Multi-task Representation Learning for Travel Time Estimation

Yaguang 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?

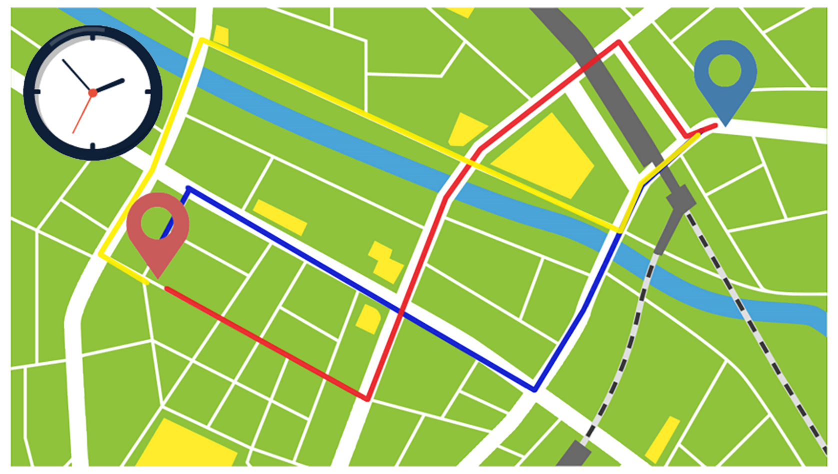
Our Solution

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

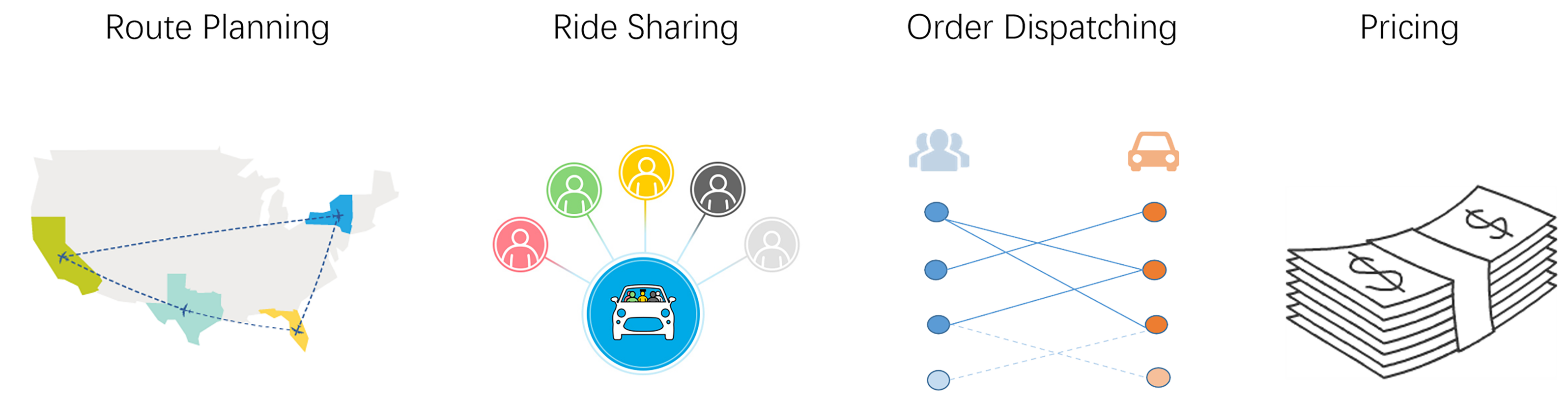
- Learning rich representation that leverages the road network structure and the spatiotemporal smoothness prior
- Multi-task learning to incorporate routes of historical trips to boost performance
- Code: `https://github.com/liyaguang/deep-eta-murat`

