Reinforcement Learning

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Sharif University of Technology

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Hossein Hasani

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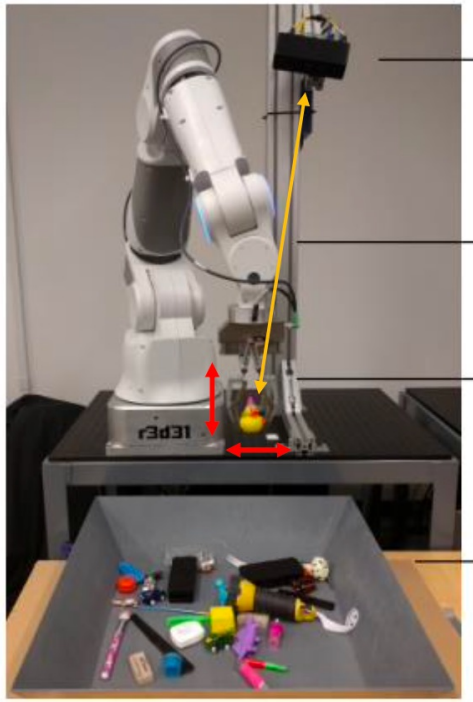
Courtesy: Some slides are adopted from CS 285 Berkeley, and CS 234 Stanford, and Pieter Abbeel's compact series on RL.

Motivation

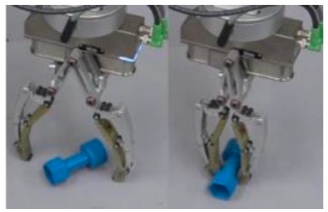
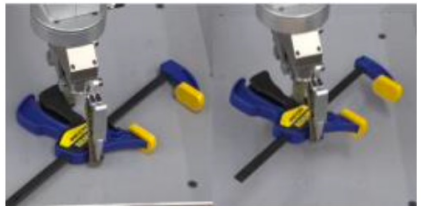
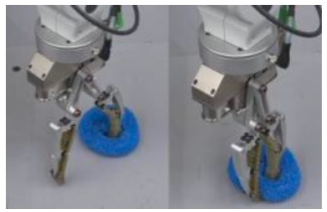


?

(x, y, z)

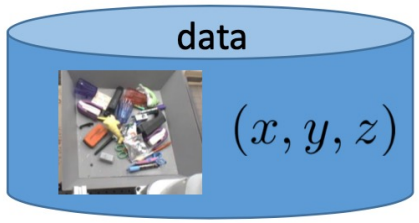
Option 1:

Understand the problem, design a solution

Option 2:

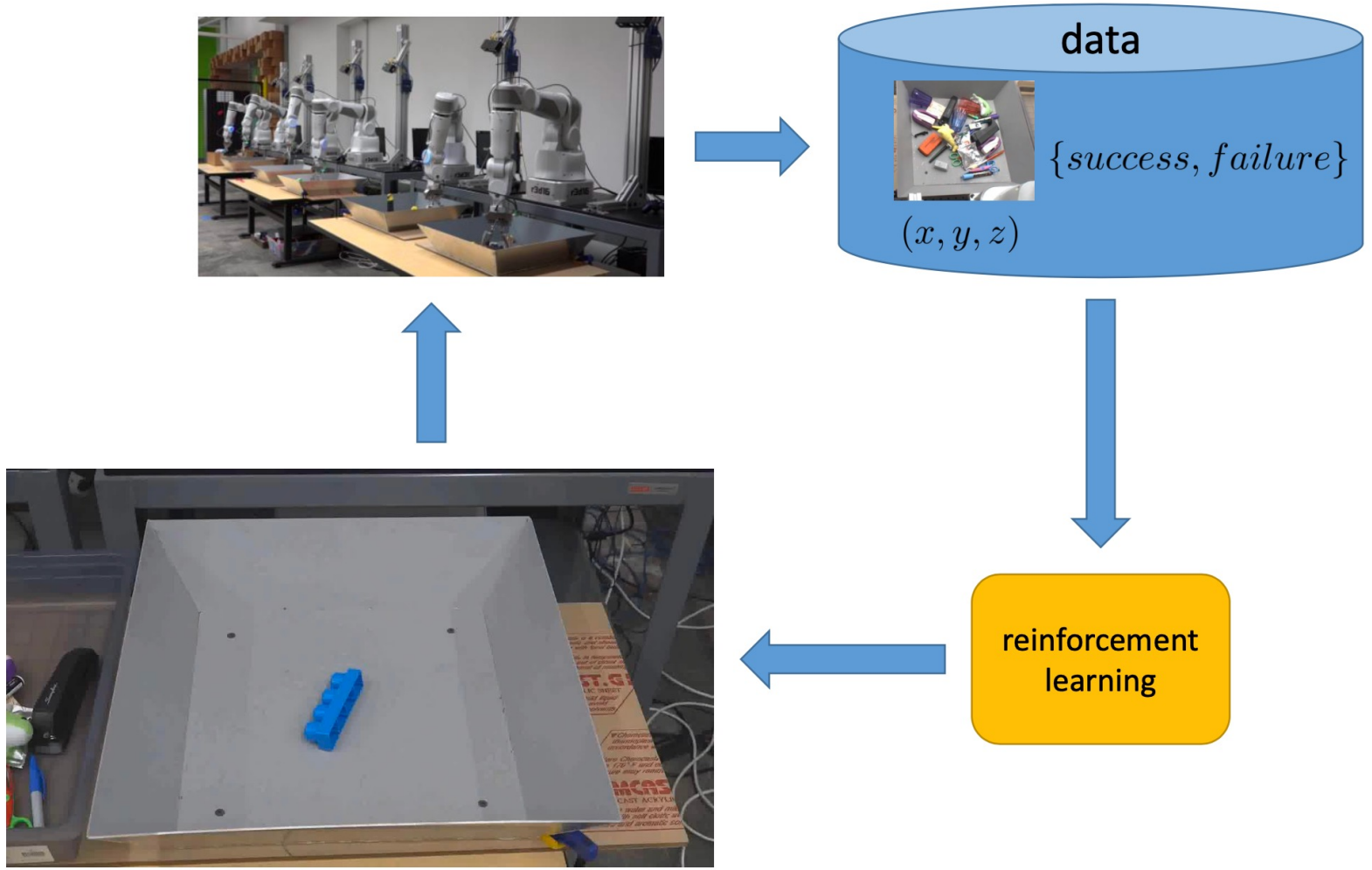
Set it up as a machine learning problem



supervised learning

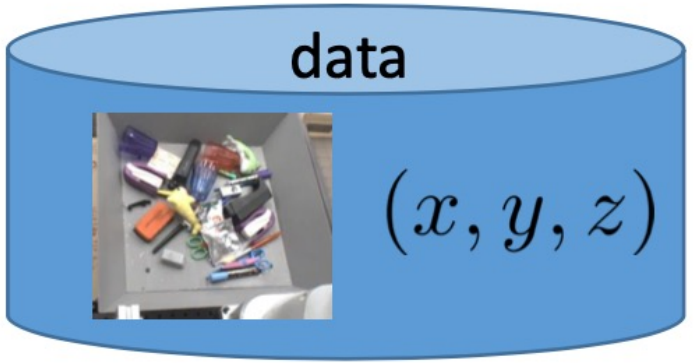
Motivation (cont.)

Motivation (cont.)

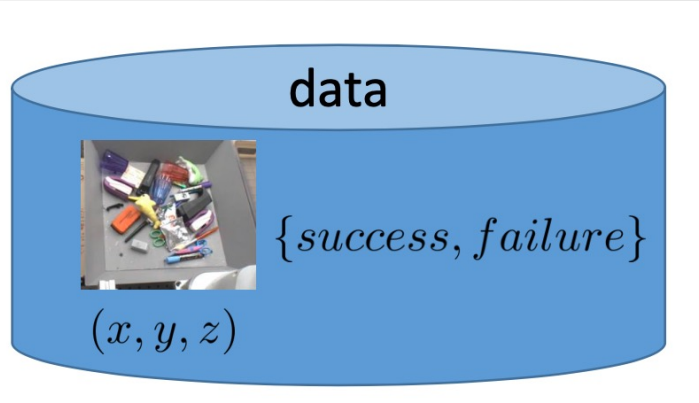


Motivation (cont.)

