Urban Route Representation Learning

General Idea

Route representation learning (RRL) is a growing area in spatiotemporal machine learning, aiming to encode entire routes (sequences of GPS points and contextual features) into meaningful vector embeddings. This representation is important for trajectory data analysis and management activities, such as route recommendation, traffic prediction, and urban dangerous goods management. However, the quality of vector embeddings cannot be directly assessed, and therefore, most embedding models are evaluated using supervised tasks like travel time estimation (TTE), estimation of time of arrival (ETA), and route similarity (RS).

Current techniques to build good route representations include reconstruction of masked subparts or similarity/dissimilarity comparison of embeddings with respect to the original route information. The objective of this work is to explore a novel route representation learning method for both intermodal routes[1], leveraging adaptive loss weighting, semantic, and compositionality route relationships. The compositionality relationships within routes can be expressed as vector-space operations (e.g., additive composition, symmetry, subroute containment, prefix/suffix consistency, route inversion, etc). For example, a complete route embedding should be approximately equal to the (vector) sum of its subroutes embeddings. Such compositionality vector operations should be grounded in scientific principles and supported by well-motivated reasoning.

Pipeline Overview

The central component is the **intermodal route representation learning module (IRRL)**. It takes as input one route and produces the embedding representation of that route (see Figure 1a).

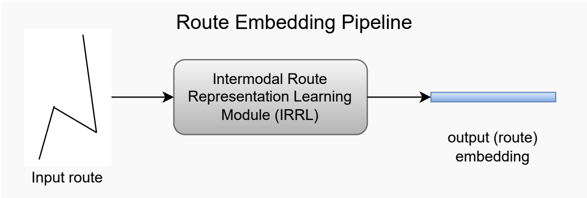
There is a set of constraints that the embedding should follow, formulated as a **multi-task optimization** problem. In this case, we minimize a global loss function made of several components. $loss = loss_1 + ... + loss_n$

To evaluate the quality of the embedding, we apply it to different downstream tasks like route similarity or travel time estimation. A downstream task takes as input a set of route embeddings (one or more, depending on the task) and produces a prediction (e.g., similarity score between 2 routes (Figure 1b) or prediction of the travel time (Figure 1c)).

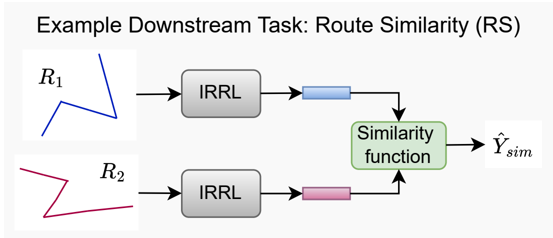
Specific Tasks for the Student

- Categorize and analyze the learning paradigm of current RRL methods, including subroute reconstruction or similarity evaluation. Research it for unimodal routes (taxi trips) and intermodal routes (walk + bike + bus in the same route).
- Research the use of compositional vector semantics in RRL.
- Research the use of “learn to weight losses/adaptive loss weighting” for model interpretability.

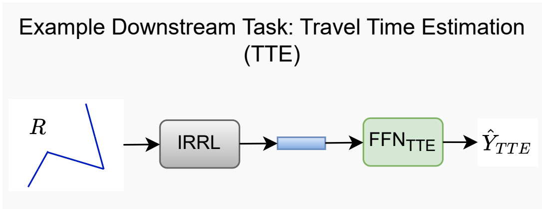
[1]Possible routes containing more than one transportation mode. E.g., {walk, bike}, {walk, car}, {bus, bike}



(a) Embedding learning



(b) RS task



(c) TTE task

Figure 1: Components overview. FFN = feed forward network.

- Define a set of compositional route relationships and intermodal route relationships. For each relationship:
  - Define the mathematical formulation
  - Research the scientific background
  - Research the motivation of use in the context of route representation learning.
  - Turn it into a loss function.

Contact Person

Steve Gounoue : steve.gounoue@cs.uni-bonn.de

- Please, send an email along with your transcript, and a link to GitHub (if available).

Prerequisites

- Solid programming skills in Python.
- Familiarity with PyTorch or TensorFlow.
- Knowledge of deep learning and embedding methods (e.g., RNNs, Transformers, GNNs).
- Interest in unsupervised learning and spatiotemporal data.
- Basic Knowledge of SQL, Knowledge graph, Git

Suggested Readings and Related Work

Adaptive Loss Weighting

- Multi-task Learning Using Uncertainty to Weigh Losses for Scene Geometry and Semantics (2018) [3] - paper

Compositional Vector Semantics

- A Matrix-Vector Recurrent Unit Model for Capturing Compositional Semantics in Phrase Embeddings (2017) [8] - paper

Route Embedding in Urban Trajectories Unimodal and Multimodal

- TIGR: Trajectory Representation Learning on Grids and Road Networks with Spatio-Temporal Dynamics (2024) [7] - paper
- Unified route representation learning for multi-modal transportation recommendation with spatiotemporal pre-training [5] paper

Possible Baselines

- TrajLearn (2025) [6]: code
- START (2024) [2]: code
- MMTEC (2023) [4]: code
- CL-TSim (2022) [1]: code

Possible Datasets

- Porto: link
- A proprietary intermodal synthetic dataset with touristic routes

References

[1] Liwei Deng, Yan Zhao, Zidan Fu, Hao Sun, Shuncheng Liu, and Kai Zheng. Efficient trajectory similarity computation with contrastive learning. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management, CIKM*, pages 365–374, 2022.

[2] Jiawei Jiang, Dayan Pan, Houxing Ren, Xiaohan Jiang, Chao Li, and Jingyuan Wang. Self-supervised trajectory representation learning with temporal regularities and travel semantics. *2Proceedings of the 39th International Conference on Data Engineering (ICDE)*, pages 843–855, 2022.

[3] Alex Kendall, Yarin Gal, and Roberto Cipolla. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In *Proceedings of the Conference on Computer Vision and Pattern Recognition, CVPR*, pages 7482–7491. Computer Vision Foundation / IEEE Computer Society, 2018.

[4] Yan Lin, Huaiyu Wan, S. Guo, and Youfang Lin. Pre-training general trajectory embeddings with maximum multi-view entropy coding. *IEEE Transactions on Knowledge and Data Engineering*, 36:9037–9050, 2022.

[5] Hao Liu, Jindong Han, Yanjie Fu, Yanyan Li, Kai Chen, and Hui Xiong. Unified route representation learning for multi-modal transportation recommendation with spatiotemporal pre-training. *VLDB J.*, 32(2):325–342, 2023.

[6] Amirhossein Nadiri, Jing Li, Ali Faraji, Ghadeer Abuoda, and Manos Papagelis. Trajlearn: Trajectory prediction learning using deep generative models. *CoRR*, abs/2501.00184, 2025.

[7] Stefan Schestakov and Simon Gottschalk. Trajectory representation learning on road networks and grids with spatio-temporal dynamics. *CoRR*, abs/2411.14014, 2024.

[8] Rui Wang, Wei Liu, and Chris McDonald. A matrix-vector recurrent unit model for capturing compositional semantics in phrase embeddings. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, CIKM*, pages 1499–1507, 2017.