Origin Destination Travel Time Estimation

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



Applications



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

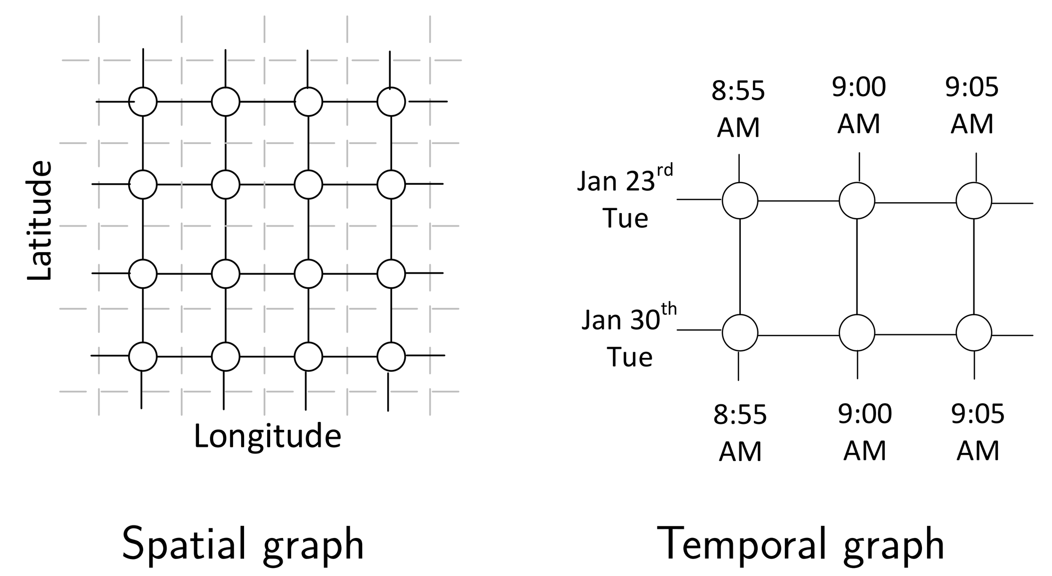
Representation Learning for Road Network

- Road network as undirected link graph: $\mathcal{G} = (\mathcal{V}, \mathbf{A})$
- Graph Laplacian: $\mathbf{L} = \mathbf{D} - \mathbf{A}$
- Link embedding: $\mathbf{E} \in \mathbb{R}^{|\mathcal{V}| \times d_l}$
- Supervised loss function: ℓ

Incorporating the network structure with graph laplacian:

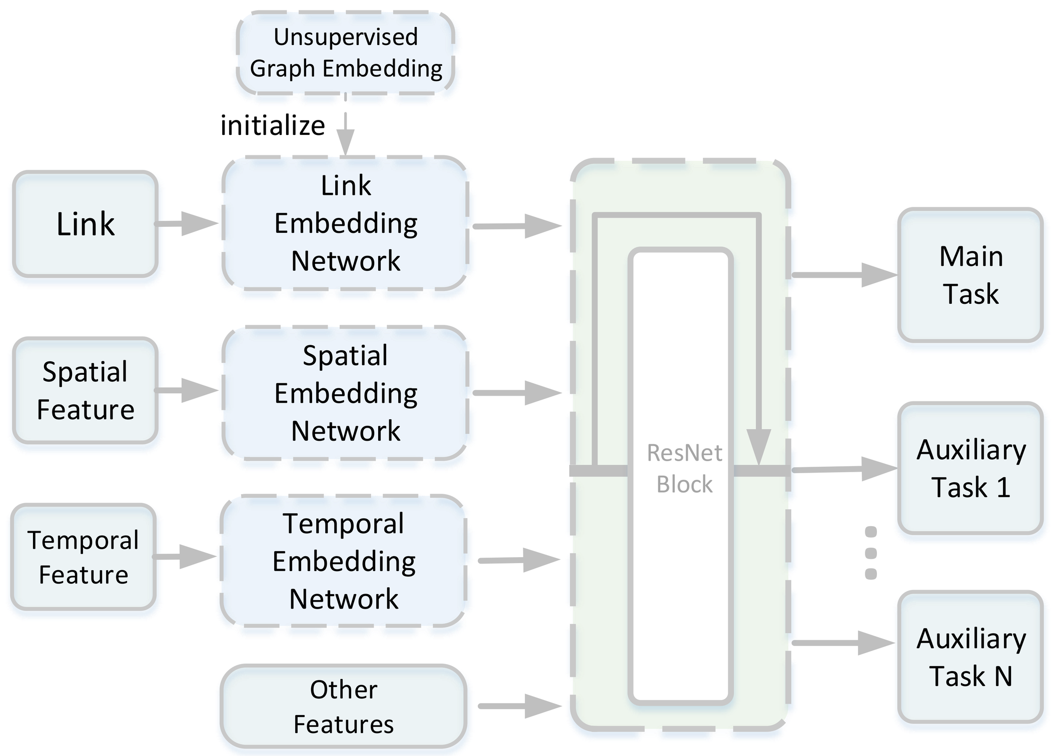
$$\tilde{\ell} = \ell + \alpha \mathrm{Tr}(\mathbf{E}^\intercal \mathbf{L} \mathbf{E}) = \ell + \alpha \sum_{i,j} A_{ij} \|\mathbf{E}_{i,:} - \mathbf{E}_{j,:}\|^2$$