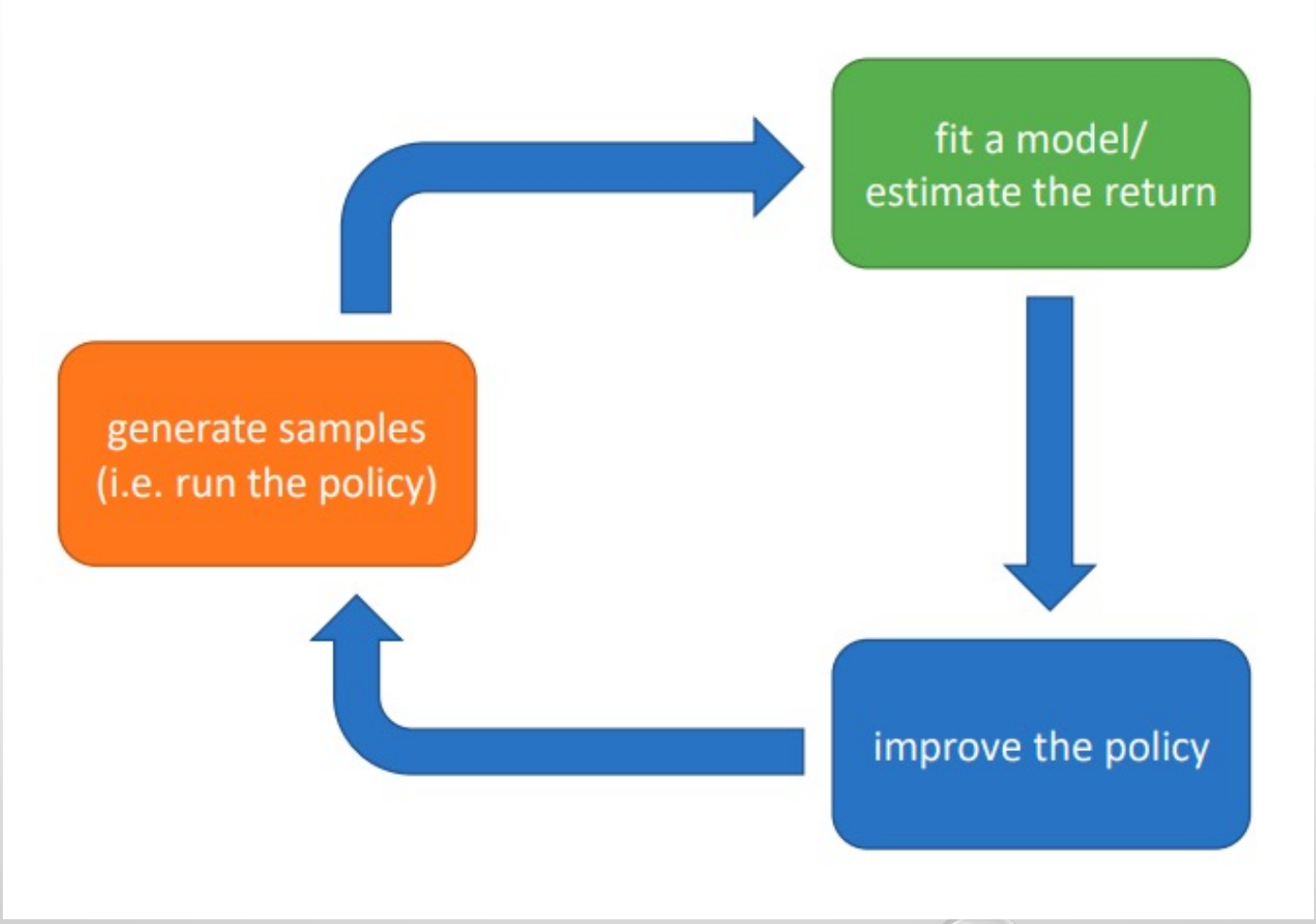
- Supervised learning:
  - Ground truth is known in advance.
  - Training data are usually static and iid.



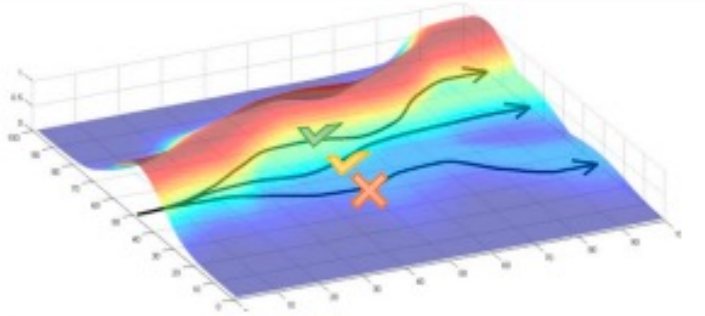
- Reinforcement learning:
  - The best action (**policy**) is usually unknown a priori.
  - Sequence of actions is needed.
  - A series of trial and error (search) is performed.
    - Usually delayed **reward** shows goodness of the trial.
  - Data is dynamic (**exploration**) and non-iid.

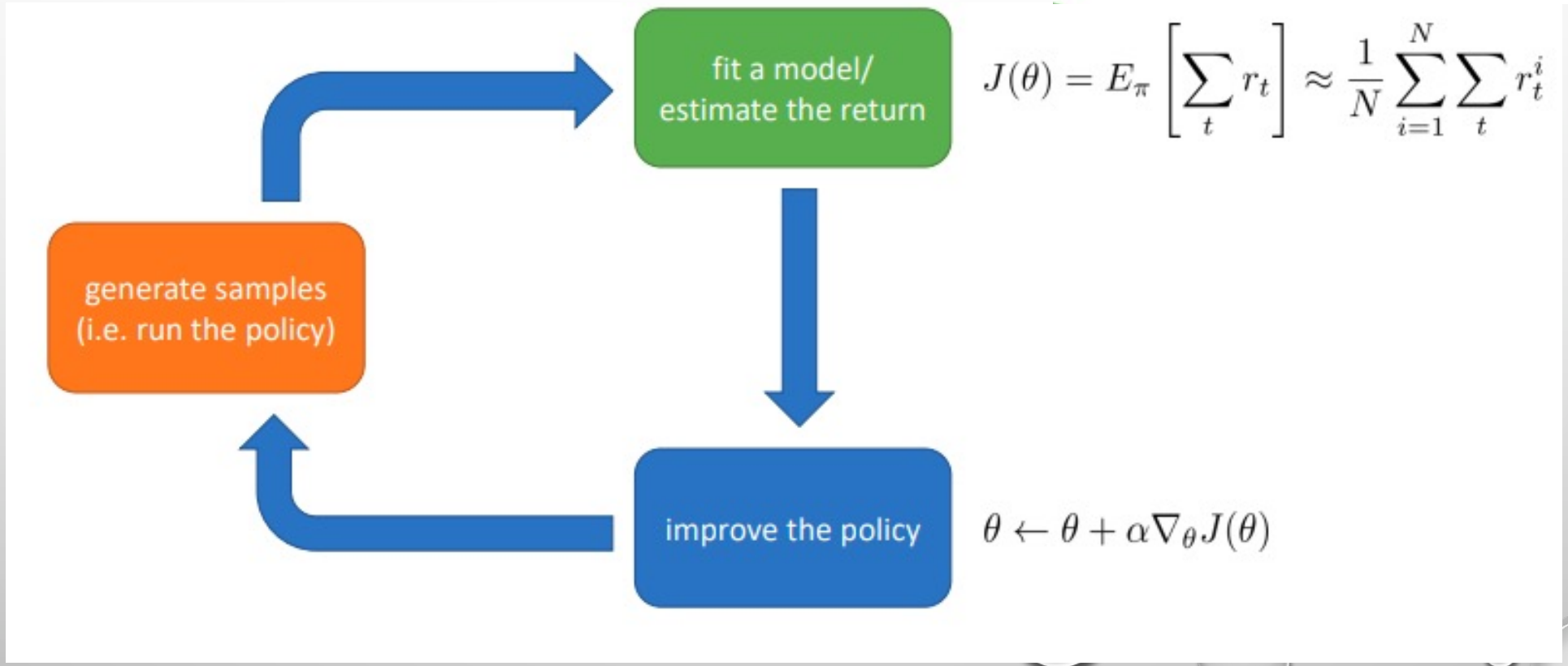


The Anatomy of Reinforcement Learning



A Simple Example





$$J(\theta) = E_\pi \left[\sum_t r_t \right] \approx \frac{1}{N} \sum_{i=1}^{N} \sum_t r_t^i$$

$$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$$

Motivation (cont.)

