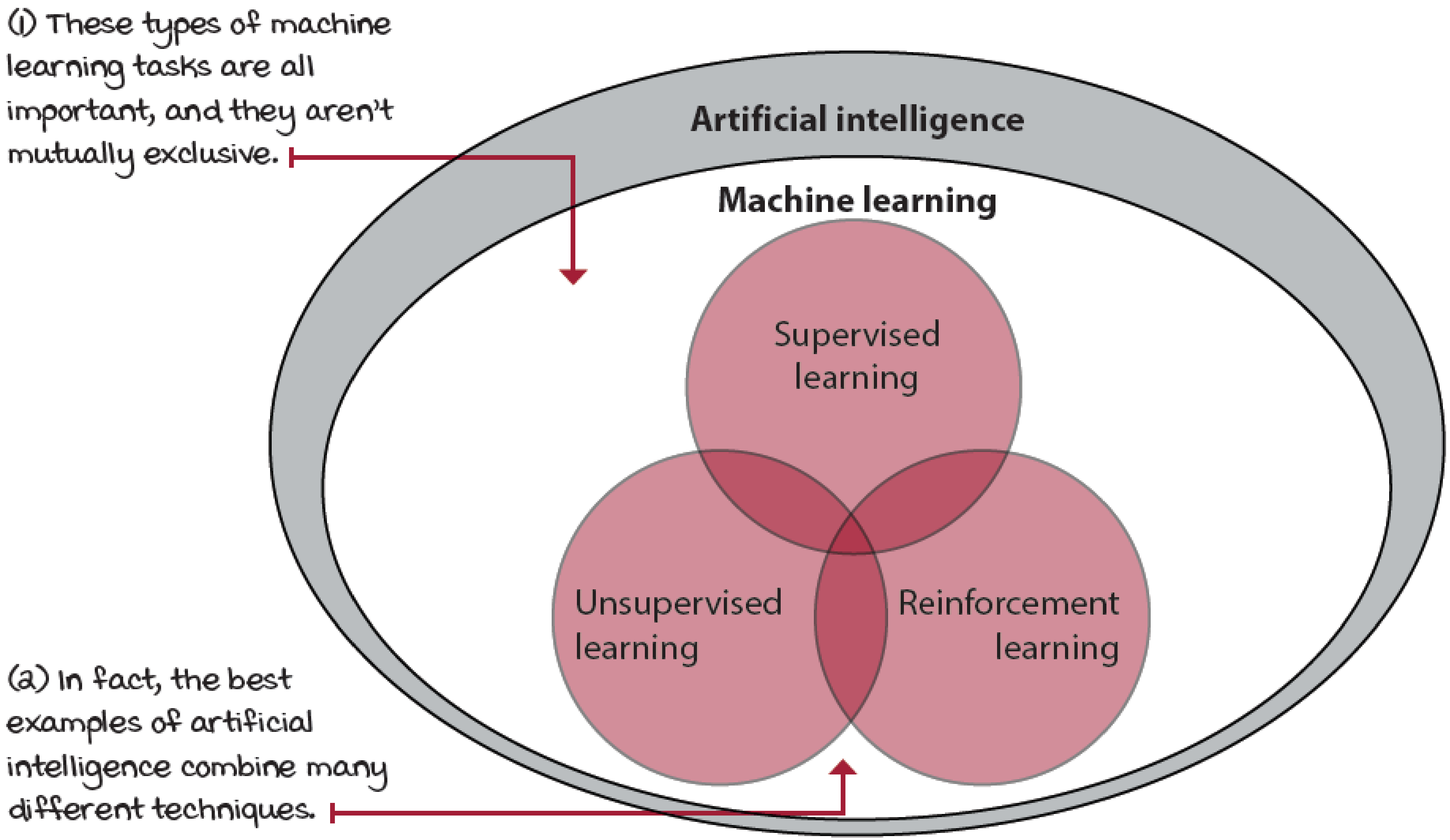
Reinforcement Learning Framework

Main branches of machine learning



MAIN BRANCHES OF MACHINE LEARNING

Supervised learning (SL) is the task of learning from labeled data. In SL, a human decides which data to collect and how to label it. The goal in SL is to generalize.

Unsupervised learning (UL) is the task of learning from unlabeled data. Even though data no longer needs labeling, the methods used by the computer to gather data still need to be designed by a human. The goal in UL is to compress.

Reinforcement learning (RL) is the task of learning through trial and error. In this type of task, no human labels data, and no human collects or explicitly designs the collection of data. The goal in RL is to act.

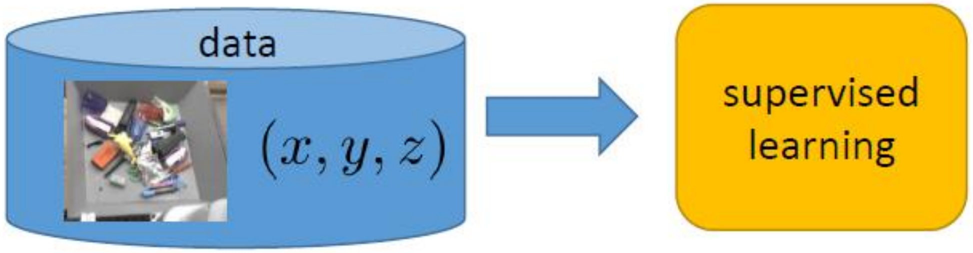
Standard (supervised) machine learning:

given $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}$

learn to predict y from $\mathbf{x}$ $\qquad f(\mathbf{x}) \approx y$

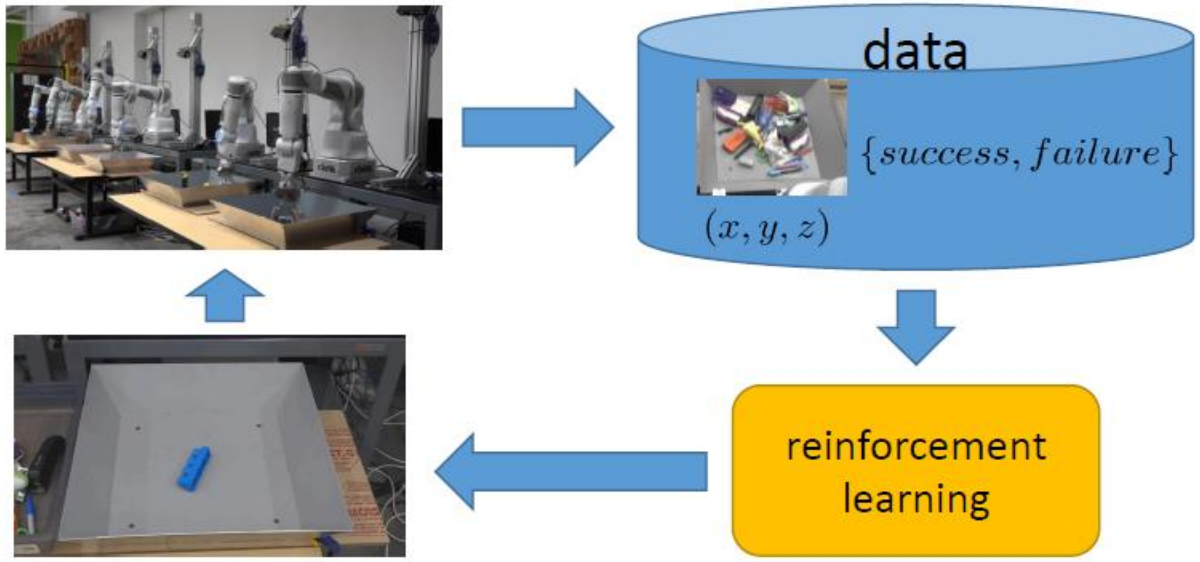
Usually assumes:

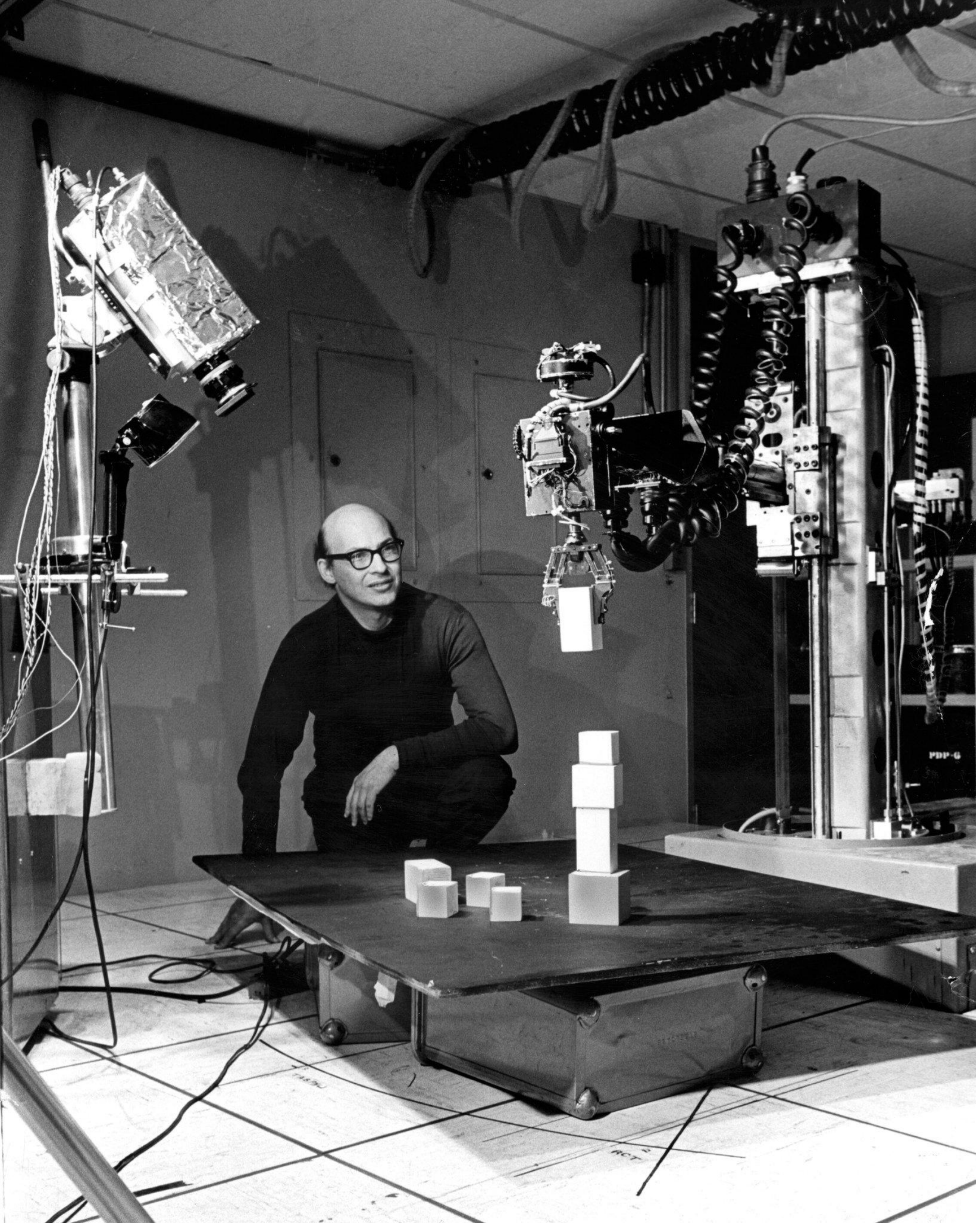
- i.i.d. data
- known ground truth outputs in training



Reinforcement learning:

- Data is **not** i.i.d.: previous outputs influence future inputs!
- Ground truth answer is not known, only know if we succeeded or failed
  - more generally, we know the reward



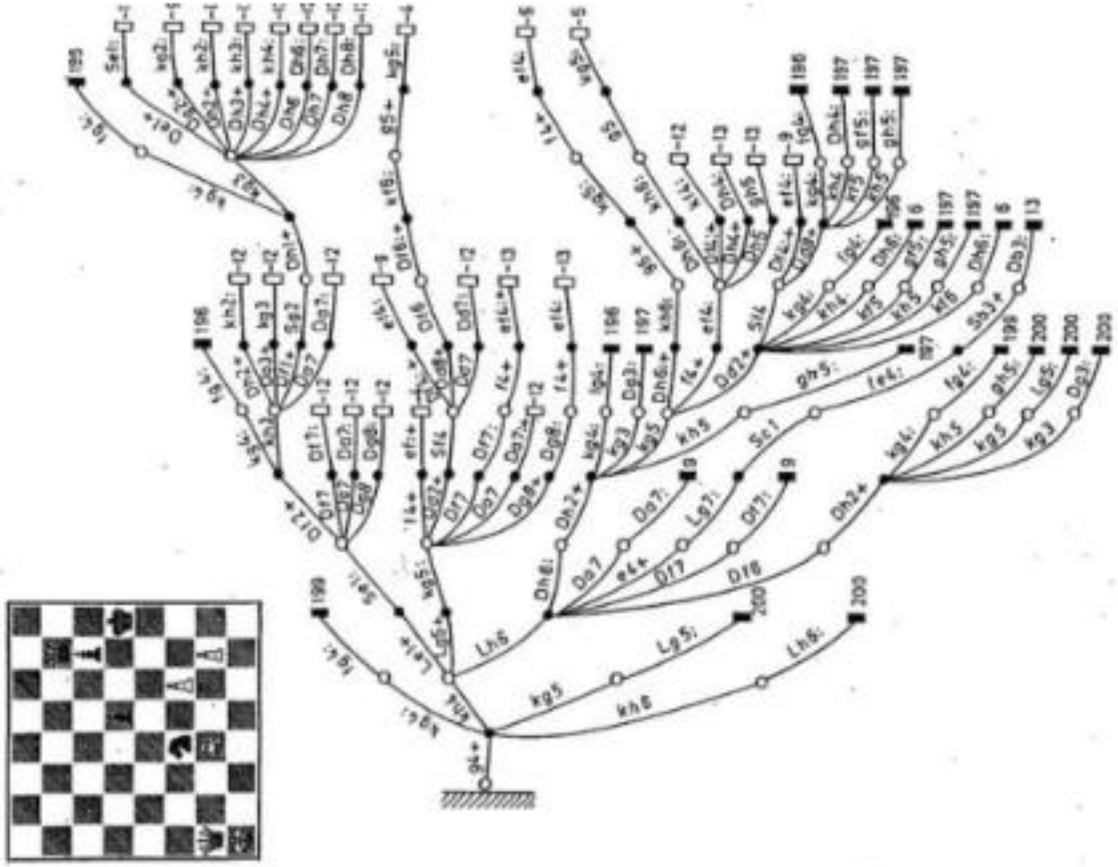


"Almost all young people working on Artificial Intelligence look around and say - What's popular? Statistical learning. So, I'll do that. That's exactly the way to kill yourself scientifically!"

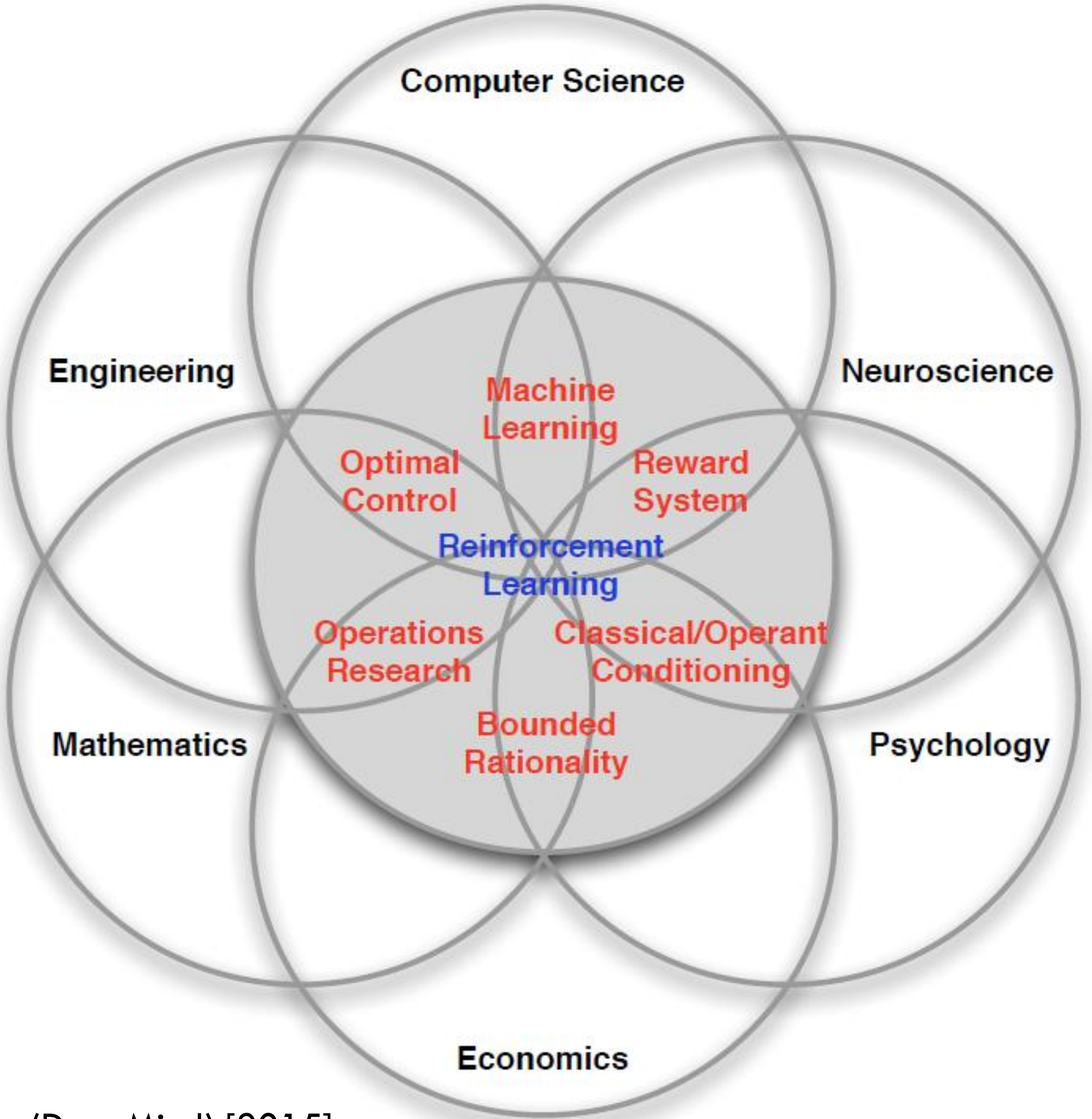
Marvin Minsky during his course called Society of Mind at MIT in 2011


Nathaniel Rochester
Marvin Minsky
John McCarthy
Oliver Selfridge
Ray Solomonoff
Claude Shannon
Trenchard More
Dartmouth Summer Research Project on Artificial Intelligence, 1956

