STAT 4830

Reinforcement Learning Racing Agent

Weekly Deliverable: PyTorch Revert, Training Stability, and Checkpointing

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Project Overview

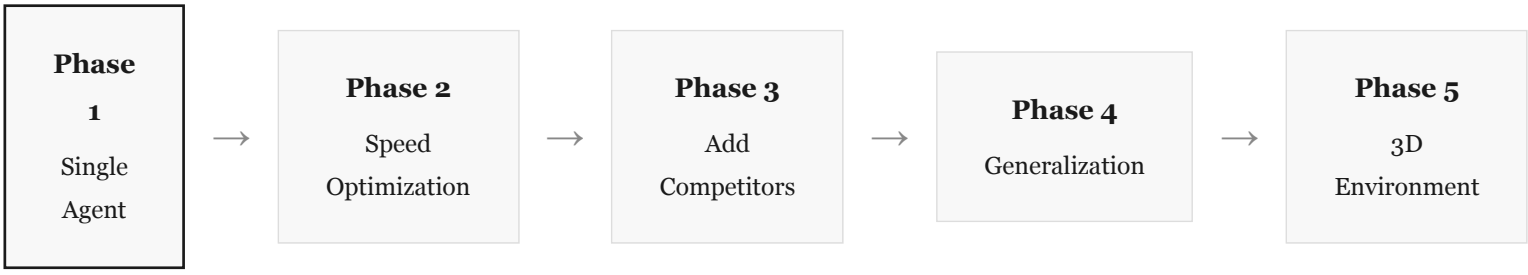
We are training an autonomous racing agent using reinforcement learning. The agent learns to drive entirely from visual input—a 96×96 RGB image representing its view of the track—and outputs continuous control signals for steering, acceleration, and braking.

The environment (*multi_car_racing*) provides realistic physics simulation and a reward signal based on track progress. Our goal is to optimize the agent's policy to complete laps quickly while avoiding crashes and staying on the track.

PPO	1M	96×96	$[-1, 1]^3$
ALGORITHM	TIMESTEPS	RGB INPUT	ACTION SPACE

Project Roadmap

This project develops in stages. We started with a single agent learning to drive on one track. Our goal is to eventually build a general-purpose racing AI that can compete against opponents on any track—and ultimately operate in 3D environments.



CURRENT FOCUS

We are in **Phase 2**. The agent can complete laps, but drives too slowly. This report covers our reward shaping experiments and the challenges of balancing speed with safety.

END GOAL

A racing agent that generalizes across tracks, competes against multiple opponents, and adapts to 3D environments with realistic physics—trained entirely through reinforcement learning.

Training Architecture

We use Proximal Policy Optimization (PPO), a policy gradient method that updates the policy while constraining how much it can change per iteration. This provides stable learning for continuous control tasks. The policy network uses convolutional layers to extract spatial features from the image input.

Batch size: 1024 **Rollout:** 1024 steps **Learning rate:** 3×10^{-4} **Discount (γ):** 0.999

Parallel envs: 8

Baseline Training Results

Initial training over 500K timesteps with default hyperparameters showed that the agent could learn basic driving behavior. Mean episode reward improved from -61 to 282+, demonstrating that the policy was converging toward useful navigation behavior.

LEARNED BEHAVIORS

- Maintains forward motion along track
- Follows track boundaries
- Completes full laps consistently
- Episodes reach max length (1000 steps)

IDENTIFIED PROBLEMS

- Excessive speed leading to corner crashes
- No braking behavior before turns
- Off-track driving to exploit shortcuts
- Speed prioritized over control

Issue 1: Speed Overweighting

The agent learned to maximize speed at all costs because the base reward function implicitly favors velocity. Track progress is measured by tiles visited per step—faster movement means more tiles, which means higher cumulative reward.

> $R_{base} = (\text{tiles visited}) \times (1000 / \text{track length}) - 0.1 \times (\text{time steps})$

The time penalty of -0.1 per step is too small to counterbalance the reward from aggressive driving. The agent discovers that high-risk, high-speed strategies yield better expected returns than cautious driving—even accounting for occasional crashes.

