots, v_t)$



- where

$$v_t \in R^n$$

, n is an observation vector of n road segments at time step t

Convolutions on Graphs



- normalized Laplacian
 - Random walk normalized Laplacian
- analogy to The Multivariate Gaussian Distribution
- Symmetric normalized Laplacian L:

$$L = \frac{1}{2} (D^{-1/2} A D^{-1/2} + D^{-1/2} A D^{-1/2})$$

- first generation of GNC

$$y_{output} = \sigma \left(U \begin{pmatrix} \theta_1 & & \\ & \ddots & \\ & & \theta_n \end{pmatrix} U^T x \right) \quad (3)$$

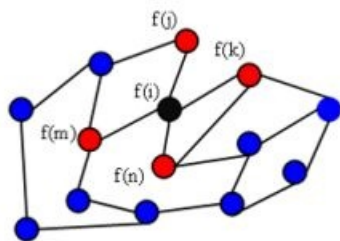
- second generation of GNC

$$y_{output} = \sigma \left(U \begin{pmatrix} \sum_{j=0}^K \alpha_j \lambda_1^j & & \\ & \ddots & \\ & & \sum_{j=0}^K \alpha_j \lambda_n^j \end{pmatrix} U^T x \right) \quad (4)$$

$$U \sum_{j=0}^K \alpha_j \Lambda^j U^T = \sum_{j=0}^K \alpha_j U \Lambda^j U^T = \sum_{j=0}^K \alpha_j L^j$$

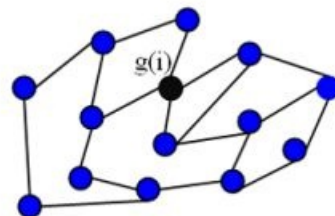
$$y_{output} = \sigma \left(\sum_{j=0}^K \alpha_j L^j x \right) \quad (5)$$

$K = 1$

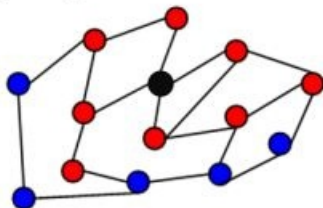


$$g(i) = \sum_{j \in N(1)} a_j f(j)$$

Graph Convolution

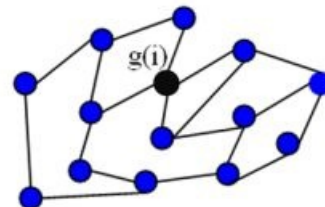


$K = 2$



$$g(i) = \sum_{j \in N(2)} a_j f(j)$$

Graph Convolution



- if $k == n$, receptive field is n hop
- third generation of GNC



- where

c_1

,

c_2

and

c_3

are fixed

- The only trainable parameters are

$$\theta_0$$

and

$$\theta_1$$

- in the final version the authors even further fix

$$\theta_0 = -\theta_1$$

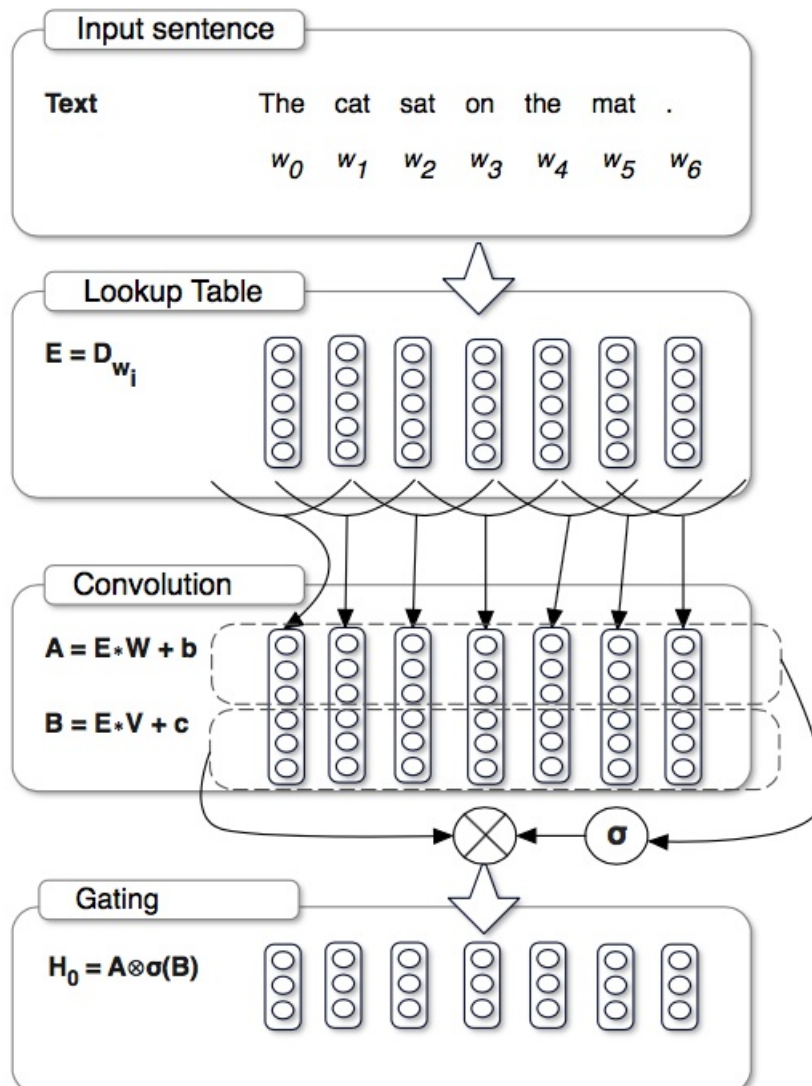


Network Architecture

- main architecture



- GLU architecture



- main equation



- final equation



Experiments

- linear interpolation method for missing values
- normalized by standard score method $((x - \text{mean}) / \text{std})$
- adjacency matrix



10,0.5

result

