Learning Control for Air Hockey Striking using Deep Reinforcement Learning

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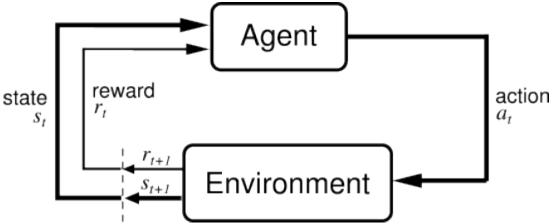
Overview

The Reinforcement Learning Setup

At each time step t:

1. Agent and environment in state s_t
2. The agent executes action a_t in the environment
3. The environment transitions to state s_{t+1} according to a_t and s_t
4. The agent observes state s_{t+1} and receives reward r_t
5. $t = t + 1$ and set $s_t = s_{t+1}$



RL Components

The RL goal is to maximize the expected accumulative reward:

RL Objective

$$\max_{\pi} \mathbb{E}^{\pi}\left[\sum_{t=0}^{T} \gamma^t r_t\right], \quad \pi : \mathcal{S} \to \mathcal{A}$$

The model is defined for the tuple $<\mathcal{S}, \mathcal{A}, \mathcal{P}, r>$, where

1. $\mathcal{A}$ - Action space
2. $\mathcal{S}$ - State space; initial state s_0
3. $\mathcal{P}$ - Transition model; $P(s'|s,a)$
4. r - Reward ; $r_t = r(s_t, a_t)$
5. γ - Discount factor

Q-Learning, Watkins (1989)

- Q-Learning - a learning version of the value iteration algorithm.
- At each step s_t, choose the action a_t which maximizes the function $Q(s_t, a_t)$.
  - Q is the estimated state-action value function it tells us how good an action is given a certain state.
- Formally: $Q(s_t, a_t) = r(s_t, a_t) + \gamma \max_a Q(s_{t+1}, a)$

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- Formally: $Q(s_t, a_t) = r(s_t, a_t) + \gamma \max_a Q(s_{t+1}, a)$
- The state-action value function can also be learned from off-policy samples $< s_t, a_t, r_t, s_{t+1} >$

$$Q(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{old\ \ value} + \underbrace{\alpha}_{learning\ \ rate} \Big[\underbrace{r_t + \gamma \max_a Q(s_{t+1}, a)}_{target} - \underbrace{Q(s_t, a_t)}_{old\ \ value} \Big]$$

- Selected action: $\pi(s) = \operatorname{argmax}_a Q(s, a) + E$
  - E – Exploration

Deep Q-Learning

- State-action transitions $< s, a, r, s' >$ are sampled from
  - Full episodes roll-outs
  - Distribution function over an external memory

$$r = r(s, a), \quad s' \sim P(\cdot|s, a)$$

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- Define the objective function to be the MSE of the Temporal Difference error

$$\mathcal{L}(\theta) = \mathbb{E}_{s,a,r,s' \sim P}\left[\left(\underbrace{r + \gamma \max_{a'} Q(s',a';\theta)}_{target} - \underbrace{Q(s,a;\theta)}_{prediction}\right)^2\right]$$

DQN & Double DQN Learning Rule, Van Hasselt et al. (2016)

- In order to reduce oscillation and increase stability, we use
  - Experience replay buffer $\mathcal{D}$
  - Additional freezed target Q-network $Q(s, a; \hat{\theta}^{-})$

$$\mathcal{L}^{DQN}(\theta) = \mathbb{E}_{s,a,r,s' \sim \mathcal{D}}\left[\left(r + \gamma \max_{a'} Q(s', a'; \hat{\theta}^{-}) - Q(s, a; \theta)\right)^2\right]$$

