CartPole RL Enhancement

A Deep Reinforcement Learning Approach with Curriculum Learning and Energy Consumption Optimization

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Project Overview

- **Objective:** Enhance the classic CartPole environment by introducing a third action ("Do Nothing") and develop a deep RL solution to manage the modified environment.
- **Key Features:**
  - Addition of a neutral action to the action space.
  - Implementation of curriculum learning to adjust reward weights dynamically.
  - Incorporation of temperature-scaled softmax for exploration-exploitation balance.
  - Logging and monitoring using TensorBoard.
  - Energy consumption as a reward component.
- **Outcome:** Achieved a high success rate with efficient energy usage after 100k training steps.

Environment Description

- **Classic CartPole:**
  - Two actions: Apply a force to the cart to push it left or right.
  - Observation Space: Cart position, cart velocity, pole angle, pole angular velocity.
  - Objective: Balance the pole by moving the cart. Episode ends if pole angle exceeds a threshold or cart moves out of bounds.

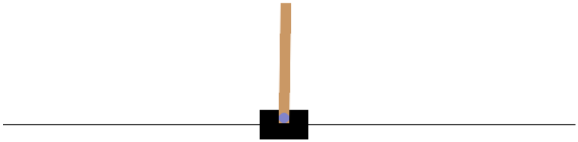


Figure: The CartPole Environments

Environment Description

- **Modified CartPole:**
  - **Third Action:** *Do Nothing* - No force applied to the cart.
  - **Reward Structure:** Split into four equal components: Alive, Distance to Center, Pole Angle, and Energy Usage.
  - **Curriculum Learning:** Adjusts reward weights based on training phases.

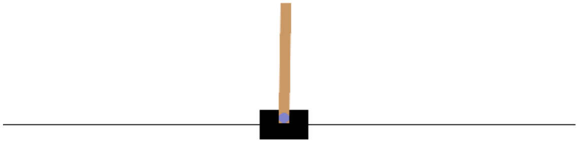


Figure: The CartPole Environments

Steps Towards the Solution

1. **Environment Modification:**
   - Added a third "Do Nothing" action to the action space.
   - Adjusted the reward function to incorporate energy consumption.
2. **Algorithm Development:**
   - Implemented a combination of Double DQN and Dueling DQN for stable learning.
   - Used a target network to improve training stability.
   - Utilized Prioritized Experience Replay to sample important transitions.
   - Applied Gradient Clipping to prevent exploding gradients.
3. **Enhancements:**
   - Introduced Curriculum Learning to adjust reward weights dynamically.
   - Integrated Temperature-Scaled Softmax for exploration-exploitation balance.
   - Tested Normalization for observations and rewards.

Steps Towards the Solution

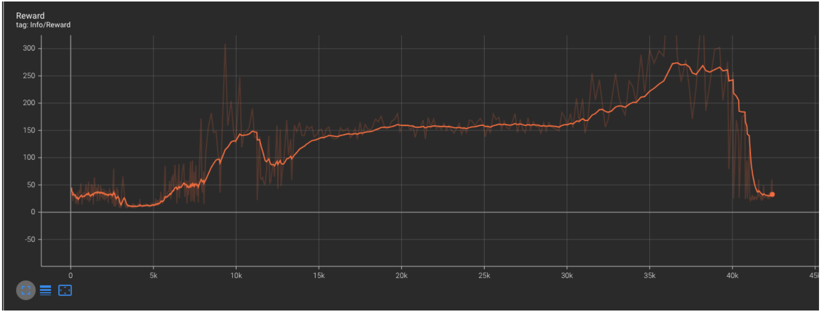


Figure: Catastrophic Forgetting occuring in the training process

Steps Towards the Solution

4. **Problems encountered:**
   - Catastrophic forgetting: The agent forgets previously learned behaviors.
     - Solution: Use non-deterministic actions and temperature scheduling.
   - Reward function is not a good metric of performance during training.
     - Solution: Run evaluations every 2k steps to track performance.
5. **Logging and Monitoring:**
   - Set up TensorBoard for real-time monitoring of training metrics.
   - Logged individual sub-rewards and penalties for detailed analysis.
   - Evaluation every 2k steps to track performance.
6. **Checkpointing:**
   - Enabled resuming training from saved checkpoints.
   - Handling crashes or interruptions during training.

