Learning Isometric Embeddings of Road Networks using Multidimensional Scaling

Technische Universität München

Fakultät für Informatik

Lehrstuhl für Echtzeitsysteme und Robotik

Background

A generalizable approach to machine learning-based autonomous driving must necessarily encapsulate all sorts of road structures - not just particular sub-categories thereof, such as multi-lane highways or intersections. However, most research in this domain tends to be limited to specific scenarios. This can be explained by the difficulties associated with engineering a feature space that generalizes across all road topologies.

In a highway driving setting, for instance, a natural approach is to consider the relative Cartesian coordinates of neighboring vehicles when designing a feature space for a deep learning-based planner. Such an approach will, however, yield a misleading representation of the environment in the general case, since the tangible distances in a road network are defined not by the Euclidean distance metric as computed in $\mathbb{R}^2$, but rather by the travel distances implied by the road geometry.

Thus, we seek to obtain an algorithm that outputs a coordinate transform $(x, y) \rightarrow (\hat{x}, \hat{y})$ that more accurately represents the scenario. Our long-term goal is that this will be integrated in downstream prediction and planning research projects, which, in order to generalize across the full spectrum of road geometries, cannot rely on naive, Cartesian coordinates for representation.

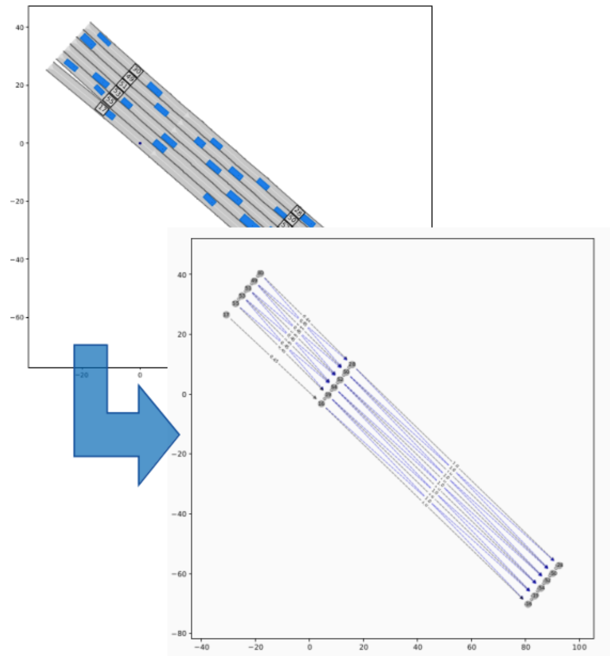

Figure 1: Example of a highway scenario in which we seek to learn distance-preserving node embeddings based on a graph representation.

Supervisor:
Prof. Dr.-Ing. Matthias Althoff

Advisor:
M.Sc. Eivind Meyer

Research project:
KoSi

Type:
BA, MA

Research area:
Autonomous driving
Graph representation learning
Metric multidimensional scaling

Programming language:
Python

Required skills:
Basic numerical optimization
Python (preferably PyTorch experience)

Language:
English

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For more information please contact us:

E-Mail: eivind.meyer@tum.de

Description

For facilitating the downstream embedding task, one would first have to convert a CommonRoad `LaneletNetwork` [1] into a corresponding graph structure. Then, the task would revolve around minimizing some variation of the multidimensional scaling objective

$$Stress(X) = \sum_{i \neq j = 1,\ldots,N} (d_{ij} - \|x_i - x_j\|)^2, \tag{1}$$

where N is the number of nodes in the resulting road graph, d_{ij} is the known travel distance between a pair of nodes, and x_i and x_j are the learned embedding coordinates for nodes i and j, respectively. In other words, our desire is to find a graph embedding (i.e. a set of coordinates for each node in the embedding space) such that the distances in the embedding space have as little distortion as possible compared to the actual distances in the underlying road network.

A multitude of relevant methods have been discussed in the literature, notably including gradient-based approaches [4, 3, 2], and should be identified and compared through an initial literature review with respect to accuracy, stability/repeatability and scalability/complexity.

A Python solution offering an implementation of the chosen algorithm (or, if found to be beneficial, your own unique approach to the problem) should then be created such that it can facilitate downstream research.

Tasks

- Perform a literature review of relevant methods.
- Implement a pre-processing algorithm for obtaining the graph representation of a CommonRoad lanelet network (prior work exists).
- Develop and evaluate an algorithm returning a distance-preserving coordinate embedding for the nodes in a given graph structure.
- Wrap your implementation in an accessible Python interface to facilitate further research.

References

[1] Matthias Althoff, Markus Koschi, and Stefanie Manzinger. Commonroad: Composable benchmarks for motion planning on roads. In *2017 IEEE Intelligent Vehicles Symposium (IV)*, pages 719–726, 2017.

[2] William L. Hamilton, Rex Ying, and Jure Leskovec. Representation learning on graphs: Methods and applications. *CoRR*, abs/1709.05584, 2017.

[3] J. B. Kruskal. Nonmetric multidimensional scaling: A numerical method. *Psychometrika*, 29(2):115–129, June 1964.

[4] Jonathan X. Zheng, Samraat Pawar, and Dan F. M. Goodman. Graph Drawing by Stochastic Gradient Descent. *arXiv:1710.04626 [cs]*, June 2018. arXiv: 1710.04626.

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