Travel Time Estimation without Road Networks: An Urban Morphological Layout Representation Approach

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IJCAI 2019

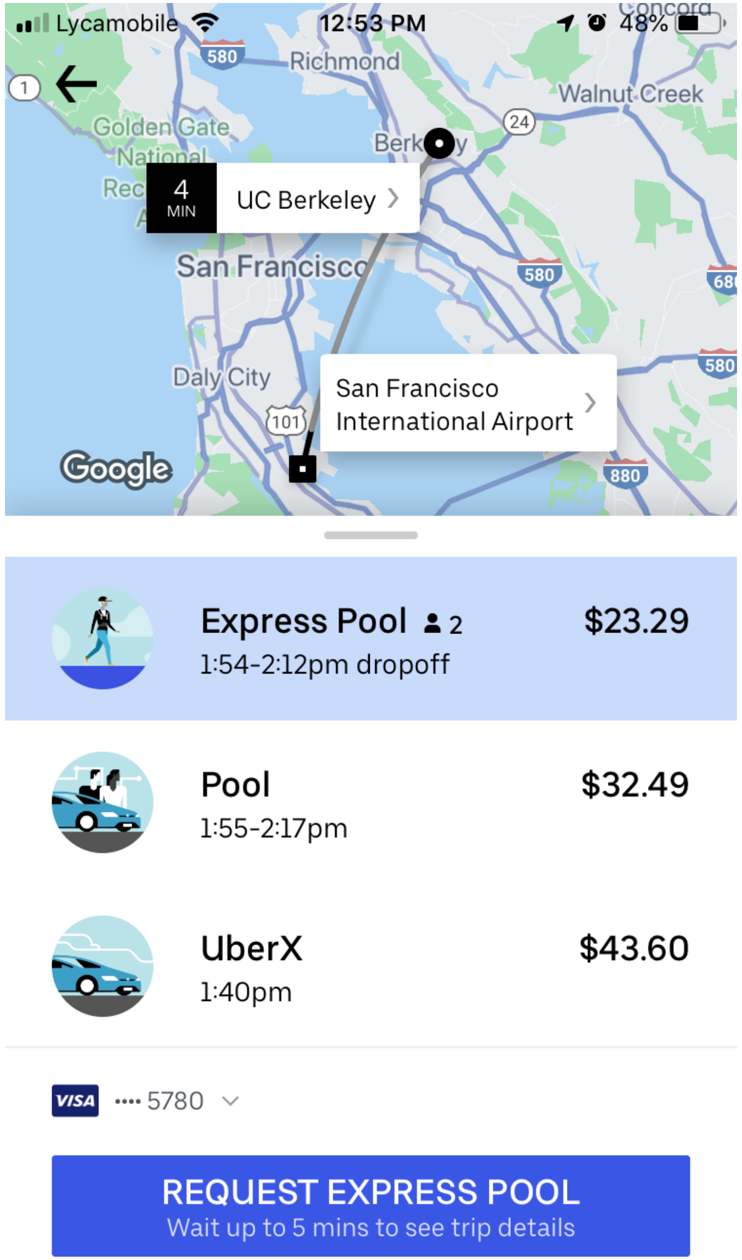
Outlines

- Problem Definition and General Solutions
- Proposed Solution
- Model Description
- Experiment Results

Travel Time Estimation

- A.k.a. Estimated Time of Arrival (ETA)

- TTE serves
  - Personal trip planning
  - Service quality of TNC companies
  - Emergency vehicles (Firefighting apparatus, Ambulance)
  - Travel exposure to air pollutants
  - Accessibility evaluation in city planning



Problem Definition

- *Path-aware ETA*

Given a trip query with departure time, origin, destination locations, and the selected route.