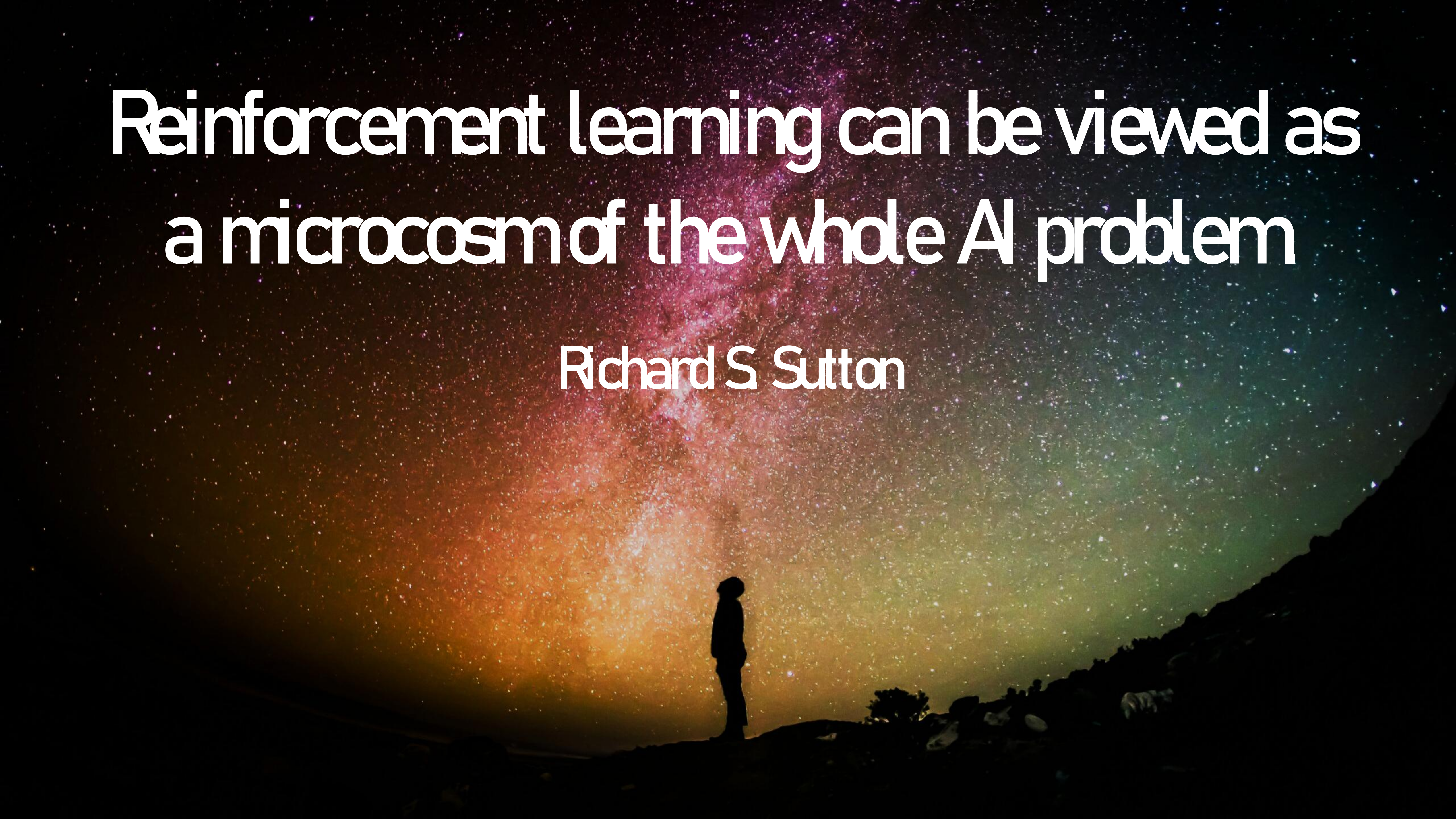
https://www.technologyreview.com/2018/12/19/138508/mighty-mouse



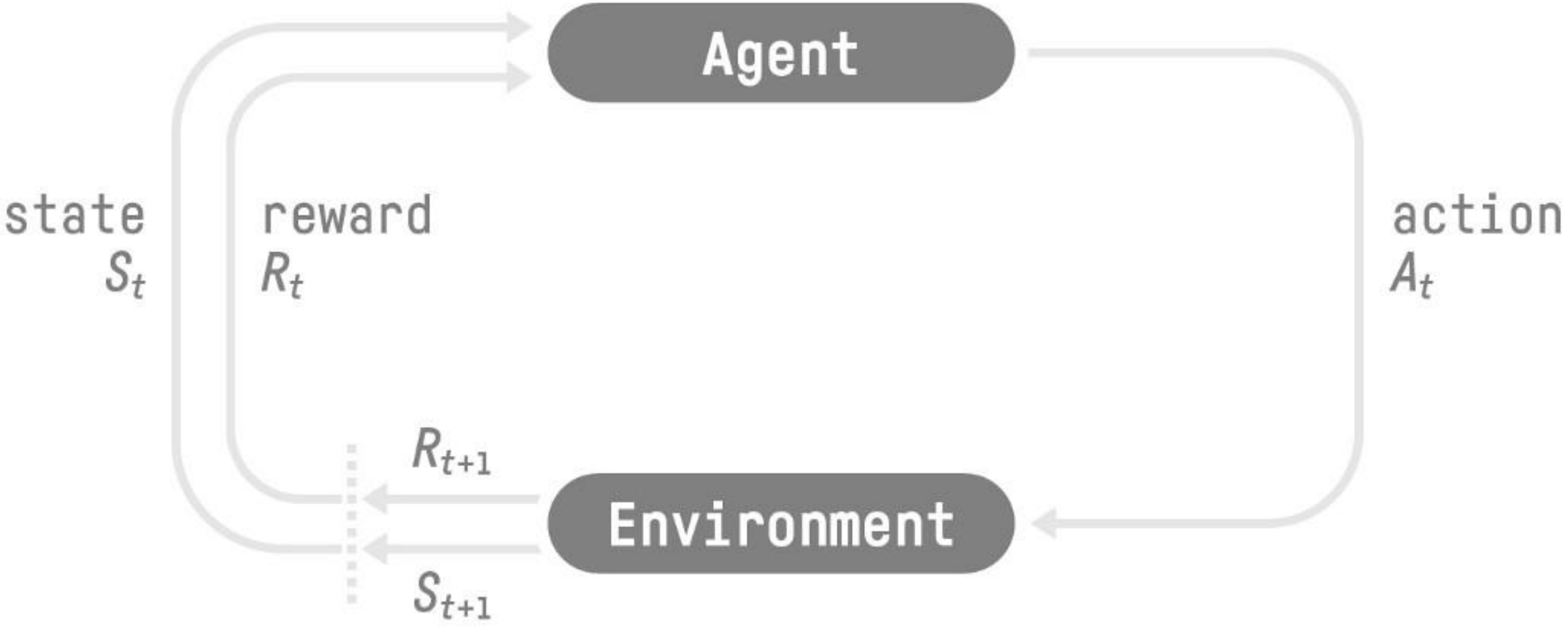
https://www.chessprogramming.org/Claude_Shannon



Introduction to RL by David Silver (DeepMind) [2015]


Reinforcement learning can be viewed as
a microcosm of the whole AI problem
Richard S. Sutton

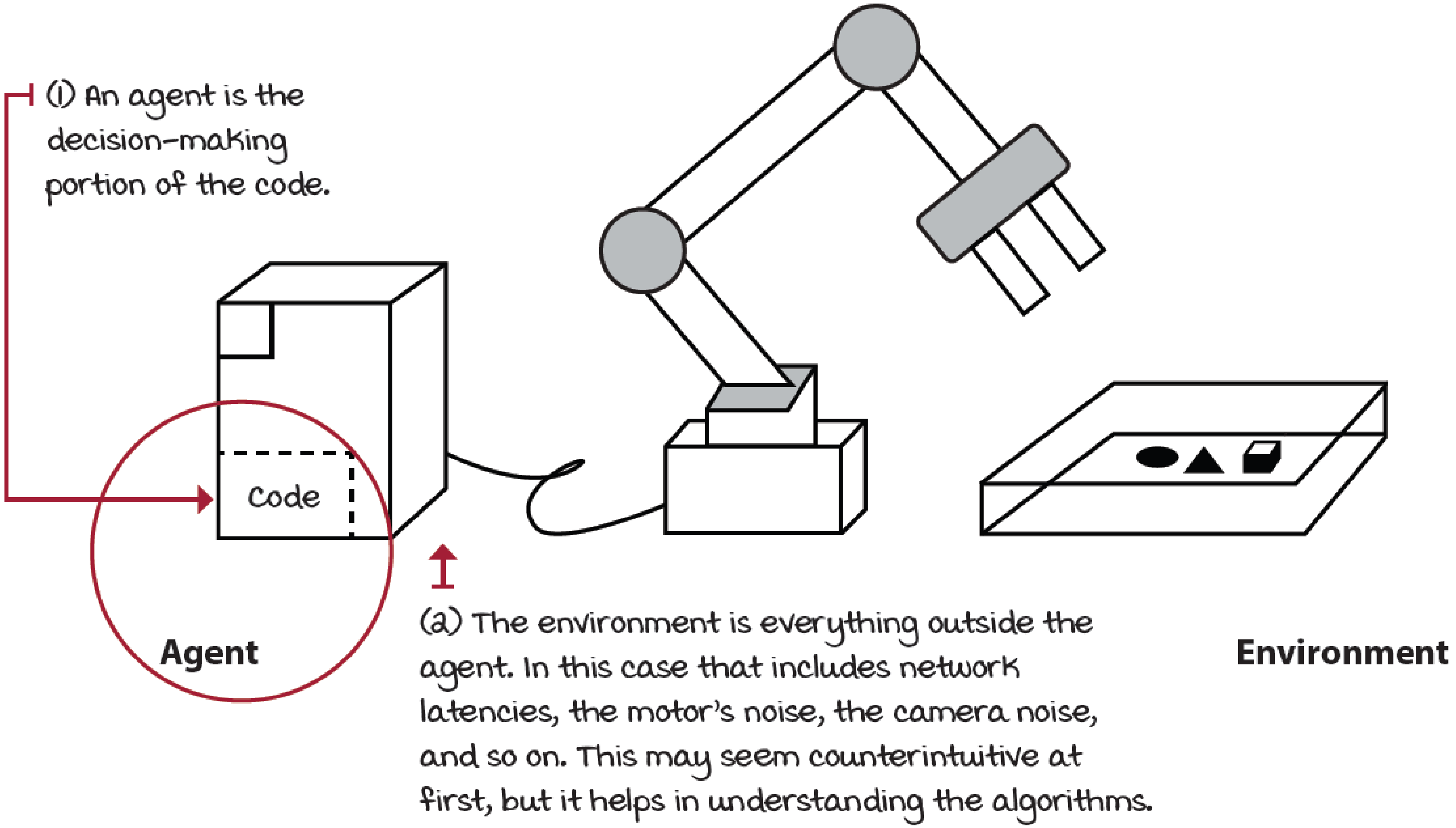
	AI Planning	SL	UL	RL	IL
Optimization	X			X	X
Learns from experience		X	X	X	X
Generalization	X	X	X	X	X
Delayed Consequences	X			X	X
Exploration				X	



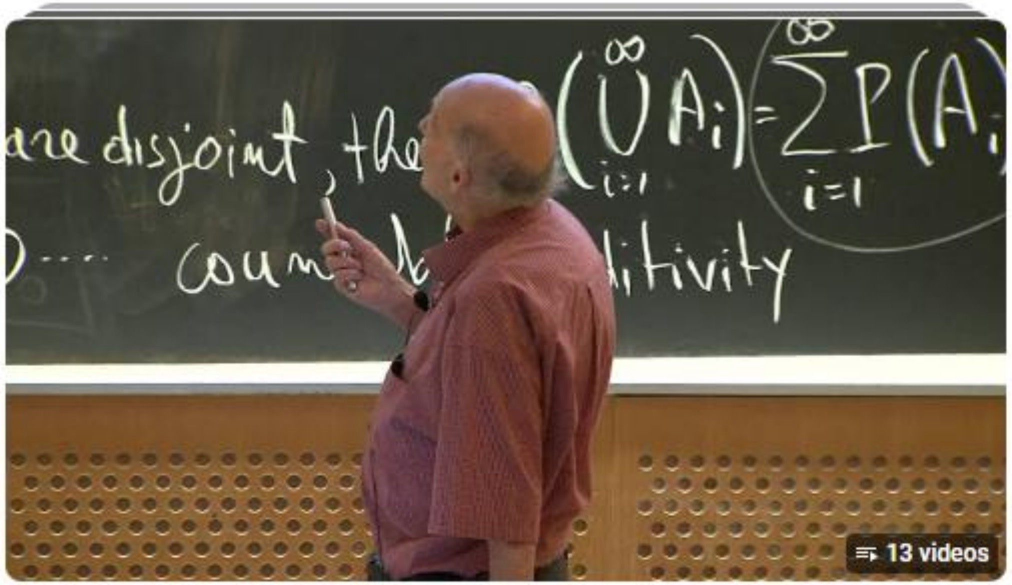
HuggingFace DeepRL Course

How should we define the boundary between agent and environment?

ENVIRONMENT AND AGENT



Grokking Deep Reinforcement Learning (Miguel Morales)



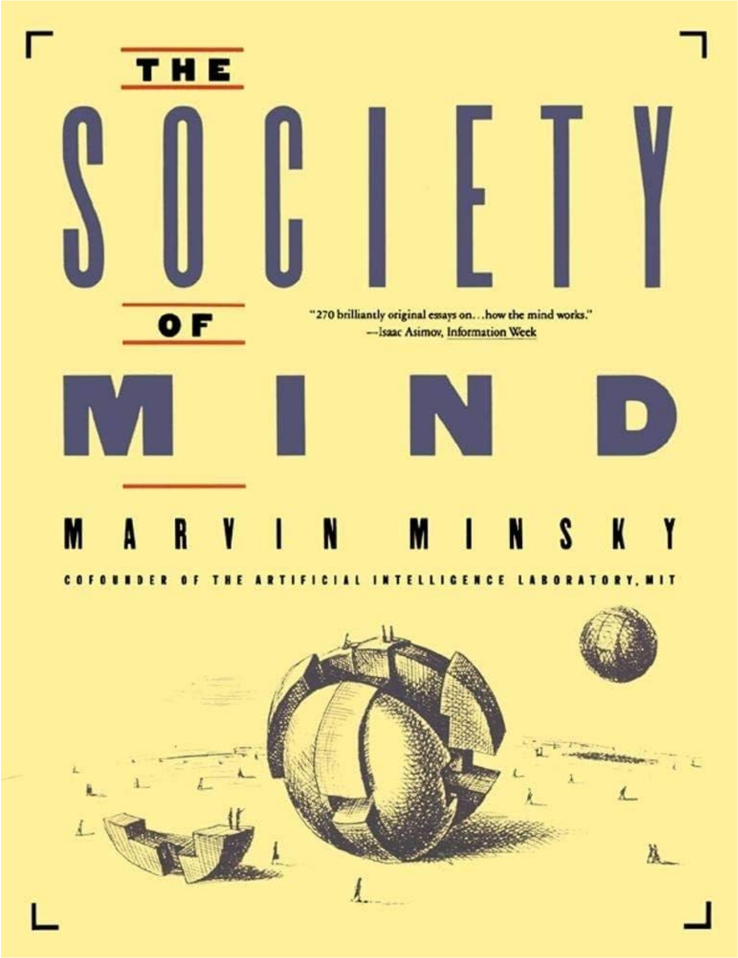
MIT 6.868J The Society of Mind, Fall 2011

