Estimating Travel Time Based on Recurrent Neural Networks

When will you arrive?[1]

Motivation

- Routes planning, Navigation
- Traffic dispatching

Previous work

- Estimate for each individual road
- Road intersections and traffic lights
- No driving habits

1. This problem is from [DataCastle 2017]

Definitions

Objective

Given: 1. path   2. driver   3. start time

Estimate:

the travel time for the given path.

Train data

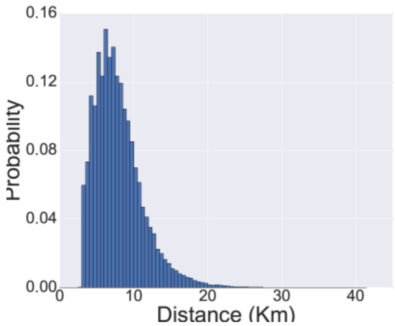
GPS trajectory

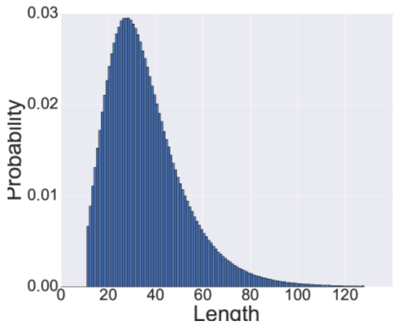
Sample points from path

Challenges

- The travel time of a specific path can be very different
  - ✓ Peak/Non-peak hour
  - ✓ The day of the week

- Diverse values of trajectory length/distance.