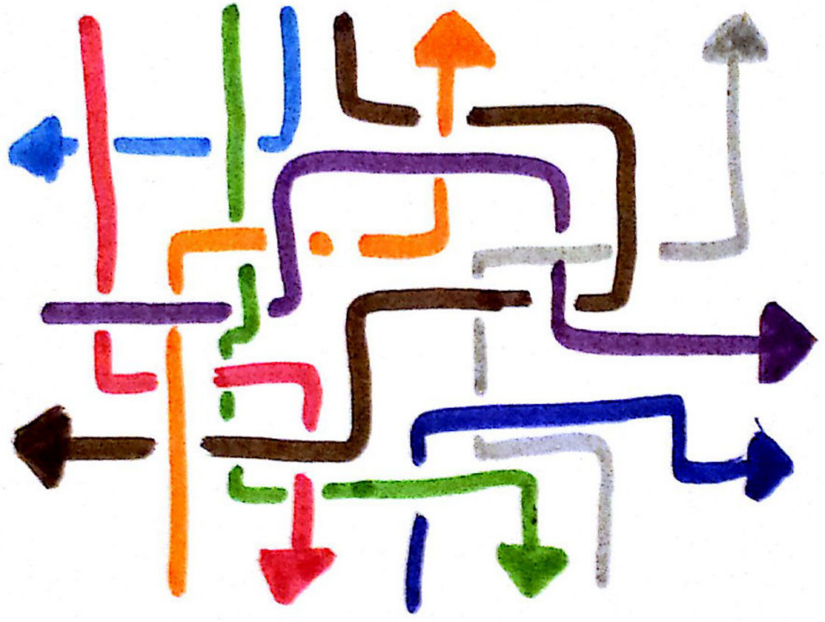
- *Path-blind ETA*

Given a trip query with departure time, origin, destination locations.

Path-blind ETA is more difficult as there are many routes between two locations in urban region.

Why ETA is not well solved?

- Dynamic traffic conditions in urban road networks
- Uncertain waiting time at traffic lights
- Varying weather conditions
- Unpredicted traffic events
- Diverse driving behavior



General Solutions

- Link based methods

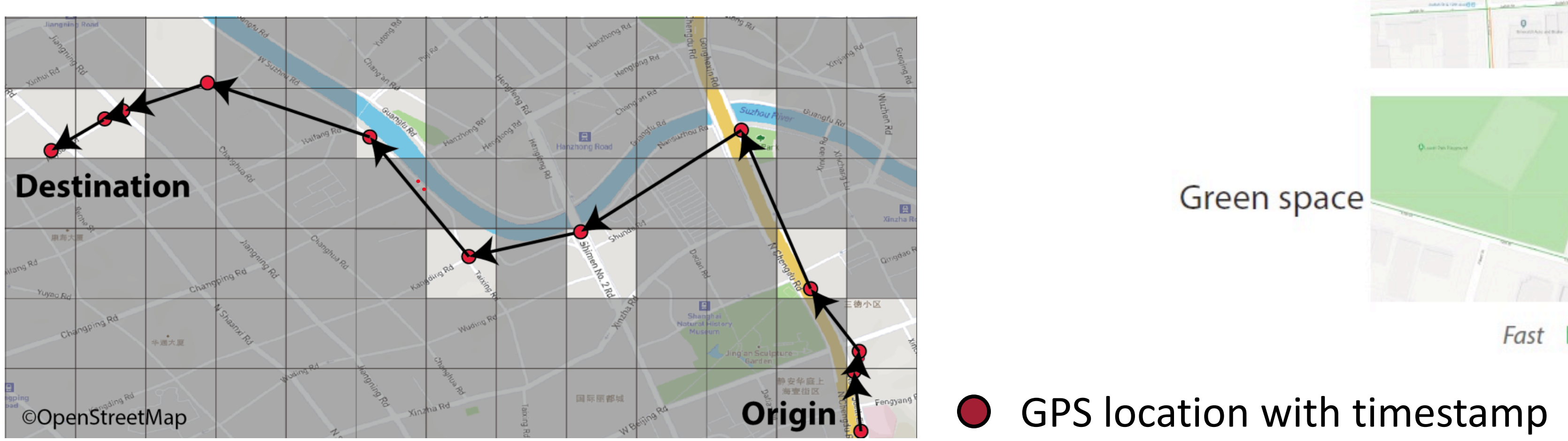
Estimating the travel time on each link, then aggregating the links in one path.

