Hands on: Reinforcement Learning

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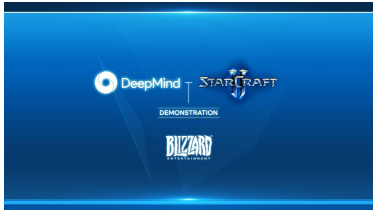
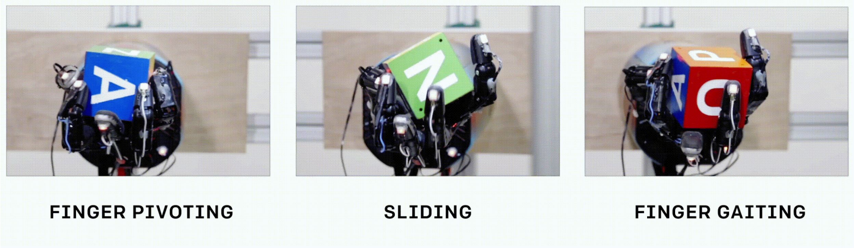
Agenda

- Motivation
- Introduction to Reinforcement Learning (RL)
- Policy Gradient Methods
- RL in 100 Lines of Code
- Additional Resources

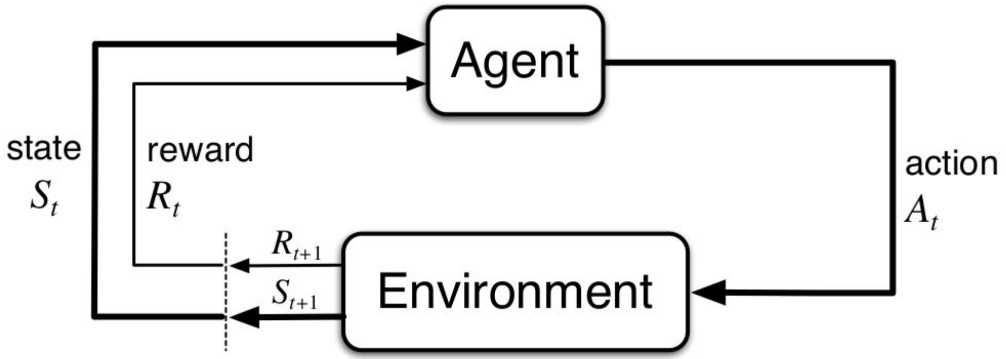
Motivation





https://deepmind.com/research/alphago/
https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/
https://openai.com/five/
https://ai.googleblog.com/2019/01/soft-actor-critic-deep-reinforcement.html
https://openai.com/blog/learning-dexterity/

Introduction to RL



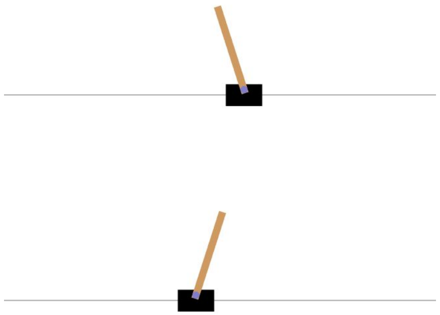
Reinforcement Learning: An Introduction (Sutton and Barto, 2018)

- Given a certain **state** within the environment the agent acts/chooses an action according to a **policy**
- The environment reacts to the action and returns a new state and a **reward**

Understanding the Policy

- Agent learns a policy $\pi(a \mid s)$
- Goal: find an optimal policy to maximize the performance of the agent i.e. get as much reward as possible (optimization problem)

Current state s



$\pi(a \mid s)$	
Push to left	Push to right
0.8	0.2
0.25	0.75

Understanding Rewards

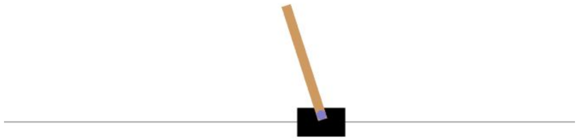
- Our goal is to get as much reward as possible
- Defined by the (discounted) return

