Title: Report on Reinforcement Learning Work for Autonomous Car in Carla Simulator

**Executive Summary:**

This report outlines our efforts in developing an efficient reinforcement learning (RL) model for autonomous cars within the Carla simulator. The primary aim was to create a model capable of navigating the simulated environment effectively using inputs such as cameras, Lidar, and GPS. The selected RL algorithm for this task was Proximal Policy Optimization (PPO), chosen for its demonstrated performance in similar domains and its suitability for managing continuous action spaces.

**1. Approach**:- Our approach comprised the following steps:

Step 1: Literature Survey

Step 2: Find Code for Paper

Step 3: Test Base Code in Carla Simulator

Step 4: Evaluate Pretrained Weights in Carla Simulator

Step 5: Initiate Training if Pretrained Weights Prove Effective

Notably, the training time was emphasized to be efficient.

**2. Basis for Selecting PPO:**

The choice of PPO was grounded in its proven success in comparable domains and its effective handling of continuous action spaces. Initial testing results further supported its suitability for our autonomous car model.

**3. Results on Pretrained Weights:**

Performance with pretrained weight

1. The car moved properly within the Carla environment until there was no intersection.
2. An issue arose at intersections, leading to premature termination of the car's run.
3. We have fixed this issue by adding changes to the code.
4. Now car is moving properly in Carla map.

Performance with our weights

1. After training more then 1000 episodes the car was not completing the route properly
2. Performance is not acceptable.
3. According to paper the model supposed to learn complete path after 900 papers

But it wasn’t happening for us.

1. The paper’s information was misleading.

**4. Intersection Problem:**

The "intersection problem" was identified as a challenge, referring to the difficulty of learning optimal policies when multiple agents interact. Extensive debugging efforts were undertaken to address the termination issue at intersections, resolving the problem and ensuring proper car movement.

**5. Training Results:**

Initial Training Results:

Promising Start: Initially, the training results showed promise, indicating that the model was learning and making progress in the task at hand.

Challenges After 500 Episodes: However, challenges arose after 500 training episodes. Issues included diminishing rewards, suggesting that the model's performance might have plateaued or started to degrade over time.

Core Dumps: Another challenge encountered was the occurrence of core dumps. Core dumps typically indicate a segmentation fault or a critical error in the program, potentially causing the training process to crash.

Learning Slowdown: Despite the version update providing temporary relief, it led to a significant slowdown in the learning process. This suggests that the newer version might have introduced changes that adversely affected the training speed.

Attempted Solutions: Carla Version Update: An attempt was made to address the challenges by updating the Carla version to 9.10. This step provided temporary relief, indicating that some issues might have been related to the simulator or its compatibility with the training environment.

**Decision to Abandon the Model:**

X Learning Slowdown Impact: The decision to abandon the model was influenced by the significant slowdown in the learning process. Slower learning rates can be impractical, especially in scenarios where real-time decision-making is crucial.

Y Long-Term Viability Concerns: The observed challenges, including diminishing rewards and core dumps, raised concerns about the long-term viability of the model for the intended task. A model that struggles to learn or is prone to crashes may not be suitable for deployment.

**Conclusion:**

This report provides a comprehensive overview of our RL work for autonomous cars in the Carla simulator, emphasizing the challenges faced, steps taken, and the decision to reject the initial model. The findings underscore the complexity of RL model development and the need for adaptability in addressing unforeseen challenges. Future endeavors will involve exploring alternative RL algorithms and refining the training process to achieve optimal results.

2. LBC(Learning by cheating)

"Our initial approach for training vision-based autonomous driving systems. This method introduced a two-stage training process to simplify the complex learning involved in urban driving. Initially, an agent with access to privileged information, like the real environment layout and traffic positions, was trained as a 'privileged agent.' Subsequently, using this knowledgeable agent as a teacher, we trained a purely vision-based sensorimotor agent without any access to privileged information or the ability to cheat.

Despite its unconventional nature, this two-stage training technique showed significant advantages, as demonstrated in our analysis. While this specific paper didn’t align with our focus on reinforcement learning, it inspired our exploration into alternative methodologies.

As we pivot in our direction, we aim to explore deeper into a different paper that aligns more closely with our goals. Our pursuit remains focused on developing an effective autonomous driving system, and we’re excited to explore alternative avenues to achieve this goal."