	AI Planning	SL	UL	RL	IL
Optimization	X			X	X
Learns from experience		X	X	X	X
Generalization	X	X	X	X	X
Delayed Consequences	X			X	X
Exploration				X	

- SL = supervised learning; UL = unsupervised learning; RL = reinforcement learning; IL = imitation learning
- Imitation learning typically assumes input demonstrations of good policies
- IL reduces RL to SL. IL + RL is promising area

Planning vs learning

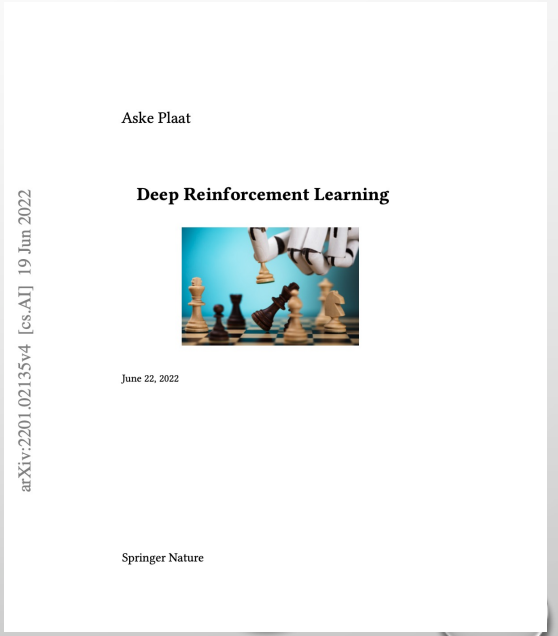
- Two fundamental problems in sequential decision making
  - Reinforcement learning:
    - The environment is initially unknown
    - The agent interacts with the environment
    - The agent improves its policy
  - Planning:
    - A model of the environment is known
    - The agent performs computations with its model (without any external interaction)
    - The agent improves its policy
    - A.K.A. Deliberation, reasoning, introspection, pondering, thought, search

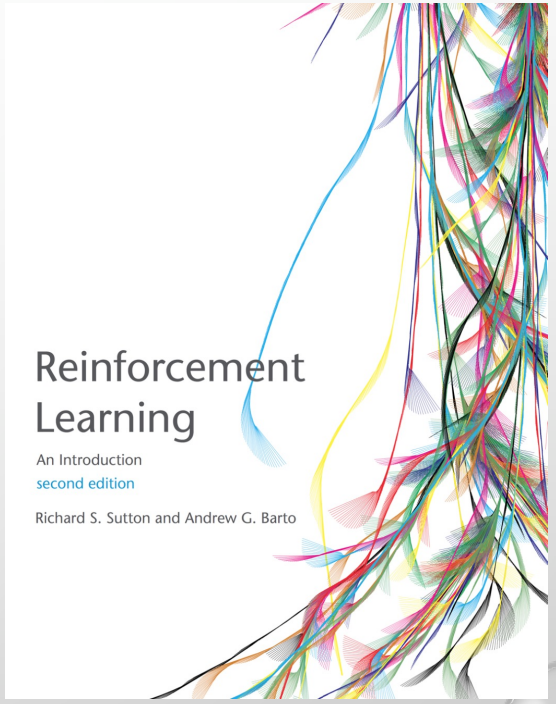
Prerequisites

- Stochastic Processes
  - Basic Probability and Statistics (Expectation, Conditional Prob. and Expectation, …)
  - Estimation Theory (Max Likelihood Estimation, Bayesian Estimation, Monte Carlo Simulation)
  - Bayesian Networks and Markov Chains
  - Basic sampling methods
  - Variational Inference
- Basic Information Theory
  - Entropy, Mutual Information, KL Divergence
- Programming in Python
- Deep Learning (concepts and practice; PyTorch)

References

- Reinforcement Learning: An Introduction by R. Sutton and A. Barto, 2nd Edition, 2020.
- Deep Reinforcement Learning by A. Plaat, 2022.
- Original papers of some methods.