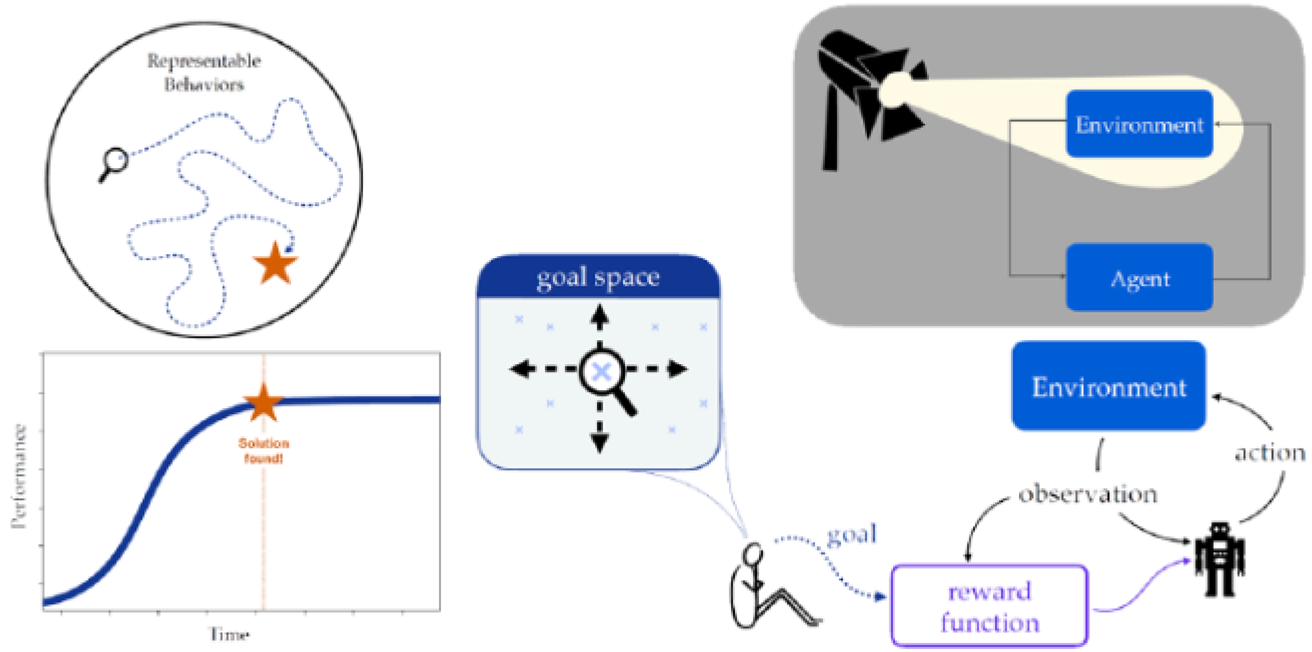
MIT OpenCourseWare · Playlist

1. Introduction to 'The Society of Mind' · 2:05:54
2. Falling In Love · 1:45:55

View full playlist

https://www.youtube.com/playlist?list=PLUl4u3cNGP61E-vNcDV0w5xpsIBYNJDkU





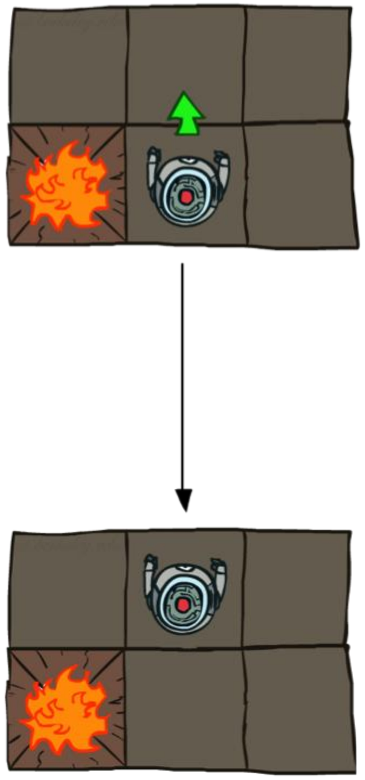
Three Dogmas of Reinforcement Learning

August 6, 2024 · Arash Alikhani

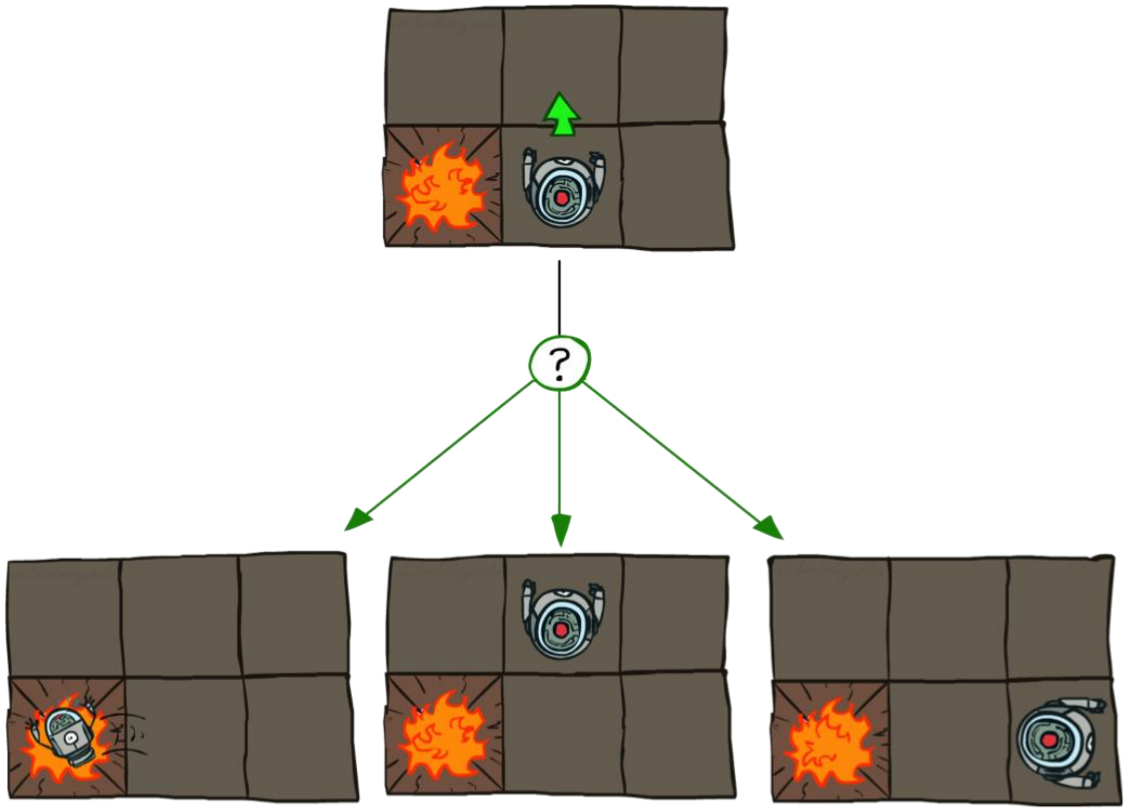
https://rljclub.github.io/posts/three-dogmas-of-reinforcement-learning

ENVIRONMENT AND AGENT

Deterministic Grid World



Stochastic Grid World



Observation Space

State: **complete description** of the state of the world (no hidden information).

Observation: **partial description** of the state of the world.

Action Space

Discrete: **finite number of possible actions**

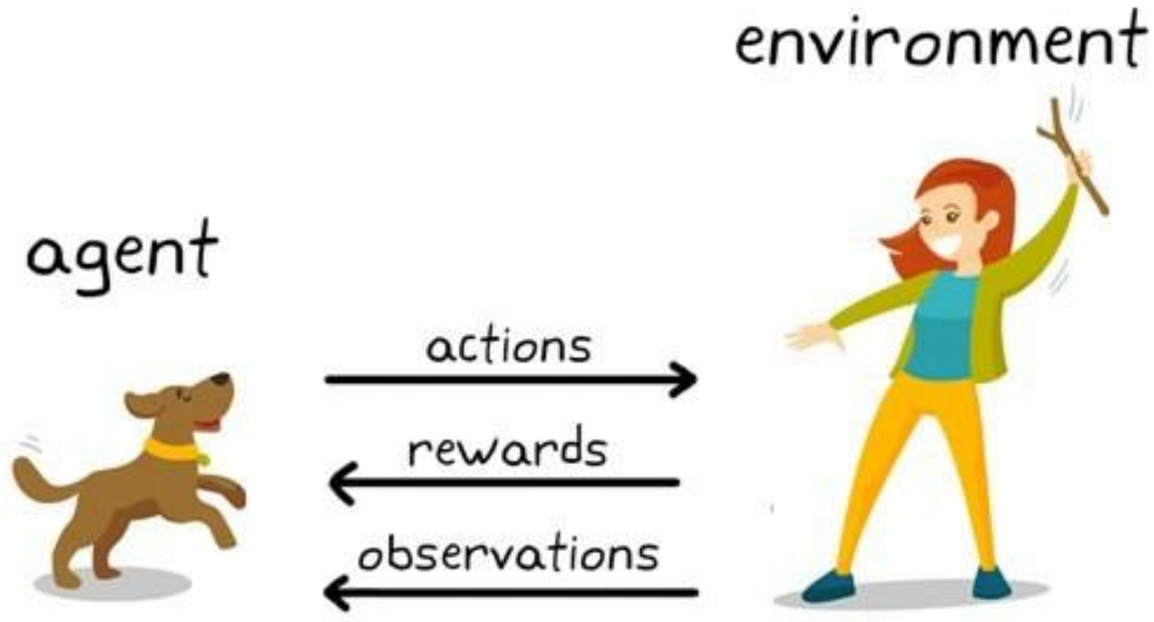
Continuous: **infinite number of possible actions**

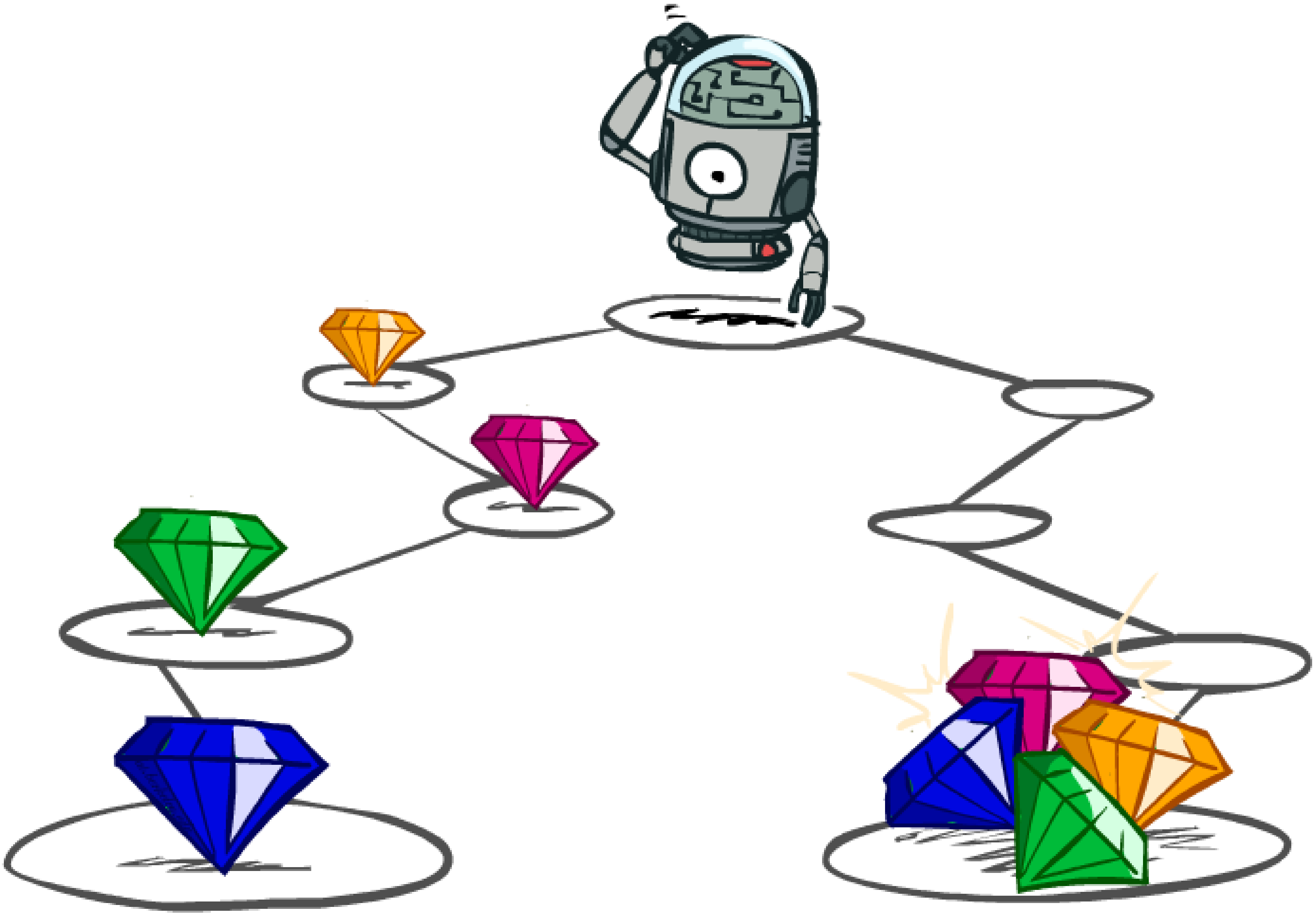
Deep RL Course

REWARD HYPOTHESIS

The Reward Hypothesis

"...all of what we mean by goals and purposes can be well thought of as maximization of the expected value of the cumulative sum of a received scalar signal (reward)"
-- Sutton (2004)





$$R(\tau) = \sum_{k=0}^{\infty} r_{t+k+1}$$

$$R(\boxed{\tau}) = r_{t+1} + r_{t+2} + r_{t+3} + r_{t+4} + \ldots$$

Return: cumulative reward

Trajectory (read Tau)
Sequence of states and actions

1

Worth Now

γ

Worth Next Step

γ^2

Worth In Two Steps

$$R(\boxed{\tau}) = r_{t+1} + \underline{\gamma} r_{t+2} + \underline{\gamma}^2 r_{t+3} + \underline{\gamma}^3 r_{t+4} + \dots$$

Return: cumulative reward

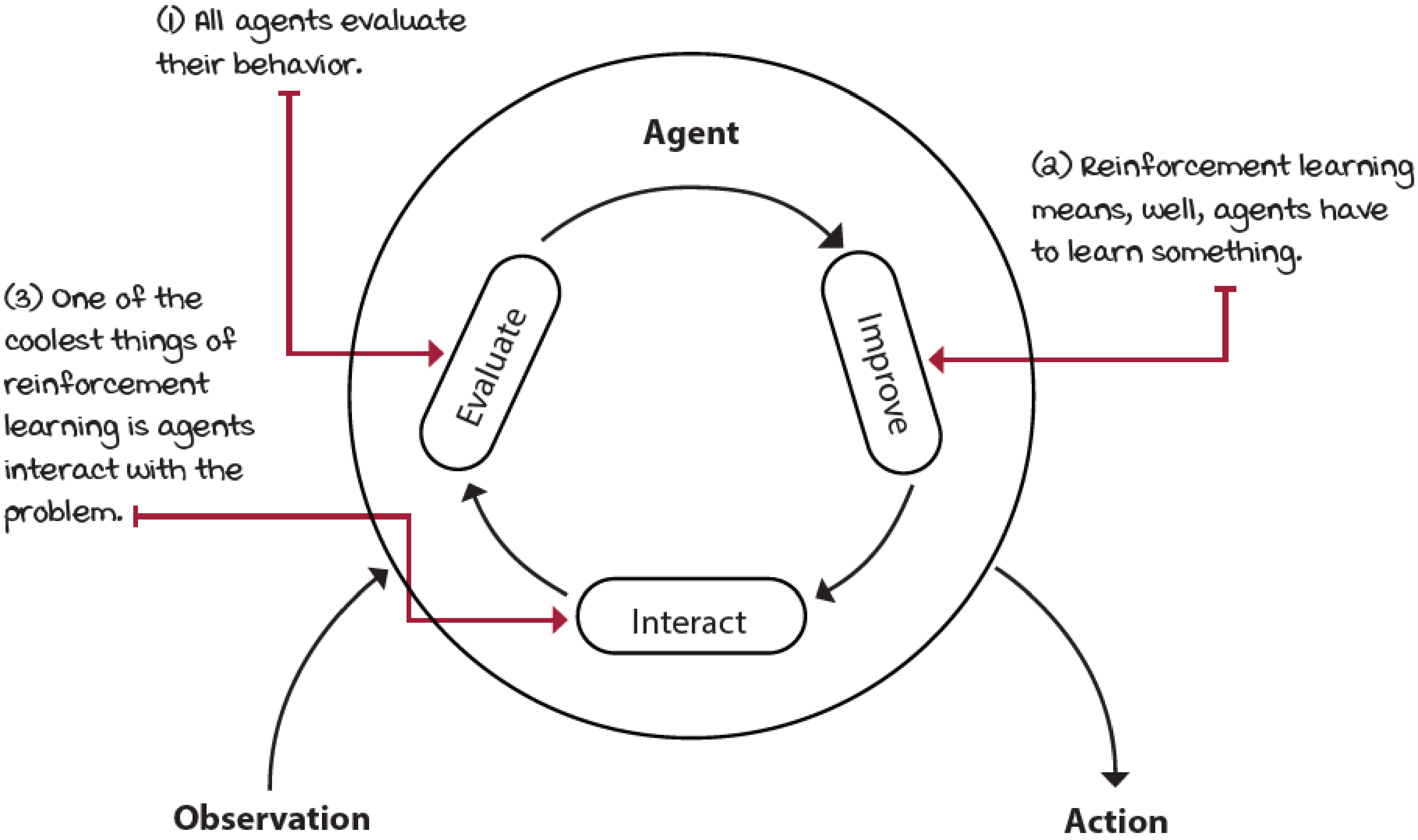
Gamma: discount rate

Trajectory (read Tau)

Sequence of states and actions

$$R(\tau) = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

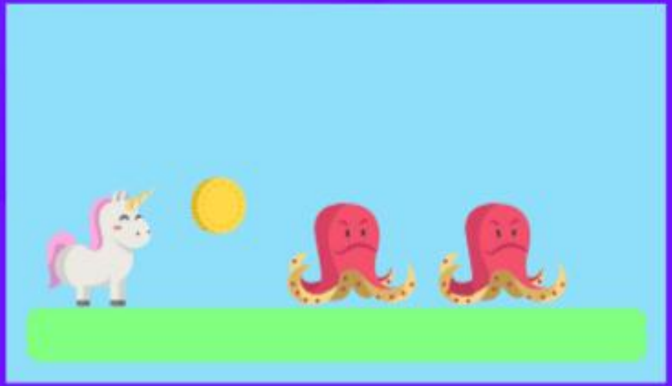
The three internal steps that every reinforcement learning agent goes through



Grokking Deep Reinforcement Learning (Miguel Morales)

The Policy π: the agent's brain

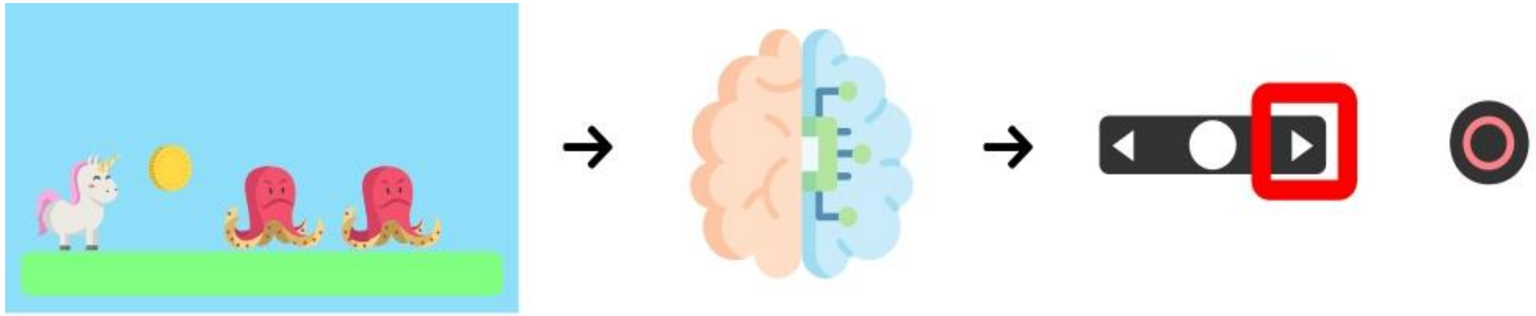
Policy π: is the **brain of our Agent,** it's the function that tell us what **action to take given the state we are.**
→ So it **defines the agent behavior at a given time.**


→

→


State → π(State) → Action

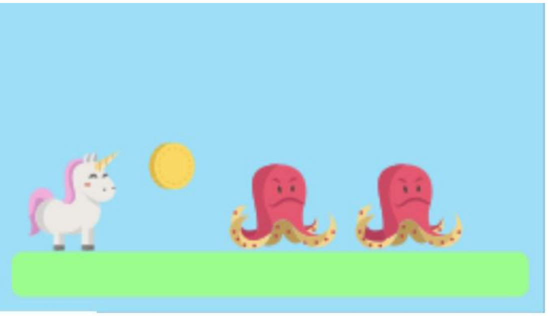
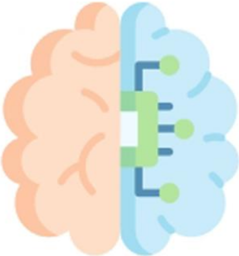
$$a = \pi(s)$$



