Road Network Metric Learning for Estimated Time of Arrival

Yiwen Sun[1], Kun Fu[2], Zheng Wang[2], Changshui Zhang[1], Jieping Ye[2]

[1]Institute for Artificial Intelligence, Tsinghua University (THUAI), State Key Lab of Intelligent Technologies and Systems, Beijing National Research Center for Information Science and Technology (BNRist), Department of Automation, Tsinghua University, Beijing, P.R.China

[2]DiDi AI Labs, Beijing, P.R.China

E-mail: syw17@mails.tsinghua.edu.cn

I Background of ETA & RNML-ETA

Estimated Time of Arrival (ETA) is one of the most fundamental problems in Intelligent Transportation System. It is considered as predicting the travel time from the origin to the destination along a given path. The route consists of a sequence of links. One of the key techniques is to use embedding vectors to represent links. However, the embedding suffers from the data sparsity problem that many links are traversed by too few floating cars even in large ride-hailing platforms. To address the problem, we propose the Road Network Metric Learning framework for ETA (RNML-ETA), as shown in Figure 1.

- We transfer the knowledge of hot links to the cold links by metric learning.
- The links' similarity is measured using their speed distribution.
- To our best knowledge, RNML-ETA is the **first** deep learning method that effectively addresses the data sparsity problem of road network.

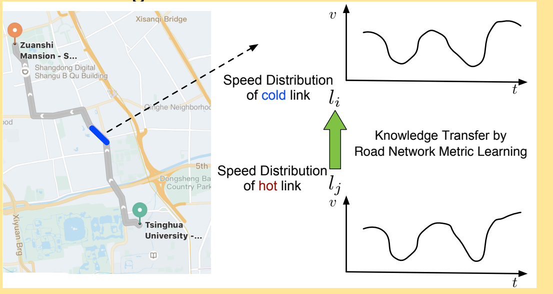


Figure 1 :The conceptual demonstration of ETA & RNML-ETA.

II Methodology

(1) Overall architecture.

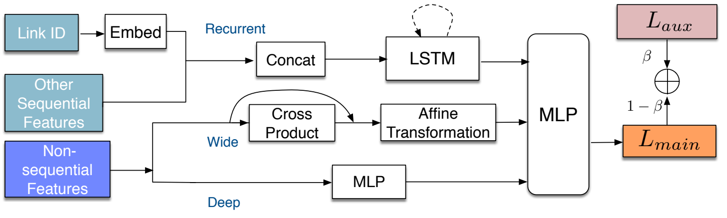


Figure 2 :The overall architecture of RNML-ETA.

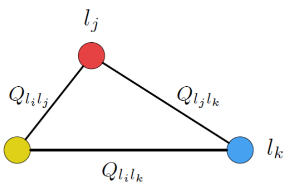
- Main task: a Wide-Deep-Recurrent model to predict the travel time.
- Auxiliary task: uses metric learning to transfer the knowledge from hot to cold links.

(2) Link Similarity.

- To statistic the average travel speed for link l and time bin τ_k
- To normalize speed histogram of link l
- The difference matrix for measuring the difference between links: $Q_{ij} = Q_{ji} = \|\tilde{v}(i) - \tilde{v}(j)\|_2$

(3) Triangle Loss.

- Restrict the lengths of the link embedding distance triangle edges to be in the same order as difference matrix triangle. → Similar Links are closer in the embedded space.
- Links take turns to act as anchor → efficient in one update.



$$L_{aux} = \frac{1}{U}\sum_{l_i,l_j,l_k}\left(\gamma_1\left[D_{l_il_j}^2 - D_{l_jl_k}^2 + \alpha_1\right]_+ + \gamma_2\left[D_{l_il_j}^2 - D_{l_il_k}^2 + \alpha_2\right]_+ + \gamma_3\left[D_{l_jl_k}^2 - D_{l_il_k}^2 + \alpha_3\right]_+\right)$$

Figure 3 : Visualized demonstration of distance triangle.

III Statistics of Dataset

- Two massive floating car datasets of Beijing from DiDi platform are collected.

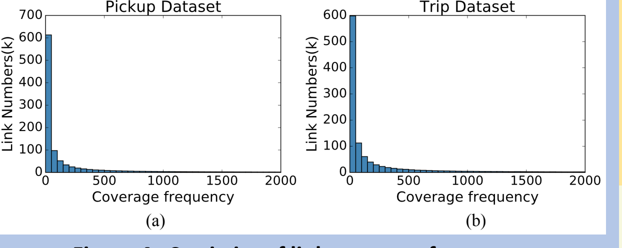


Figure 4 : Statistics of link coverage frequency.

- Both datasets suffer from the road network sparsity problem.

IV Experimental results

- For the overall prediction accuracy, RNML-ETA outperforms all the competitors.

Table I. Results of the pickup dataset

	MAPE (%)	MAE (sec)	RMSE (sec)
Route-ETA	25.010	69.008	106.966
WDR-no-link-emb	20.845	59.018	95.876
WDR	19.386	54.686	89.976
RNML-ETA	**19.215**	**53.546**	**87.617**

Table II. Results of the trip dataset

	MAPE(%)	MAE (sec)	RMSE (sec)
Route-ETA	15.440	150.560	248.736
WDR-no-link-emb	12.742	117.337	197.652
WDR	11.737	108.919	186.083
RNML-ETA	**11.597**	**108.519**	**185.897**

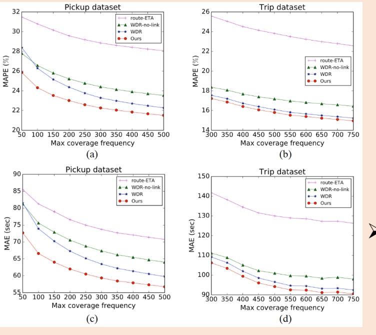


Figure 5 : Results of the finer evaluation on subsets with different link coverage level.

- RNML-ETA outperforms WDR model significantly in the road network sparse part.