Issue 2: Sharp Turn Handling

The agent had no mechanism for anticipating curves. It would enter sharp turns at full speed and either crash or lose control. To address this, we implemented curvature-based reward shaping that encourages braking when approaching high-curvature track segments.

```
# Detect sharp turns by measuring track curvature ahead curvature =
measure_track_curvature(lookahead=6) is_sharp_turn = (curvature > 0.35) # radians #
Reward braking only when needed (approaching turn while fast) if is_sharp_turn and speed
> 5.0: brake_reward = min(brake_action × 0.4, 0.5) # capped per step
```

This conditional reward avoids penalizing speed globally. The agent only receives the braking bonus when it's both approaching a sharp turn and moving fast enough that braking is appropriate.

Issue 3: Off-Track Exploitation

The agent discovered it could cut corners by driving on grass, bypassing difficult track sections entirely. Without a strong disincentive, off-track driving became a viable exploitation strategy.

SOLUTION: TERMINAL OFF-TRACK PENALTY

We made off-track events terminate the episode immediately with a large negative reward. This creates a clear, unambiguous learning signal that leaving the track is catastrophic—not just suboptimal.

```
if car_on_grass: reward += -1.0 # per-step penalty while off-track reward += -100.0 # terminal penalty done = True # episode ends immediately
```

Reward Function Design

Our modified reward function combines the environment's base reward with additional shaping terms. The total reward at each step is:

> $$R_{total} = R_{progress} - R_{time} + R_{brake} - R_{steer} - R_{off\text{-}track}$$

POSITIVE SIGNALS

- **Progress:** +1000/L per new tile visited
- **Braking:** +0.4 × brake action (on sharp turns)
- **Centerline bonus:** +0.1 to +0.5 for optimal position

NEGATIVE SIGNALS

- **Time:** -0.1 per step
- **Steering jitter:** -0.05 × |Δsteer|
- **Off-track:** -1.0/step, -100 terminal

Current Challenge

Our reward shaping successfully reduced crashes and off-track events, but introduced an unintended side effect: the agent now drives slowly everywhere. Instead of learning context-dependent speed control, it learned that slow driving is universally safe.

OBSERVED BEHAVIOR

- Consistently low velocity on all track sections (straights and curves)
- No speed differentiation based on track geometry
- Braking reward may be encouraging unnecessary caution
- Poor lap times despite high completion rate

This illustrates a fundamental challenge in reward shaping: local incentives produce global behavioral effects. The braking reward, intended only for corners, shifted the entire policy toward conservative driving.

Lessons Learned

- **Reward functions define learned behavior:** The agent optimizes exactly what we reward. Implicit biases in the reward (like tile-based progress) lead to unintended strategies (like speed maximization).
- **Local shaping has global effects:** Adding a braking reward for sharp turns made the agent cautious everywhere, not just on corners. Reward terms interact in non-obvious ways.
- **Terminal penalties provide strong gradients:** Making off-track events end the episode gave the clearest learning signal. The agent quickly learned to avoid the track boundary.
- **Balance is difficult:** Over-penalizing risky behavior produces overly conservative policies. Under-penalizing allows exploitation. The optimal reward function is narrow and problem-specific.

Next Steps: Velocity-Based Rewards

To fix the slow-car problem, we will redesign the reward to explicitly encourage efficient forward movement rather than just track progress. The key insight is to reward velocity in the track direction, not tiles visited.

```
# Replace tile-based progress with directional velocity reward R_velocity =
dot(car_velocity, track_direction) # Increase time penalty to create urgency
time_penalty = -0.5 # was -0.1 # Remove explicit brake reward (prevents point farming) #
Instead: Speed-to-Curvature penalty safe_speed = f(curvature) # lower for sharp turns if
current_speed > safe_speed: penalty = -(current_speed - safe_speed) × 0.3 # Scale off-
track penalty by speed off_track_penalty = -(1.0 + speed × 0.5)
```

Additional Strategies

CURRICULUM LEARNING

Begin training on tracks with gentle curves, then progressively introduce sharper turns. This allows the agent to master speed control incrementally rather than facing the full complexity from the start.

CONTEXT-AWARE SPEED TARGETS

Define optimal speed profiles for each track segment based on curvature. Reward the agent for matching target speeds: fast on straights, slow on corners—encoding the behavior we want explicitly.

