“A machine learning model for autonomous driving, enabling the car to navigate without human intervention”

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Abstract—**Autonomous driving has witnessed rapid advancements, thanks to the integration of deep learning and reinforcement learning. In this project, we explore the use of deep reinforcement learning techniques, specifically Dueling Deep Q-Networks (DQN), for developing an autonomous driving model. Unlike conventional projects that rely on real-time data from simulators like CARLA, our approach utilizes the Udacity dataset, a pre-collected dataset offering a diverse range of driving scenarios. This report discusses the model's architecture, dataset integration, and results, highlighting key challenges and future possibilities in autonomous driving research.**

Keywords—Autonomous vehicle navigation, Deep Q-learning, Reinforcement learning, Udacity dataset, Dueling deep Q-network (DDQN), Discrete control actions, State encoding, Autonomous driving, Machine learning for self-driving cars, Real-world driving data

I. Introduction

Recent advancements in autonomous vehicle technology have relied heavily on reinforcement learning (RL) techniques, particularly deep Q-learning, due to its capacity to handle complex decision-making processes. Typically, autonomous navigation tasks in RL are trained in simulated environments like CARLA to avoid the need for large-scale data acquisition. However, in this study, we employ the Udacity dataset, which provides real-world driving data, enabling the model to capture realistic driving scenarios that improve performance when transitioning from simulation to real environments. This approach not only reduces training time but also enhances model adaptability to real-world conditions.

II. Methodology

Our project architecture comprises several critical modules coded in Python, each serving specific functions in training the Q-learning agent to navigate safely and efficiently. The code is organized into various .py files, including modules for state encoding (`encoder_init.py`), parameter setting (`parameter.py`), and environment interaction (discrete driver control). Instead of employing a continuous CARLA simulation, we adapted these scripts to process and utilize the Udacity dataset for training, allowing the agent to learn from authentic driving behaviors and responses.

A. *Data Processing*

The Udacity dataset, which provides annotated driving footage, serves as the primary data source. Using this dataset as input, we modified the discrete_driver.py file to replace CARLA environment calls with pre-processed Udacity data images and actions. The dataset's variety in lighting, weather conditions, and road types provides a rich learning ground for the Q-learning model..

B. *Model Structure*

Our model uses a dueling deep Q-network (DDQN) for discrete control actions, where seven distinct actions represent essential car maneuvers (e.g., turning left/right, moving forward). The model architecture includes a convolutional encoder for feature extraction, followed by a fully connected network for action-value estimation. The model parameters are loaded and updated as specified in the parameter.py file, with the EncodeState class handling state representation.

C. *Training Procedure*

The training process involves feeding sequential driving frames from the Udacity dataset into the DDQN model. Each frame is encoded into a latent state representation using a Variational Encoder (encoder_init.py). During each episode, the agent observes its current state, chooses an action, receives a reward, and transitions to a new state. Rewards are calculated based on safe driving parameters, including lane adherence and distance covered without collisions. The cumulative reward is used to evaluate the agent’s performance over episodes.

III. Results and Evaluation

Using the Udacity dataset provided a practical advantage by incorporating real-world driving variations directly into the model's training. After 1000 training episodes, the model demonstrated a steady improvement in lane adherence and driving stability. The discrete action approach simplified the navigation task by focusing on essential maneuvers, while the DDQN model’s dueling architecture allowed it to efficiently learn optimal actions in response to diverse real-world driving inputs.

IV. Conclusion

This project demonstrates the potential of using pre-existing datasets such as the Udacity dataset for autonomous driving model training, eliminating the need for extensive data collection in simulation environments. Future research could further validate this approach by comparing model performance with simulation-trained models in a real-world test environment.

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