- Path based methods

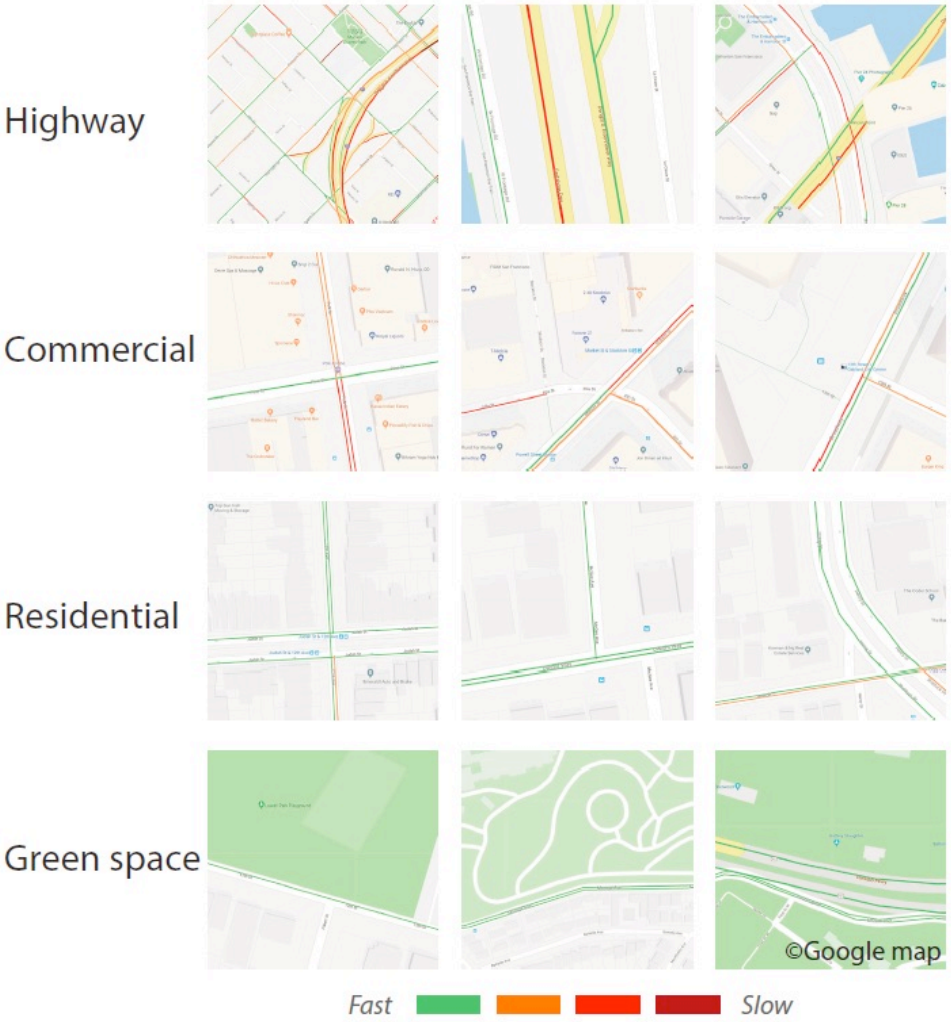
Estimating the path travel time using features and the representation of temporal and spatial relation between locations.

Our solution

- Learning travel time without road networks, thus avoiding map-matching.
- Learning the traffic delay from the build environmental images

