Deep Generative Models for Road Network Synthesis

Background

Deep learning-based algorithms are known to be data-hungry in the sense that they require vastly more data than the human brain in order to deliver reliable output. In the autonomous driving domain, where core learning problems such as prediction and planning are both inherently multi-modal and sensitive to the specific characteristics of the traffic scene, large and complex architectures are required in order to provide sufficient representative power for neural network-based models. Accordingly, even more training samples will likely be needed before the model converges to a set of parameters yielding satisfactory performance.

While existing driving datasets (e.g. [6, 2, 11, 8]) offer substantial amounts of naturalistic driving data, the number of unique geographical locations is typically relatively small due to the constraints imposed by the typical means of recording (e.g. fixed traffic cameras or drones). For the purpose of training deep learning-based models that generalize across road geometries, their usefulness is thus somewhat limited, as the learned correlations will be overfitted to the specific scenarios.

On the other hand, tools such as Globetrotter [5] allow us to automatically extract road networks from real-world map data. However, in order to be truly *liberated*, both from data limitations, engineering overhead, computing load and memory requirements, we seek to develop and train a deep generative model offering unlimited, on-demand synthesis of realistic-looking road networks.

If successful, such a pre-trained generative model could, together with a well-designed API, both facilitate downstream learning tasks and accelerate further research in the field. In a reinforcement learning settings, for instance, we can imagine that the agent encounters a completely unseen road geometry at each training episode, and that this will greatly enhance the efficiency and extent to which it learns intelligent driving policies that generalize across the entire spectrum of traffic scenarios.

Description

As a starting point, it is natural to consider road networks as graph tuples $G = (V, E, X)$, where the set of edges E consists of the road segments in the network, the set of nodes V corresponds to the intersection points where two or more road segments meet, and the node feature matrix X contains Cartesian coordinates for each node.

In order to formulate a tractable learning problem, it is useful to consider the adjacency matrix A (a dense representation of E). The output of the generative model will then be new instances $(\hat{A}, \hat{X})$, effectively defining the structure of the road network. Whether the size of the graph is provided as an input parameter, or generated internally by the model, is a design choice that can be considered at a later stage. Additionally, one can further advance the capabilities of the model by also generating edge feature matrices $\hat{X}_e$, representing segment-specific information such as direction of traffic and connection type (e.g. successor, intersection, adjacent lanes).

In recent years, multiple promising methods to generative graph modeling have been suggested, notably including graph variational auto-encoders [4, 9], recurrent networks-based approaches [7, 10] and graph generative adversarial networks [3]. The main contribution of the project would be to adopt such a method and apply it to the problem at hand.

Tasks

1. Perform a literature review in order to identify the most promising approach(es) for deep learning-based graph generation.
2. Obtain sufficient amounts of training data represented as Commonroad [1] scenarios, for instance by utilizing the Globetrotter tool developed in [5].

Technische Universität München

Fakultät für Informatik

Lehrstuhl für Echtzeitsysteme und Robotik

Supervisor:
Prof. Dr.-Ing. Matthias Althoff

Advisor:
M.Sc. Eivind Meyer

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Autonomous driving
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For more information please contact us:

E-Mail: eivind.meyer@tum.de

3. Implement a pre-processing method for converting Commonroad scenarios into corresponding graph structures (prior work exists).
4. Develop a PyTorch-based implementation of a generative model for road network synthesis that can be trained to output synthetic graph structures similar to the ones extracted from the training samples.
5. Train, optimize and evaluate the model.
6. Wrap the model in an API (i.e. as a Python module) for easy use in downstream applications.

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