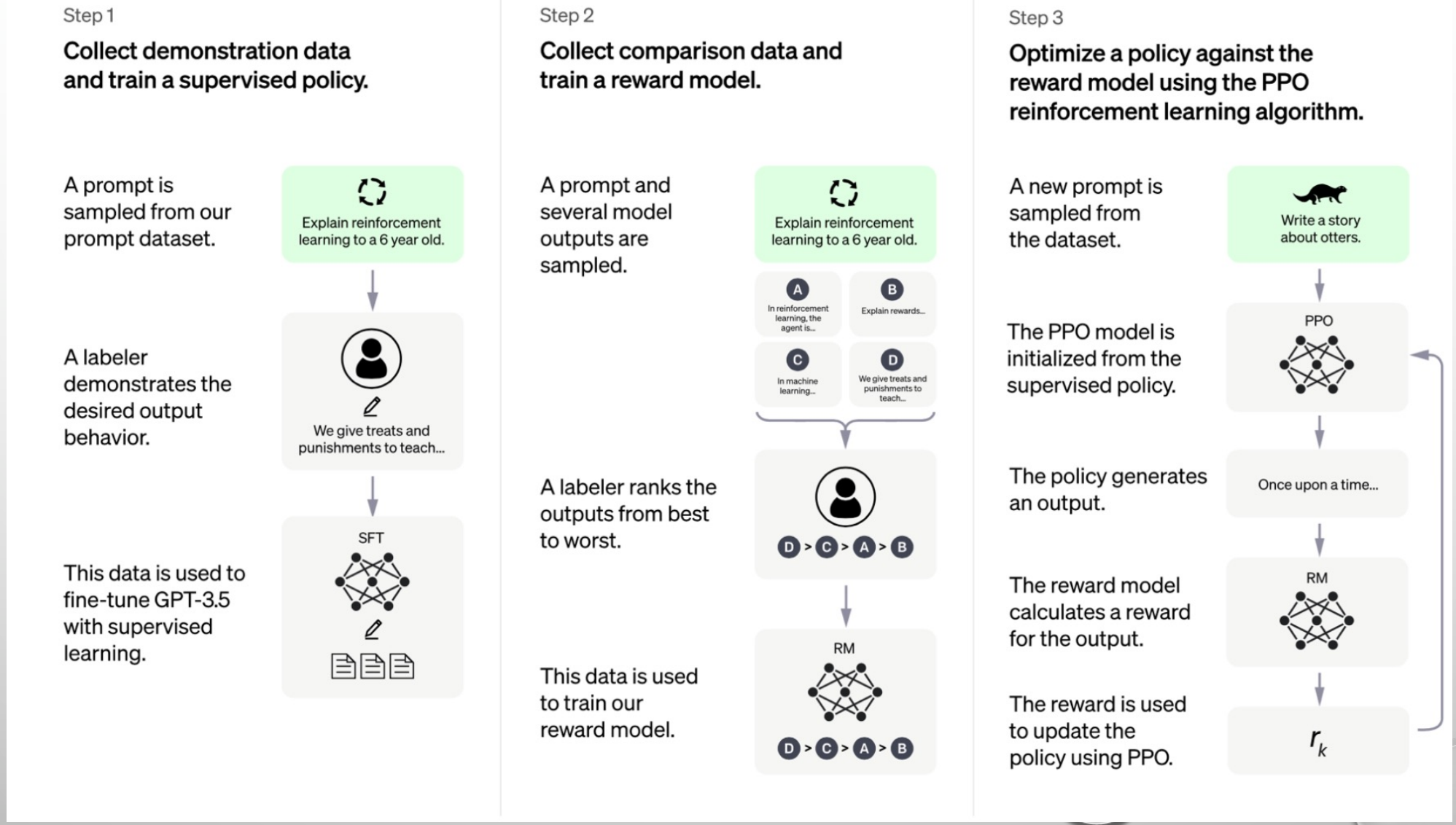




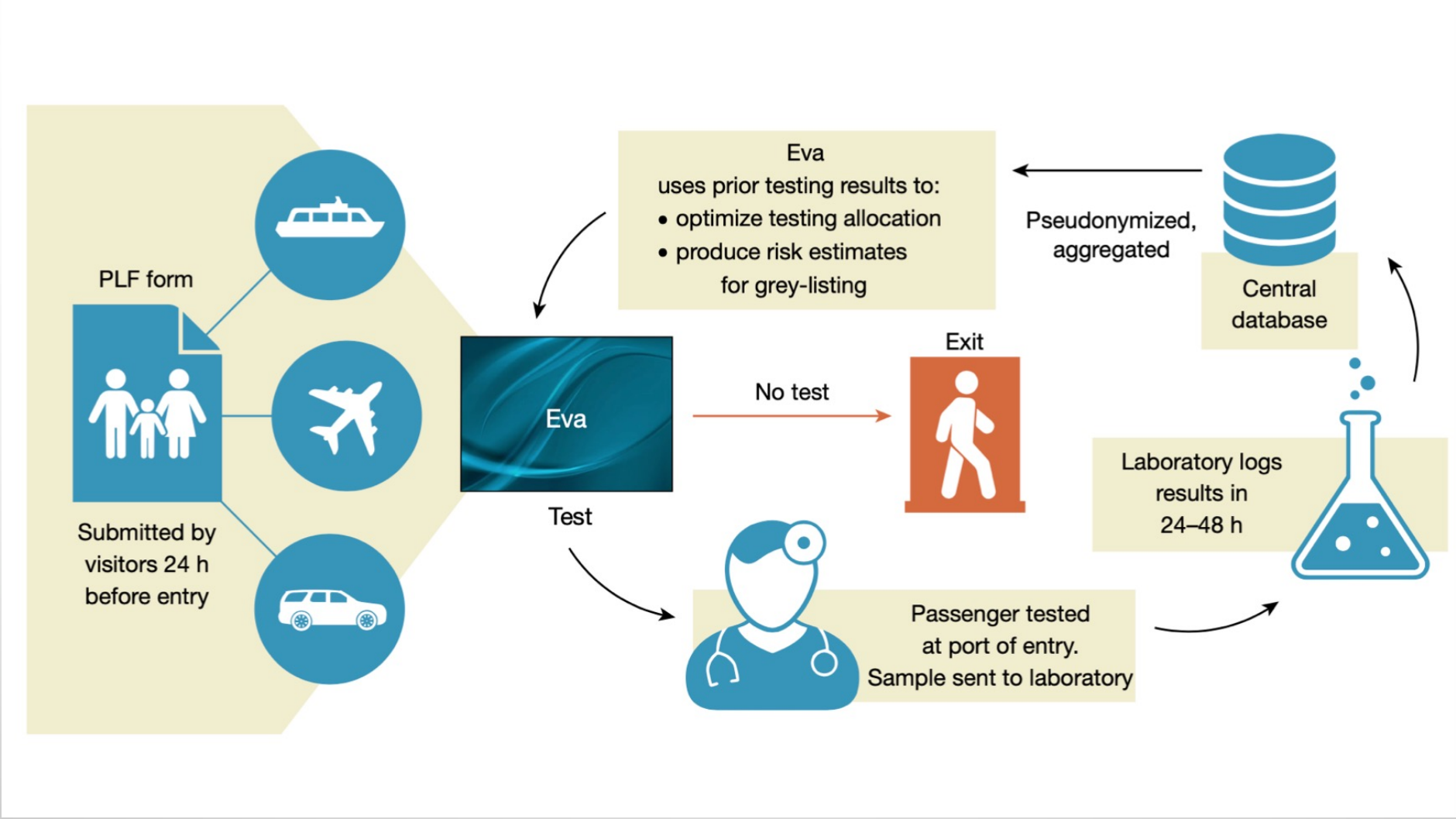
Teaching Assistants

- Negin Hashemi (Head TA)
- Roozbeh Razavi
- Sepehr Ghobadi
- Hossein Khalili
- Mohammad Mozafari
- Parsa Haghighi
- Soroush Vafaei Tabar
- Mohammad Mousavi
- Ali Kahe
- Aida Afshar
- Amir Mesbah
- Kiana Asgari
- Seyed Abolfazl Rahimi
- Bardia Mohammadi

Motivation (cont.) ChatGPT; Why RL?!



Motivation (cont.)

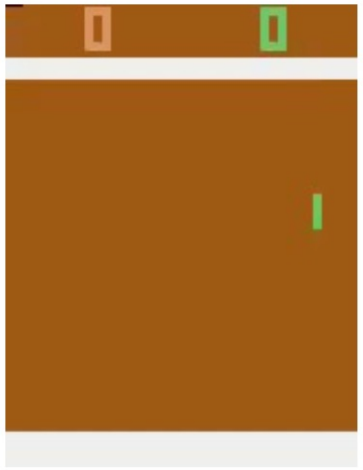


- https://www.nature.com/articles/s41586-021-04014-z

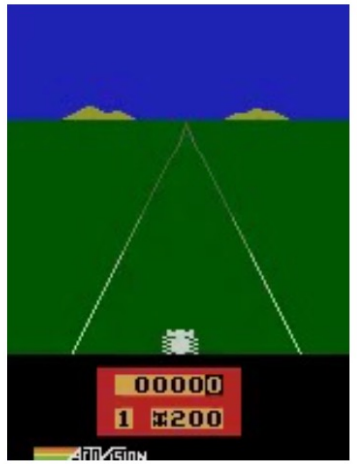
History

2013

Atari (DQN)
[Deepmind]

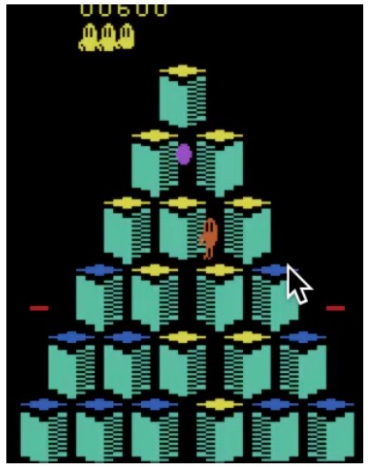


Pong



Enduro

Beamrider

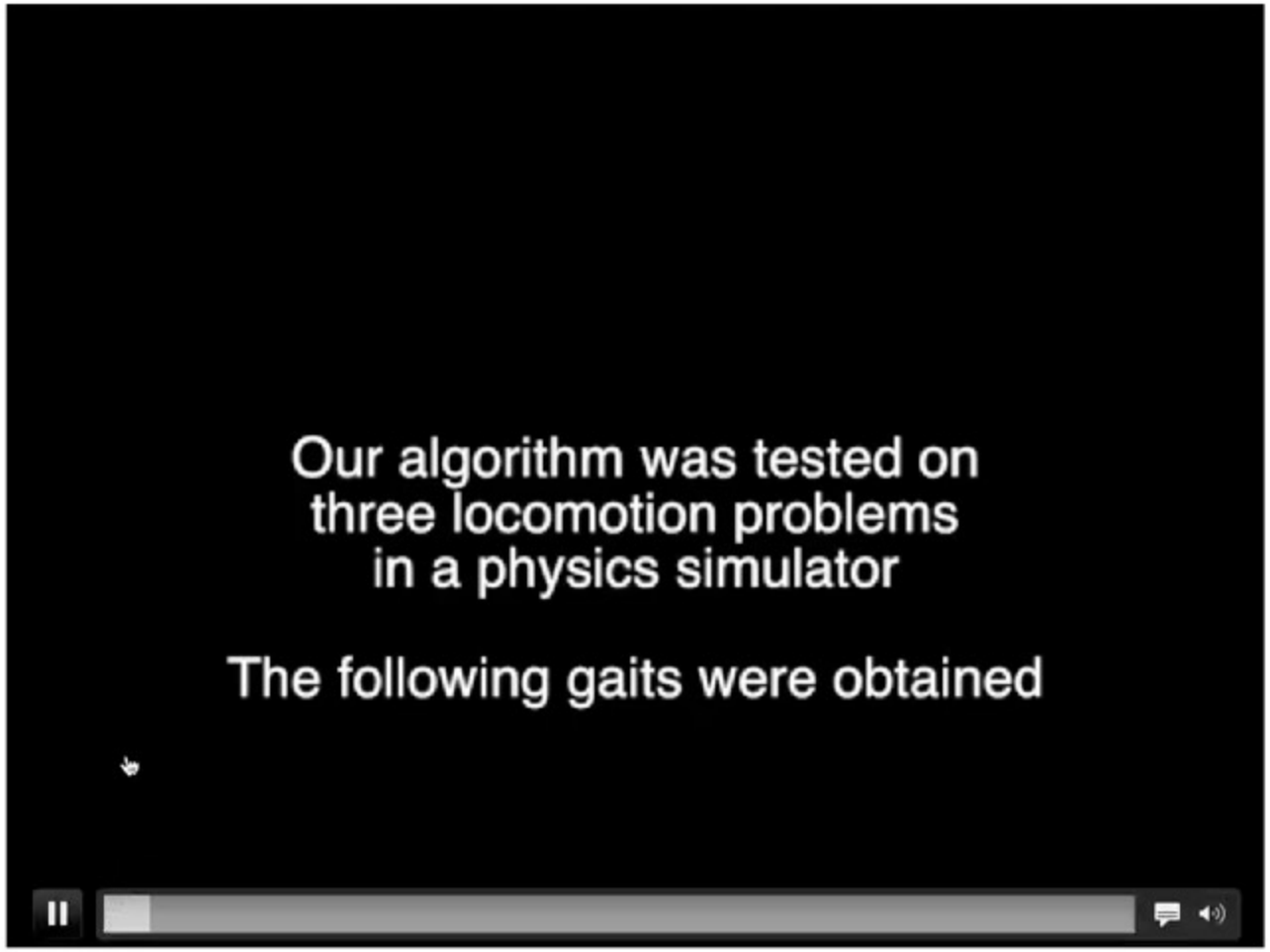


Q*bert

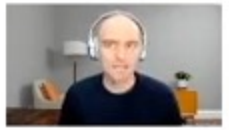
A Few Deep RL Highlights

2013 Atari (DQN) [Deepmind]

2014 2D locomotion (TRPO) [Berkeley]