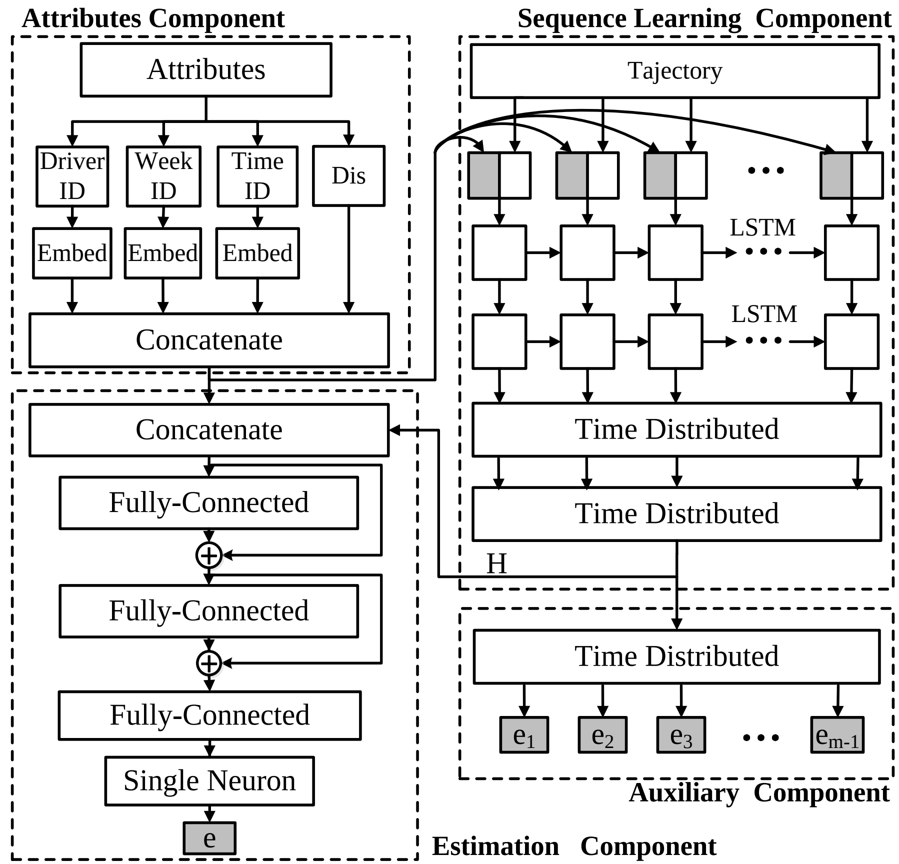




- Different driving habits

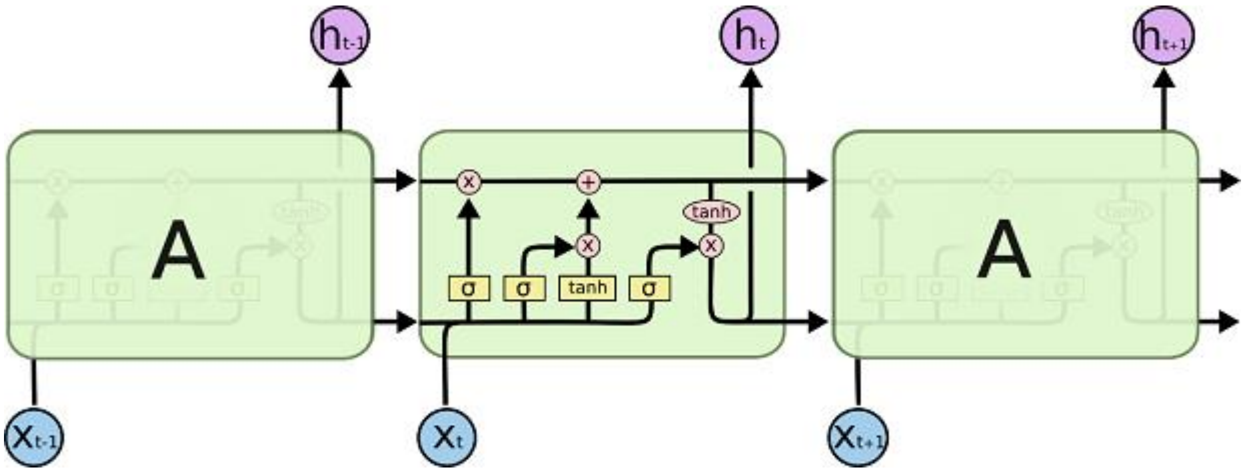
Architecture

1. Use Attributes Component incorporate various factors
2. Use Sequence Learning Component to handle trajectory
3. Use Estimation Component to predict the travel time
4. Extend to multi-task learning by introducing an Auxiliary Component



Sequence Learning Component

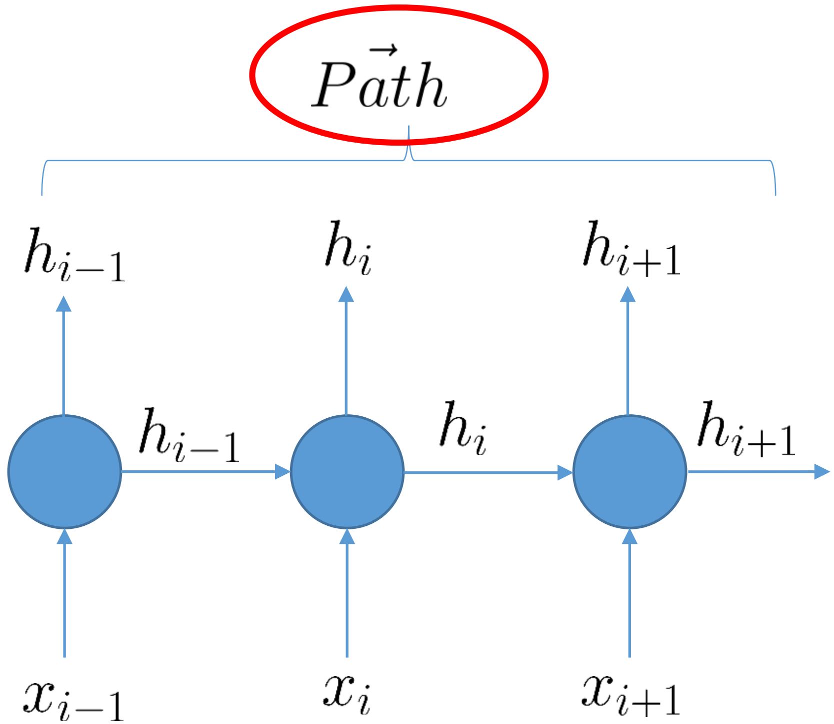
- RNN(Recurrent Neural Network)
- LSTM (Long Short Term Memory)
- Time dependence and spatial dependence



$$x_i = (lng_i, lat_i, lng_{i+1}, lat_{i+1}, d_{i,i+1})$$

Sequence Learning Component

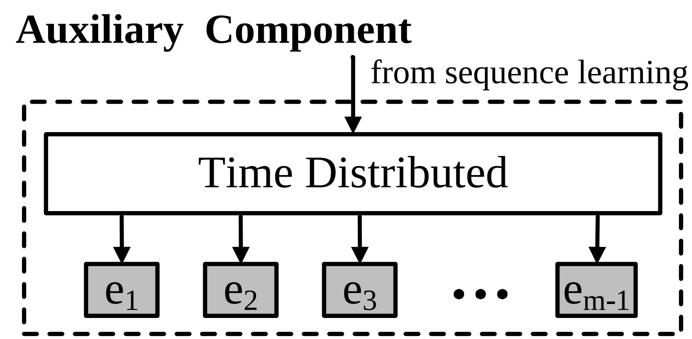
- x_i -> h_i
  - Abstract of the first i points
  - Deal the new point
- Trajectory -> Vector
  - Represent the whole trajectory with all h_i.
- Handling different trajectory lengths
  - Mean Pooling Trick
  - Sampling Trick