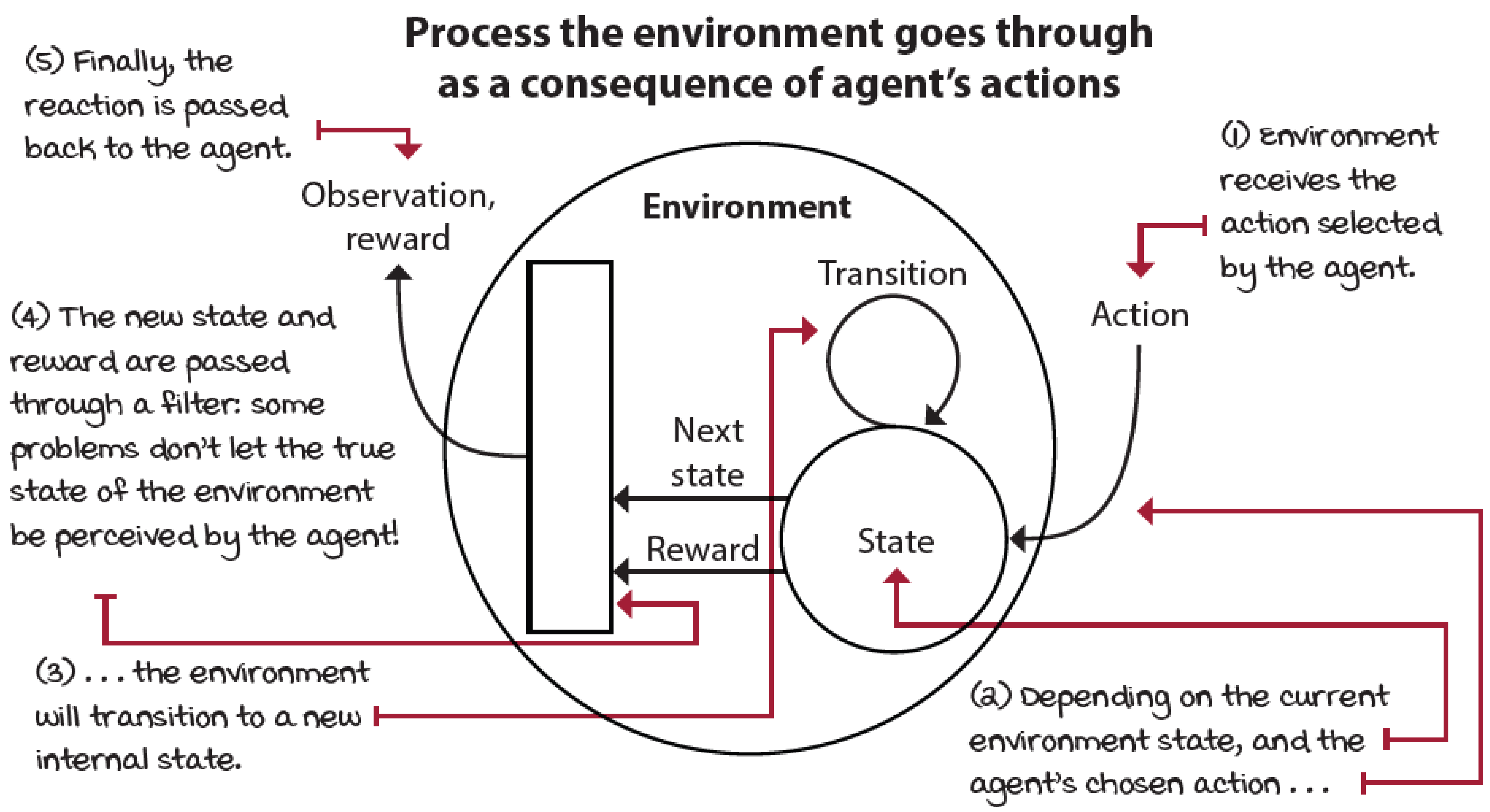
State s_0 → $\pi(s_0)$ → a_0 = Right

$$\pi(a|s) = \boxed{P[A|s]}$$

Probability Distribution over the set of actions given the state

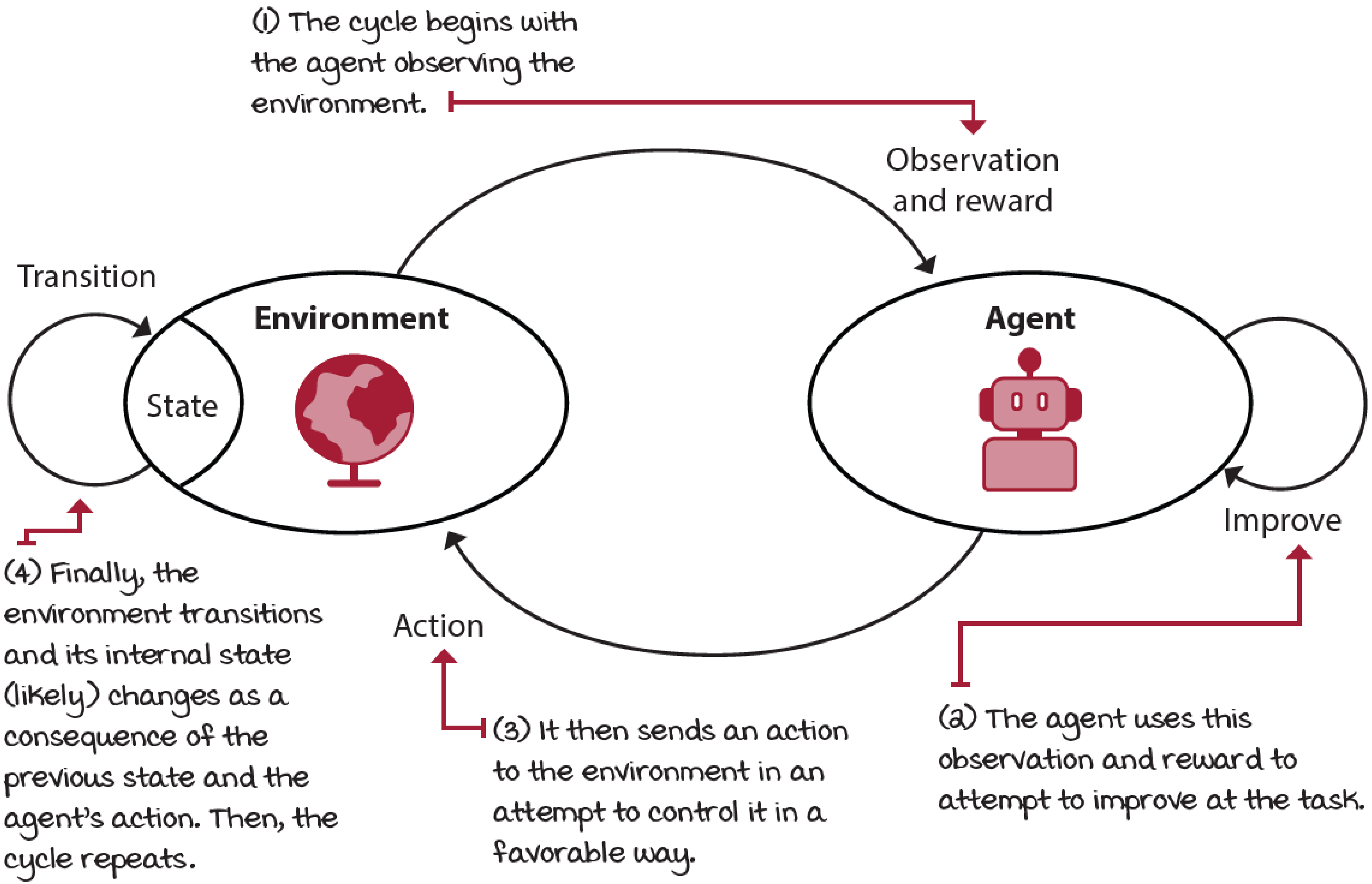
 →  → 

State s_0 → $\pi(A|s_0)$ → [Left: 0.1, Right: 0.7, Jump: 0.2]



Grokking Deep Reinforcement Learning (Miguel Morales)

The reinforcement learning cycle



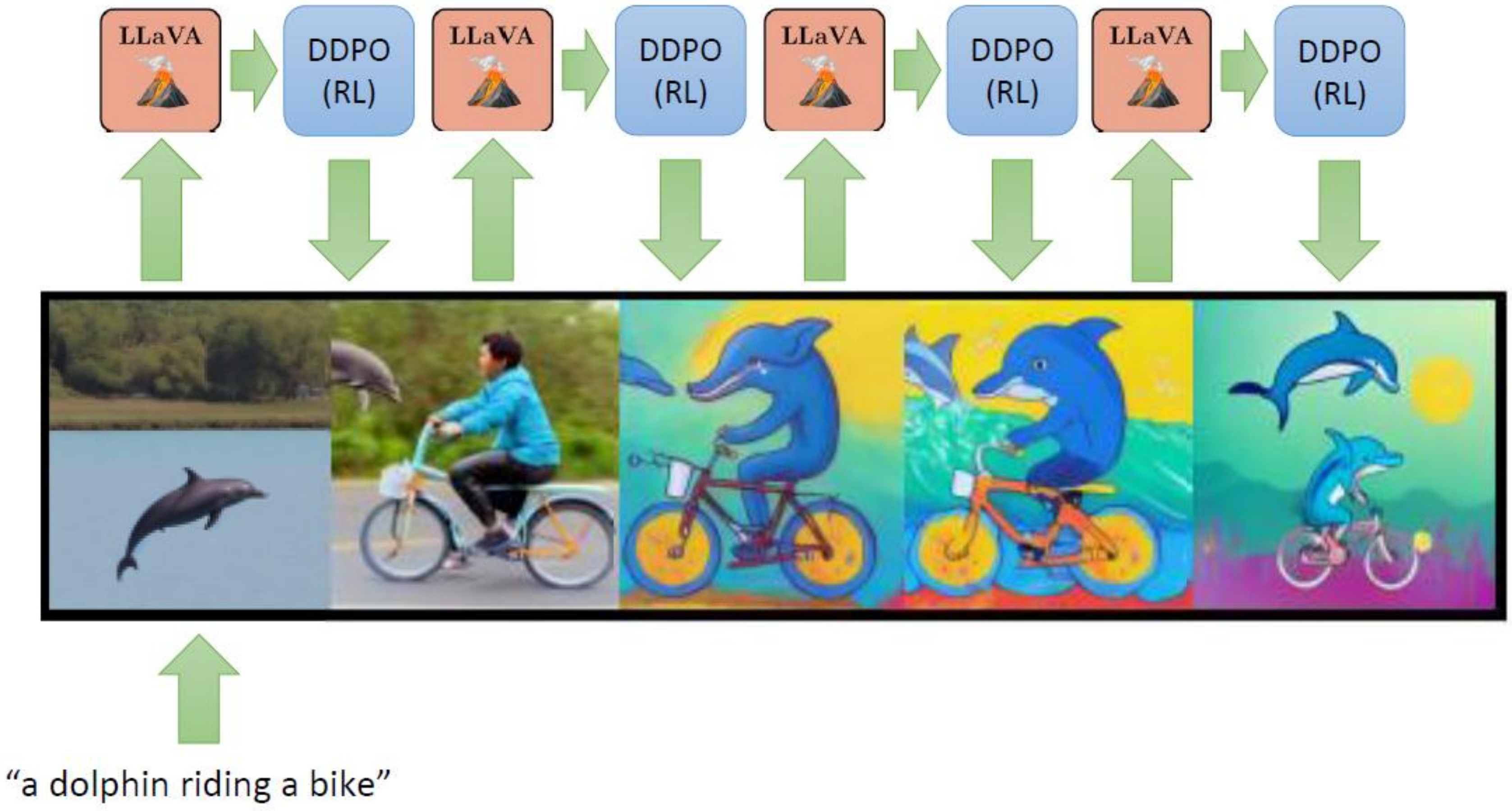
Grokking Deep Reinforcement Learning (Miguel Morales)

Actions: muscle contractions
Observations: sight, smell
Rewards: food

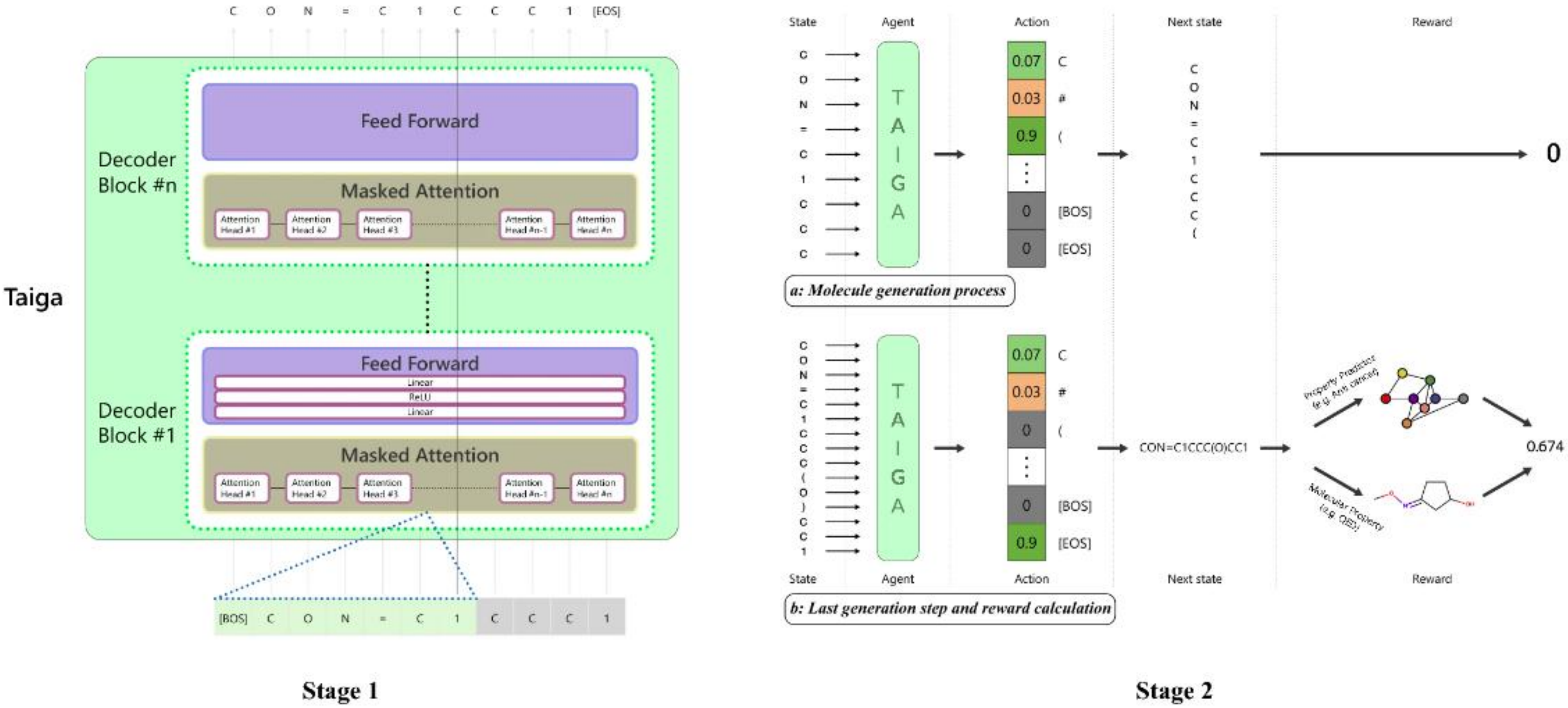
Actions: motor current or torque
Observations: camera images
Rewards: task success measure (e.g., running speed)

Actions: what to purchase
Observations: inventory levels
Rewards: profit

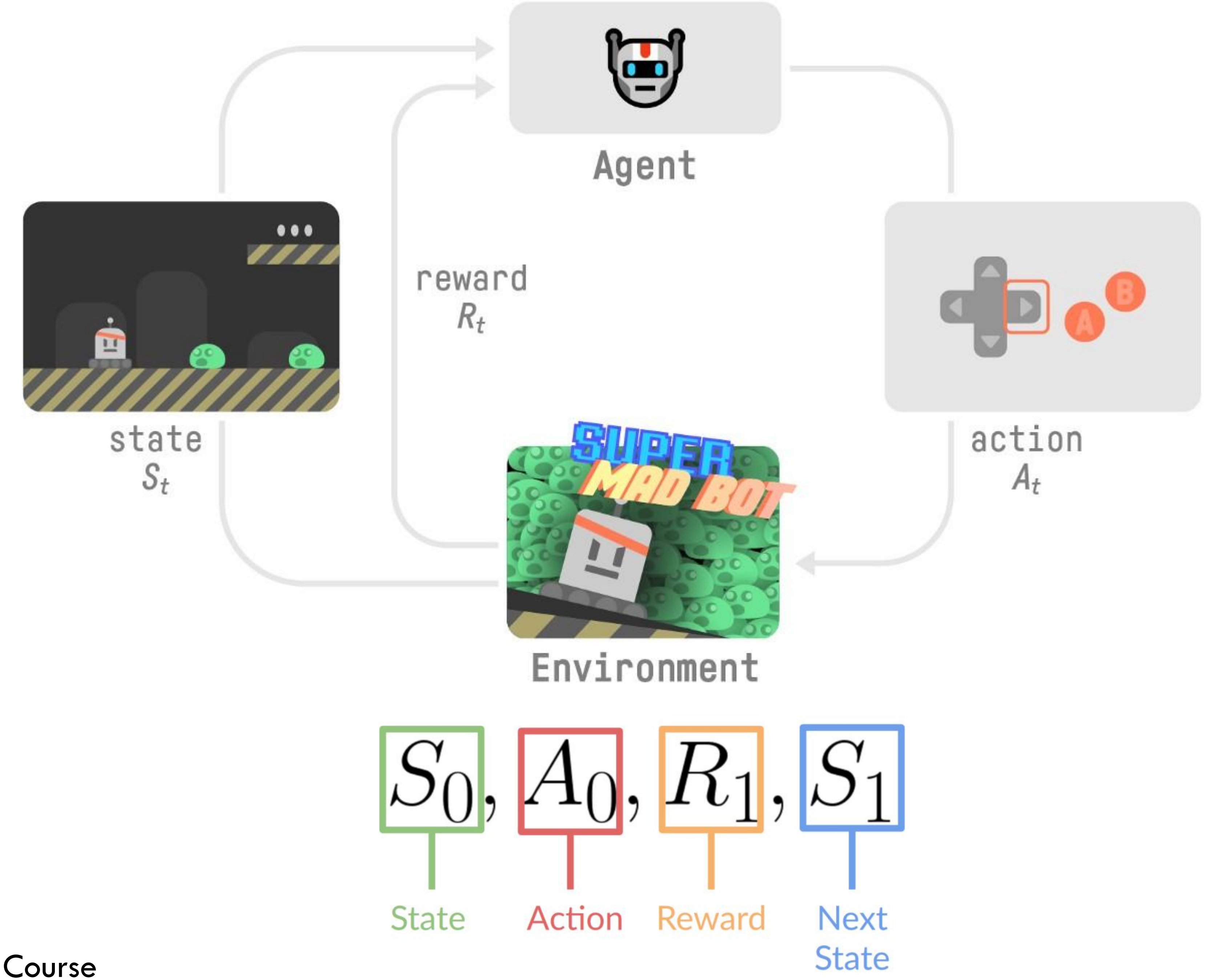
Reinforcement learning with image generation



Kevin Black*, Michael Janner*, Yilun Du, Ilya Kostrikov, Sergey Levine. **Training Diffusion Models with Reinforcement Learning**. 2023.