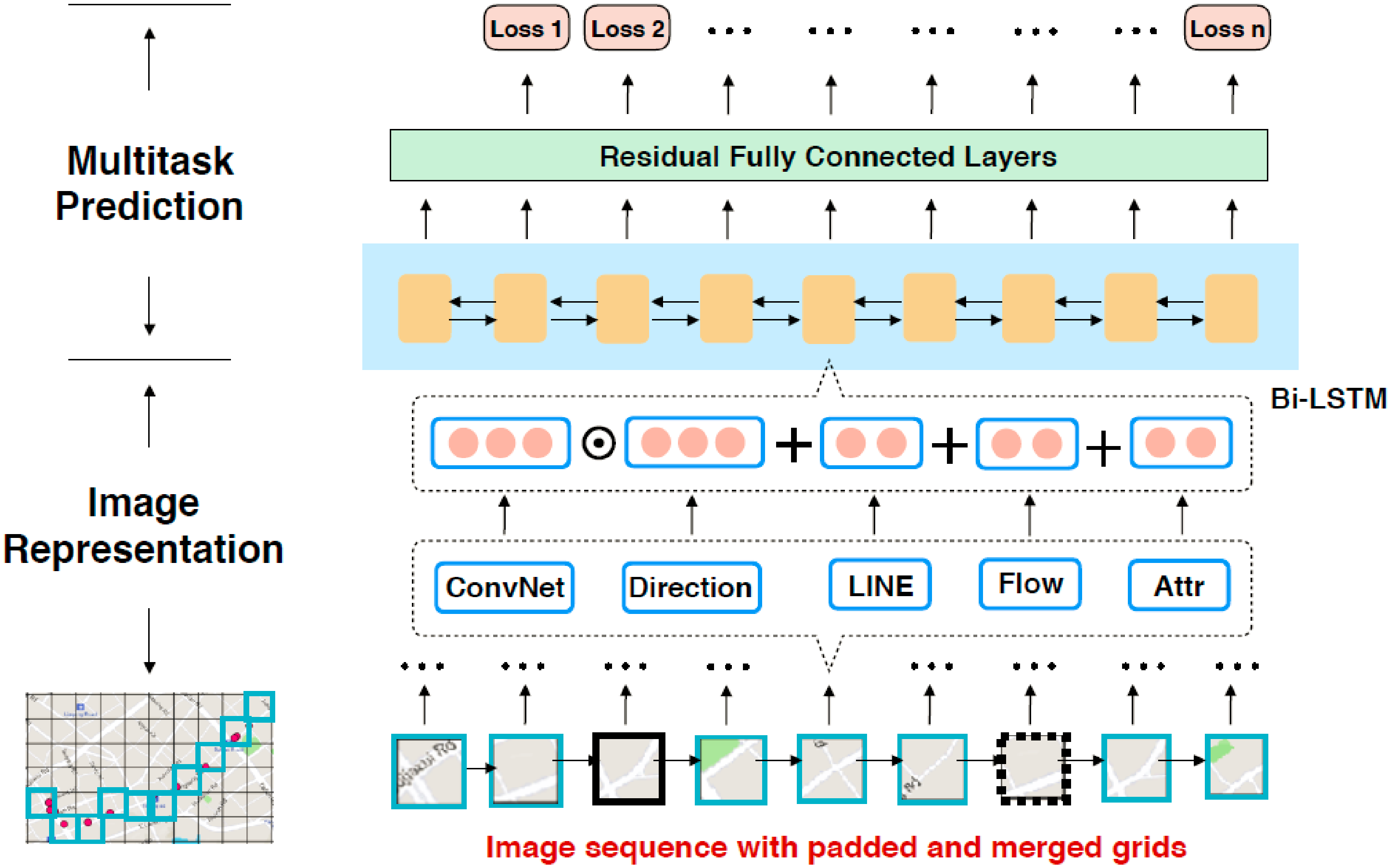


A sample trip



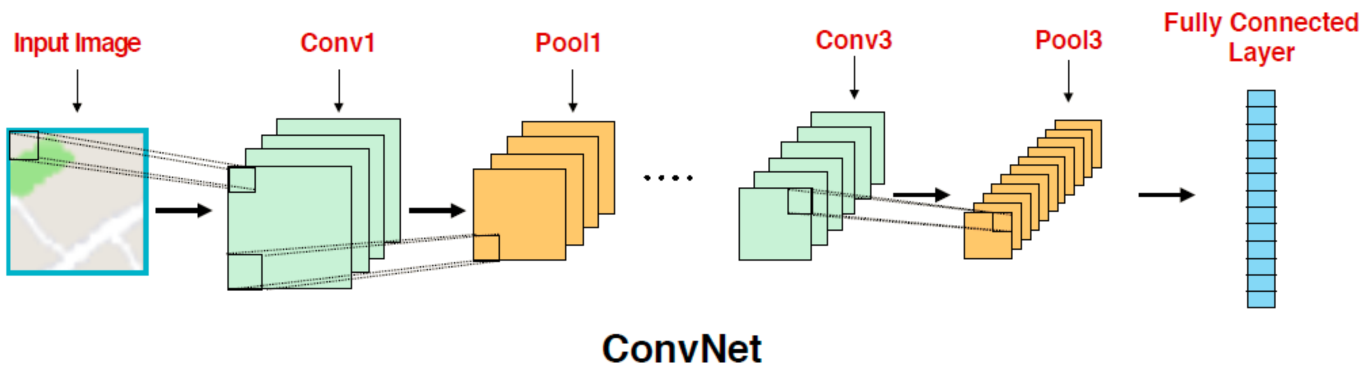
Structure of Model - Deep Image to Time (DeepI2T)

1. Merging or padding the raw trace
2. Representing each grid image with CNN
3. Collecting other features, combining all features together
4. Feeding the features to bi-LSTM

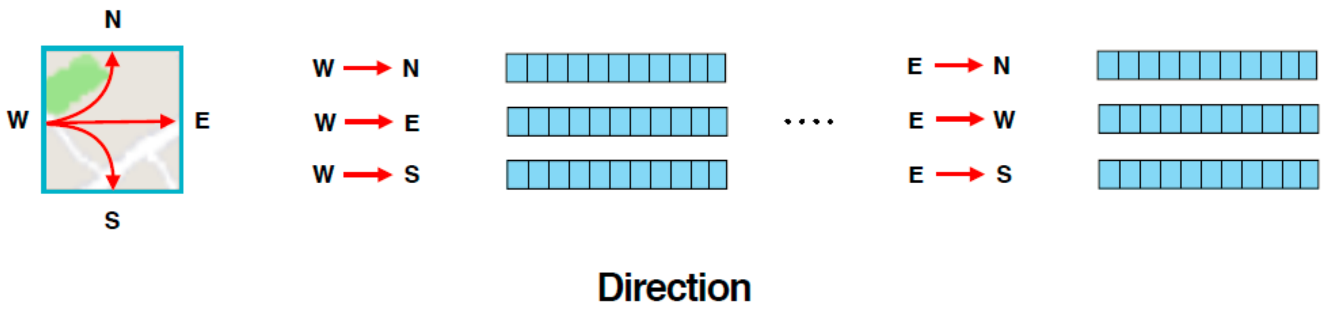


Features collection

- Image representation



- Driving direction (12 directions in total)



Feature collection

- Spatial relation

  We construct grid network and apply network embedding to capture this spatial locality. LINE [Tang et al., 2015] is used for network embedding.
- Traffic count in each block

  We count the number of vehicle in each grid per hour. Each grid is associated with a flow vector with 24 elements, representing the change of traffic conditions every hour.
- Vehicle ID
- Departure time (minute in one day, day in week)
- Weather

Multi-task learning

- Given a trip with L grids, $\{g_1, g_2, \ldots, g_L\}$, we consider not only the mean absolute percentage error (MAPE) of the whole path from g_1 to g_L, but also the MAPE of sub-paths from g_1 to the medium grid g_l.
- Loss function

$$\mathcal{L} = \frac{1}{L-1} \sum_{l=2}^{L} \left(w_l \cdot \frac{|\hat{T}_l - T_l|}{T_l} \right) \qquad (2)$$

where $T_l = t_l - t_1$ denotes the travel time from grid g_1 to g_l and $\hat{T}_l$ denotes its estimation; w_l is the predefined weight, $w_l = 2l/(L^2 + L - 2)$, where $1 < l \leq L$ and $\sum_{l=2}^{L} w_l = 1$. In this way, we emphasize the longer sub-trips, to make sure model put more effort on whole trip estimation.

