DL4CV Project

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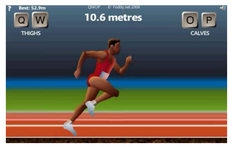
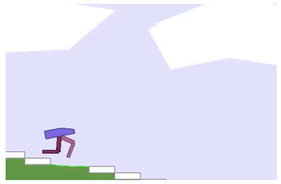
Introduction

- Achieve better performance on various environments such as QWOP and OpenAI Gyms' BipedalWalker
- Apply Computer Vision approaches to represent states of Reinforcement Learning



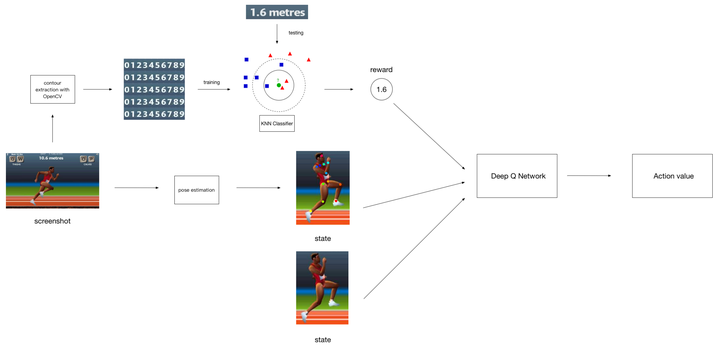
QWOP



BipedalWalker

Deep Q Network plays QWOP

- Train a KNN classifier to recognize numbers and use CNN to perform pose estimation from screenshot



- Use CNN + FC to Approximate the optimal action-value function

$$Q^*(s,a) = \max_a \mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + ...|s_t = s, a_t = a, \pi]$$

- Use Experience Play to Learn From the Past and Q-learning Update

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s')\sim U(D)}[(r + \gamma \max_{a'} Q(s', a'; \theta_i^-) - Q(s,a;\theta_i))^2]$$

- Use uinput to simulate the process of press button since QWOP is a closed-sourced

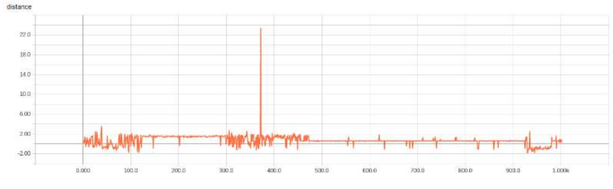


Fig: raw pixel as input of Deep Q Network

Deep Q Network plays QWOP

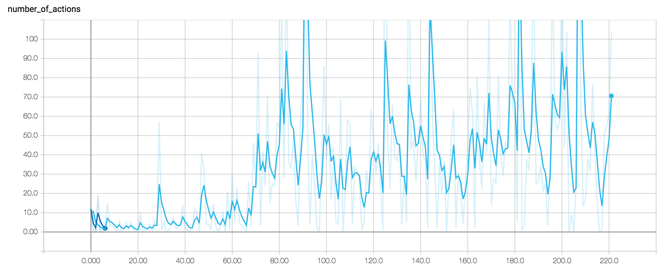


Fig: pose as input of Deep Q Network

DDPG and PPO plays BipedalWalker

DDPG

- Update critic by minimizing the loss

$$L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$$

- Update actor policy using the sampled policy gradient

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|s_i$$

DDPG and PPO plays BipedalWalker

PPO

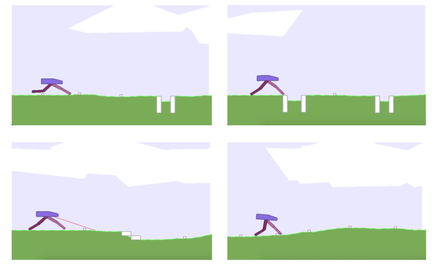


Fig: states after 50, 150, 250 and 450 episodes

4. Reference

References

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