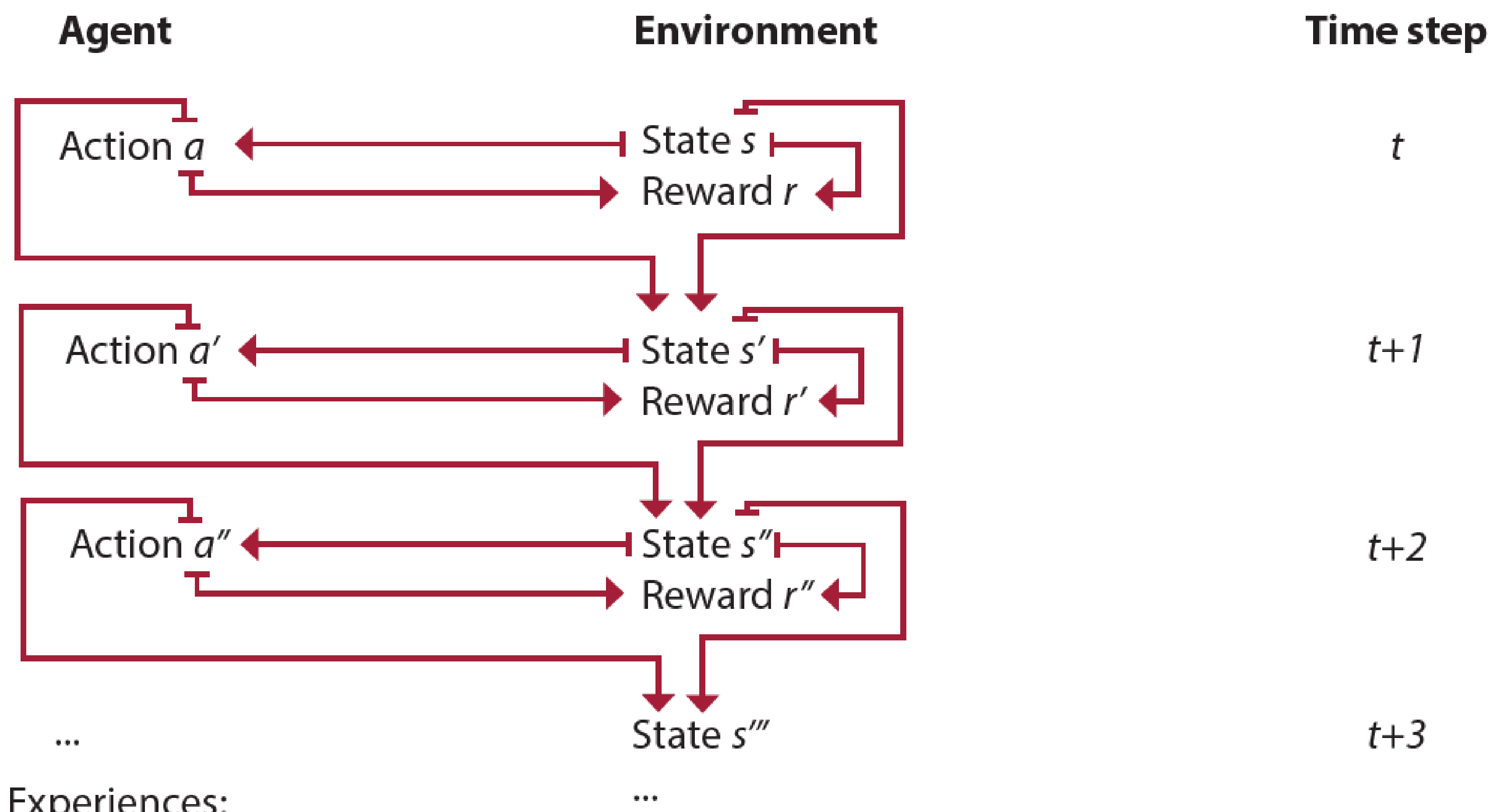


Taiga
Decoder Block #n
Feed Forward
Masked Attention
Attention Head #1
Attention Head #2
Attention Head #3
Attention Head #n-1
Attention Head #n
Decoder Block #1
Linear
ReLU
[BOS]
[EOS]
State
Agent
Action
Next state
Reward
TAIGA
0.07
0.03
0.9
0
a: Molecule generation process
b: Last generation step and reward calculation
CON=C1CCC(O)CC1
0.674
Stage 1
Stage 2



HuggingFace DeepRL Course

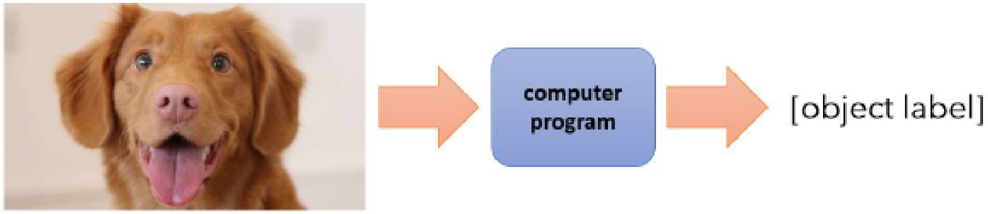
Experience tuples



Experiences:
t, (s, a, r′, s′)
t+1, (s′, a′, r″, s″)
t+2, (s″, a″, r‴, s‴)
...

Grokking Deep Reinforcement Learning (Miguel Morales)

supervised learning



input: $\mathbf{x}$

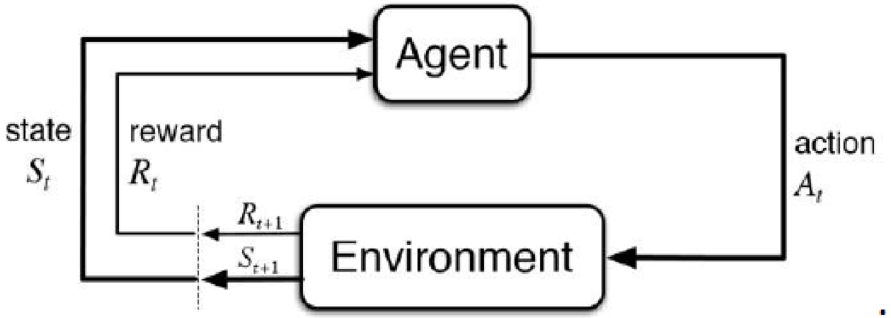
output: $\mathbf{y}$

data: $\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}$

goal: $f_\theta(\mathbf{x}_i) \approx \mathbf{y}_i$

someone gives this to you

reinforcement learning



input: $\mathbf{s}_t$ *at each time step*

output: $\mathbf{a}_t$ *at each time step*

data: $(\mathbf{s}_1, \mathbf{a}_1, r_1, \ldots, \mathbf{s}_T, \mathbf{a}_T, r_T)$

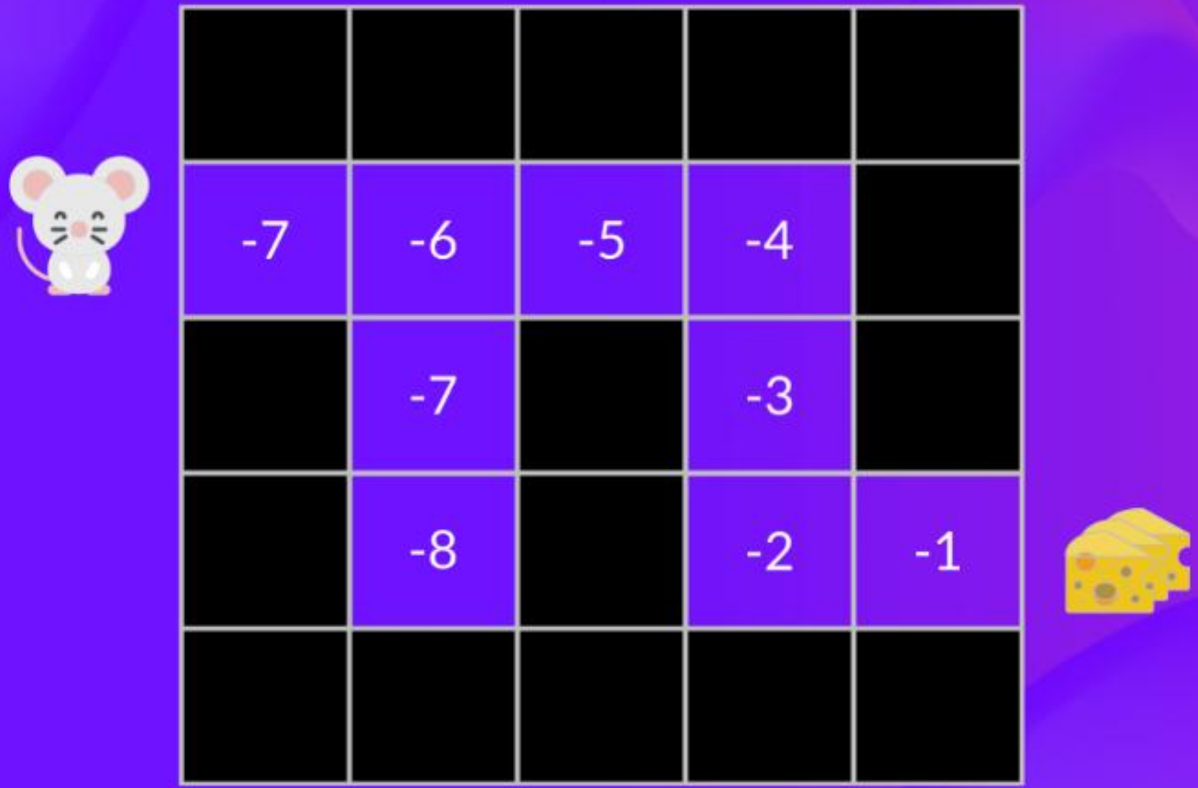
goal: learn $\pi_\theta : \mathbf{s}_t \rightarrow \mathbf{a}_t$

to maximize $\sum_t r_t$

pick your own actions

The State Value Function

State Value Function: calculate the **value of a state.**



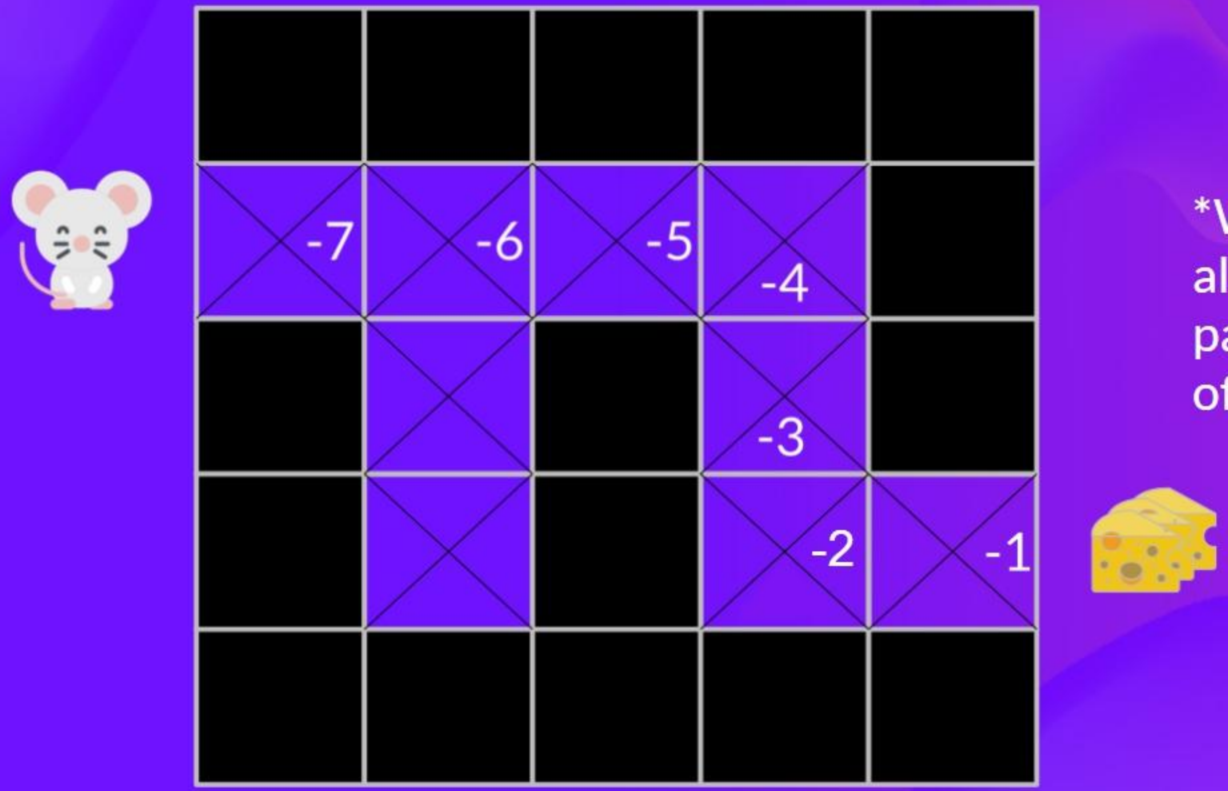
$$\underbrace{V_\pi(s)}_{\text{Value of state s}} = \underbrace{\mathbf{E}_{\boxed{\pi}}[G_t}_{\text{Expected return}} | \underbrace{S_t = s}_{\text{If the agent starts at state s}}]$$

And uses the policy to choose its actions for all time steps

For each state,
the state-value function outputs
the expected return
if the agent starts in that state
and then follows the policy forever after.

The Action Value Function

Action Value Function: calculate the **value of state-action pair.**



*We didn't fill
all the state-actions
pair for the example
of Action-value function