Play 0:06 – 0:25



History

2013	Atari (DQN) [Deepmind]
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2015	**AlphaGo [Deepmind]**

Tian et al, 2016; Maddison et al, 2014; Clark et al, 2015

A Few Deep RL Highlights

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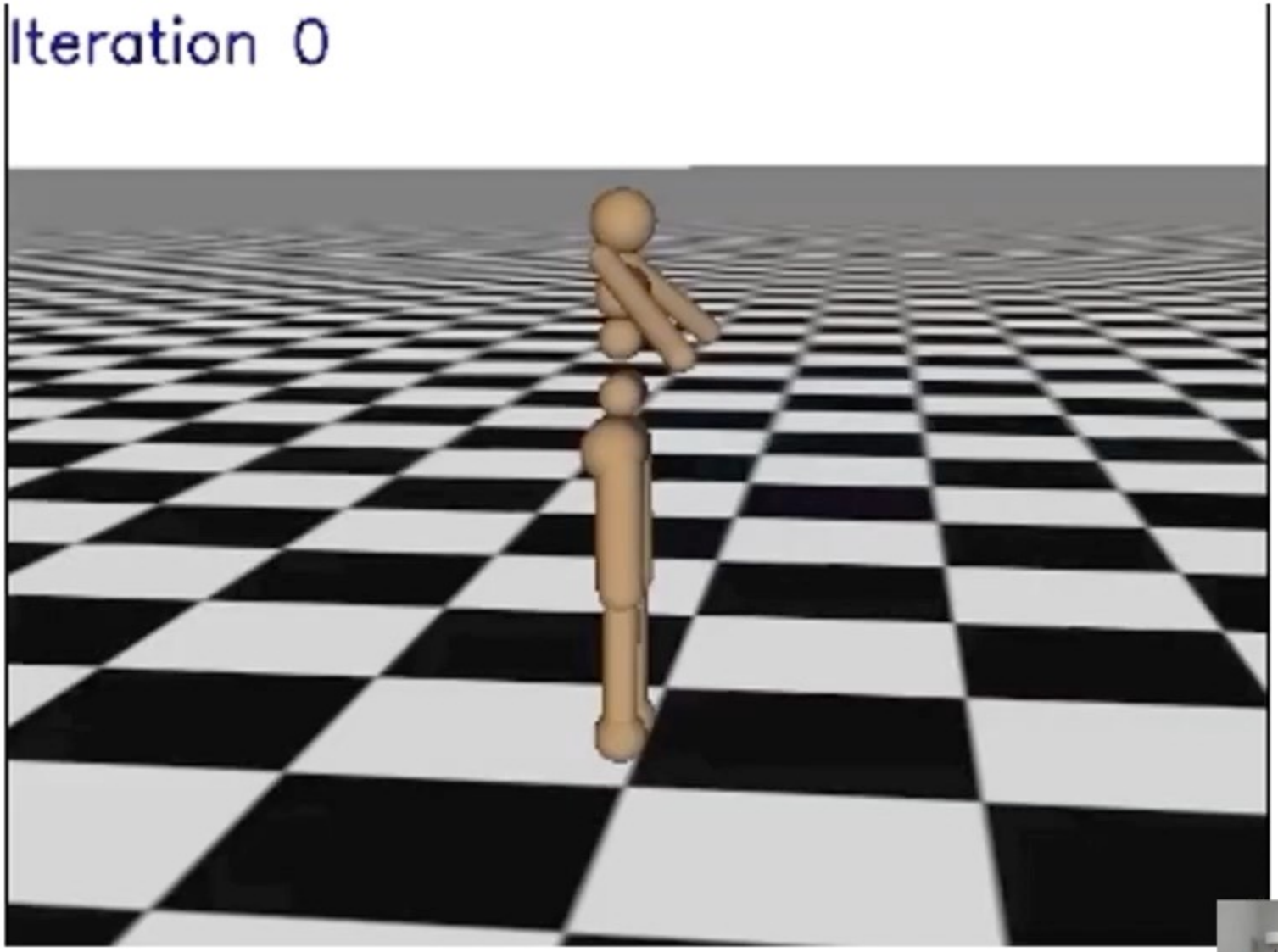
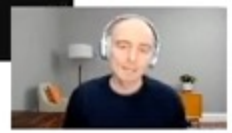


[Schulman, Moritz, Levine, Jordan, Abbeel, ICLR 2016]



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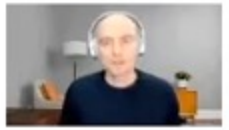
2016	**Real Robot Manipulation (GPS) [Berkeley]**

[Levine*, Finn*, Darrell, Abbeel, JMLR 2016]



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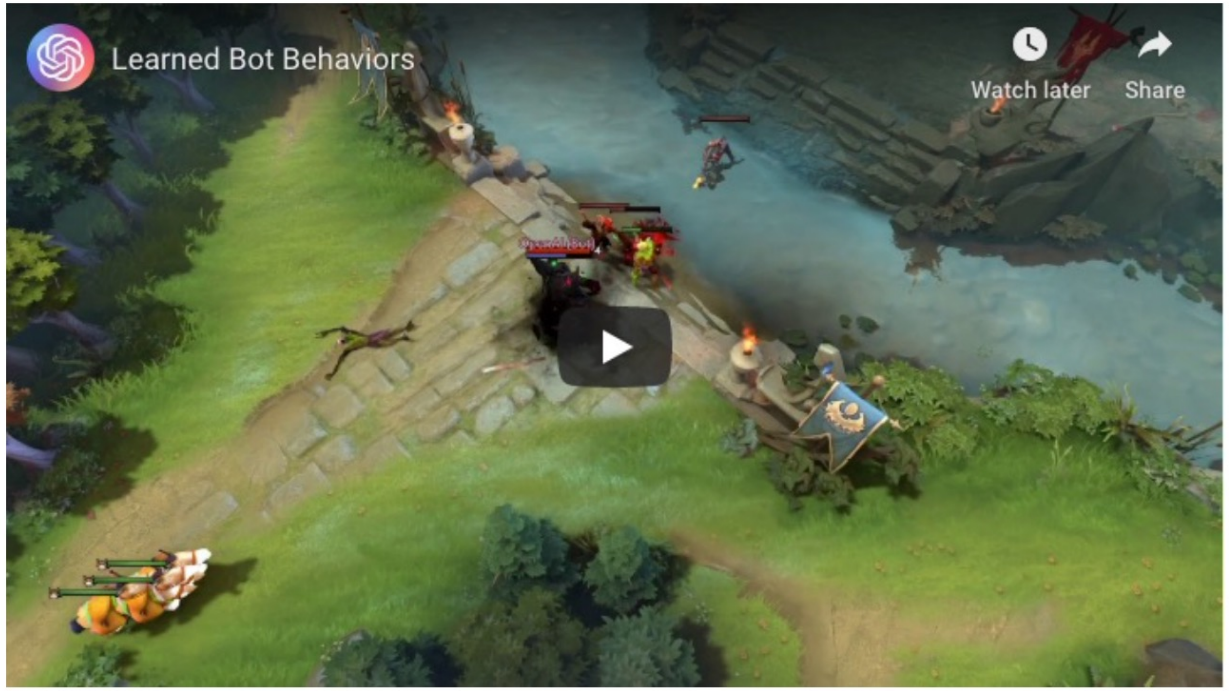
2017	**Dota2 (PPO) [OpenAI]**



OpenAI Dota Bot beat best humans 1:1 (Aug 2018)