Travel Time Estimation

- Path-aware

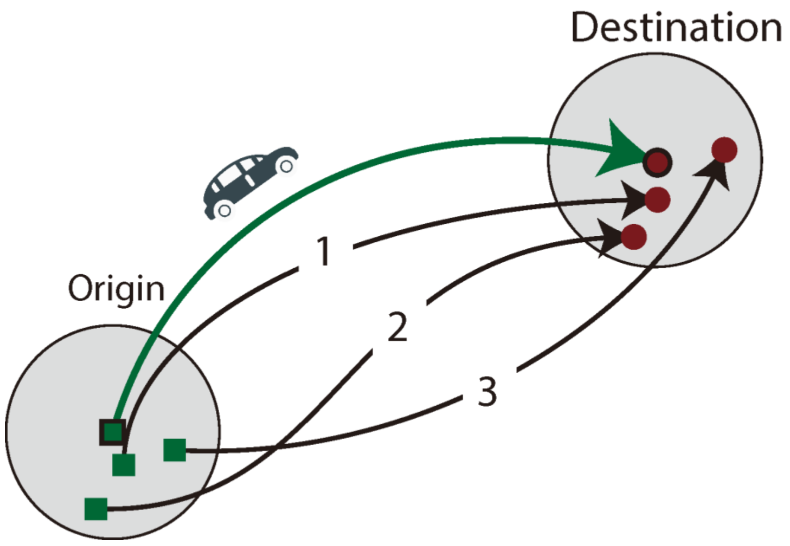
  The whole path is given in the trip query, along with the Vehicle ID and departure time.

- Path-blind

  Only vehicle ID and departure time is given.

  We design a neighboring strategy to tackle the path-blind query in the testing phase.

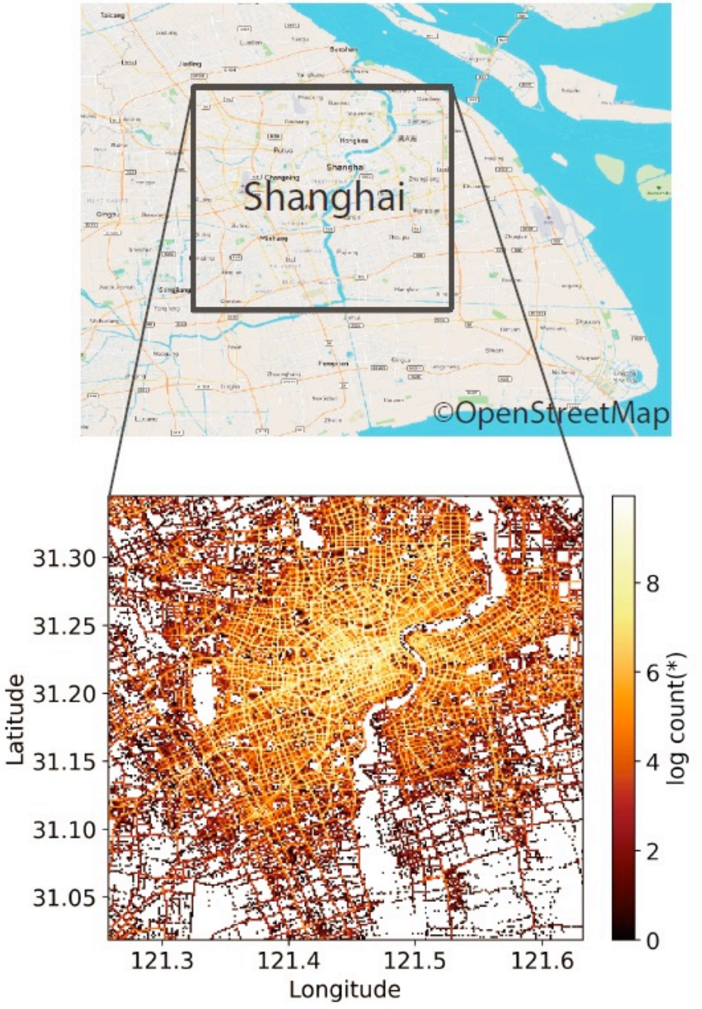
$$\hat{T}_{test} = \frac{1}{N_e} \sum_{i=1}^{N_e} \frac{L_{test}}{L_i} \hat{T}_i$$

