Risk-based Safety Model: Unified Perception and Prediction Module

Background

The safe deployment of autonomous vehicles relies on the development of robust risk estimation models that can consider the uncertainties of dynamic and unpredictable environments. Risk in autonomous driving could be defined as the combination of the probability of occurrence of harm and the extent of that harm [1]. These models are vital for detecting potential hazards and enabling reliable decision-making across diverse scenarios. A key element within many of these frameworks is intention prediction including behavior and trajectory prediction. This process anticipates the movements of surrounding agents while integrating uncertainty into the overall risk evaluation. Together, these components help minimize accident likelihood and enhance operational safety.

Description

We aim to develop a unified risk-quantification framework for autonomous driving that jointly integrates behavior-aware trajectory prediction, uncertainty and risk quantification, and risk-informed planning. The system will predict both continuous trajectories [2] and discrete behaviors [3] of surrounding agents while capturing aleatoric and epistemic uncertainties. These uncertainty-aware predictions will be fed into dynamic risk field models (e.g., EDRF [4]) to compute spatiotemporal risk distributions, which will guide adaptive motion planning and decision-making. The framework will be validated in CARLA simulator environments as well as with real-world data using urban and highway scenarios with occlusion, ambiguous behaviors, and sensor limitations.

For this position you will develop a joint modeling pipeline that unifies trajectory prediction, behavior classification, and road topology understanding. The output will be processed and used as input for the downstream risk quantification.
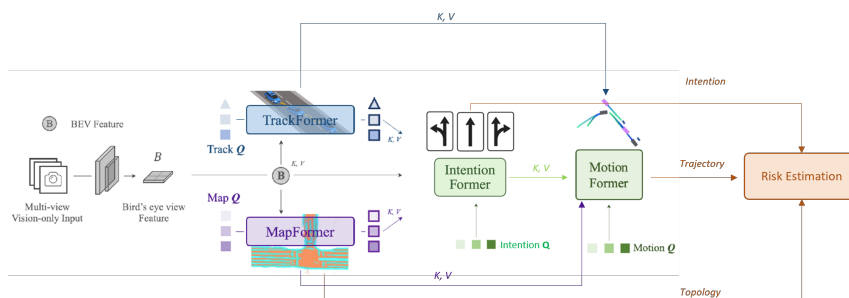

Figure 1: Illustration of an example unified framework.

Tasks

- Implement a unified perception and prediction framework like UniAD [5] based on state-of-the-art models with multi-view camera inputs.
- Use behavior prediction or road topology (Alternative to high-precision maps) result to guide trajectory regression.
- Prepare modular outputs (trajectory, behavior class, road topology and final goal) for downstream risk assessment.

- Utilize public datasets (e.g., nuPlan [6]) to evaluate the performance of networks.

References

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