A Few Deep RL Highlights

2013 Atari (DQN) [Deepmind]

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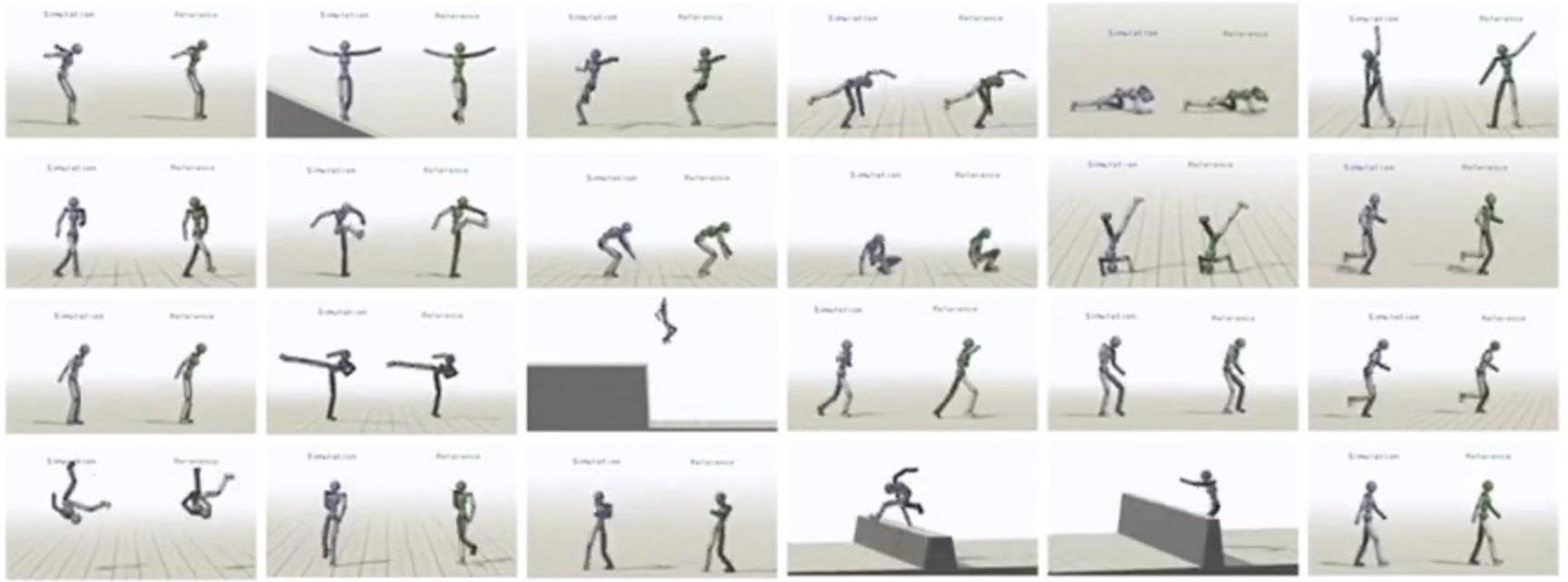
2016 3D locomotion (TRPO+GAE) [Berkeley]

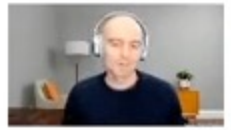
2016 Real Robot Manipulation (GPS) [Berkeley, Google]

2017 Dota2 (PPO) [OpenAI]

2018 DeepMimic [Berkeley]



[Peng, Abbeel, Levine, van de Panne, 2018]



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2019	**AlphaStar [Deepmind]**

A Few Deep RL Highlights

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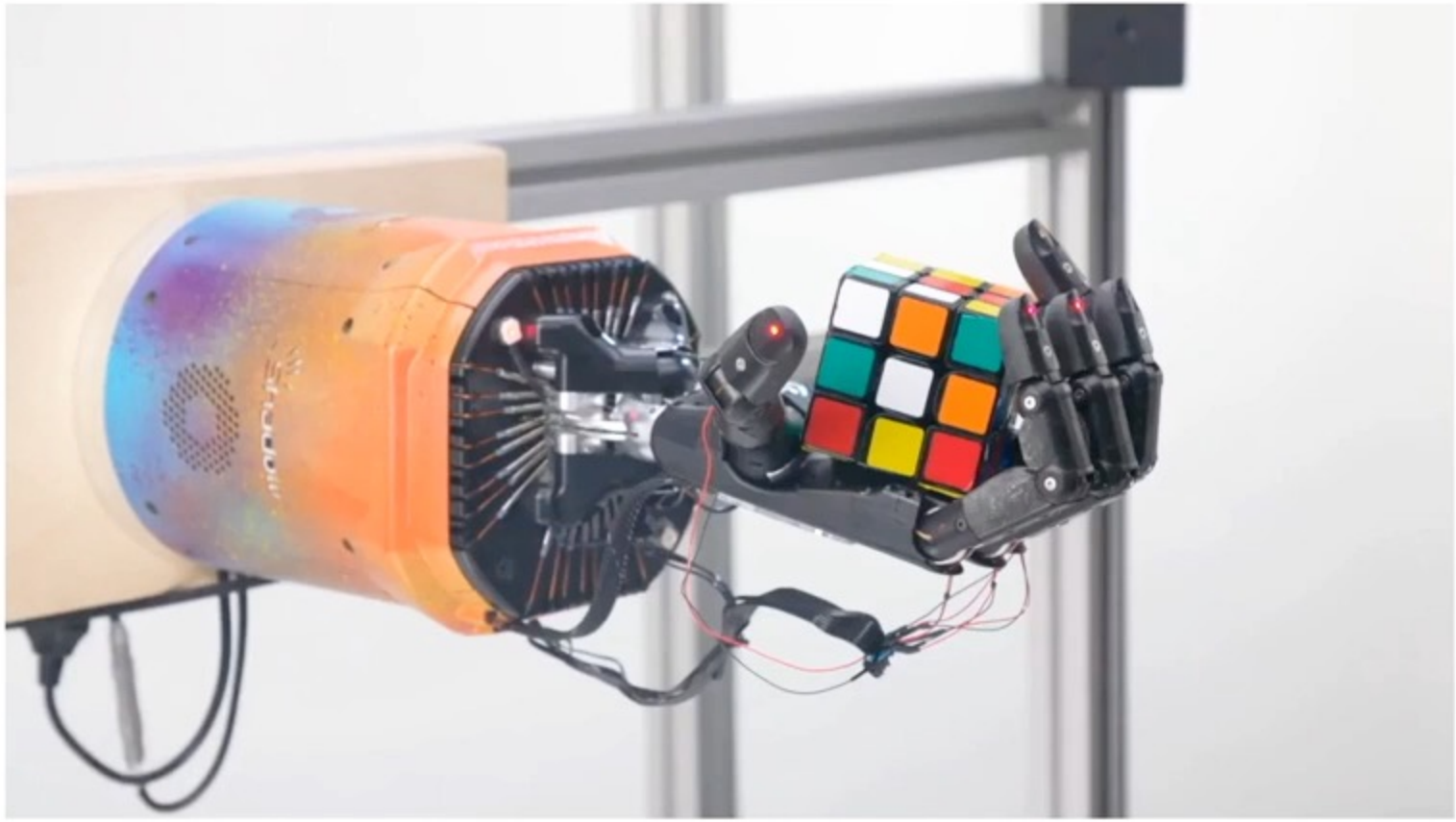
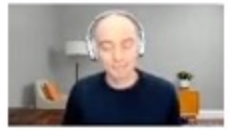
2018	DeepMimic [Berkeley]
2019	AlphaStar [Deepmind]
2019	**Rubik's Cube (PPO+DR) [OpenAI]**

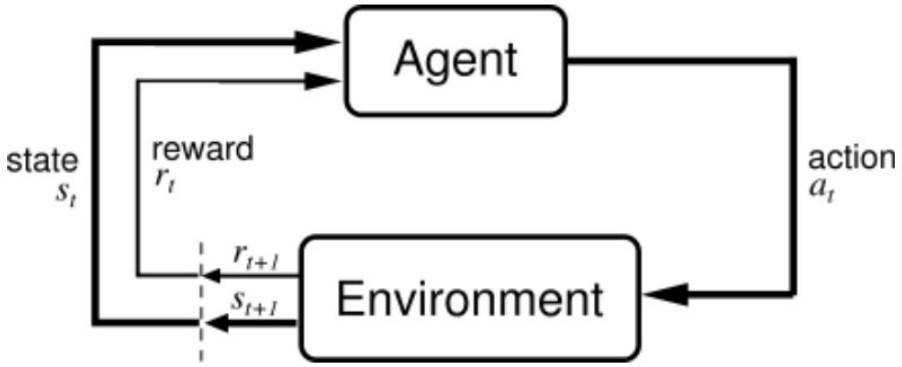




Let's Begin: Markov Decision Processes (MDPs)

An MDP is defined by:

- Set of states S
- Set of actions A
- Transition function $P(s' \mid s, a)$
- Reward function $R(s, a, s')$
- Start state s_0
- Discount factor γ
- Horizon H



The Goal

- The policy is $\pi_\theta : S \to A$ for infinite horizon or

  $\pi_\theta : S \times \{0, \dots, H\} \to A$ for finite horizon MDP.

