Multi-task Representation Learning for Travel Time Estimation

Yuguang Li, Kun Fu, Zheng Wang, Cyrus Shahabi, Jieping Ye, Yan Liu

University of Southern California, DiDi AI Labs

Problem

How to accurately estimate the travel time of a trip without route information?

Our Solution

Multi-task Representation learning for Arrival Time estimation (MURAT)

Learning rich representation that leverages the road network structure and the spatiotemporal smoothness prior

Multi-task learning to incorporate routes of historical trips to boost performance

Origin Destination Travel Time Estimation

Problem Statement Given an Origin, a Destination and a departure time, estimate the Time of Arrival (OD ETA).

Applications

Route Planning, Ride Sharing, Order Dispatching, Pricing

Challenges

Actual route is not available: limited amount of information for online prediction

Complicated spatiotemporal dependency in the underlying road network

Multi-task Representation Learning Framework

Representation Learning for Road Network

Road network as undirected link graph: \( G = (V, A) \)

Graph Laplacian: \( \mathbf{L} = \mathbf{D} - \mathbf{A} \)

Link embedding: \( \mathbf{E} \in \mathbb{R}^{V \times d} \)

Supervised loss function: \( \ell \)

Incorporating the network structure with graph laplacian:

\[ \ell = \ell + \alpha \text{Tr} [ \mathbf{E}^	op \mathbf{E} ] = \ell + \alpha \sum_{i,j} A_{ij} || \mathbf{E}_i - \mathbf{E}_j ||^2 \]

Spatiotemporal Representation Learning

Integrating the prior knowledge: e.g., spatiotemporal smoothness, the recurring nature of traffic, by constructing the spatial/temporal graphs in the embedding space

Model Architecture

Embedding the link and spatiotemporal information into the learned spaces

Feeding the learned representations into a deep residual network

Jointly learning multiple tasks, e.g., travel distance, number of links, lights etc.

Experiments

Data Statistics

<table>
<thead>
<tr>
<th>Name</th>
<th>BJS-Pickup</th>
<th>BJS-Small</th>
<th>NYC-Trip</th>
</tr>
</thead>
<tbody>
<tr>
<td># Samples</td>
<td>61.4M</td>
<td>4.8M</td>
<td>21.9M</td>
</tr>
<tr>
<td>Avg. trip time</td>
<td>191 s</td>
<td>335 s</td>
<td>600 s</td>
</tr>
<tr>
<td># Links</td>
<td>1.1M</td>
<td>30K</td>
<td>73K</td>
</tr>
</tbody>
</table>

Baselines

Linear regression (LR); Gradient boosted machine (GBM); Spatial temporal deep neural network (ST-NN); TEMP+R: a nearest neighbor based approach

MURAT-NR: the variant of the MURAT without explicit representation learning

Performance Comparison

Effect of Link and Spatiotemporal Representations

Learning representations of the link, i.e., the road network structure, and spatiotemporal features results in better performance

Effect of Multi-task Learning

Ratio/weight of the main task vs. overfitting and performance

Introducing auxiliary tasks reduces overfitting and can result in better performance

Visualization of Learned Representation

(a) The learned representation for time in day forms a circular shape, from 00:00 to 24:00 with smooth transitions between adjacent time intervals. (b) Weekends are clearly separated from weekdays, where Tue, Wed, Thu are close to each other, while Mon and Fri with different traffic patterns are relatively far away.