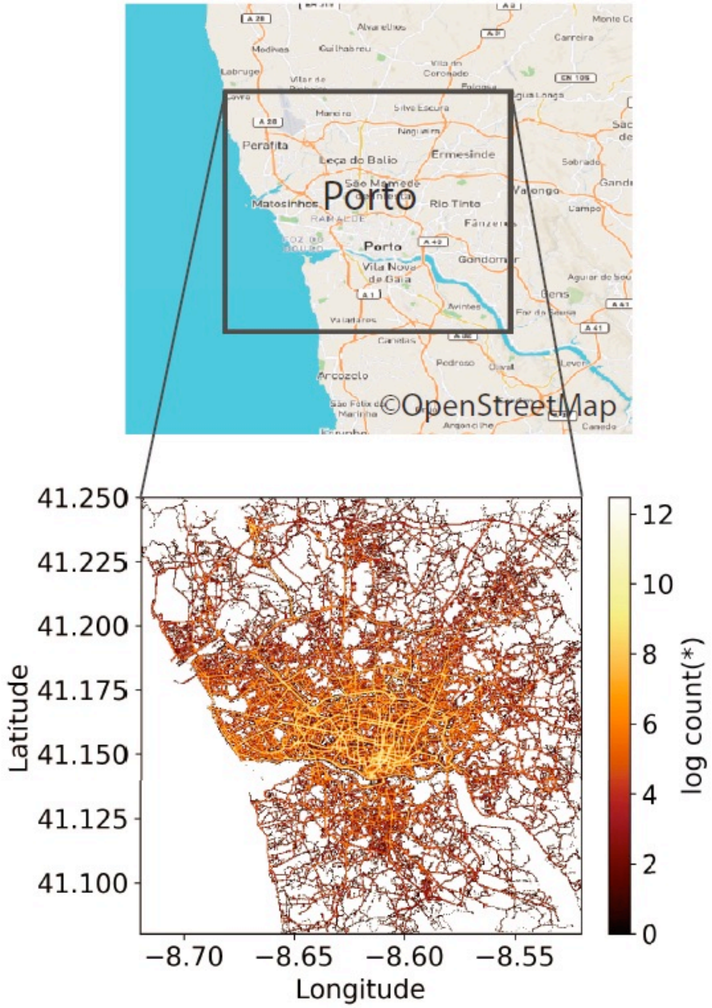


Experiments

- Test the model with data in two cities

- Shanghai
  - # vehicles: 15,000
  - # days for training: 61
  - # days for testing: 15
- Porto
  - # vehicles : 442
  - # days for training: 273
  - # days for testing: 90





Experiments

- Performance evaluation

$$MAE(T,\hat{T}) = \frac{1}{N}\sum_{i=1}^{N}|T_i - \hat{T}_i|$$

$$MAPE(T,\hat{T}) = \frac{1}{N}\sum_{i=1}^{N}\frac{|T_i - \hat{T}_i|}{T_i} \times 100\%$$

$$SR(T,\hat{T}) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|T_i - \hat{T}_i|}{T_i} \le 10\%\right) \times 100\%$$

satisfaction rate

Method	Shanghai			Porto		
	MAE (s)	MAPE (%)	SR (%)	MAE (s)	MAPE (%)	SR (%)
LR	186.5	27.64	23.87	287.9	49.02	17.20
AVG	158.9	22.30	29.35	235.86	30.43	24.65
GBM	144.3	22.55	30.45	238.17	37.83	22.97
TEMP [Wang *et al.*, 2016]	**141.0**	21.93	**31.24**	231.10	29.84	25.67
DeepTTE [Wang *et al.*, 2018a]	147.61	19.02	31.13	167.94	20.44	32.34
GridLSTM	117.12	16.98	37.00	139.55	18.10	38.45
DeepI2T (*path-blind*)	143.61	**20.47**	30.62	**186.65**	**25.28**	**30.08**
DeepI2T (*path-aware*)	**105.43**	**15.20**	**42.23**	**128.26**	**17.08**	**38.97**

Table 3: Overall performance comparison on Shanghai and Porto Data. Path-aware methods are highlighted in gray shadow.