TensorBoard Metrics

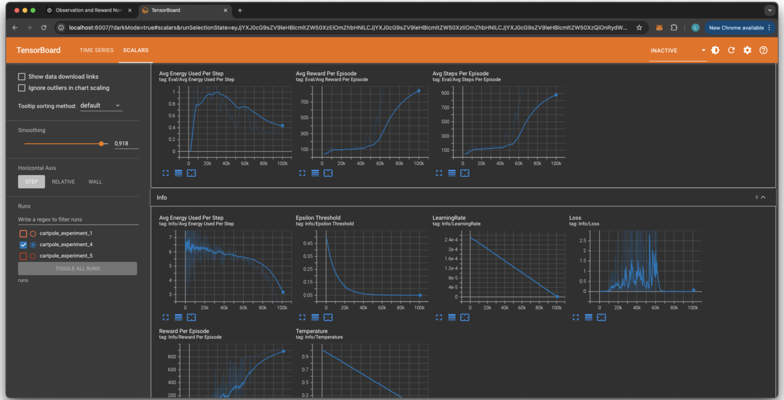


Figure: TensorBoard Dashboard showing training metrics

Algorithm Enhancements

- **Double DQN:** Mitigates overestimation bias by decoupling action selection and evaluation.
- **Prioritized Experience Replay:** Samples important transitions more frequently to accelerate learning.
- **Normalization:**
  - *Observation Normalization:* Stabilizes training by normalizing input features.
  - *Reward Normalization:* Ensures consistent reward scaling.
- **Curriculum Learning:**
  - Phases:
    1. **0-20k steps:** 50% Alive Reward, 50% Pole Angle Reward.
    2. **20k-50k steps:** 33% Alive, 33% Pole Angle, 33% Distance to Center.
    3. **Above 50k steps:** 25% each for Alive, Pole Angle, Distance to Center, and Energy Usage.

Algorithm Enhancements

- **Temperature-Scaled Softmax:**
  - Initial Temperature: 1.0
  - Final Temperature: 0.1
  - Linearly decreases over training to reduce exploration over time.

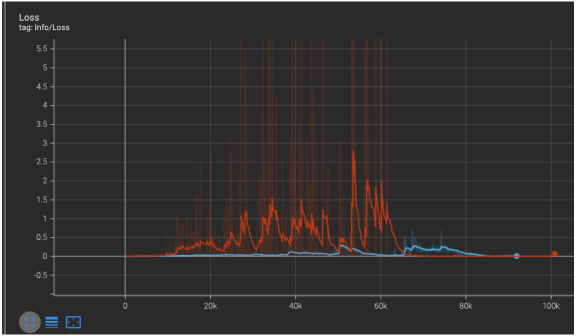


Figure: Loss Stabilization: Prioritized (blue) vs. Uniform Replay (red)

Possible Extensions

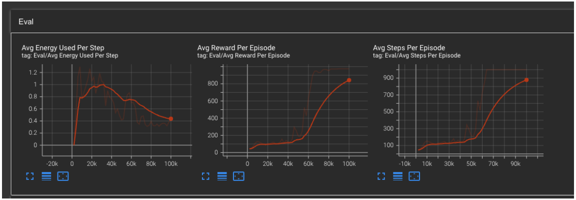
- **Stratification:**
  - Implement stratified sampling to ensure diverse experiences in replay buffer.
- **Distribution-Aware Buffer:**
  - Explore Cosine Similarity or Variational Autoencoders (VAEs) to model state distributions and enhance replay buffer sampling.
- **Parallel Environments:**
  - Increase to 16 parallel environments for faster experience collection and improved training efficiency.
- **Reward Function Refinement:**
  - Schedule Pole Angle and Distance to Center rewards to decrease over time, focusing more on energy optimization.
- **Model Checkpointing:**
  - Maintain multiple checkpoints to preserve best-performing models across different training phases.
- **Advanced Exploration Strategies:**
  - Incorporate other exploration methods like entropy regularization or intrinsic motivation (e.g., curiosity).

Possible Shortcomings

- **Algorithm Tuning:**
  - Deep RL algorithms require extensive hyperparameter tuning for optimal performance.
- **Overfitting:**
  - The model may overfit to the specific environment configuration, limiting generalizability.
- **Fixed Length Episodes:**
  - Fixed-length episodes combined with energy consumption reward may lead to suboptimal behavior where the agent overfits to short-term gains.
- **Training For Too Long Might Decrease Performance:**
  - The agent might overfit to near-perfect behavior and forget more complex situations.
- **Learning Stability:**
  - Other on-policy algorithm like PPO might be more stable and efficient.

Results and Analysis

- **Training Outcome after 100k Steps:**
  - **Average Reward:** 975/1000
  - **Energy Consumption:** Under 0.4 per step (Full Power = 10 per step)
  - **Success Rate:** 100% during evaluation (No failures)
- **Evaluation Strategy:**
  - Conducted evaluations every 2k steps.
  - Essential for monitoring performance due to off-policy learning, non-deterministic actions, and exploration.
- **Prioritization Analysis:**
  - Prioritized Experience Replay helped stabilize loss.
  - Did not significantly enhance overall performance compared to uniform sampling.



Conclusion

- Successfully enhanced the CartPole environment with a third "Do Nothing" action and optimized reward structure for energy consumption.
- Developed a robust deep RL solution incorporating curriculum learning and temperature-scaled softmax for effective exploration-exploitation balance.
- Achieved high performance with minimal energy usage and a perfect success rate in evaluations.
- Identified areas for improvement, including further algorithm tuning and exploring advanced buffer management techniques.