- Periodically update parameters $\hat{\theta}^{-} \leftarrow \theta$

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- To reduce value overestimation we decouple the action selection from the action evaluation yielding

$$\mathcal{L}^{DDQN}(\theta) = \mathbb{E}_{\ s,a,r,s'\sim\mathcal{D}}\left[\left(r + \gamma Q(s',a';\hat{\theta}^{-}) - Q(s,a;\theta)\right)^2\right]$$

$$a' = \operatorname*{argmax}_{a} Q(s',a;\theta)$$

Deep Q-Network Learning Scheme

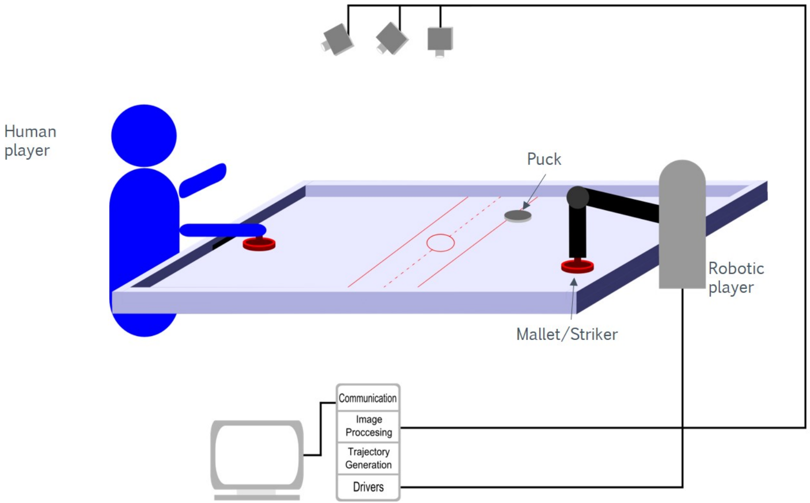
Initialize:

1. Experience replay buffer $\mathcal{D}$
2. Online network with weights θ
3. Target network with weights $\hat{\theta}^{-} \leftarrow \theta$

Start at state s_0 and repeat for M steps

1. In state s_t execute action $a_t = \max_a Q(s_t, a; \theta)$ / explore
2. Observe reward r_t and new state s_{t+1}
3. Store transition $< s_t, a_t, r_t, s_{t+1} >$ in experience replay buffer $\mathcal{D}$
4. Sample uniformly N transitions from $\mathcal{D}$
5. Update Q-network $Q(s, a; \theta)$ according to $\mathcal{L}(\theta)$
6. Set $s_t \leftarrow s_{t+1}$
7. update target Q-network with $\hat{\theta}^{-} \leftarrow \theta$ every C steps

The Air Hockey Physical Setup



Air Hockey Striking Problem Formulation

Goal

Finding a policy for the agent to strike the puck (skill), such that the puck will move in a desired attack pattern

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- Puck is stationary
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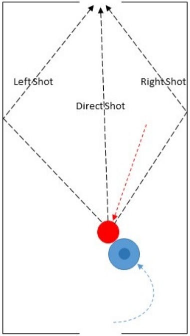
Requirements:

- Maximum velocity after impact (puck)
- Puck is aimed to the center of the goal
- Puck's trajectory according to the selected skill



Agent's Dynamics

State space:

- Combination of the agent's (m) and puck's (p) positions and velocities

$$s_t = \left[m_x,\ m_{V_x},\ m_y,\ m_{V_y},\ p_x,\ p_{V_x},\ p_y,\ p_{V_y}\right]^T$$

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Action Space:

- Acceleration commands (motor torques) $\left[a_x,\ a_y \right]^T, \quad |a_{x,y}| \leq A_{max}$
- Discretized in order to fit the Q-networks scheme
- Boundary and zero actions are taken (among other) to include the known Bang-Zero-Bang profile

$$A = \left[-A_{max},\ -A_{max}/2,\ 0,\ A_{max}/2,\ A_{max} \right]^2$$

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Simulation dynamical model:

- 2-D 2^{nd} order kinematics (integrator) with constraints
- Collision models are ideal, with restitution coefficient $e = 0.99$

Time Optimal Control Formulation

Control problem

$$
\begin{aligned}
\underset{a_k}{\text{minimize}} \quad & \phi(s_T) + \sum_{t=1}^{T} 1 \\
\text{subject to} \quad & s_{k+1} = f(s_k, a_k) \\
& s_k^{(i)} \in [S_{min}^{(i)}, S_{max}^{(i)}], \qquad i = 1, \dots, 8 \\
& a_k^{(j)} \in [A_{min}^{(j)}, A_{max}^{(j)}], \quad j = 1, 2 \\
& s_0 = s(0)
\end{aligned}
$$