Experiments

MAPE by departure time

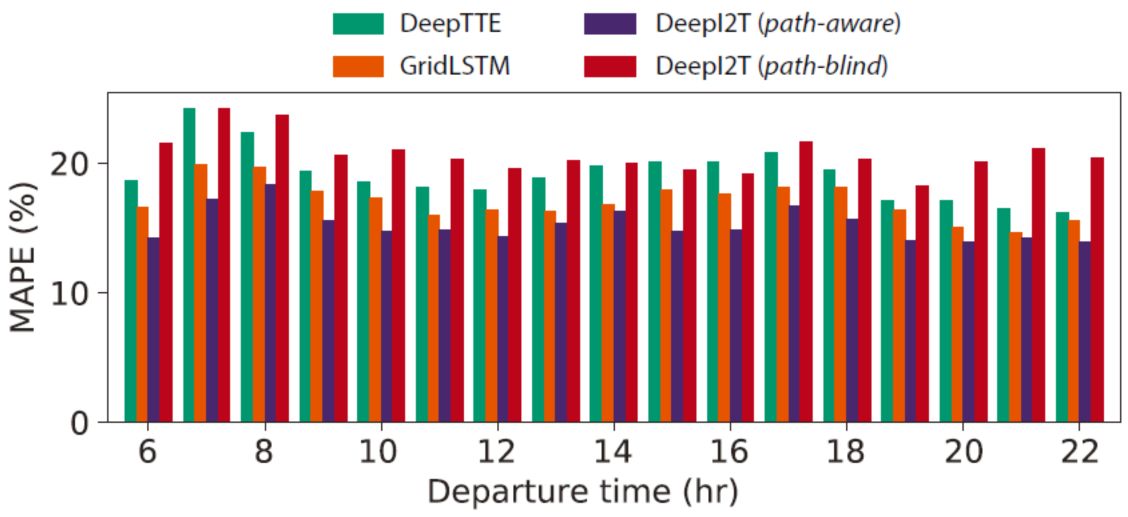


Figure 6: Estimation error for trips with different departure time.

MAPE by travel time

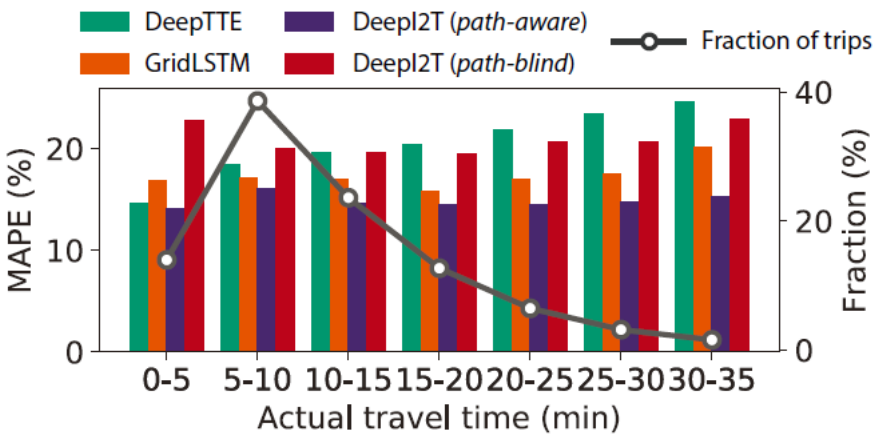


Figure 7: Estimation error for trips with different travel time. The right y-axis shows the distribution of testing trips.

Future directions

- Integrating recent traffic conditions is helpful to improve the performance of DeepI2E.
- This model can be used to estimate other attributes of trips, e.g., fuel emission, energy consumption of EVs.
- The representation of grid images might be useful for other geo-locations related urban problems, e.g., crime rate prediction, local air quality estimation.
- Map images could be replaced by satellite images, which have more rich information.

Thank you!

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