

Road Network Metric Learning for Estimated Time of Arrival

Yiwen Sun¹, Kun Fu², Zheng Wang², Changshui Zhang¹, Jieping Ye²

¹Institute 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 ²DiDi Al Labs, Beijing, P.R.China

Background of ETA & RNML-ETA



- Estimated Time of Arrival (ETA): predicting the travel time from the origin to the destination along a given path.
- The route consists of a sequence of links → Embedding (key technique).
- •The embedding suffers from the data sparsity problem of road network.
- •RNML-ETA: Transfer the knowledge of hot links to the cold links by metric learning.
- •The links' similarity is measured \rightarrow speed distribution.

Fig.1. The conceptual demonstration of ETA & RNML-ETA.

Overall architecture



Fig.2. The overall architecture of RNML-ETA.

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

$$L = (1 - \beta) \cdot L_{main} + \beta \cdot L_{aux}$$

$$L_{main} = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - y'_i|}{y_i}$$

Link Similarity

• To statistic the average travel speed for link l and time bin τ_k

$$\bar{v}_k(l) = \frac{1}{Z} \sum_{i=1}^N \sum_{j=1}^{T_i} v_{ij} I_{s_i \in \tau_k} I_{l_{ij}=l},$$
$$Z = \sum_{i=1}^N \sum_{j=1}^{T_i} I_{s_i \in \tau_k} I_{l_{ij}=l},$$

• The normalized speed histogram of link *l*

 $\widetilde{\boldsymbol{v}}(l) = [\widetilde{v}_1(l), \ \widetilde{v}_2(l), \ \widetilde{v}_3(l)]^T$

• The difference matrix for measuring the difference between links

$$Q_{ij} = Q_{ji} = \|\widetilde{\boldsymbol{v}}(i) - \widetilde{\boldsymbol{v}}(j)\|_2$$

Triangle Loss

• Without loss of generality, we assume the relationships among 3 difference matrices

 $Q_{l_i l_j} < Q_{l_j l_k} < Q_{l_i l_k}$

• The Euclidean distances between the link embedding vectors

$$D_{l_i l_j} = \|\widetilde{\boldsymbol{E}}_L(:, l_i) - \widetilde{\boldsymbol{E}}_L(:, l_j)\|_2$$

• The triangle loss
$$L_{aux} = \frac{1}{U} \sum_{l_i, l_j, l_k} \left(\gamma_1 \left[D_{l_i l_j}^2 - D_{l_j l_k}^2 + \alpha_1 \right]_+ \right. + \left. \gamma_2 \left[D_{l_i l_j}^2 - D_{l_i l_k}^2 + \alpha_2 \right]_+ \left. + \left. \gamma_3 \left[D_{l_j l_k}^2 - D_{l_i l_k}^2 + \alpha_3 \right]_+ \right]_+ \right]_{aux}$$



Fig.3. Visualized demonstration of distance triangle.

Dataset & Evaluation Metrics

TABLE ISTATISTICS OF DATASETS

	size	pickup	trip
training set validation set test set # traversed link	25 weeks 1 week 1 week	111.0M 4.0M 4.1M 1.2M	105.5M 4.5M 3.9M 1.3M



Mean Absolute Error

MAE =
$$\frac{1}{N} \sum_{i=1}^{N} |y_i - y'_i|$$

Rooted Mean Square Error

RMSE =
$$\left[\frac{1}{N} \sum_{i=1}^{N} (y_i - y'_i)^2\right]^{1/2}$$

Fig.4. Statistics of link coverage frequency.

Experimental results

TABLE IIResults 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 III					
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



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

Thank you for listening.