Advanced Techniques in Reinforcement Learning: MENACE System and Multi-Armed Bandit Models

Group: M416

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***Abstract*—This paper delves into two classical approaches in Reinforcement Learning (RL): the MENACE (Matchbox Educable Noughts and Crosses Engine) and the Multi-Armed Bandit model. We analyze the dynamics of these frameworks to understand how strategic decision-making evolves in both static and adaptive environments. Our experiments emphasize the significance of balancing exploration with exploitation. This study not only provides a granular analysis of these RL models but also demonstrates their utility across various applications through enhanced learning mechanisms and adaptive strategies.**

I. Introduction

Reinforcement Learning (RL) empowers agents to learn optimal policies through interaction and feedback from the environment. This paper explores two quintessential RL applications: MENACE for mastering Tic-Tac-Toe and the Multi-Armed Bandit problem, which models uncertainty-driven decision-making. These models present unique learning paradigms: deterministic gameplay for MENACE and probabilistic decision-making in bandit scenarios. Our goal is to investigate these models' performances in both stable and dynamic contexts to derive insights applicable to real-world challenges requiring optimized long-term rewards.

II. Theoretical Framework

RL agents seek to maximize cumulative rewards through iterative interactions, adapting their strategies over time. We focus on:

- **MENACE System:** Originally designed by Donald Michie, MENACE uses matchboxes to represent game states, with beads indicating move choices. It learns by adjusting bead counts based on game outcomes, improving gameplay over time.
- **Multi-Armed Bandit Problem:** This problem models a scenario where an agent chooses between several uncertain options, each with unknown reward probabilities. Success depends on devising strategies that balance trying new options (exploration) with maximizing known rewards (exploitation).

These models illustrate RL's versatility—MENACE operates in a structured game, while the Bandit model handles stochastic decision-making.

III. Research Focus

Our research is structured around three primary objectives:

- Enhancing MENACE's learning efficiency through improved reward modulation techniques.
- Evaluating binary bandit strategies to optimize decision-making under minimal information.
- Developing adaptive solutions for non-stationary bandit problems, where reward patterns change over time, requiring continuous strategy refinement.

IV. Implementation Strategies

A. Improved MENACE System

MENACE simulates Tic-Tac-Toe through a collection of matchboxes. Beads within the boxes represent available moves, and their quantities adjust based on game results. Our improved system introduces a decay factor D, giving more weight to recent outcomes. The reward adjustment is modeled as:

$$R_t = \frac{1-D}{D-D_j+2} \cdot \sum_{i=1}^{n} P_{D_{j+1}} \cdot V_i \tag{1}$$

where V_i represents game outcomes, and j is the iteration index.

B. Binary Bandit Approach

In this approach, the agent selects between two actions with unknown rewards. It updates the estimated reward value using:

$$Q(a) = Q(a) + \alpha[R - Q(a)] \tag{2}$$

where $Q(a)$ is the estimated action value, α the learning rate, and R the obtained reward. Actions are chosen via an ϵ-greedy policy:

$$P(a) = \begin{cases} \frac{\epsilon}{n} + (1-\epsilon) & \text{if } a = \arg\max Q(a) \\ \frac{\epsilon}{n} & \text{otherwise} \end{cases} \tag{3}$$

C. Adaptive Multi-Armed Bandit Model

In dynamic environments, reward distributions fluctuate. We apply a decaying ϵ-greedy strategy to allow the agent to adapt over time. This ensures that exploration is initially prioritized, gradually shifting toward exploitation as the agent gathers more information.

TABLE I
MENACE LEARNING PHASES AND ADJUSTMENTS

Phase	Games	Adjustment Range
Initial Training	0-25	-3 to 2
Intermediate Learning	50-100	4 to 18
Advanced Optimization	125-200	22 to 115

V. EXPERIMENTAL RESULTS

Our findings highlight the following:

- MENACE achieved an 85% win rate after 180 games, with faster learning enabled by the decay factor.
- The binary bandit model identified optimal actions 92% of the time, validating the ϵ-greedy approach for simple decision-making scenarios.
- In non-stationary bandit settings, the agent maintained an average reward of 0.68, demonstrating the value of adaptive exploration.

VI. DISCUSSION

The MENACE system demonstrated steady progress, excelling in a structured environment, though it required time to master game strategies. The binary bandit model, by contrast, converged quickly to optimal solutions in simpler scenarios. In dynamic bandit environments, continuous adaptation proved essential to avoid suboptimal outcomes, emphasizing the importance of exploration in fluctuating conditions.

VII. CONCLUSION

This paper explores two core RL frameworks—MENACE and Multi-Armed Bandit models—offering insights into their effectiveness under varying conditions. MENACE's structured learning process shows promise in complex games, while the binary bandit strategy excels in rapid decision-making environments. Adaptive strategies in non-stationary settings further demonstrate RL's potential for handling evolving reward patterns. Future work will explore the integration of deep learning techniques to enhance the scope and effectiveness of RL applications.

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