Reinforcement Learning for Leaf and Fruit Collection in a Grid-Based Tree Environment

In-Depth Analysis of PPO and Dueling DQN with LSTM Classifier

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Introduction

Objective:

- Train Reinforcement Learning (RL) agents to collect falling leaves and fruits in a **20×20 grid-based TreeEnvironment**.

Inspiration:

- Derived from dynamic scheduling problems *(Chang et al., 2019)*

RL Frameworks Used:

- Proximal Policy Optimization (PPO)
- Dueling Deep Q-Network (Dueling DQN) with LSTM Classifier

Focus Areas:

- Detailed working of both algorithms
- Comprehensive performance comparison between PPO and Dueling DQN + LSTM

TreeEnvironment Overview

Setup:

- 20×20 grid; each cell represents a tree branch
- Each branch can hold **0–5 leaves** and **0–5 fruits**
- Leaves and fruits fall based on **random timers (1–4 time units)**

Action Space:

- Move **left**, **right**, **up**, **down**, or **stay**

Reward Structure:

- **+1** for collecting a leaf
- **+5** for collecting one fruit
- **+6** for collecting a fruit + leaf together
- **Penalty:** $-(\text{leaves} + \text{fruits}) \times 5$ if fruit has **2 or more leaves**

Episode Termination:

- Episode ends after **100 time steps**

PPO – Algorithm Overview

Algorithm:

- Proximal Policy Optimization (PPO)

Key Features:

- Policy gradient method
- Clipped surrogate objective for training stability

Architecture:

- **Actor Network:** 128 $\rightarrow$ 64 units, softmax output (action probabilities)
- **Critic Network:** 128 $\rightarrow$ 64 units, linear output (state values)

Hyperparameters:

- Actor LR: 0.0001, Critic LR: 0.0005
- Discount Factor (γ): 0.99
- GAE Lambda (λ): 0.95
- Clipping Epsilon: 0.3

PPO – Working and Training

Workflow:

- Actor selects action using policy $\pi_\theta(a|s)$
- Environment returns reward r_t and next state s_{t+1}
- Critic computes advantages:

$$A_t = \sum (\gamma\lambda)^k \delta_{t+k}, \quad \text{where } \delta_t = r_t + \gamma V_\phi(s_{t+1}) - V_\phi(s_t)$$

Training Setup:

- 600 episodes, 100 steps each

Actor Update:

- Clipped PPO loss:

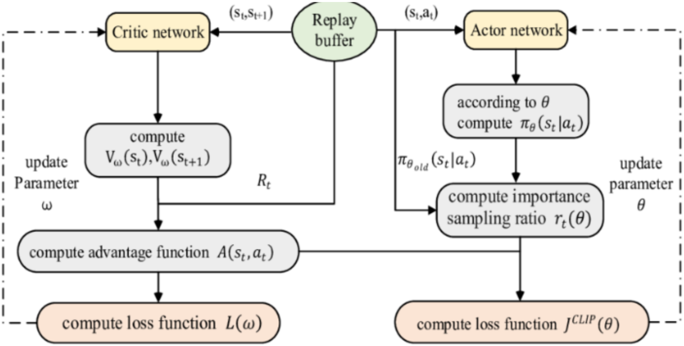
$$L_{\text{actor}}(\theta) = \mathbb{E}_t \left[\min \left(\frac{\pi_\theta}{\pi_{\theta_{\text{old}}}} A_t, \text{ clip} \left(\frac{\pi_\theta}{\pi_{\theta_{\text{old}}}}, 1-\epsilon, 1+\epsilon \right) A_t \right) \right]$$

Critic Update:

- MSE Loss:

PPO - Training Architecture Diagram

- Illustrates the interaction between Actor-Critic networks in PPO.
- **Workflow Visualized:**
  - Actor network computes action probabilities using policy π_θ.
  - Critic evaluates the state using value function $V_\omega(s)$.
  - Advantage and loss functions are computed for updates.
  - Stabilization technique: Importance sampling ratio and clipped surrogate objective.



Dueling DQN with LSTM Classifier - Algorithm Overview

Algorithm: Dueling DQN + LSTM Classifier

LSTM Classifier:

- Predicts item availability (leaves/fruits).
- Architecture:
  - Two LSTM layers: 64 units and 32 units.
  - Followed by Dense layers: 16 units and 2 units with softmax activation.

Dueling DQN:

- Separates value and advantage streams.
- Architecture:
  - LSTM layer with 128 units.
  - Followed by Dense layers: 64 and 32 units.

Hyperparameters:

- $\gamma = 0.95$
- ϵ: decays from 1.0 to 0.01 (decay $= 0.999$)
- Learning Rate (LR): 0.001

Dueling DQN with LSTM Classifier - Working (Part 1)

LSTM Classifier Workflow:

- Trained on 1000 sequences (length 10) to predict item presence.
- **Inputs:** Historical timer patterns.
- **Outputs:** Probability of leaves/fruits availability.

Dueling DQN Workflow:

- Uses LSTM predictions to inform action selection.
- Computes Q-values using the formula:

$$Q(s,a;\theta) = V(s;\eta) + \left(A(s,a;\psi) - \frac{1}{N_{\text{action}}} \sum_{a'} A(s,a';\psi) \right), \quad N_{\text{action}} =$$

- Action selection: Epsilon-greedy policy (ϵ decays from 1.0 to 0.01).

Dueling DQN with LSTM Classifier - Working (Part 2)

Training Process:

- 600 episodes, 100 steps each.
- Stores transitions in replay buffer (size 5000).
- Samples batch (size 32) for training.

