Deep Learning-Based High-Level Corridor Selection in Optimization-Based Motion Planning

Background

Current paradigms to solve motion planning problems for autonomous vehicle can broadly be categorized into classical approaches, which involve optimization, sampling or search and learning-based methods, which use data-driven techniques to train an agent for decision-making and planning. While rule-based methods may be limited in terms of their ability to handle uncertainty, purely learning-based methods (e.g., end-to-end planning) are nearly impossible to verify. Thus, hybrid planning approaches combining both paradigms can alleviate the aforementioned drawbacks. In previous works, different approaches have been proposed to construct such frameworks. [1, 2]. For this work, we want to employ a learning-based method for high-level maneuver selection.

Description

In this thesis a learning-based approach which ranks and selects high-level maneuvers for underlying optimization-based trajectory planner shall be developed. Especially for optimization-based planners, creating suitable solution spaces (so-called maneuvers) to derive constraints for the optimizer is highly important. In this work, we represent these maneuvers as driving corridors obtained from the reachable set of the ego vehicle [3] (see Fig. 1). In our previous works we have shown that set-based corridors are an efficient way to compute solution spaces for different types of trajectory planners [4, 5]. However, choosing an appropriate corridor, in case multiple options exist, is yet an open question.

In this thesis, a learning-based approach to select a driving corridors should be developed. In a previous work [6], an initial concept has been developed which classifies different corridors in terms of feasibility for the underlying planner. Therein, a first data generation and training pipeline using CommonRoad scenarios [7] has been implemented. In this work, this concept should be extended to rank different corridors for selection. Thus, the trained model should be able to predict a-priori, which corridor / maneuver is the "best" for trajectory planning w.r.t. to predefined criteria.

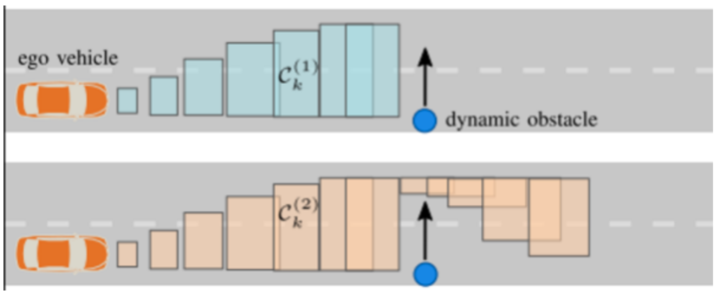

Figure 1: Two driving corridors for a simple dynamic traffic scene, corresponding to a stopping maneuver and an evasive maneuver [8].

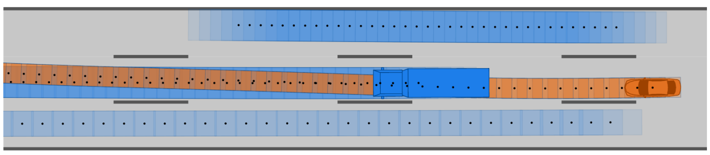

Figure 2: Ego vehicle trajectory (orange) planned using an optimization-based planner [4] for a given corridor.

Advanced previous knowledge in applied deep learning is required, e.g., terminology (e.g. Feature, Layer, Head), layer types (e.g. Linear, Convolution, Batchnorm, Fully-Connected, ResNet Bottleneck, LSTM, Skip-Connection etc.), basic architecture types (e.g. GAN, AutoEncoder) and basic PyTorch knowledge.

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Outline

Given the data set and our planner, we aim to predict a ranking of different corridors w.r.t. the value of the cost function and/or whether the corridor is feasible for the planner. Thus, a network architecture [9, 10] should be developed which uses the corridor representation as input, with additional scenario-related features, e.g., distance to a reference path or obstacles. As output, we want both a classification for feasibility / drivability [9] [6] and a function approximation [11] for the cost function of the planner. Therefore, the network should have a combined function approximation and classification architecture / head. One possible starting point could be a cloud-based network [12] as a backbone and build a vertex-based function approximation and classification architecture around it.

Tasks

- Familiarization with existing approaches for reachable set computation, driving corridor extraction and planning [8], [4], [6] and our optimization-based planner and the dataset generated in previous works.
- Literature research on learning-based feasibility and drivability estimation and a specific literature research on deep learning network architectures [10], especially for function approximation and classification.
- Conceptualization of a network architecture which is suitable for the given task.
- Implement, train and evaluate the network architecture using CommonRoad scenarios.
- Documentation of results.

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