Project Title: Hierarchical Decision Making and Control in RL-based Autonomous Driving for Improved Safety in Complex Traffic Scenarios

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Project Description:

In this work, we propose a framework for vehicle planning and decision-making and vehicle control. We formulate the vehicle control problem as an MDP (Markov Decision Process) and leverage reinforcement learning to learn high-quality autonomous driving strategies. The motivation behind this research stems from the complexity of highway driving, which requires the seamless coordination of multiple tasks to ensure safe and efficient navigation. In the realm of vehicle control research, various methodologies have been explored, including model-based and rule-based approaches, as well as data-driven methods such as supervised learning and reinforcement learning. Model-based and rule-based methods provide transparency and interpretability in decision-making processes, but they necessitate tailored controllers for diverse driving scenarios. On the other hand, data-driven methods like supervised learning require extensive dataset collection, while reinforcement learning generates its own data through simulations and learns driving strategies through interactions with the environment. A common limitation across prior works in reinforcement learning lies in their reliance on single-layer controllers, lacking higher-level decision-making capabilities.
Furthermore, existing studies often focus on relatively simplistic traffic scenarios, limiting the generalizability of their findings. To address these limitations and to address the challenges posed by complex highway driving scenarios, we adopt a Hierarchical Deep Reinforcement Learning (HDRL) framework. Specifically, the upper-level controller will set the vehicle's target speed and desired lane or lane change behavior, while the lower-level controller undertakes the fine-grained task of managing the driving dynamics of the vehicle's longitudinal acceleration and lateral steering control. This hierarchical framework endows the controller with enhanced interpretability and empowers it to navigate complex and intricate traffic environments more effectively than single-layer counterparts. By incorporating high-level decision-making abilities, our proposed approach presents a significant advancement over traditional reinforcement learning-based controllers. We contemplate two pivotal advantages from this approach. Firstly, HDRL facilitates the hierarchical decomposition of decision-making tasks, enhancing the efficiency of task execution. Secondly, within the HDRL framework, the dual layers of controllers exhibit distinct exploration capabilities in unfamiliar environments. This empowers us to harness the upper-level controller's proficiency in mapping potential driving trajectories within intricate autonomous driving settings, while concurrently engaging the lower-level controller for precise real-time adjustments and control of vehicle behavior. By leveraging the advantages of hierarchical learning, we aim to achieve better coordination and decision-making capabilities, leading to improved safety and exploration in high-stakes environments. Through comprehensive simulations and experiments, we aim to demonstrate the superiority of our hierarchical controller in handling complex driving situations and contribute to the advancement of safe and efficient autonomous driving technology. We will design driving scenarios, including challenging scenarios, to test our reinforcement learning framework and compare its performance with traditional single-layer reinforcement learning controllers.
These traps involve other traffic vehicles obstructing the autonomous vehicle's desired path, testing the system's ability to identify and navigate around such obstructions. By evaluating the performance of our

controller and refining the HDRL framework, we endeavor to strike an optimal equilibrium between safety imperatives and decision making and operational efficiency.

Outputs:

1. We will release an open-source codebase that embodies our novel hierarchical reinforcement learning framework for complex traffic scenarios. This will provide researchers and developers with a valuable resource to study, adapt, and build upon.

2. Our research findings will be documented in research papers and conference presentations. By publishing our work, we aim to contribute to the advancement of knowledge in the field, sharing insights into the efficacy and innovation of our approach.

Outcomes/Impacts:

The anticipated outcome of our research is the successful development and validation of a hierarchical reinforcement learning framework tailored for complex traffic scenarios. By incorporating safety factors into the design of reward functions, we aim to enhance the safety culture and decision-making capabilities of autonomous vehicles. Through our experiments and simulations, we expect to demonstrate that our proposed hierarchical framework enables the autonomous agent to effectively navigate and explore the driving environment while considering safety considerations. Specifically, when the vehicle encounters slow-moving traffic and becomes stuck in a trap, we anticipate that the agent will demonstrate its ability to autonomously identify safe escape routes, showcasing its enhanced decision-making skills in critical situations. Furthermore, we will design and conduct driving scenarios to compare the performance of our hierarchical framework with traditional single-layer reinforcement learning approaches. We anticipate that the hierarchical structure will exhibit superior exploration capabilities, efficiently learning safe and optimal driving behaviors in complex traffic environments. Overall, we envisage our research to yield promising results that highlight the potential of hierarchical reinforcement learning for enhancing vehicle safety exploration in challenging traffic scenarios. By addressing safety factors and integrating human-centric decision-making processes, our anticipated outcome will contribute to the advancement of safe and efficient autonomous driving technology, ultimately fostering a safer transportation ecosystem.