Physics-Based Character Animation/Control with Deep Reinforcement Learning

Inria Center At Rennes University

Introduction

Physically capable agents have wide-ranging impacts:

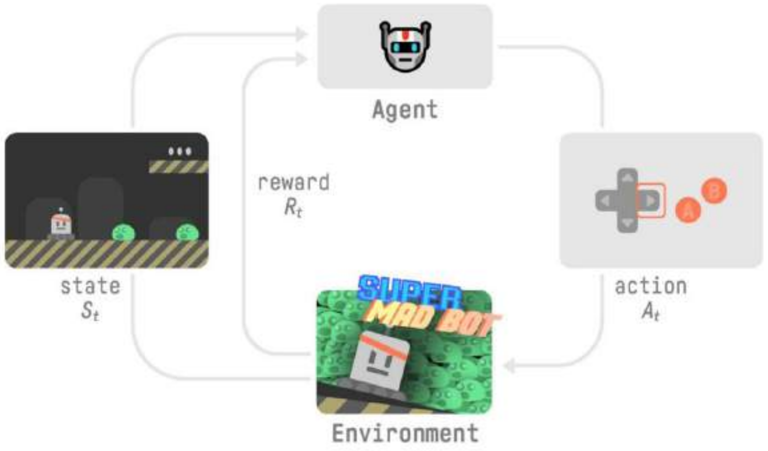
- Expanded Robot Operability: Human-like physical abilities for robots can extend operational domains beyond lab/factory settings into real-world challenging environments.
- Naturalistic Virtual Characters: Enhanced virtual character movements open doors for realistic graphics, eliminating artist intervention, and offering immersive user experiences.
- Biomechanics & Rehab: Advanced models of human motions support biomechanics studies, injury prevention, physiotherapy, customized prosthetics enhancing users' natural ranges of motion.

Peng Xue Bin, Acquiring Motor Skills Through Motion Imitation and Reinforcement Learning 2021

Notions on Reinforcement Learning

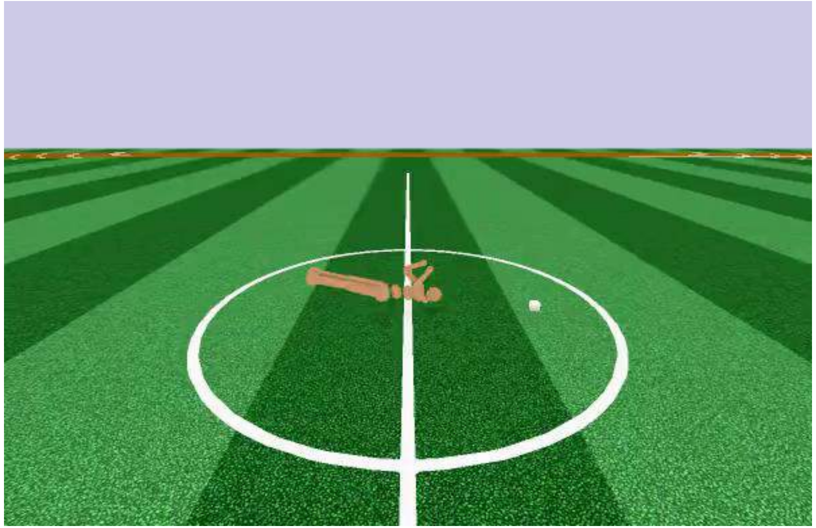
- An agent get observation of the state of the world, decides on an action to take. The environment changes when the agent acts on it.
- The agent perceives a reward signal from the environment, a scalar that tells how good or bad the current world state is after the previous action.

Goal: to maximize its cumulative reward.



Sutton, Richard S., and Andrew G. Barto. Reinforcement learning: An introduction. MIT press, 2018.

Use of Reinforcement Learning

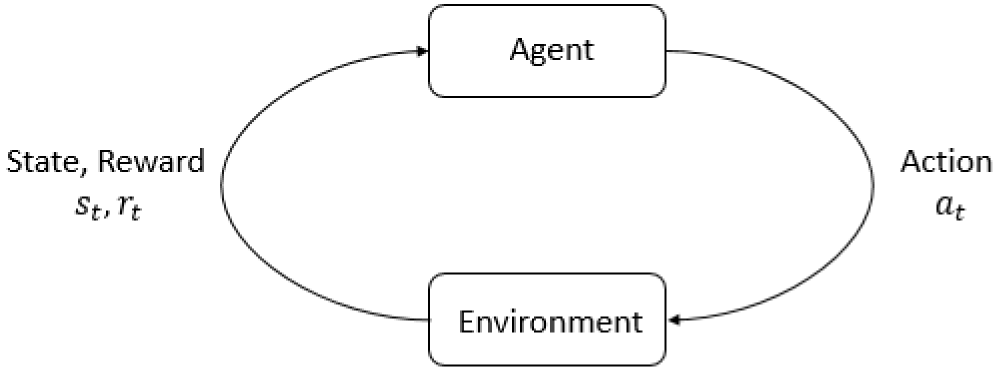


https://spinningup.openai.com/

https://humanoid-transformer.github.io/

Notions on Reinforcement Learning

- States and observations,
- Action spaces,
- Policy
- Trajectories
- Rewards and Return
- RL optimization



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Notions on Reinforcement Learning

States and observations:

- **State s**: Description of the entire World State, containing absolutely no hidden information. Knowledge of (s) enables the Agent to grasp the full context of the Environment without any uncertainties.
- **Observation o**: Fragmentary portrayal of the actual State. It offers limited insights compared to knowing the whole State.

Sutton, Richard S., and Andrew G. Barto. Reinforcement learning: An introduction. MIT press, 2018.

Notions on Reinforcement Learning

Action Spaces:

Various Environments accommodate diverse sets of feasible Actions.

- **Discrete Action Spaces**: In certain classic games, such as Atari or Go, the Agent utilizes a restricted collection of permissible Moves
- **Continuous Action Spaces**: Agent manipulates objects within Physical Worlds, Actions correspond to multidimensional Real-Valued Vectors.

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Notions on Reinforcement Learning

Policy:

- Guidelines directing an Agent to select Actions
- Two major classes: Deterministic & Stochastic

– **Deterministic Policies**

- Represented as: $\mu(s_t)$
- Generates constant Actions corresponding to a State (s_t)

Example: Automobile driving at fixed speed regardless of road conditions

– **Stochastic Policies**

- Denoted as: $\pi(\cdot \mid st)$
- Yields randomized Actions depending on a State (st)

Example: Autonomously deciding speed limits based on traffic flow probabilities

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Notions on Reinforcement Learning

Trajectories:

- Sequences of linked States & Actions in the Environment
- Ordered series of alternating States (s_t) & Actions (a_t): $\tau=(s_0, a_0, s_1, a_1, \ldots)$

- First State (s_0) drawn randomly from initial state distribution, denoted as ρ_0:

$$s_0 \sim \rho_0(\cdot)$$

Transition Dynamics:

- Deterministic: st+1=f(st, at)
- Stochastic: st+1~P(·|st, at)

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