MDP (S, A, T, R, γ, H), goal: $max_\pi \mathrm{E}[\sum_{t=0}^{H} \gamma^t R(S_t, A_t, S_{t+1}) | \pi]$

Sometimes the policy could be stochastic: $\pi : S \times A \to [0,1]$, which is

$\pi(a|s) = \Pr(A_t = a | S_t = s)$.

Example: Grid World

An MDP is defined by:

- Set of states S
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- Reward function $R(s, a, s')$
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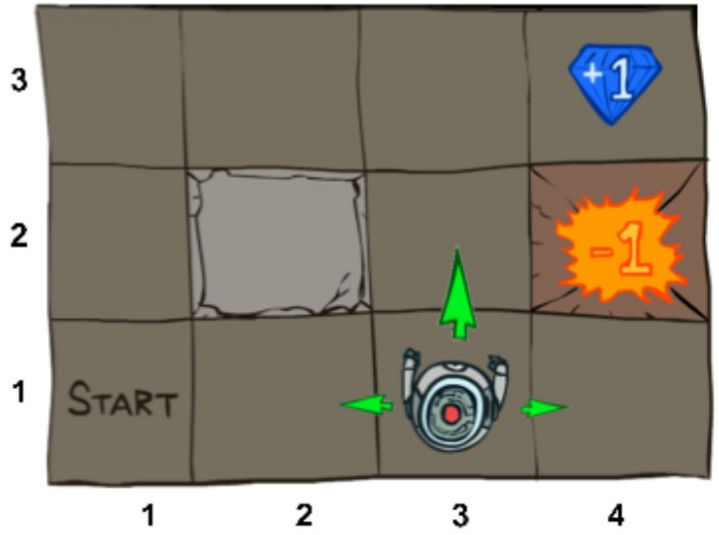
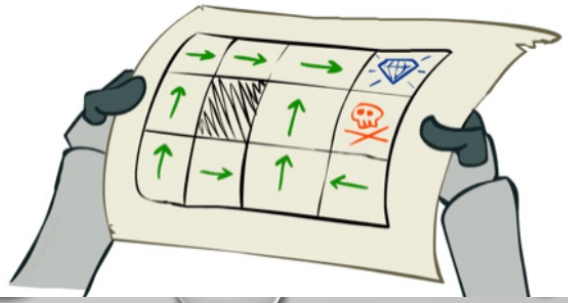
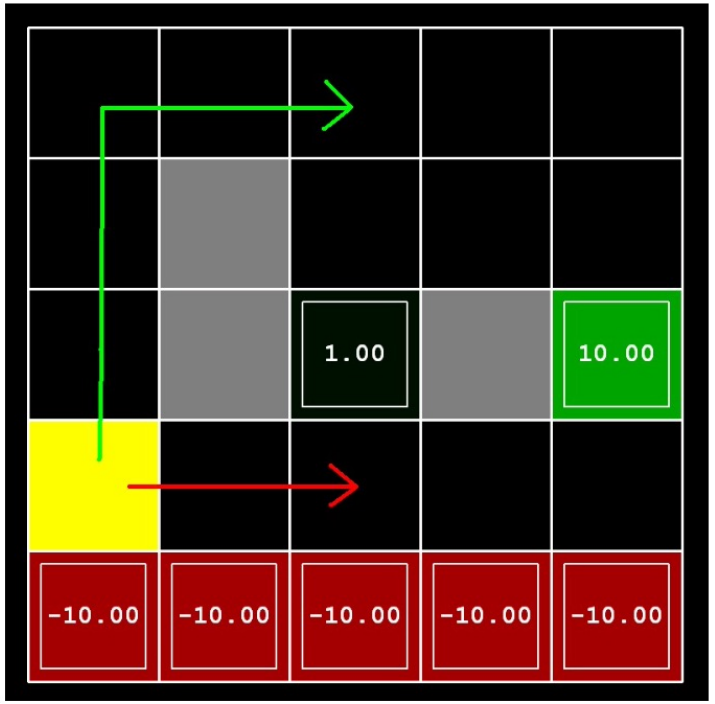


Goal: $$max_\pi \mathrm{E}[\sum_{t=0}^{H} \gamma^t R(S_t, A_t, S_{t+1}) | \pi]$$

π:



Exercise



(a) Prefer the close exit (+1), risking the cliff (-10)

(b) Prefer the close exit (+1), but avoiding the cliff (-10)

(c) Prefer the distant exit (+10), risking the cliff (-10)

(d) Prefer the distant exit (+10), avoiding the cliff (-10)

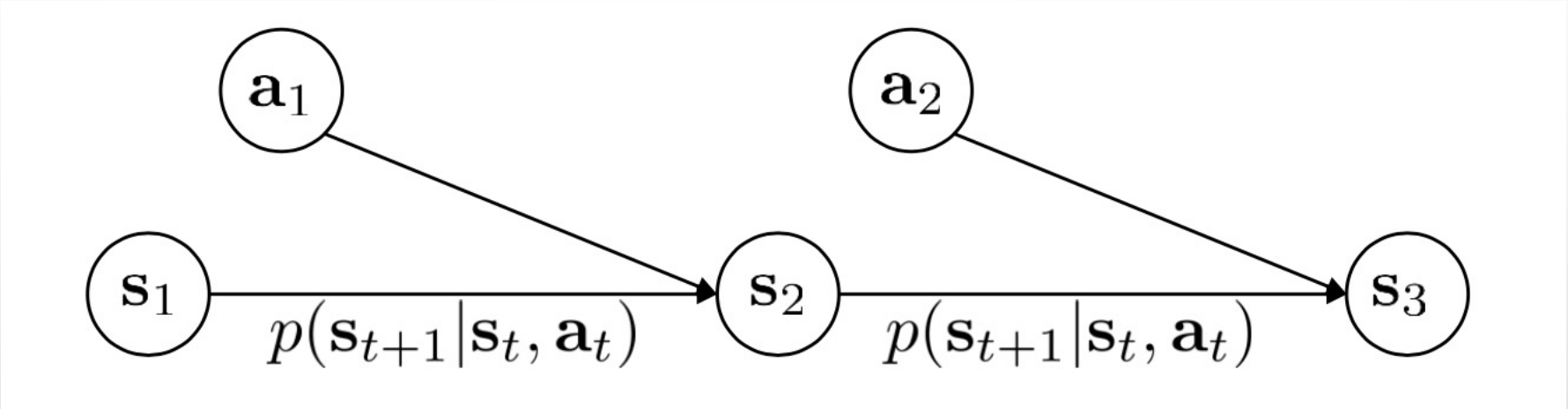
(1) $\gamma = 0.1$, noise = 0.5

(2) $\gamma = 0.99$, noise = 0

(3) $\gamma = 0.99$, noise = 0.5

(4) $\gamma = 0.1$, noise = 0

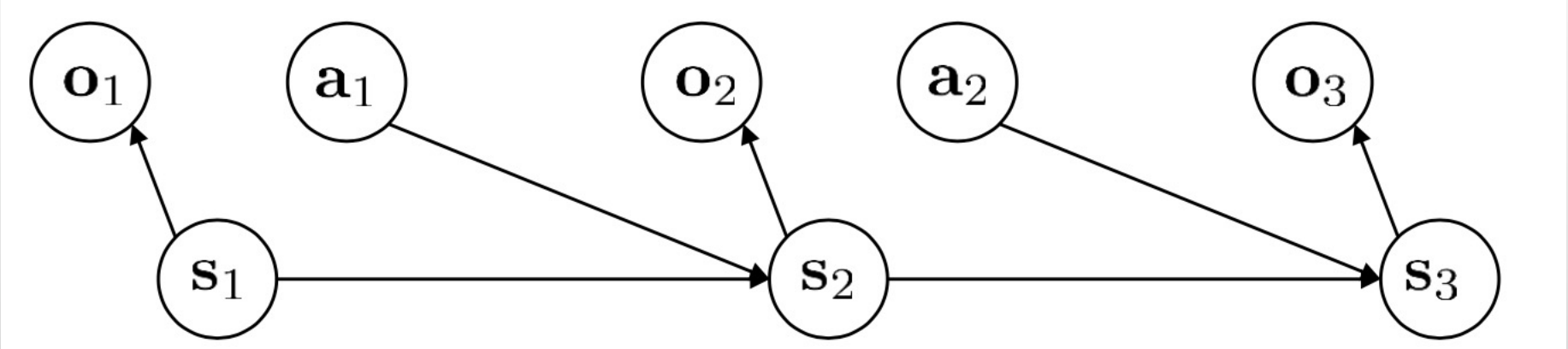
Graphical Model of MDPs



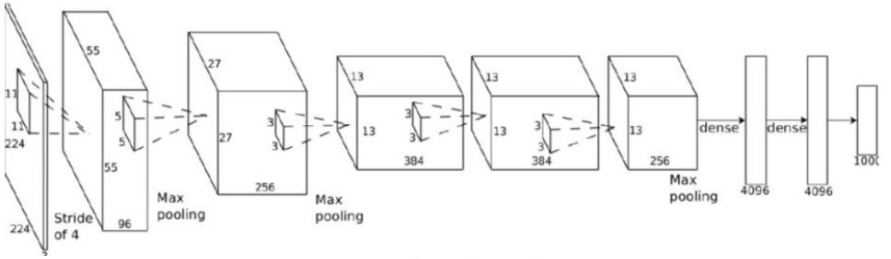
Partially Observable MDPs (POMDPs)

- Often times the state S_t is hidden from the agent,

  and only noisy or incomplete measurement of it is available O_t.