$$Q_\pi(s,a) = \mathbf{E}_{\boxed{\pi}}[G_t | S_t = s, A_t = a]$$

Value of state-action pair s,a

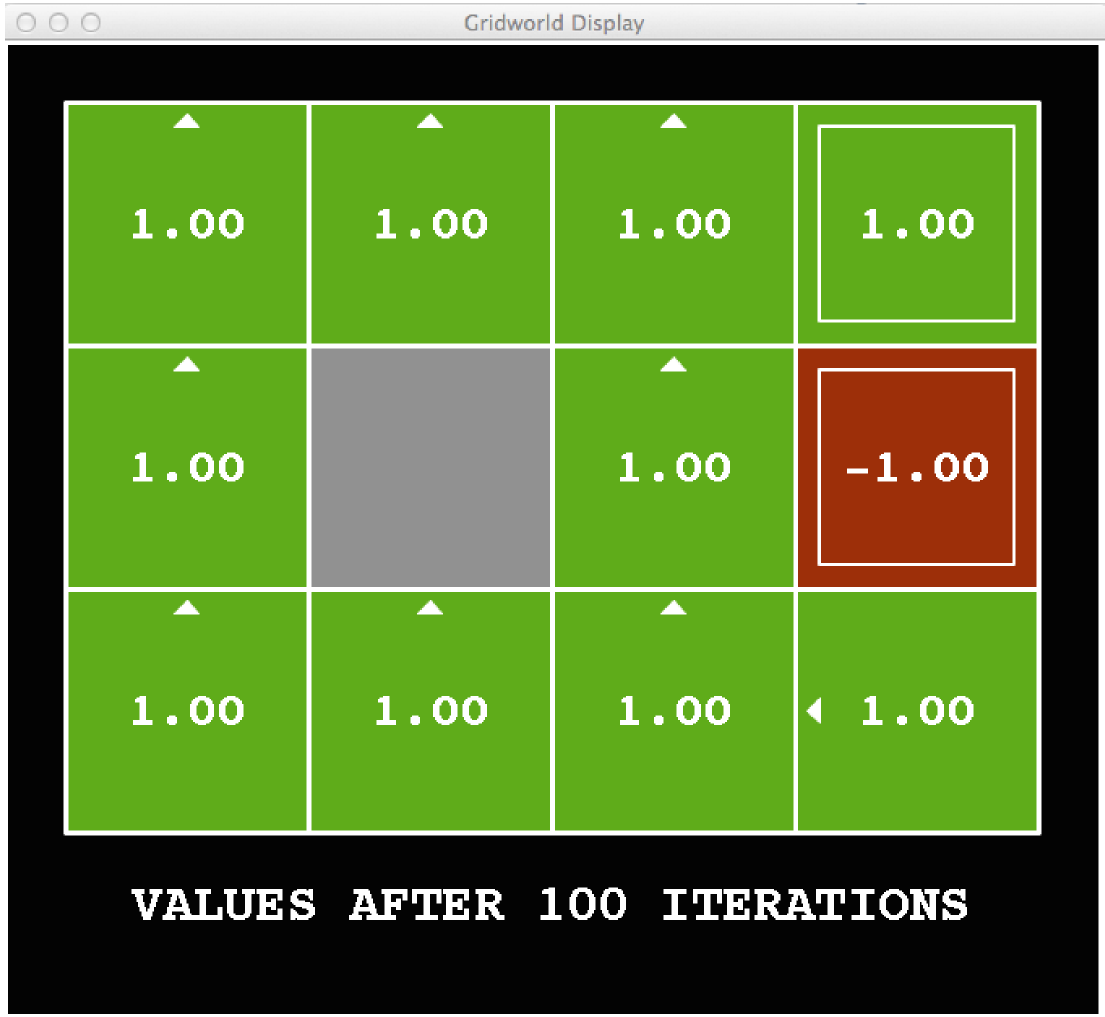
Expected return

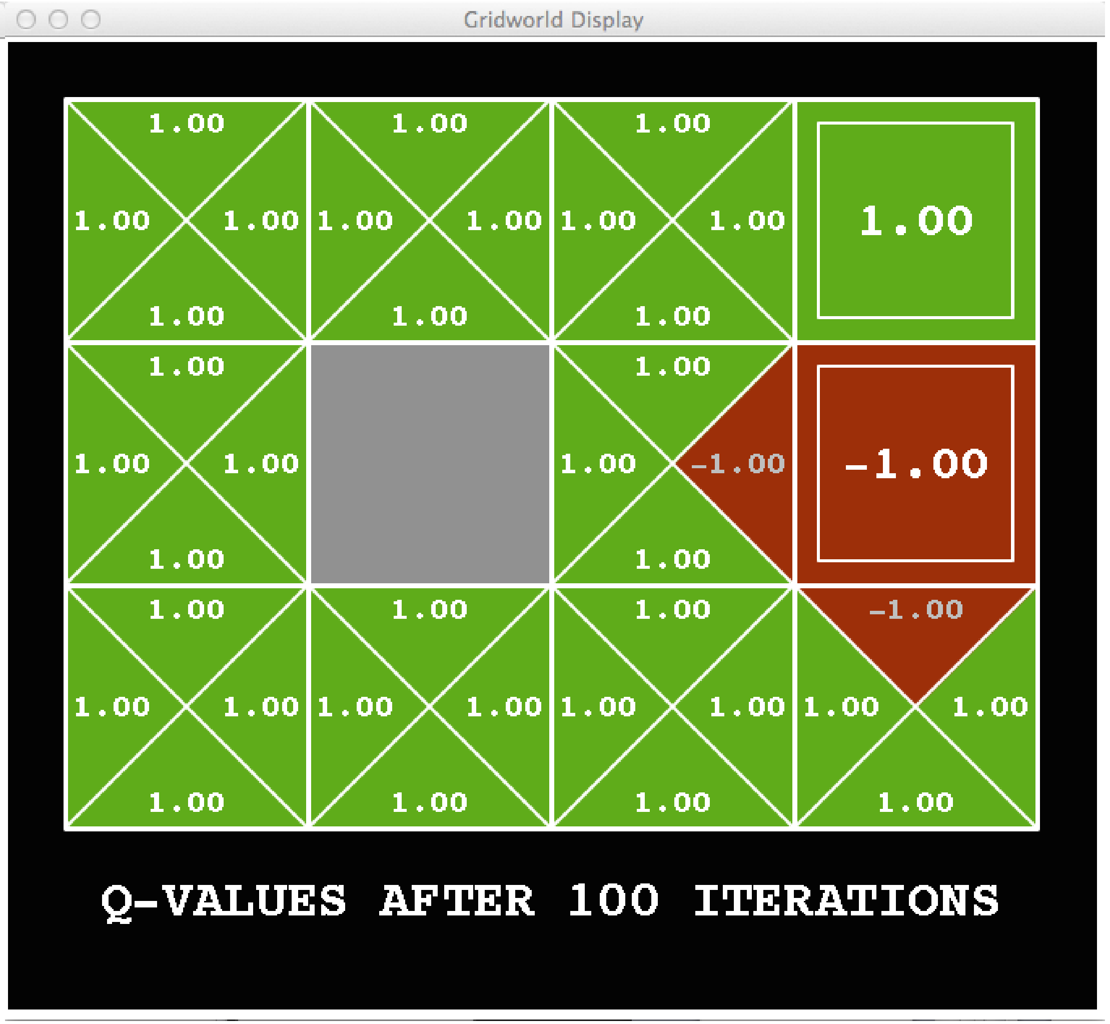
If the agent starts at state s

and chooses action a

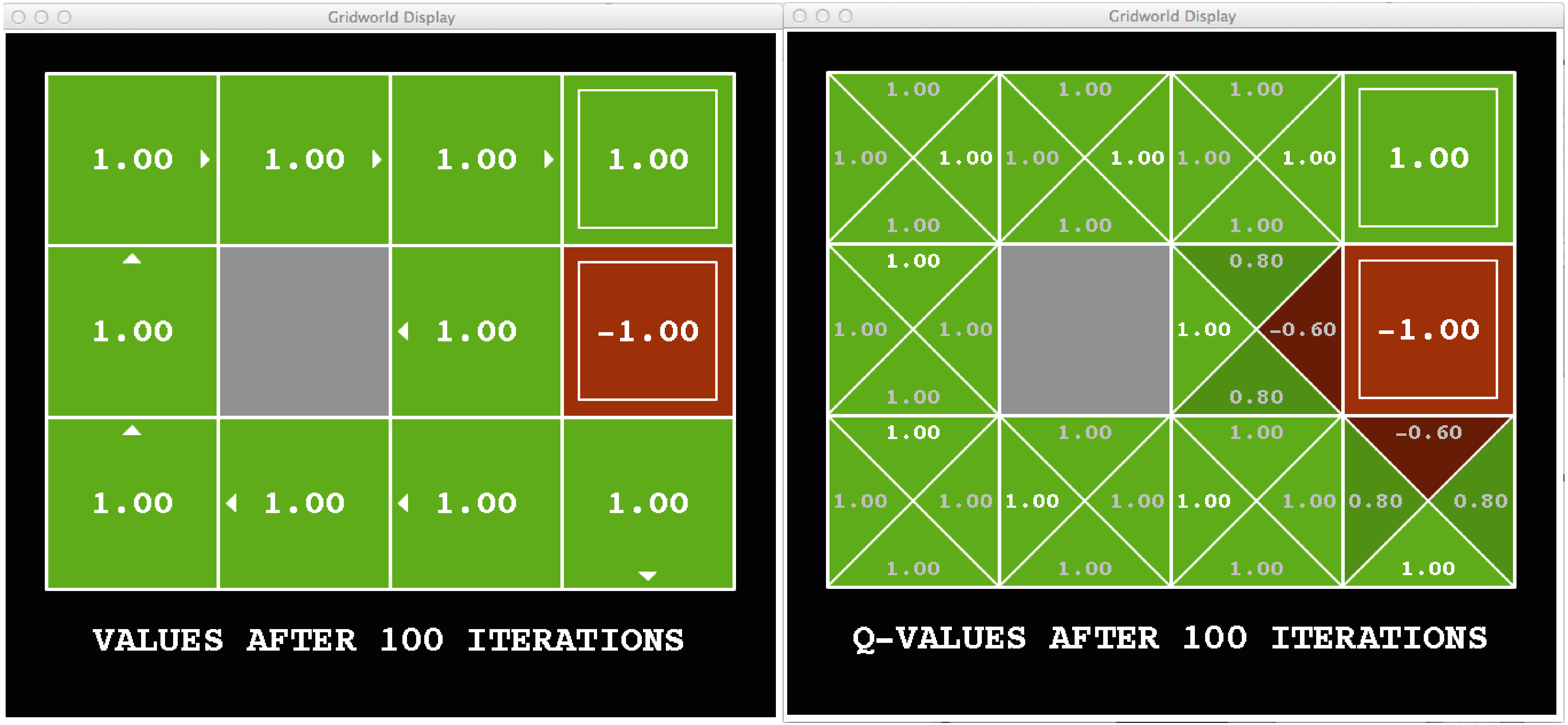
And then uses the policy to choose its actions for all time steps

For each state and action,
the action-value function outputs
the expected return
if the agent starts in that state
and takes the action
and then follows the
policy forever after.

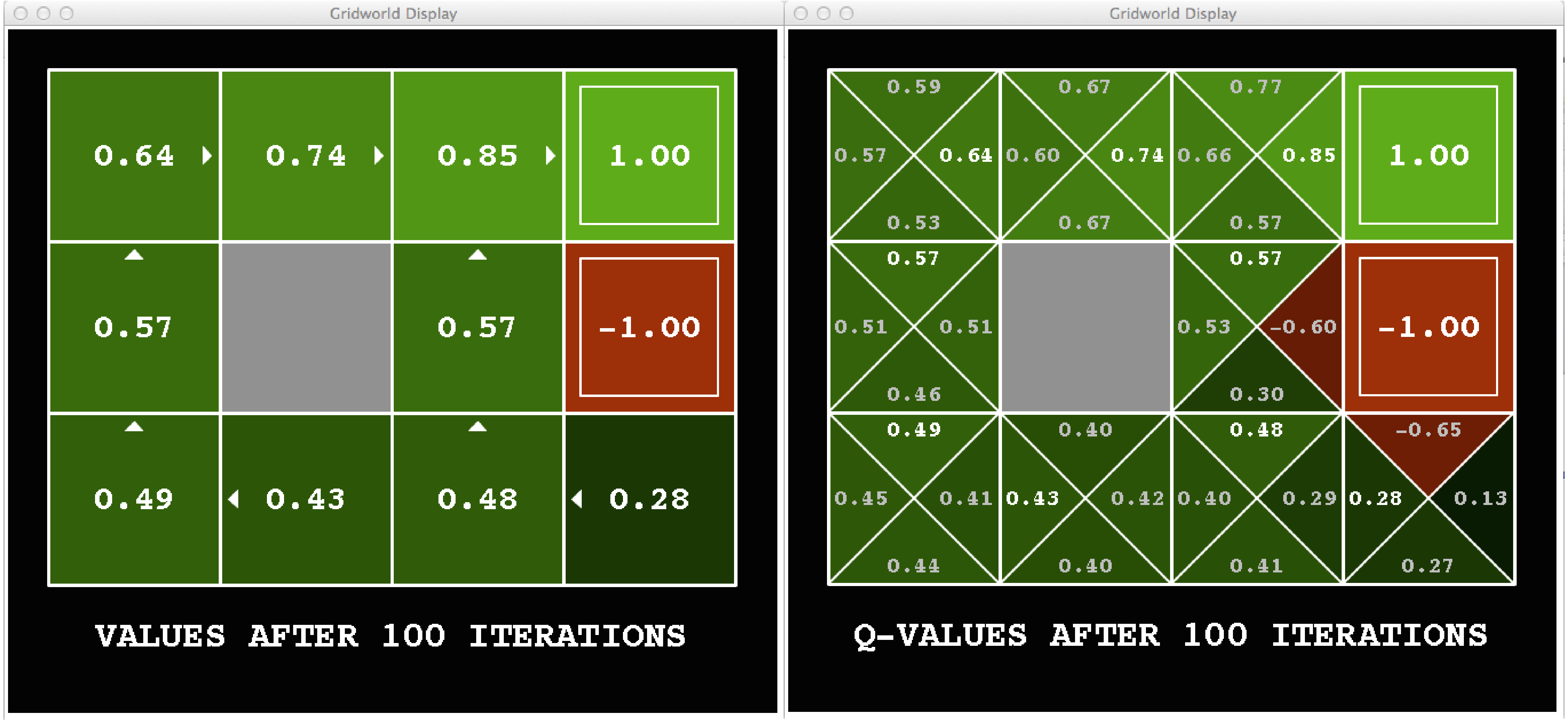




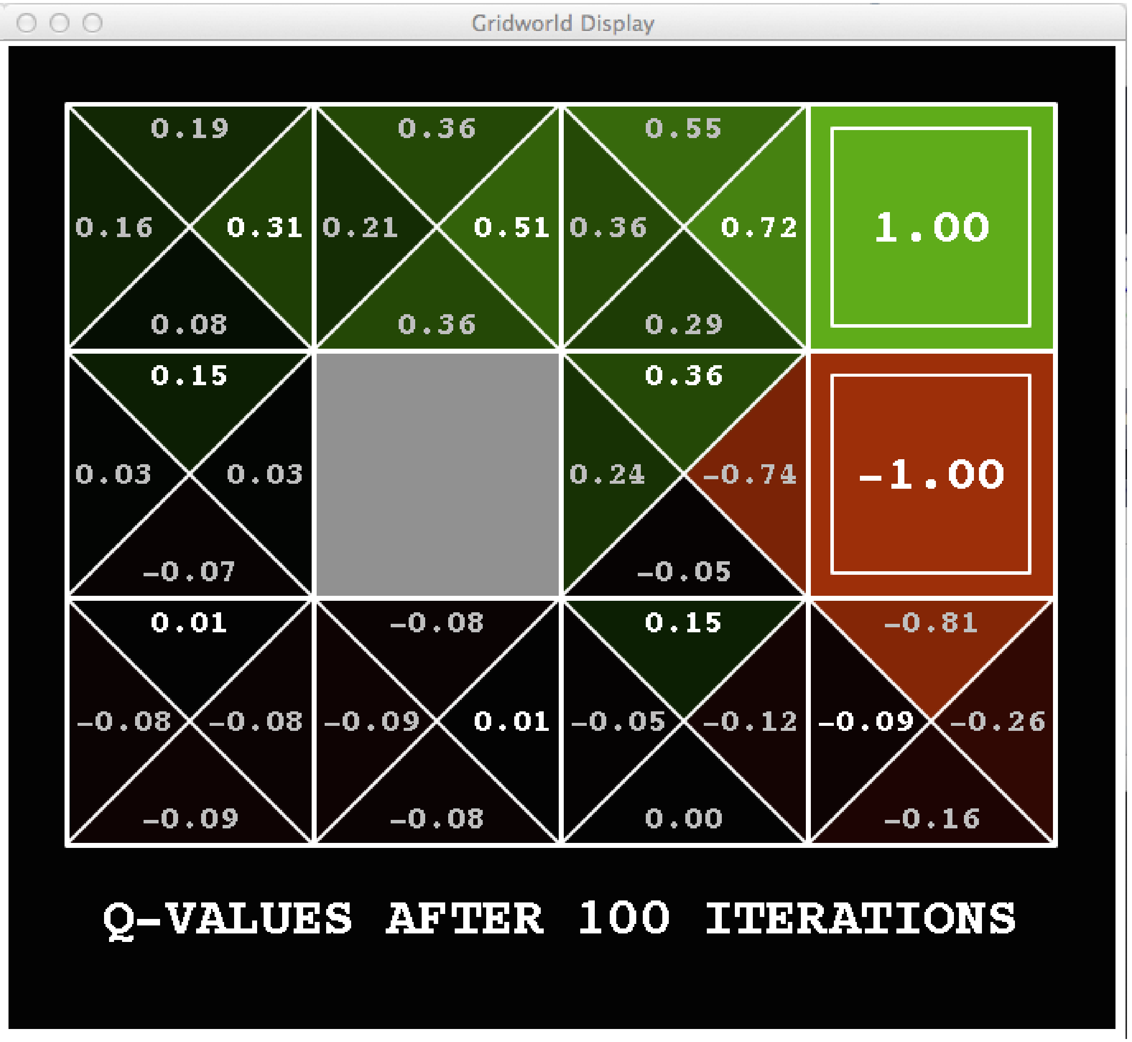
Noise = 0
Discount = 1
Living reward = 0



Noise = 0.2
Discount = 1
Living reward = 0



Noise = 0.2
Discount = 0.9
Living reward = 0



Noise = 0.2
Discount = 0.9
Living reward = -0.1

WHAT WE HAVE LEARNED SO FAR?

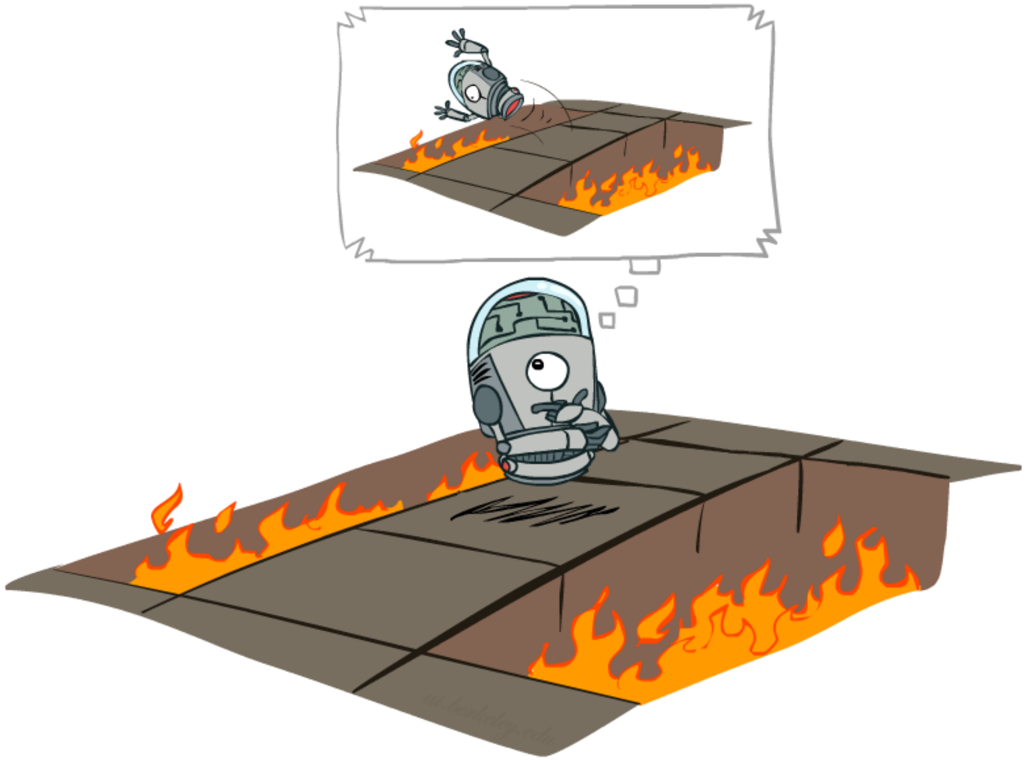
- what is reinforcement learning and its actual place & significance
- reinforcement learning framework & basic concepts
  - agent
  - environment
  - state/observation
  - action
  - reward
  - policy
  - model
  - experience/trajectory/horizon
  - discount factor
  - state value function
  - action value function

Challenges of Reinforcement Learning

Type of tasks

Episodic: **starting point** and an **ending point** (a terminal state)

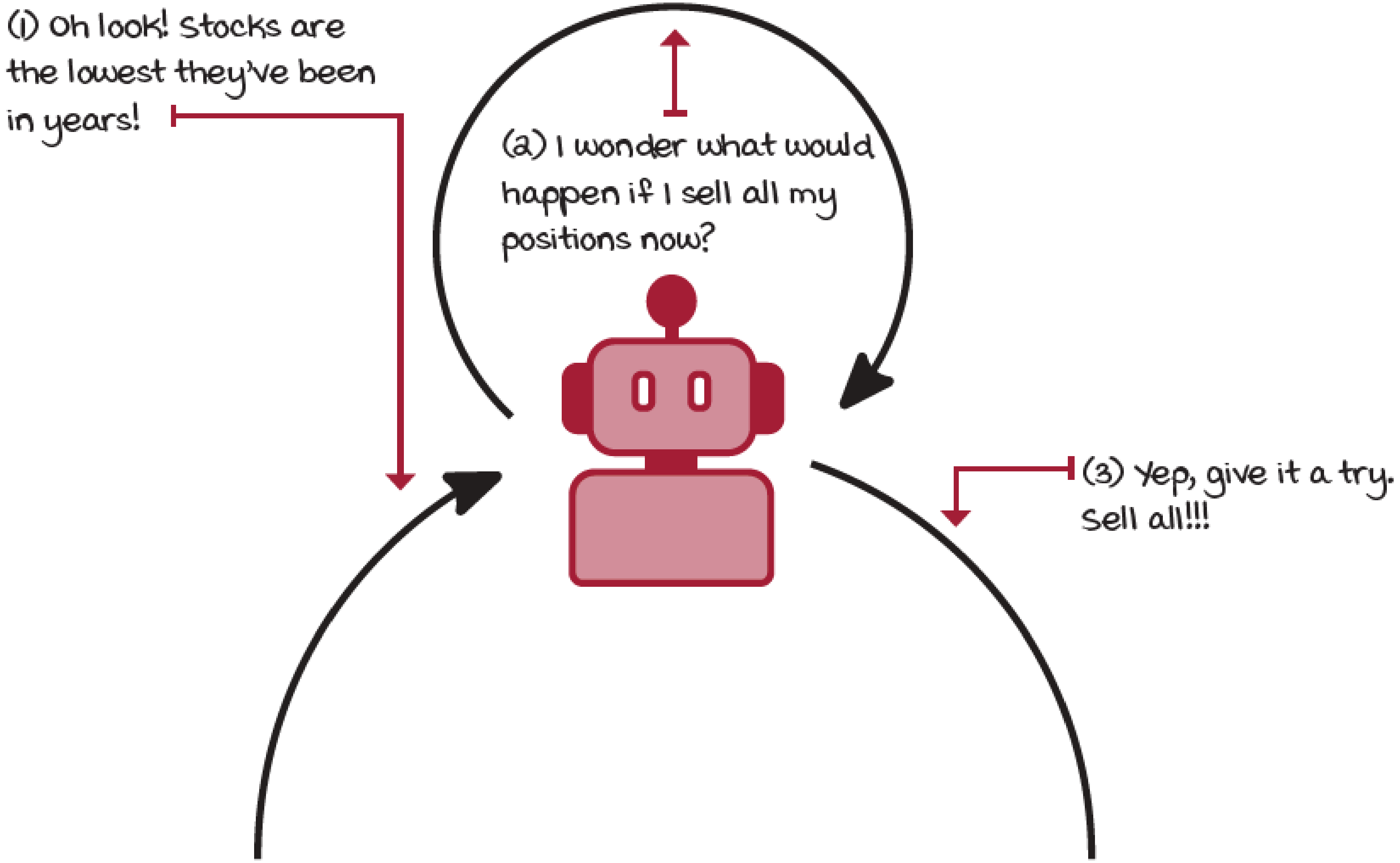
Continuing: task that **continue forever** (no terminal state)



Offline Solution

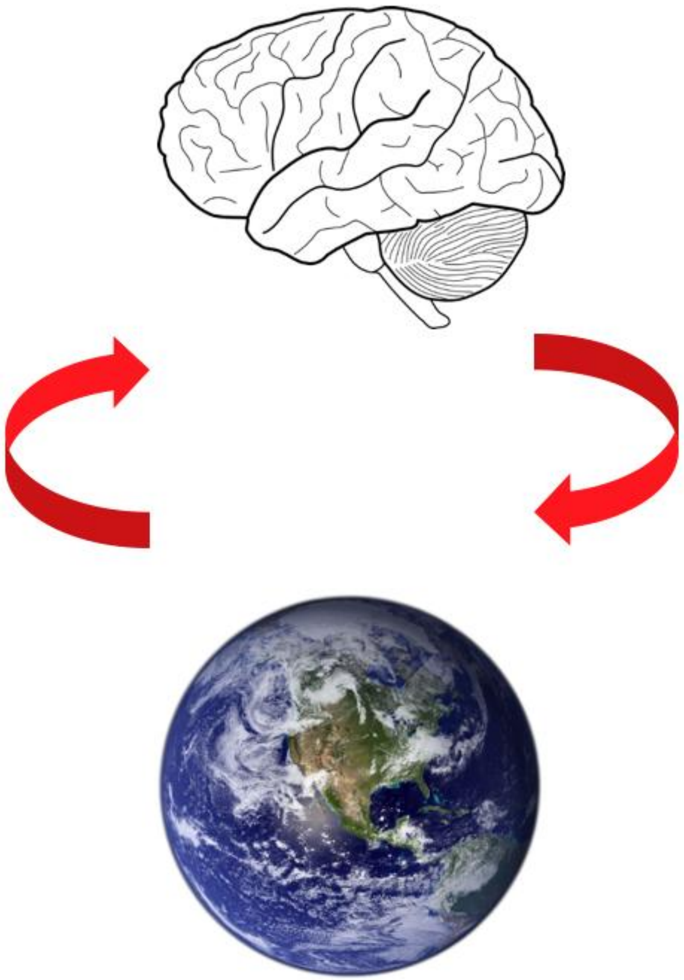
Online Learning

Deep reinforcement learning agents will explore!
Can you afford mistakes?