VELOCITY DECOMPOSITION

Separately reward forward velocity (along track) and penalize lateral velocity (sliding). This encourages controlled cornering while maintaining speed through optimal racing lines.

MULTI-OBJECTIVE OPTIMIZATION

Treat speed and safety as separate objectives. Use Pareto optimization techniques to explore the trade-off frontier rather than collapsing everything into a single scalar reward.

Project Roadmap (Long-Term)

Beyond solving the speed optimization problem, we have a broader vision for this project. Our current agent drives alone on a single track—but real racing involves competitors, varied environments, and eventually, more complex 3D dynamics.

PHASE 1: ADD COMPETITORS

Introduce other cars on the track. The agent must learn not just to drive fast, but to navigate around opponents, avoid collisions, and find opportunities to overtake. This transforms the problem from single-agent to multi-agent RL.

PHASE 2: GENERALIZATION

Train a policy that works on any track layout with any number of competitors. This requires the agent to learn generalizable driving skills rather than memorizing a single environment—a significant step toward robust racing AI.

LONG-TERM: 3D RACING ENVIRONMENT

Eventually, we want to move to a 3D racing simulator. This introduces new challenges that our current 2D setup doesn't capture:

- **Elevation changes:** Hills, slopes, and banking affect vehicle dynamics and visibility
- **3D observation space:** Larger visual input, more complex feature extraction
- **Realistic physics:** Weight transfer, tire grip, aerodynamics become factors
- **Computational cost:** Higher-dimensional state space requires more training resources

What We Changed

This week we made three main changes to the stack and training setup:

1. REVERTED TO PYTORCH

Codebase is back on PyTorch (Stable-Baselines3 PyTorch backend and/or custom training loop). Single, well-understood stack for debugging and reproducibility.

2. TRAINING INCONSISTENCY → RE-WRITING PIPELINE

Training became **really inconsistent**; the car is **pretty stagnant** with no reliable improvement. We are **re-writing the PyTorch training pipeline** to restore stable learning.

3. NN.MODULE AND CHECKPOINTS

Policy is implemented as a **PyTorch** `nn.Module` (as seen in class). Checkpoints save/load `state_dict` so we can **continually try** different runs—resume, compare, iterate—without losing progress.

```
# Checkpoint flow: save/load for resumable training
torch.save(policy.state_dict(), path) policy.load_state_dict(torch.load(path))
```

Observation

After our changes, we observe the following:

- Inconsistent training curves; high run-to-run variance
- Agent often stagnant — no clear improvement in lap time or control
- Stable, improving lap behavior not yet achieved

What Is Missing

We explicitly call out what is not yet achieved. These are the gaps we are addressing next.

STABLE, CONSISTENT TRAINING

No reliable convergence yet; training curves vary strongly across runs. We need a reproducible, stable training loop before claiming performance gains.

IMPROVED DRIVING PERFORMANCE

Car is still stagnant — no clear speed or control improvement from current runs. Lap times and reward do not show consistent upward trend.

VALIDATED CHECKPOINT FLOW

`nn.Module` and checkpointing are in place (or in progress) but not yet exercised over long, stable training runs. Resume and comparison workflows need validation.

SPEED / REWARD TRADE-OFF

Speed optimization and context-dependent speed control (fast on straights, slow in corners) remain open; previous reward shaping led to overly conservative driving.

Summary and Next Steps

We reverted to PyTorch, saw training become inconsistent and the car pretty stagnant, and implemented the policy as `nn.Module` (as in class) for checkpoints so we can continually try runs. We are re-writing the PyTorch training pipeline for stability.

DONE THIS WEEK

- Reverted codebase to PyTorch
- Identified inconsistent training; car stagnant
- Implemented policy as `nn.Module` for checkpoints
- Re-writing PyTorch training pipeline for stability

NEXT STEPS

- **Stabilize training** — reproducible curves, convergence
- **Validate checkpoint flow** — save/load and resume
- **Re-address reward/speed** and evaluation once training is stable
- Velocity-based reward redesign; add competitors; generalize; 3D

> *Goal: Stable training first; then performance and generalization.*