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Integration Of Agent Models And Meta Reinforcement Learning (Meta-RL) Algorithms For Car Racing Experiment

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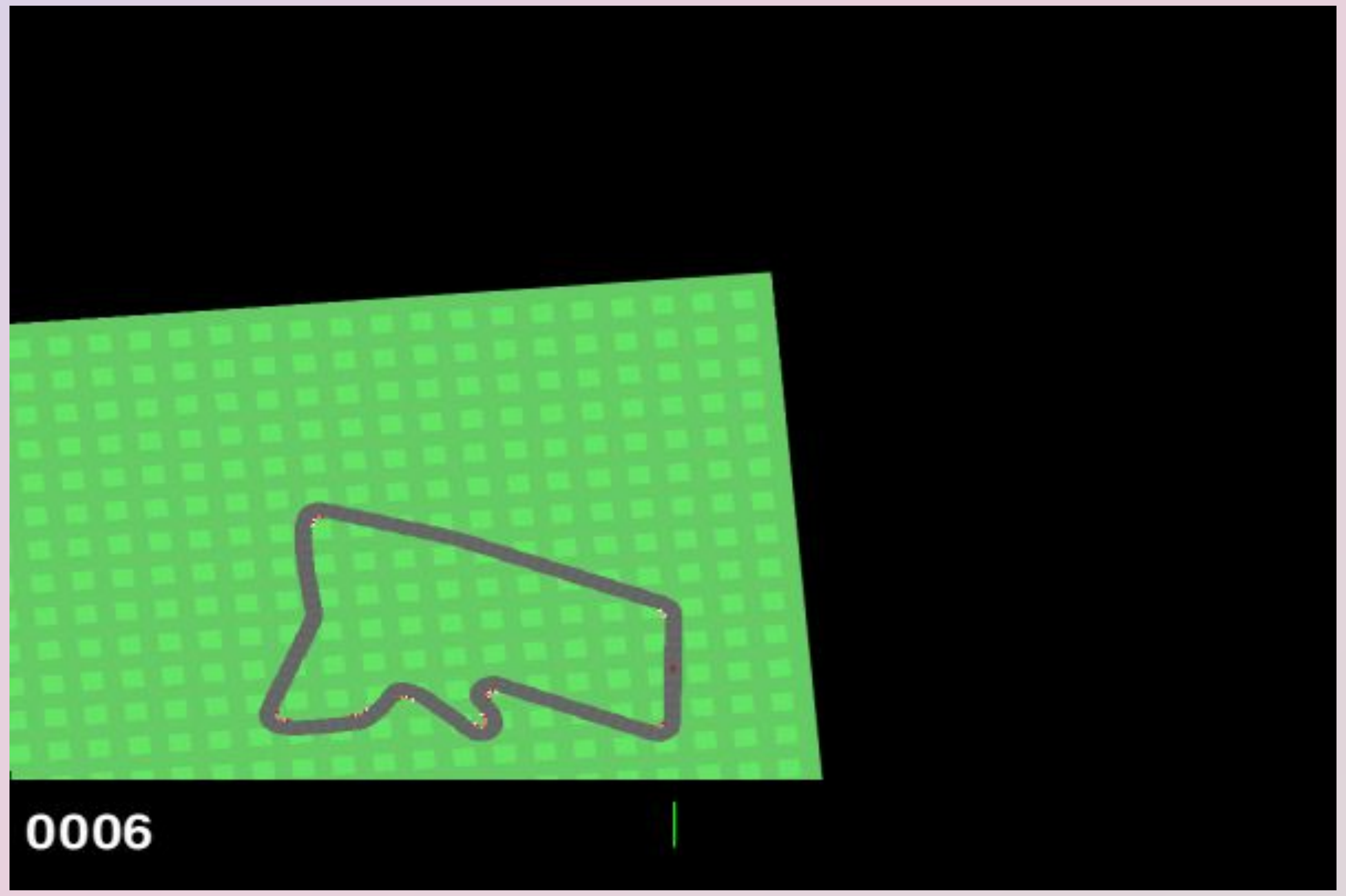
INTRODUCTION

OBJECTIVE:

Enhancing decision-making and adaptability in 2D racing simulations through cutting-edge Meta-RL.



SIGNIFICANCE:

- Importance:
  Addressing optimization challenges in AI-driven racing simulations.

- Broader impact:
  Leveraging these advancements for more general AI applications in gaming and beyond.

METHODS

MAML:

Utilized for its rapid adaptation capabilities across diverse track conditions.

Training Details:

Trained on a diverse set of simulated racing tracks with varying curvature and obstacle configurations.

PPO:

Implemented to refine and optimize policies post-MAML adaptation, focusing on long-term reward maximization.

METHODS (contd.)

Experimental Framework:

Car Racing-v2, configured to test under varied environmental conditions.

Tools and Technologies:

Developed using PyTorch, with CUDA acceleration to enhance computational efficiency.

Metrics of Performance:

Efficiency in lap times reduction, error rates, and response times to environmental shifts, compared to baseline models.

RESULTS (PRELIMINARY FINDINGS)

Lap Time Reduction (Work In-progress):

Reduced average lap times improving over baseline non-meta-learned models.

Adaptability to New Tracks:

Improved adaptation, as measured by the ability to handle new track configurations.

Error Rates in Navigation:

Decreased navigation error rates by approximately 5% compared to traditional reinforcement learning models.

World Models vs. MAML for Carracing-v2

World Models

Definition and Function:
Utilizes VAEs and RNNs to create a compressed and predictive model of the environment.

Key Findings:
In a controlled setting, World Models reduced prediction error by up to 12% compared to classical deep learning approaches.

MAML

Definition and Function:
Focuses on learning optimal initializations for quick adaptation to new tasks.

World Models vs. MAML for Carracing-v2 (contd.)

Key Findings:
Demonstrated a reduction in necessary training epochs when adapting to new racing environments, achieving comparable performance.

Practical Contrast

World Models:
More effective in environments where the dynamics are complex but consistent.

MAML:
Superior in scenarios requiring rapid adaptation to frequently changing conditions.

Conclusion and Future Research

Summary:

MAML's ability to quickly adapt combined with PPO's optimization capabilities leads to significant performance enhancements in racing simulations.

Future Directions:

Testing these approaches in more complex 3D environments and investigating their applications in real-world scenarios such as autonomous driving and dynamic routing.

ANY QUESTIONS?

THANK YOU!