Research purpose

• Build a model that can properly learn the spatial-temporal dynamicity of transportation network data
• Find out which kind of weight is appropriate to improve the accuracy of short term traffic prediction on transportation network
• Build a graph neural network that can consider multiple kinds of weights at the same time
  • Thus learning full characteristics of a network

• The proposed network will have ability to accurately predict the short-term traffic.
• Also, the network will have scalability on attaching and detaching multiple weight on graph structure.
  • With more data, more accurate prediction will be achieved with only little change in parameters
Weight consideration

- **In/out flow**
  - Inflow and outflow weights are treated as separate weighted adjacency matrices

- **Speed limit**
  - **RATIO**
    - Speed limit is a critical factor on choice of path for drivers
    - If all other factors are the same, drivers would prefer to drive on the traffic links with higher speed limit
    - \[ \frac{\text{limit}_{\text{next}}}{\text{limit}_{\text{current}}} \]
    - \[ W_{ij} = \frac{\text{limit}_{j}}{\text{limit}_{i}} \]

- **CATEGORY**
  - Larger weight to the roads with higher speed limit
  - \[ w^{sl_c}_{ij} = \text{speed limit of link } j \]

- **CHANGE**
  - Weights on the edges where speed limit changes
  - \[ w^{sl_{ch}}_{ij} = 1 \text{ if speed limit of link } i \neq \text{ speed limit of link } j \]
Weight consideration & Traffic forecasting problem

- **Distance**
  - Two distance measures are used
    1. Distance between two traffic links
      - \( w_{ij} = \exp\left(-\frac{d_{ij}^2}{\sigma_{dist}^2}\right), i \neq j \) & \( A_{ij} > 0 \)

- **Angle**
  - Drivers would prefer to choose the traffic link on straight direction
    - \( \theta^{ij} = |\pi - \theta_0^{ij}| \)
    - \( W_{ij} = \exp\left(-\frac{1}{\theta^{ij}}\right) \)

- The number of weighted adjacency matrices will be
  - \textit{number of weight consideration} * 2\textit{(in/outflow)} * \textit{number of considered ranks}

- **Traffic Forecasting Problem**
  - Given historical observation of traffic speed of \( h \) time steps from time \( t \) \{\( x_{t-h+1}, ..., x_t \)\}, the goal is to predict the speed after \( p \) time steps.
Proposed model

\[ \Theta = \{ \theta_{w_{h1}}, \ldots, \theta_{w_{h2}}, \ldots, \theta_{w_{p1}}, \ldots, \theta_{w_{p2}}, \ldots, \theta_{w_{k1}}, \ldots, \theta_{w_{k2}} \} \in \mathbb{R}^{c_{h1} \times c_{h2} \times \ldots \times c_{p1} \times \ldots \times c_{p2} \times \ldots \times c_{k1} \times \ldots \times c_{k2}} \]

- \( c_{h1} \): number of input channel (1 at default)

Graph Convolution Operations

- Weighted adjacency matrices, \( W \in \mathbb{R}^{N \times N} \)

- \( f \): (road-wise) fully connected operation

- Dim. reduc. conv: Dimension reduction convolution

- Output from rank 1, Output from rank 2, Output from rank k

Temporal modeling
- LSTM

Input \( i \in \mathbb{R}^n \) at time \( t - h, h \in \{0, \ldots, tp - 1\} \)
- \( tp \): the number of time step used for prediction
- \( N \): the number of traffic links
Graph Convolution Operation – Traffic Graph Convolution (Cui et al. 2018)

\[ \tilde{A}^k \odot \theta_{W_i} X_t \in R^{N_{links}} \]
- \( A^k \): K-th rank weighted adjacency matrix
- \( \theta_{W_i} \): weight parameter for each weighted adjacency matrix
- \( X_t \): input at time t
- \( \odot \): Hadamard product (element-wise product)

\[ W_i \in R^{N_{links} \times N_{links}} \]: weighted adjacency matrix (one for each weight consideration of each rank)

\[ X_t \in R^{N_{links} \times cin} \]: input at time t

\[ \theta_{W_i} \in R^{N_{links} \times N_{links}} \]: weight parameter for each weighted adjacency matrix

\[ \odot \]: Hadamard product (element-wise product)
Data & Study Areas

• 5 min average taxi speed dataset on traffic links of Seoul is used
  • Acquired from topis.seoul.go.kr
  • Date: 2018.04 (1 month)

• Two targeted study area is chosen for testing
  1. Urban-Core (304 links)
     • To test the model performance on homogenous link area
     • Links from one of the most congested area of Seoul
     • The length of links is rather homogeneous
     • All the links have speed limit of 60

  2. Expanded-Mix (1007 links)
     • To test the model performance on rather heterogeneous link area
     • The area is located around the Han-river (CheonHo Bridge ~ DongJak Bridge)
     • The area includes the urban highway, bridges, urban roads, and rather small roads.
## Results

### Urban-Core

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>MAPE</th>
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</tr>
</thead>
<tbody>
<tr>
<td>HA</td>
<td>5.145 / 5.528 / 5.828</td>
<td>13.831 / 15.336 / 16.483</td>
<td>3.467 / 3.792 / 4.038</td>
</tr>
</tbody>
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### Urban-Mix

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<tr>
<td>VAR</td>
<td>5.841 / 6.542 / 7.049</td>
<td>13.690 / 15.229 / 16.490</td>
<td>3.520 / 3.918 / 4.252</td>
</tr>
<tr>
<td>MW-TGC</td>
<td>3.889 / 4.023 / 3.962</td>
<td>10.358 / 10.653 / 10.500</td>
<td>2.574 / 2.647 / 2.607</td>
</tr>
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RMSE on each link for Urban-Mix dataset. (MW-TGC vs. ST-GCN)

\[ \text{# links s.t. } \text{RMSE}_i > \mu_{\text{RMSE}} + \sigma_{\text{RMSE}} \]

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Conclusion

- Proposed a way to feed multiple types of weights, or information, into a single graph convolutional networks model.
- The difference exist in the performance gain between two datasets
  - Feeding more information reduces unpredictability of roads with minor characteristics in heterogeneous network environment
  - Imply that with more information, MW-TGCN can achieve even better performance