

# Deep Reinforcement Learning with Value Function Approximation of the Q-Action

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*Deep Reinforcement Learning*

## ABSTRACT

This work investigates Deep Reinforcement Learning (DRL) methods based on action-value function approximation in visually rich continuous control environments. Using MuJoCo tasks from the DeepMind Control Suite accessed via Gymnasium, we study locomotion and obstacle avoidance problems where the agent observes only RGB images instead of low-dimensional state vectors. As a baseline, we implement a Deep Q-Network (DQN) with a convolutional encoder followed by fully connected layers that jointly learn a visual state representation and an approximate Q-function over a discretized action space. We then extend this baseline to Rainbow DQN by incorporating key algorithmic improvements such as Double Q-learning, Prioritized Experience Replay, Dueling architecture, n-step returns, Distributional RL, and Noisy Networks. Through a series of experiments, we compare DQN and Rainbow in terms of sample efficiency, learning stability, and exploratory behavior in locomotion tasks. We further perform an ablation study on selected Rainbow components to quantify their individual impact, and finally evaluate both agents in obstacle-rich environments where agents must both move forward and avoid collisions. The results provide empirical insight into the benefits and limitations of advanced DQN variants in complex visual control settings, and help develop critical experimental criteria for DRL in continuous control.

**Key words:** Deep Reinforcement Learning, Deep Q-Network, Rainbow DQN, MuJoCo, DeepMind Control Suite, Gymnasium, Visual Control, Continuous Control, Locomotion, Obstacle Avoidance

**Repository:** <https://github.com/pepert03/DQN-Rainbow-Pixel-Control>

## 1 INTRODUCTION

### 1.1 Deep Q-Networks Fundamentals

Deep Reinforcement Learning (DRL) deals with high-dimensional state spaces, such as images, which are not feasibly handled with traditional RL methods.

**1.2 Rainbow DQN**

**1.3 Environments: MuJoCo and Deepmind Control Suite**

**1.4 Environments Framework: Gymnasium**

**2 TRAVELING VIA DQN**

**2.1 Methodology**

**2.2 Results and Discussion**

**2.3 Conclusions**

**3 TRAVELING VIA RAINBOW-DQN**

**3.1 Methodology**

**3.2 Results and Discussion**

**3.3 Conclusions**

**4 ABLATION STUDY OF RAINBOW-DQN**

**4.1 Methodology**

**4.2 Results and Discussion**

**4.3 Conclusions**

**5 TRAVELING IN AN ENVIRONMENT WITH OBSTACLES**

**5.1 Methodology**

**5.2 Results and Discussion**

**6 CONCLUSIONS**

**REFERENCES**