Updates:

- **Target Q-value:**

$$Q_{\text{target}}(s_t, a_t) = r_t + \gamma \max_{a'} Q_{\text{target}}(s_{t+1}, a'; \theta^-), \quad \gamma = 0.95$$

- **DQN update: Bellman error:**

$$L(\theta) = \mathbb{E}[(Q(s, a; \theta) - Q_{\text{target}}(s, a))^2], \quad \text{Learning Rate} = 0.001$$

- Target network updated every 10 steps.

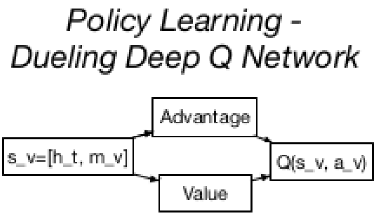
Dueling DQN and LSTM Architecture

Top: Dueling DQN Module

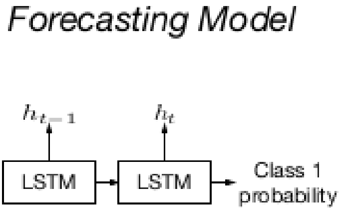
- Decomposes Q-values:
  - **Advantage function:** Measures importance of actions.
  - **Value function:** Measures importance of states.
  - Combines both: $Q(s,a) = V(s) + A(s,a)$

Bottom: LSTM Classifier

- Used for sequence prediction and state forecasting.
- LSTM cell passes hidden state $h_{t-1} \rightarrow h_t$, outputting class probabilities.



Dueling DQN



Results Overview

PPO:

- Training reward: **-433.49**, Time: **6043.28s**
- Evaluation reward: **-385.76**, Success rate: **0.00%**
- Penalty avoidance: **51.87%**

Dueling DQN with LSTM:

- Training time: **1162.36s** (~5x faster)
- Evaluation reward: **8.32**, Success rate: **60.50%**
- Penalty avoidance: **96.50%**

Comparison of Algorithms - Metrics

Metric	PPO	Dueling DQN with LSTM
Average Reward	-385.76	8.32
Success Rate	0.00%	60.50%
Penalty Avoidance	51.87%	96.50%
Good Outcomes Accuracy	51.87%	60.50%
Training Time (seconds)	6043.28	1162.36

Key Insight: *Dueling DQN outperforms PPO across all metrics.*

Comparison of Algorithms - Reward Distribution

PPO Reward Distribution:

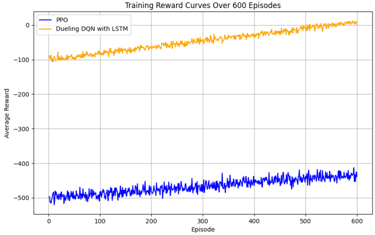
- Penalty: 48.13%
- Other: 29.60%
- Leaves: 6.43%
- One Fruit: 9.98%
- Fruit + Leaf: 5.85%

Dueling DQN Reward Distribution:

- Penalty: 3.50%
- None: 31.75%
- Leaves: 24.75%
- One Fruit: 19.75%
- Fruit + Leaf: 16.00%

Insight: *Dueling DQN achieves balanced collection, significantly reducing penalties.*

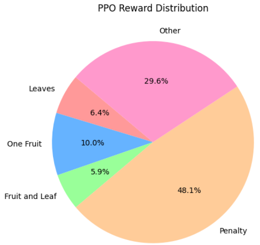
Training Reward Curve vs Metrics Comparison



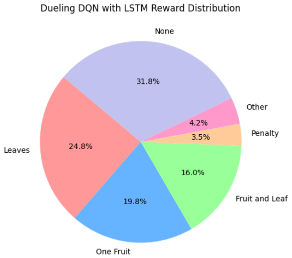
figureReward Curves

figureMetrics Comparison

Reward Distribution: PPO vs DQN



figurePPO Reward Distribution



figureDQN Reward Distribution

Comparison of Algorithms: Why Dueling DQN Excels

- **Temporal Prediction:**
  - LSTM predicts item falls, enabling strategic navigation.
- **Dueling Architecture:**
  - Separates value and advantage for better Q-value estimation.
- **Sequential Actions:**
  - Processes actions incrementally, reducing action space.
- **Exploration:**
  - Epsilon-greedy + replay ensures robust state-action coverage.
- **Penalty Avoidance:**
  - Dueling DQN: **3.50%** penalties vs. PPO: **48.13%**.

Applications

- **Reinforcement Learning Research:**
  - Benchmark for dynamic RL tasks.
- **Robotics:**
  - Autonomous navigation for agricultural robots.
- **Real-Time Example:**
  - Robot in an orchard: LSTM predicts falls, Dueling DQN navigates.
- **Benefits:**
  - Efficiency, cost reduction, scalability, sustainability.

Conclusion

- **Summary:**
  - Dueling DQN with LSTM Classifier outperforms PPO.
  - Superior reward (8.32 vs. -385.76), success rate (60.50%), and penalty avoidance (96.50%).
  - Driven by temporal prediction, dueling architecture, and efficient exploration.
- **Impact:**
  - Advances RL research and robotics applications.
  - Aligns with Chang et al. (2019) insights.

Future Work and References

- **Future Work:**
  - Scale to larger grids (e.g., 50x50).
  - Explore advanced RL methods (Soft Actor-Critic, Rainbow DQN).
  - Integrate with physical robots.
- **References:**

  - Chang et al. (2019). *Dynamic Measurement Scheduling*. PMLR 97.
  - Schulman et al. (2017). *PPO Algorithms*. arXiv:1707.06347.
  - Wang et al. (2016). *Dueling DQN*. ICML.

End !

Thank You!