Auxiliary Component

To utilize the "local information"

- estimate the travel time of each sub-trajectory
- extend to a multi-task model
- used as the auxiliary output



Model Training

- Evaluate: mean absolute percentage error (MAPE)
  - Estimation Component

$$\mathrm{loss}_{seq} = \left| e - \Delta t_{p_1 \to p_{L_m}} \right| / \Delta t_{p_1 \to p_{L_m}}.$$

  - Auxiliary Component

$$\mathrm{loss}_{aux} = \frac{1}{m-1} \sum_{i=1}^{m-1} \frac{\left| e_i - \Delta t_{p_{L_i} \to p_{L_{i+1}}} \right|}{\Delta t_{p_{L_i} \to p_{L_{i+1}}} + \epsilon}.$$

  - Final loss:

$$\mathrm{loss} = \mathrm{loss}_{seq} + \alpha \cdot \mathrm{loss}_{aux}$$

Experiment

Data Description

- 1.4 billion GPS records of 14,864 taxis in Oct. 2014 in Chengdu.
- Total number of trajectories: 9,653,822. (60GB)
- Use the last 7 days (from 24th to 30th) as the test set and the remaining ones as the training set.

Experiment

Table: Performance Comparison

Model	MAPE
Gradient Boosting	20.32%
MLP-3 layers	16.17%
MLP-5 layers	15.75%
Vanilla RNN	18.85%
DeepTTE	**13.14%**

Experiment

Table: Performance of Different Number of Samples

#Samples	MAPE	Time (per epoch)
DeepTTE-10	15.45%	674s
DeepTTE-30	13.14%	1729s
DeepTTE-70	13.02%	3879s
DeepTTE-100	12.74%	5484s
DeepTTE-Var	12.87%	5841s

Experiment

Effects of Components

- Eliminate Estimation Component, 28.44%;
- Eliminate Auxiliary Component, 13.95%;
- Our entire model, 13.14%.

Experiment

Table: Effects of Attribute Component

Model	MAPE
DeepTTE-30	**13.14%**
Eliminate driverID	13.37%
Eliminate weekID	13.58%
Eliminate both	13.59%

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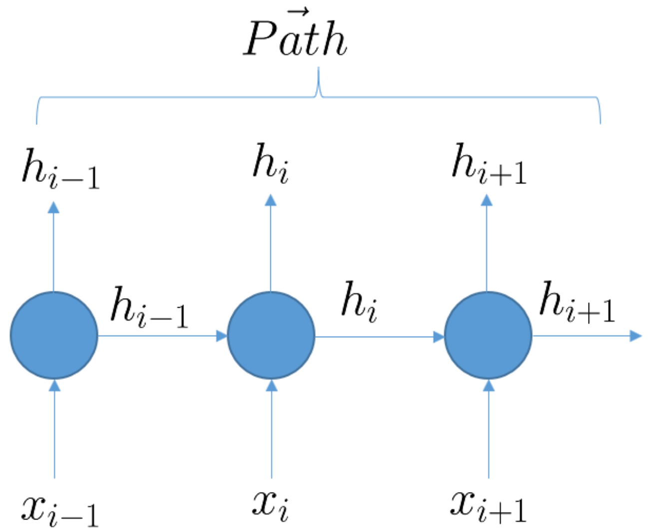
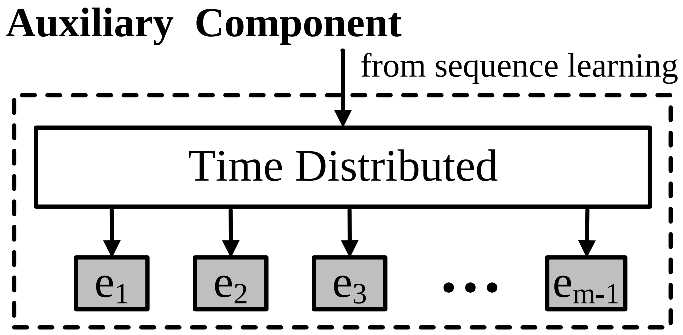
Conclusion

1. New block for handle trajectory (with LSTM)
2. Extend to multi-task learning by introducing an Auxiliary Component





Thank you