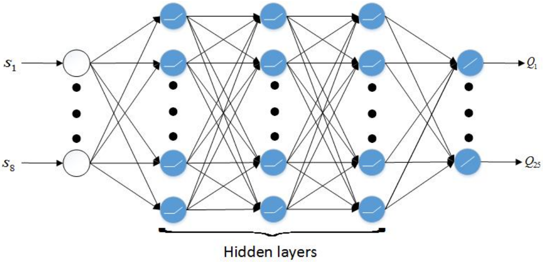
- $\phi(s_T)$ is the constraint on the final condition
- $f(s_k, a_k)$ is the physical model
- $S_{min/max}$, $A_{min/max}$ are constraints on the space and actions respectively
- s_0, s_T are the initial and final conditions
- The collision model is embedded within the state and final condition

The NN Controller

- **Input** - physical state vector of the game, i.e position and velocities

$$s_t \in \mathbb{R}^8$$

- **Output** - 25 Q values (5 actions in each axis)
- **Network** - Feedforward Neural Network with 4 Layers



- **Activations** - ReLU

Reward Definition

Reward Function

$$\begin{cases} r_t = -r_{time} & \text{if } s_t \text{ is not terminal} \\ r_t = r_c + r_v + r_d & \text{if } s_t \text{ is terminal} \end{cases}$$

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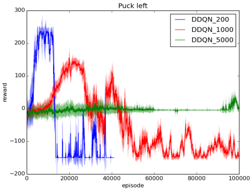
- r_c is a reward given for striking the puck
- r_v is a reward for maximal velocity in the direction of the goal

$$r_v = \text{sign}(V) \cdot V^2$$

- r_d is a reward for the puck reaching the desired point at the opponent's goal

$$r_d = \begin{cases} c & |x - x_g| \leq w \\ c \cdot e^{-d(|x - x_g| - w)} & |x - x_g| > w \end{cases}$$

Applying the DQN scheme to the air hockey problem
(testing for different update periods)



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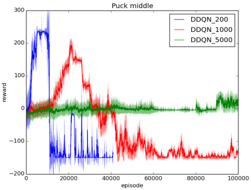
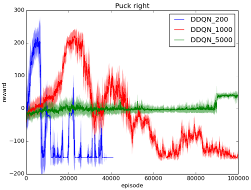


(b) Middle



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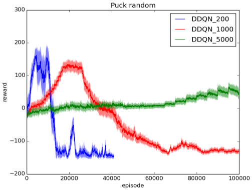
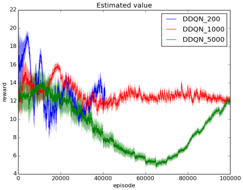


(d) Random



(e) Estimated value

Challenges

Observations:

- DQN takes a long time to start to rise (no feature learning)
- Best policy learned is suboptimal
- Sharp drop in score values - obtaining oscillating policy
- Average value is noisy and oscillating
- Learning error (TD) diverges
- DQN is very inconsistent

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Possible explanations:

- Continuous state space
- Physical model dynamics
- Lack of rewards

Exploration/Exploitation in Continuous Domains

- ϵ-greedy

$$a_t = \begin{cases} a_t^* & \text{with probability } 1-\epsilon \\ \text{random action} & \text{with probability } \epsilon \end{cases}$$

- Local Exploration

$$a_t = a_t^* + \mathcal{N}_t$$

$\mathcal{N}_t$ - temporally correlated random process

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- ϵ-greedy gets filtered in physical systems with inertia, the system functions as a low pass filter
- Local exploration needs to be around the optimum to work

Learning Guidance with On-line Demonstrations

- Combine knowledge with present experience mechanism for one stage learning
  1. With probability ϵ_p instruct the agent to act according to $\pi(s)$ for a **full episode**
  2. Store transitions in replay buffer for learning

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  1. With probability ϵ_p instruct the agent to act according to $\pi(s)$ for a **full episode**
  2. Store transitions in replay buffer for learning

- Acting scheme:
  with probability ϵ_p perform a guided episode

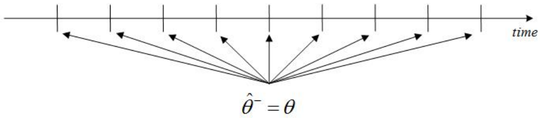
$$a_t = \pi_g(s_t)$$

with probability $1 - \epsilon_p$ act according to the E/E scheme

$$a_t = \begin{cases} \max_a Q(s_t, a) + \mathcal{N}_t & \textit{with probability } 1 - \epsilon \\ \textit{random action} & \textit{with probability } \epsilon \end{cases}$$