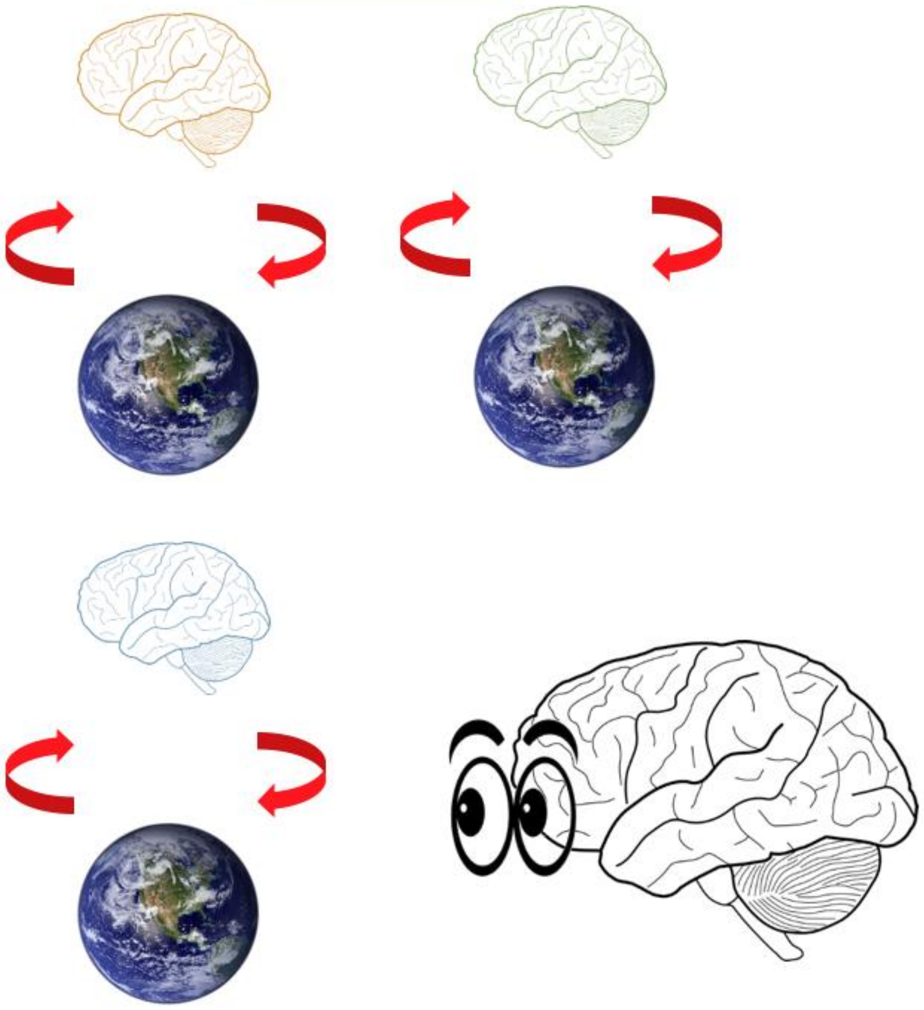


Grokking Deep Reinforcement Learning (Miguel Morales)

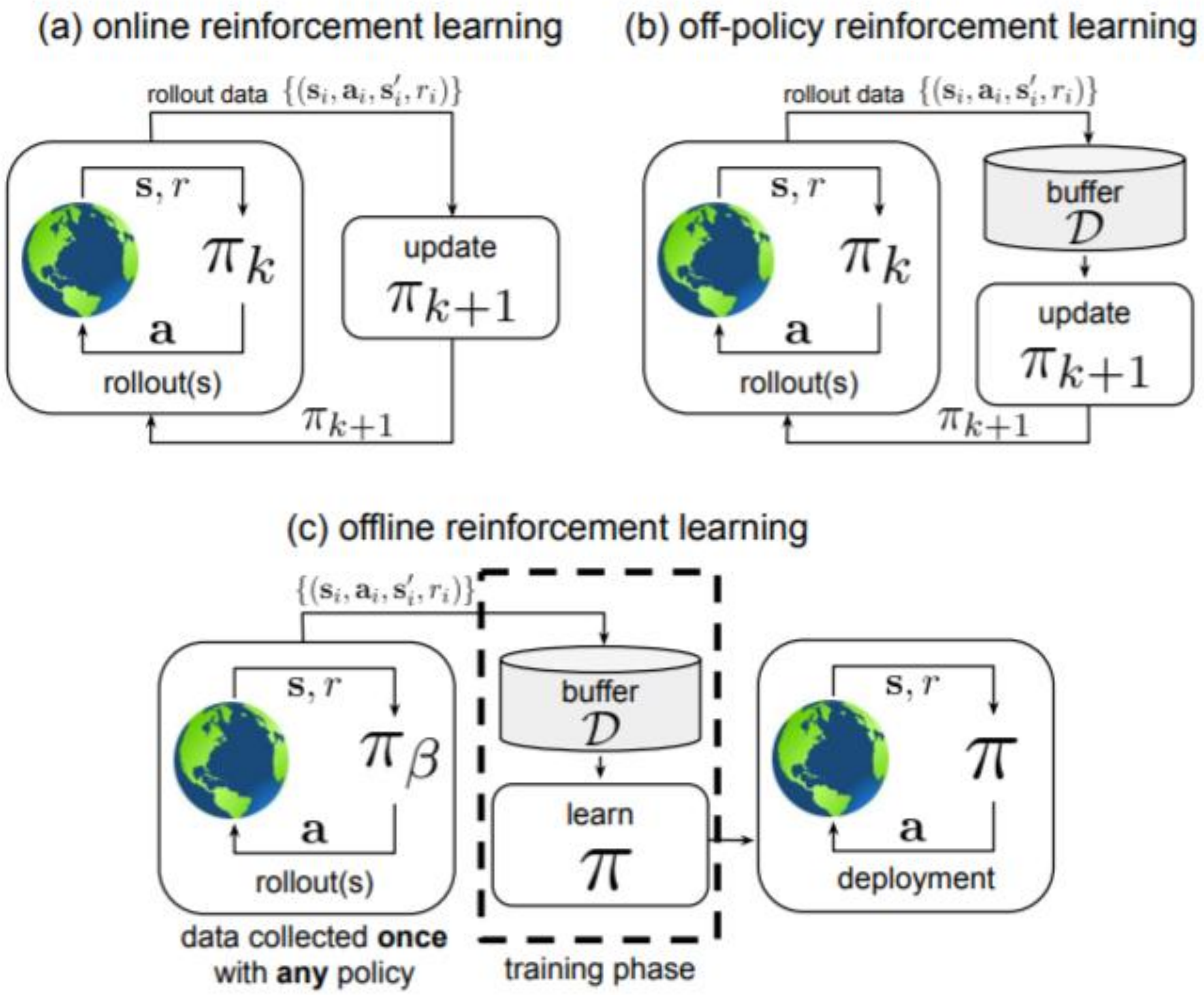
On-policy



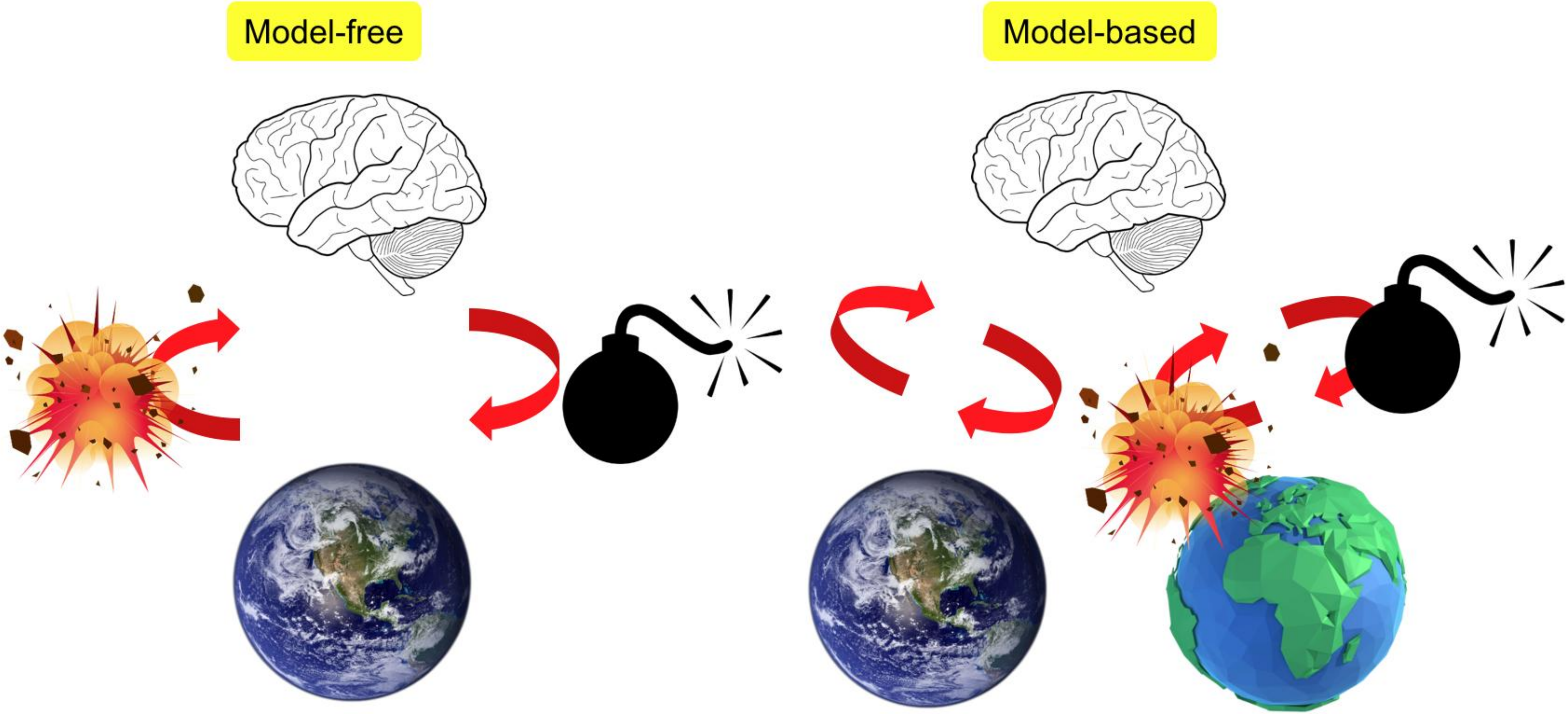
Off-policy



http://www.juyang.co/reinforcement-learning-ii-markov-decision-process-and-rl-agent

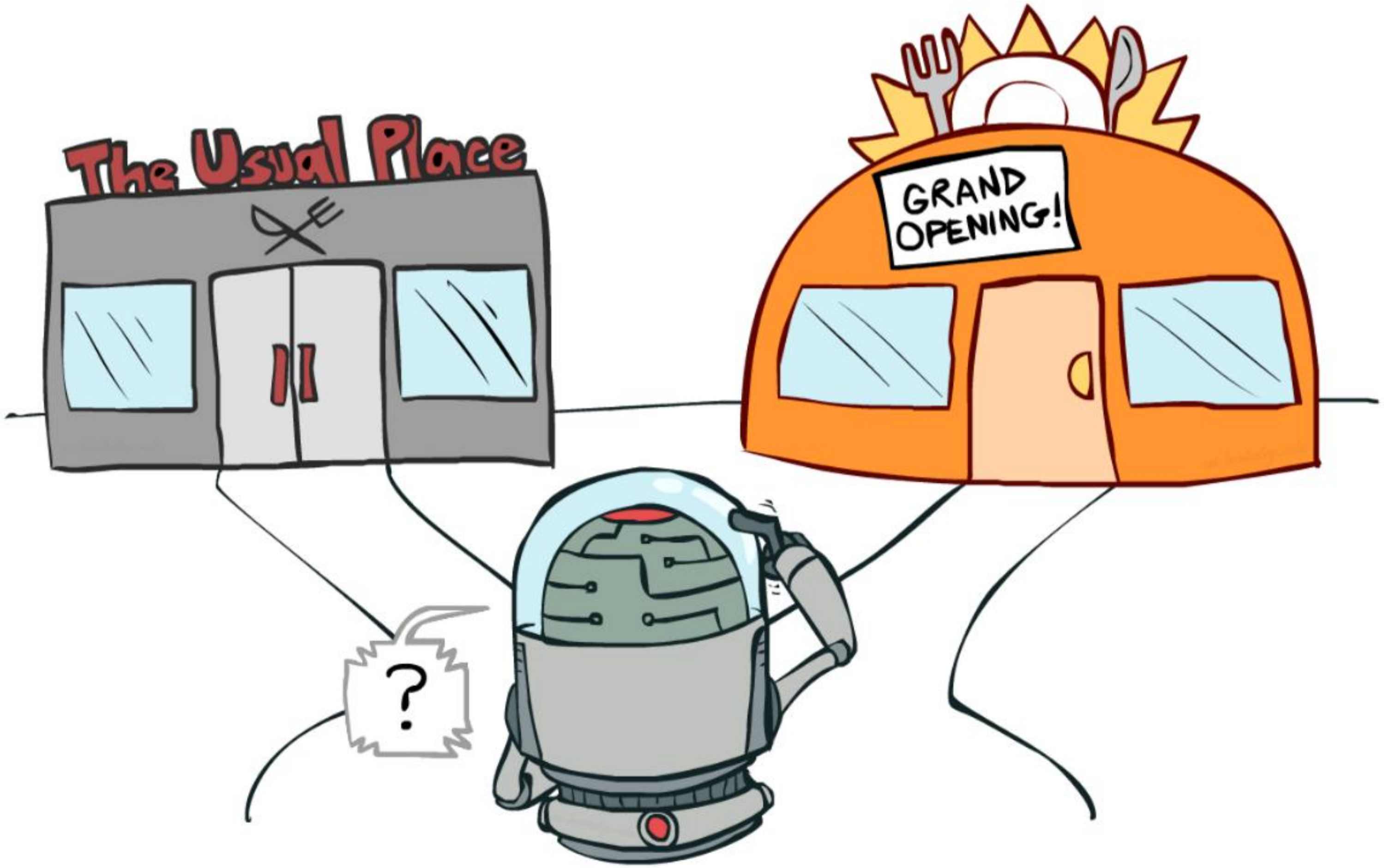


Levine, Sergey, et al. "Offline reinforcement learning: Tutorial, review, and perspectives on open problems." *arXiv preprint arXiv:2005.01643* (2020).



http://www.juyang.co/reinforcement-learning-ii-markov-decision-process-and-rl-agent

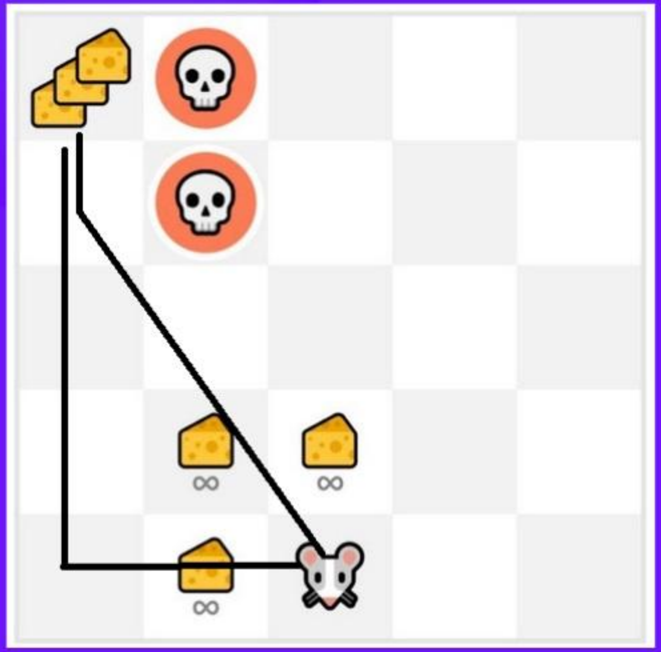
EXPLORATION VS. EXPLOITATION DILEMMA



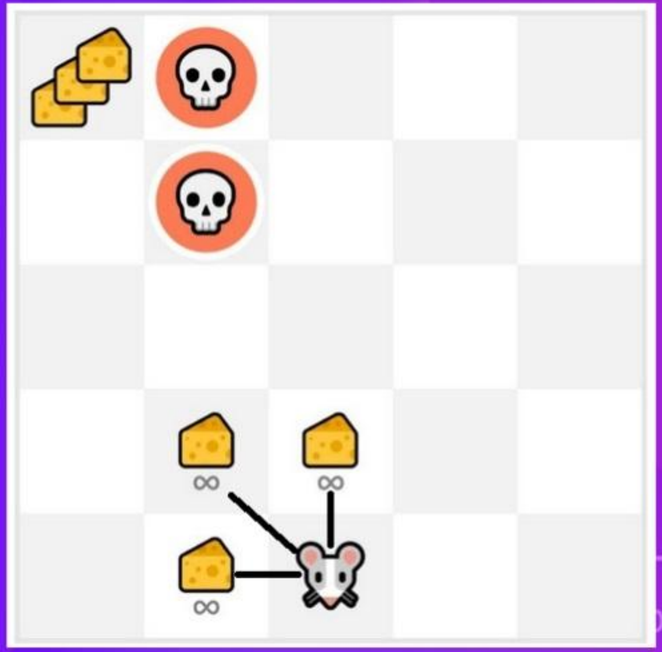
Artificial Intelligence (CS188 Berkeley)