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

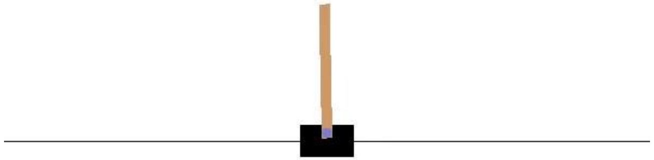
- Discounting between [0, 1]
  - < 1 keeps the sum finite (mathematical convenience)
  - Trade-off between influence of immediate and future rewards

Understanding the State-Value

- State-value function $v(s) = \mathbb{E}\big[G_t \mid S_t = s\big]$



Close to failure, we do not **expect** to get that much future reward



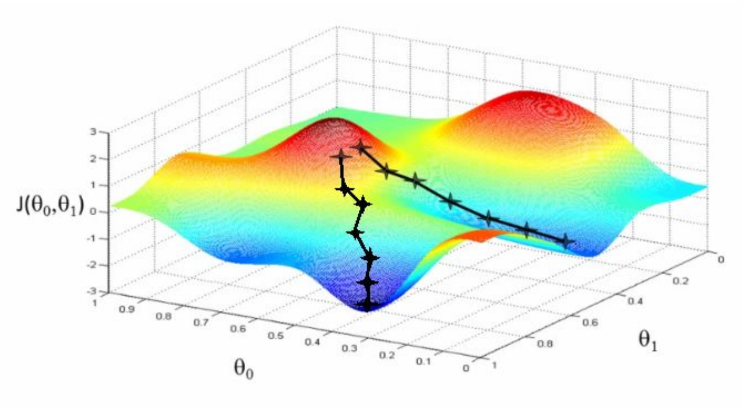
Perfect, we **expect** lots of future reward

Policy Gradient Methods

- Policy is parameterized $\pi(a \mid s; \boldsymbol{\theta})$ (e.g. with a neural network)
- Differentiability allows us to perform stochastic gradient ascend
- REINFORCE (Williams, 1992)

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \alpha G_t \frac{\nabla \pi(A_t \mid S_t; \boldsymbol{\theta}_t)}{\pi(A_t \mid S_t; \boldsymbol{\theta}_t)}$$

- State-of-the-art methods also often learn a state-value function $v(s; \boldsymbol{\theta}_v)$



http://blog.datumbox.com/tuning-the-learning-rate-in-gradient-descent/

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Policy Gradient Methods

REINFORCE: Monte-Carlo Policy-Gradient Control (episodic) for π_*

Input: a differentiable policy parameterization $\pi(a|s, \boldsymbol{\theta})$
Algorithm parameter: step size $\alpha > 0$
Initialize policy parameter $\boldsymbol{\theta} \in \mathbb{R}^{d'}$ (e.g., to $\mathbf{0}$)

Loop forever (for each episode):
    Generate an episode $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$, following $\pi(\cdot|\cdot, \boldsymbol{\theta})$
    Loop for each step of the episode $t = 0, 1, \ldots, T-1$:
        $G \leftarrow \sum_{k=t+1}^{T} \gamma^{k-t-1} R_k$ $\quad (G_t)$
        $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha \gamma^t G \nabla \ln \pi(A_t|S_t, \boldsymbol{\theta})$

Reinforcement Learning: An Introduction (Sutton and Barto, 2018)

RL in 100 Lines of Code

Additional Resources

- Two courses on RL at JKU
  - WS: Special Topics: Reinforcement Learning (CP)
  - SS: Special Topics: Deep Reinforcement Learning (ML)

- Online Resources:
  - David Silver's lecture at UCL
  - Deep Reinforcement Learning UC Berkeley
  - Deep RL Bootcamp
  - OpenAI's Spinning up in Deep RL

- Reinforcement Learning: An Introduction (Sutton and Barto, 2018)

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