Fixed Target Update

- Samples in the replay buffer (dataset) are not stationary.
  - Fast updates can follow changes rapidly, but may diverge



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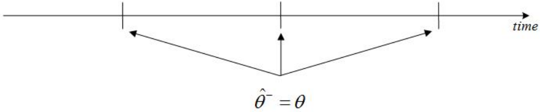

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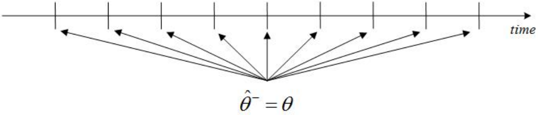

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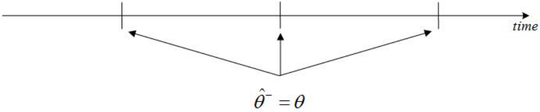
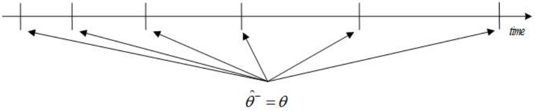


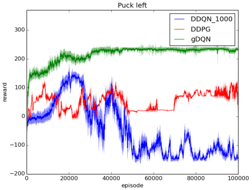
- Every update set: $C = C \cdot C_r, \quad C_r \geq 1$



  - C – update rate

Guided-DQN

GDQN, Double DQN and Deep Deterministic Policy Gradients (DDPG)



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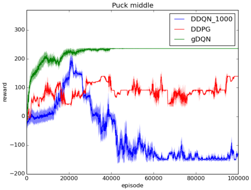

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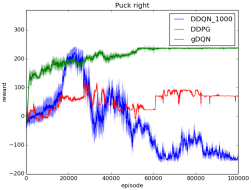

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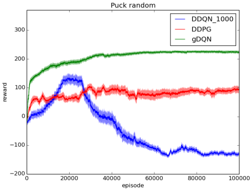

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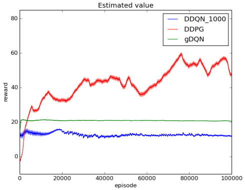
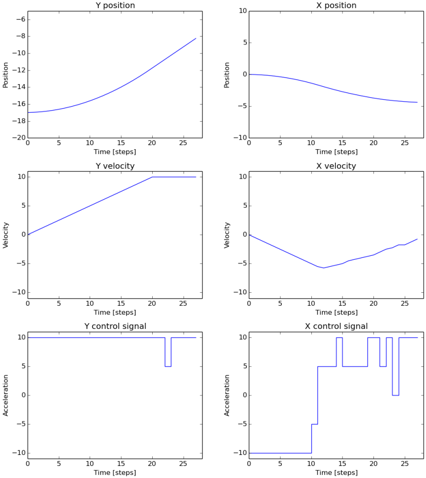
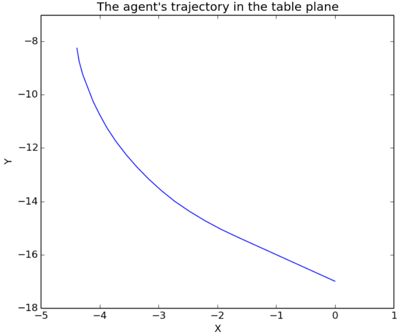


(e) Estimated value

Control Profile and Trajectory



(a) Profiles

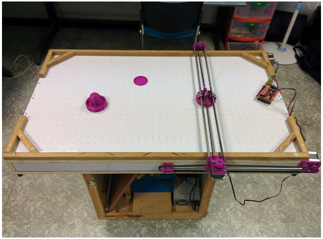


(b) Trajectory

OpenAI Striking Simulation

Summary

- Conclusion
  - Formalizing an optimal control problem as a learning problem.
  - Combining different methods of exploration.
  - Injecting prior knowledge into the exiting learning form experience framework.
  - Addressing the problem of non-stationarity in experience.
- Future Work
  - Extending the setting for a moving puck.
  - Extending the learning scheme for continuous actions.
  - Implementing the learning algorithm in physical environment.



Thats All Folks!

Thank You