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

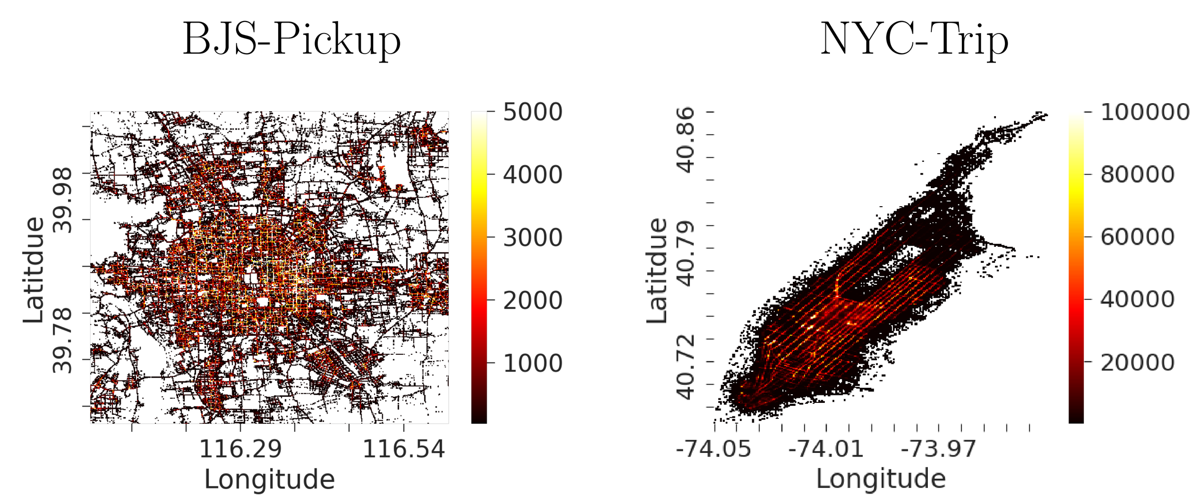
Model Architecture



- 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

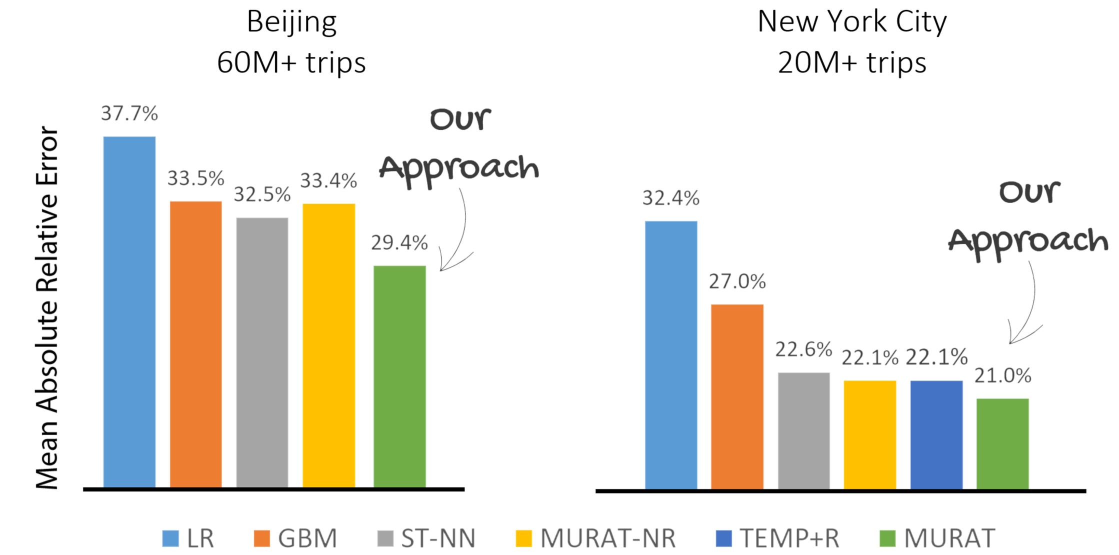


Name	BJS-Pickup	BJS-Small	NYC-Trip
# Samples	61.4M	4.8M	21.9M
Avg. trip time	191 s	335 s	660 s
# Links	1.1M	30K	73K