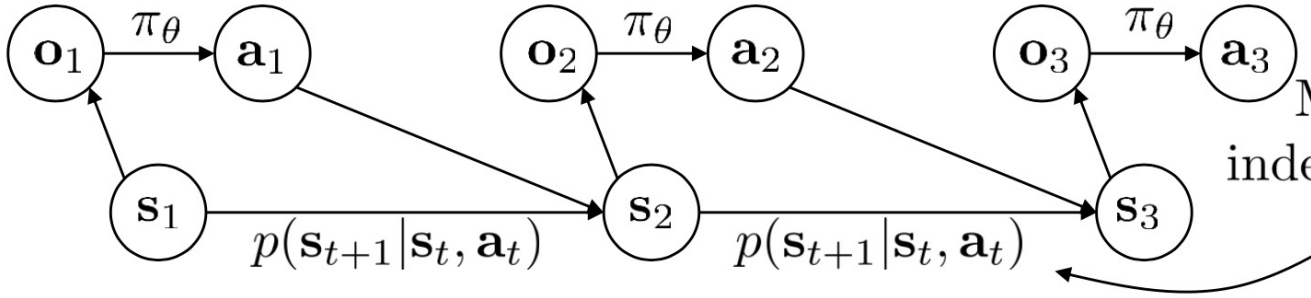
Policy as a function of S_t or O_t



$\mathbf{o}_t$ $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ $\mathbf{a}_t$

$\mathbf{s}_t$ – state
$\mathbf{o}_t$ – observation
$\mathbf{a}_t$ – action

$\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ – policy
$\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$ – policy (fully observed)



Markov property
independent of $\mathbf{s}_{t-1}$

Optimal Value Function

MDP (S, A, T, R, γ, H), goal: $max_\pi \mathrm{E}[\sum_{t=0}^{H} \gamma^t R(S_t, A_t, S_{t+1})|\pi]$

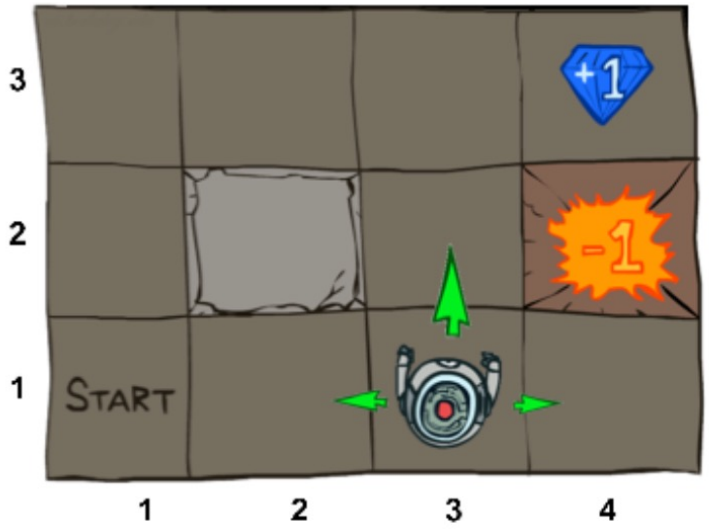
$$V^*(s) = \max_\pi \mathbb{E}\left[\sum_{t=0}^{H} \gamma^t R(s_t, a_t, s_{t+1}) \mid \pi, s_0 = s\right]$$

= sum of discounted rewards when starting from state s and acting optimally

Optimal Value Function

$$V^*(s) = \max_{\pi} \mathbb{E}\left[\sum_{t=0}^{H} \gamma^t R(s_t, a_t, s_{t+1}) \mid \pi, s_0 = s\right]$$

= sum of discounted rewards when starting from state s and acting optimally



Let's assume:

actions deterministically successful, gamma = 1, H = 100

V*(4,3) =

V*(3,3) =

V*(2,3) =

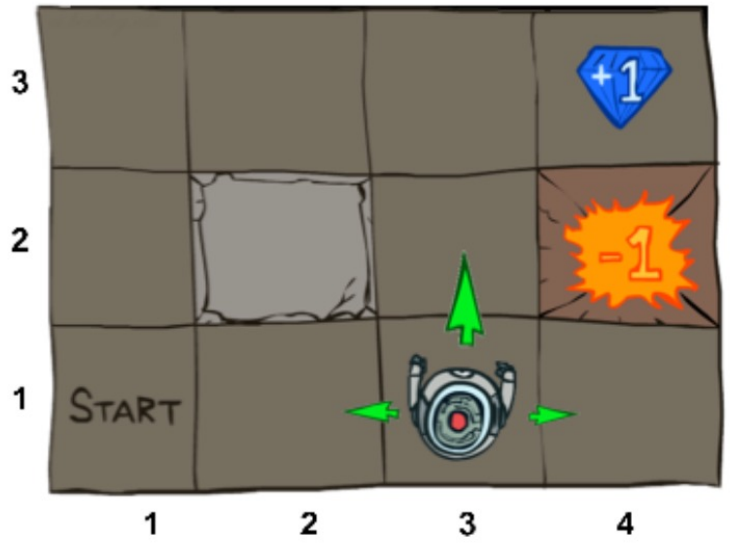
V*(1,1) =

V*(4,2) =

Optimal Value Function

$$V^*(s) = \max_{\pi} \mathbb{E}\left[\sum_{t=0}^{H} \gamma^t R(s_t, a_t, s_{t+1}) \mid \pi, s_0 = s\right]$$

= sum of discounted rewards when starting from state s and acting optimally



<u>Let's assume</u>:
actions deterministically successful, gamma = 0.9, H = 100

V*(4,3) =

V*(3,3) =

V*(2,3) =

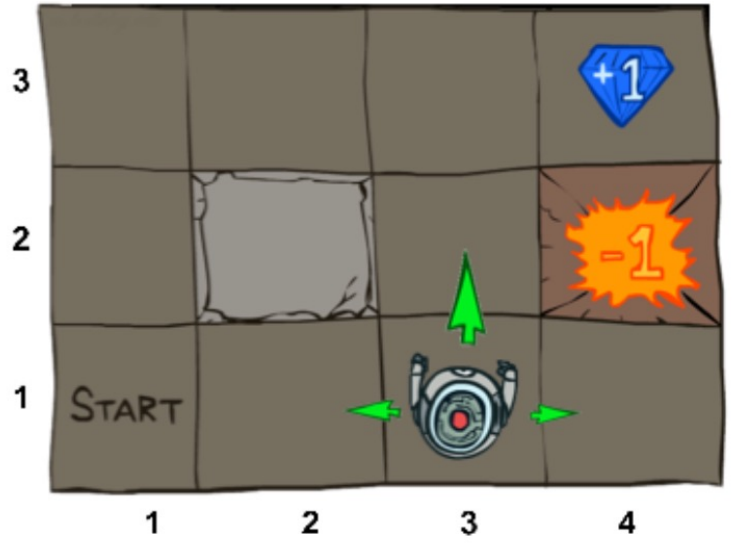
V*(1,1) =

V*(4,2) =

Optimal Value Function

$$V^*(s) = \max_{\pi} \mathbb{E}\left[\sum_{t=0}^{H} \gamma^t R(s_t, a_t, s_{t+1}) \mid \pi, s_0 = s\right]$$

= sum of discounted rewards when starting from state s and acting optimally



Let's assume:
actions successful w/probability 0.8, gamma = 0.9, H = 100

V*(4,3) =

V*(3,3) =

V*(2,3) =

V*(1,1) =

V*(4,2) =