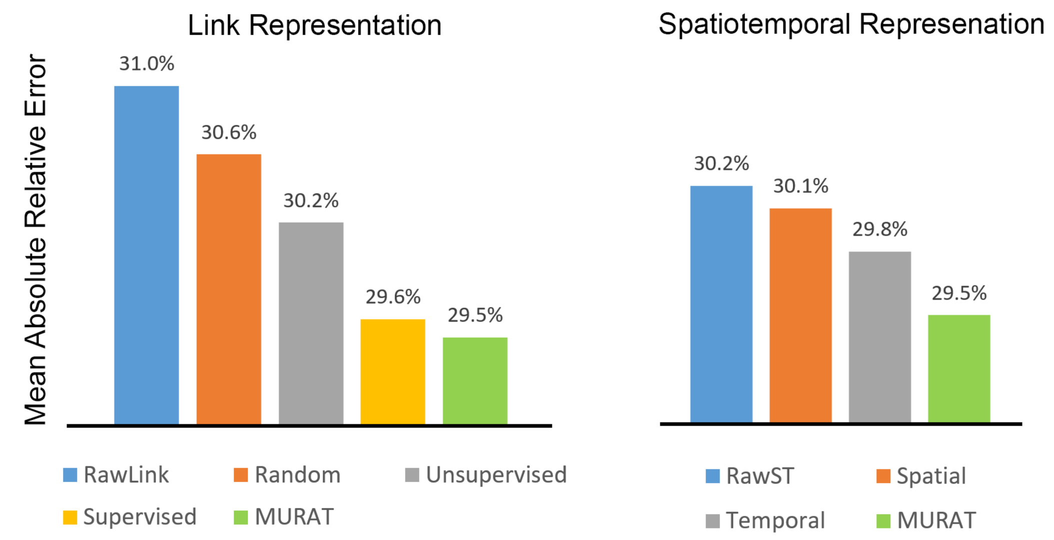
Baselines

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

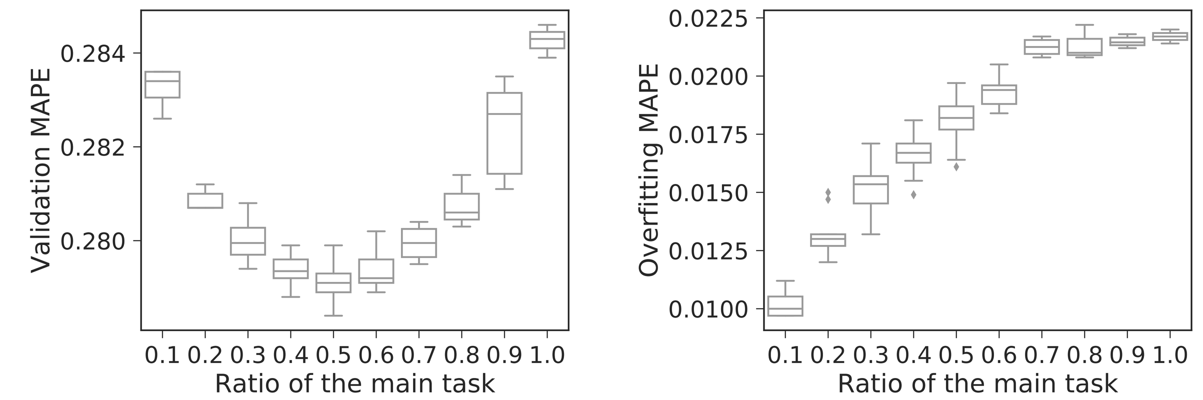


Effect of Link and Spatiotemporal Representations



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

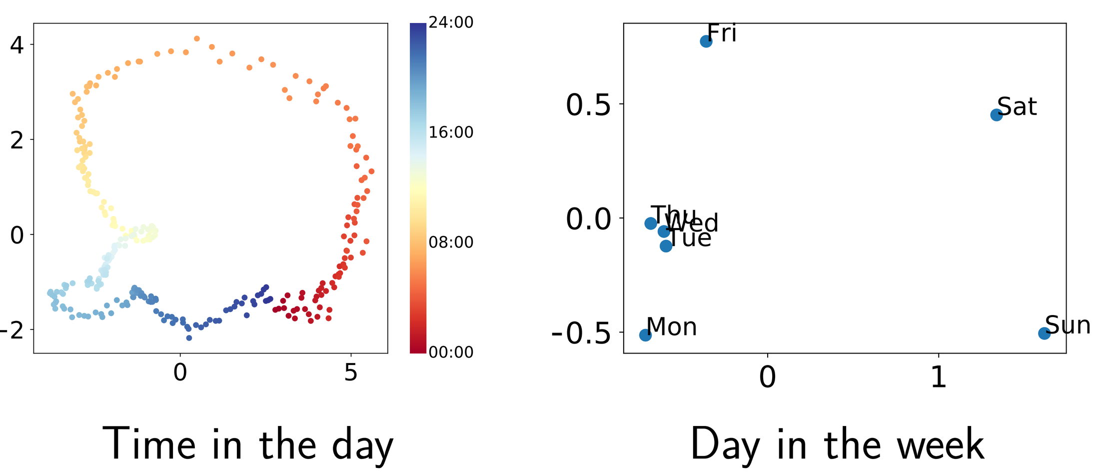
Effect of Multi-task Learning



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.