Exploration/ Exploitation tradeoff

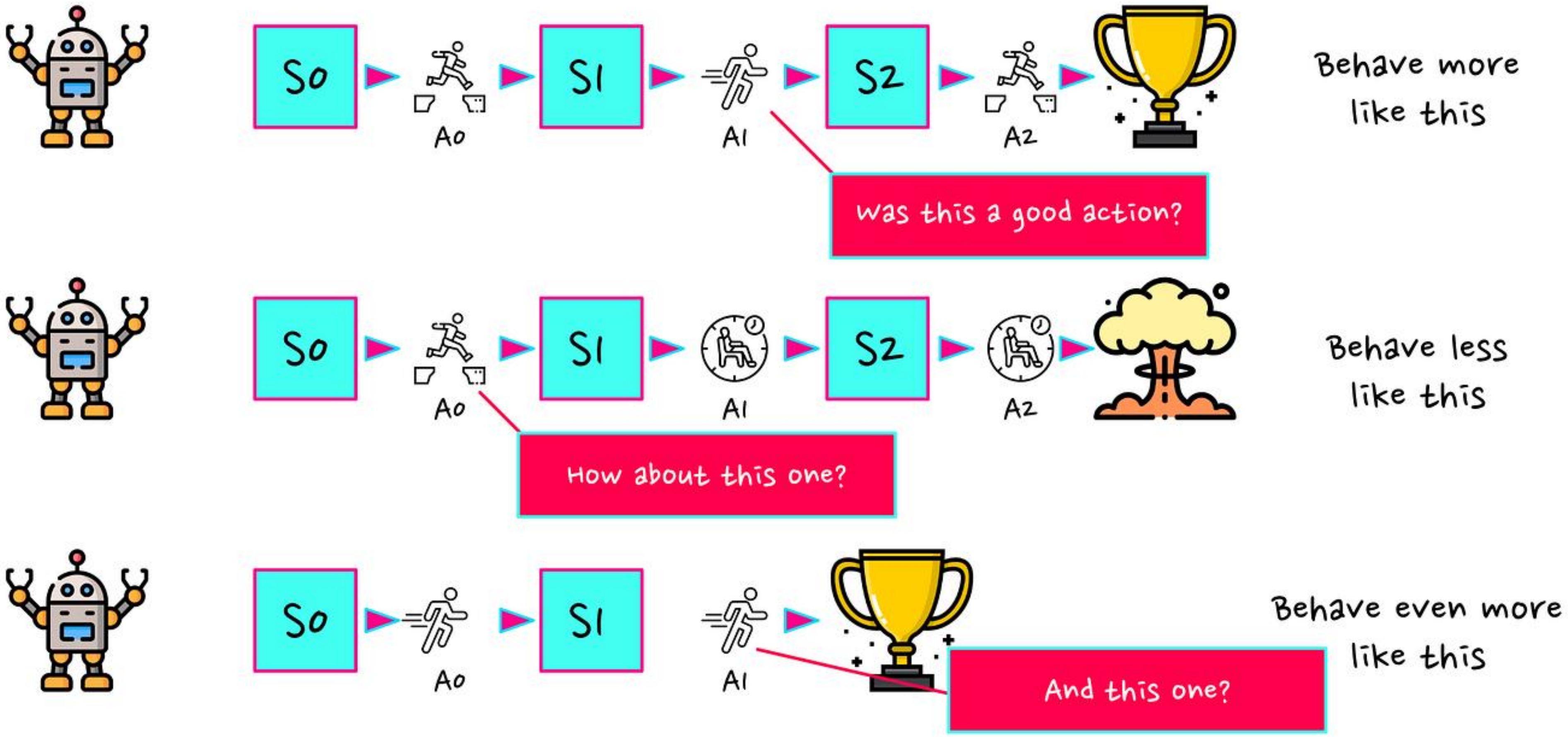
Exploration: trying **random actions** in order to find **more information about the environment.**



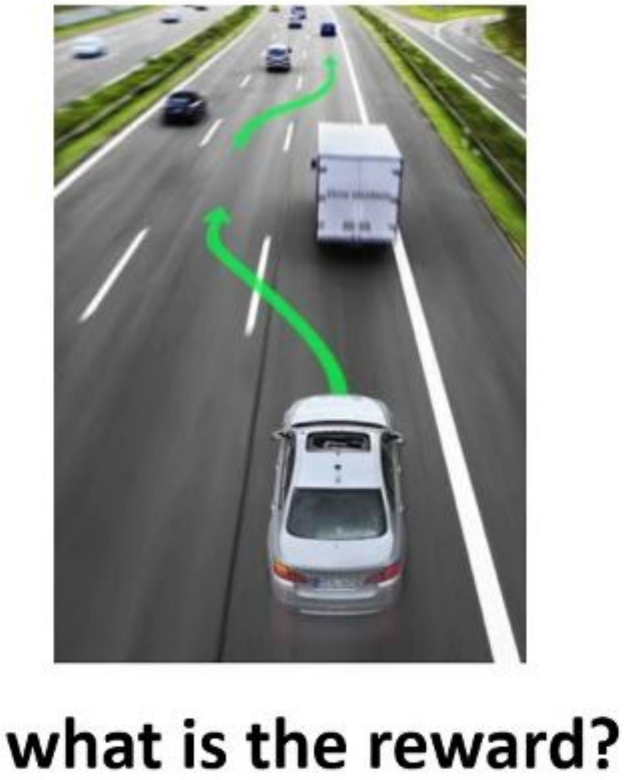
Exploitation: using known information to **maximize the reward.**



CREDIT ASSIGNMENT PROBLEM



REWARD ENGINEERING PROBLEM

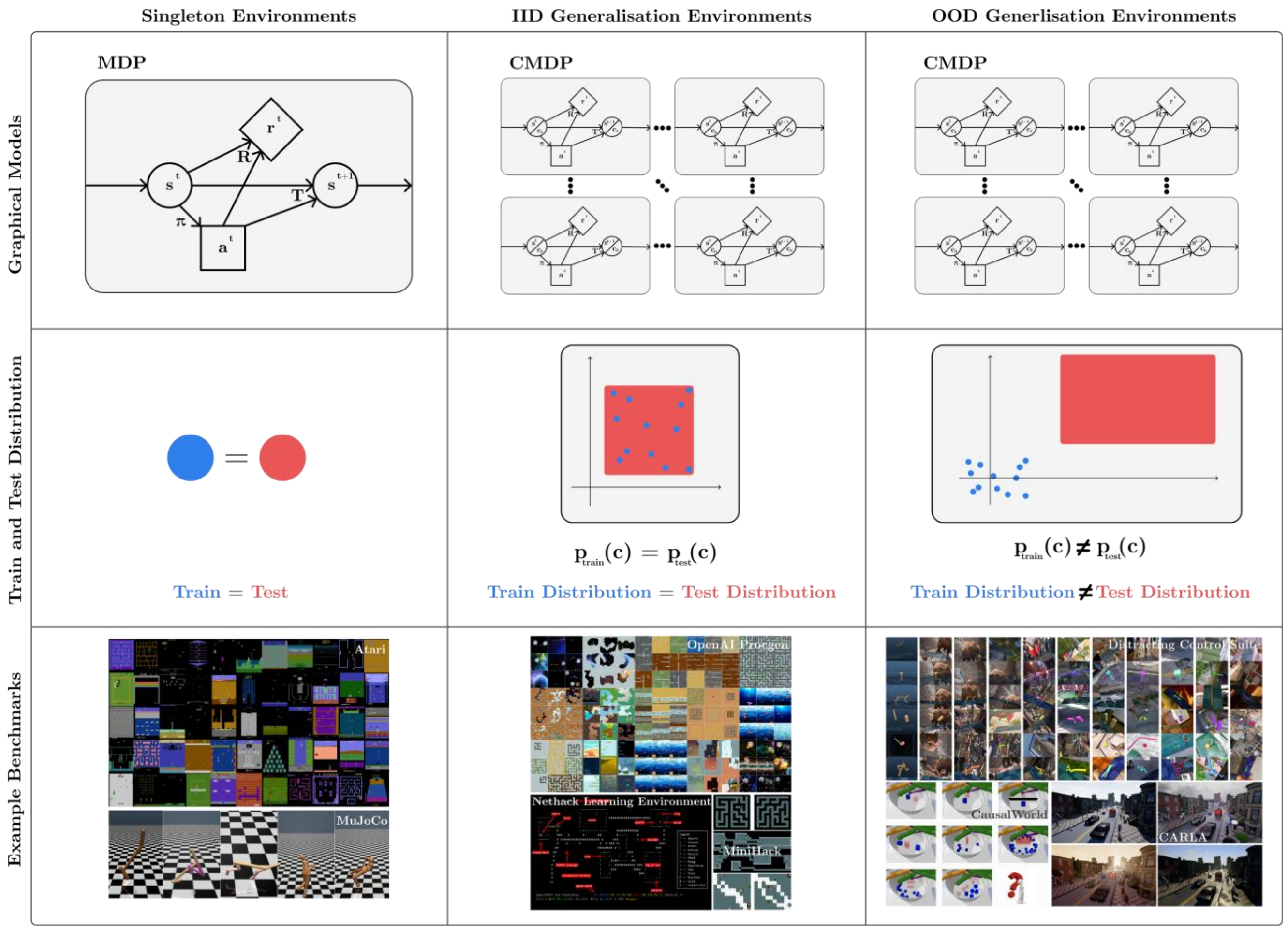


- Fly a helicopter → **Reward**: air time, inverse distance, ...
- Manage an investment portfolio → **Reward**: gains, gains minus risk, ...
- Control a power station → **Reward**: efficiency, ...
- Make a robot walk → **Reward**: distance, speed, ...
- Play video or board games → **Reward**: win, maximise score, ...

If the goal is to learn via interaction, these are all reinforcement learning problems
(Irrespective of which solution you use)

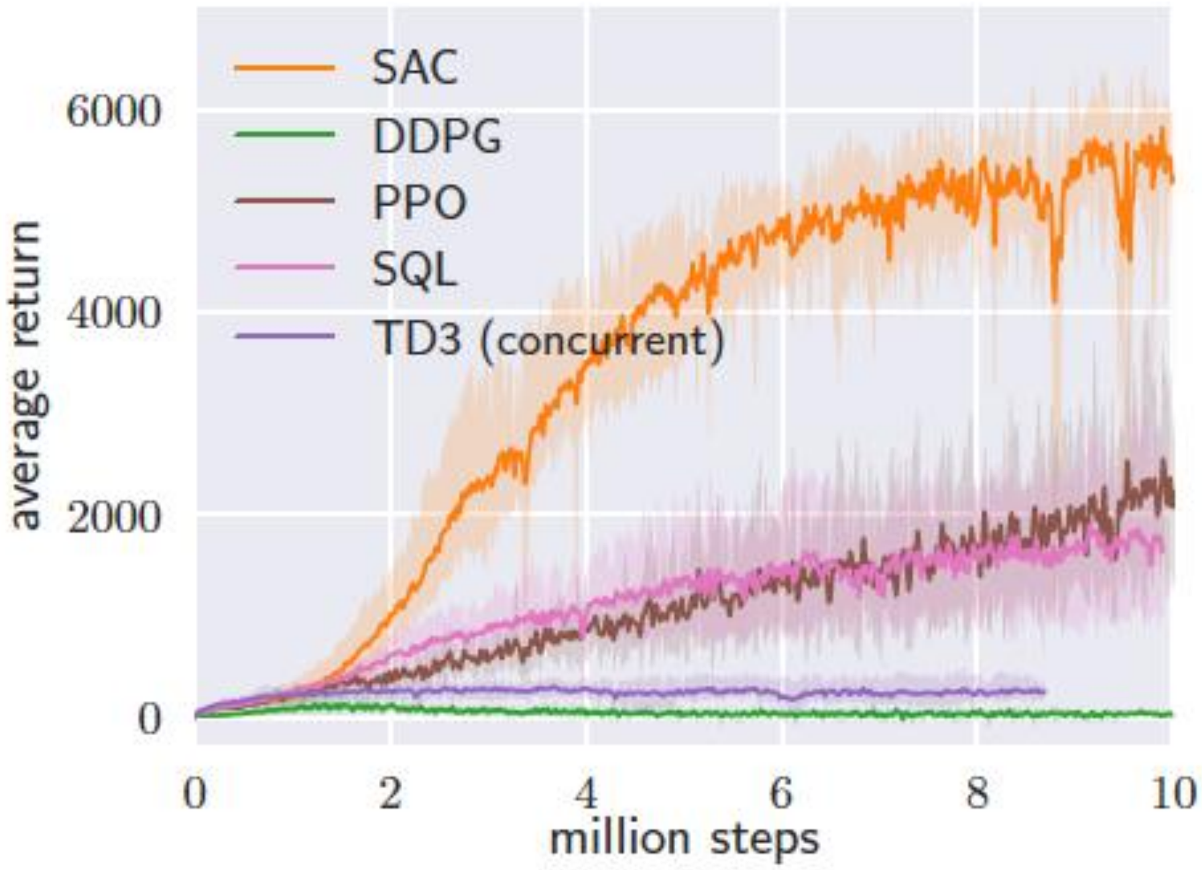
Introduction to RL by David Silver (DeepMind) [2015]

GENERALIZATION PROBLEM

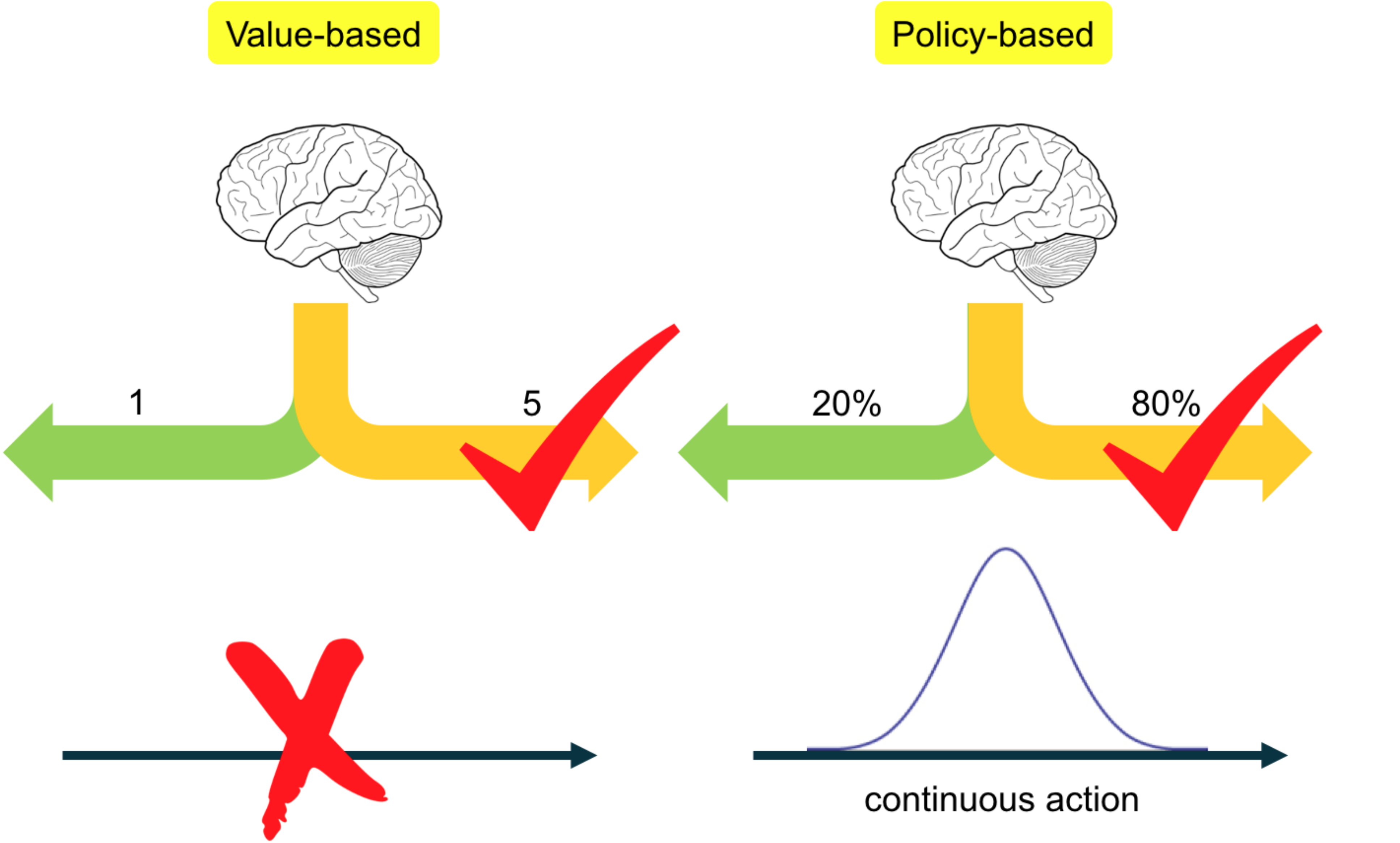


Kirk, Robert, et al. "A survey of zero-shot generalisation in deep reinforcement learning." *Journal of Artificial Intelligence Research* 76 (2023): 201-264.

SAMPLE EFFICIENCY PROBLEM



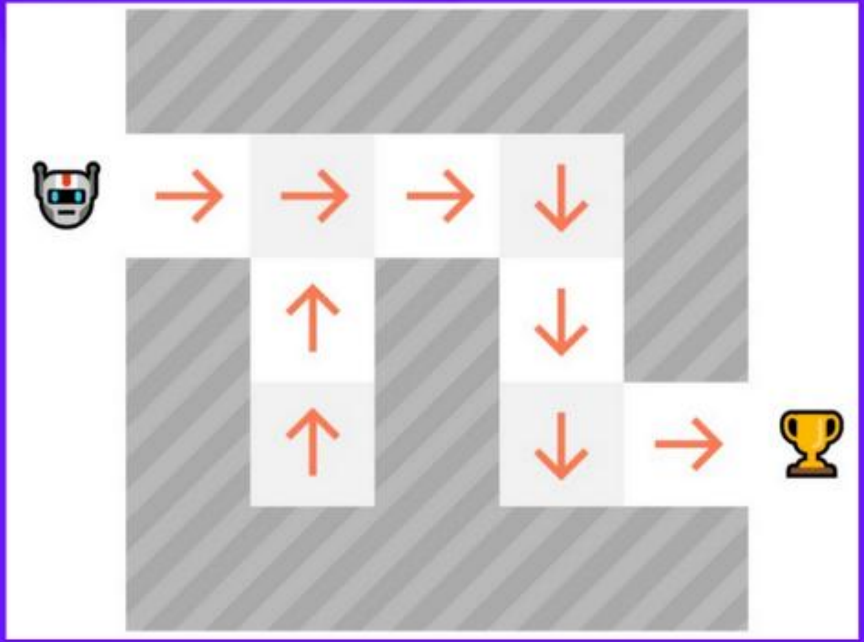
Haarnoja, Tuomas, et al. "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor." *International conference on machine learning*. PMLR, 2018.



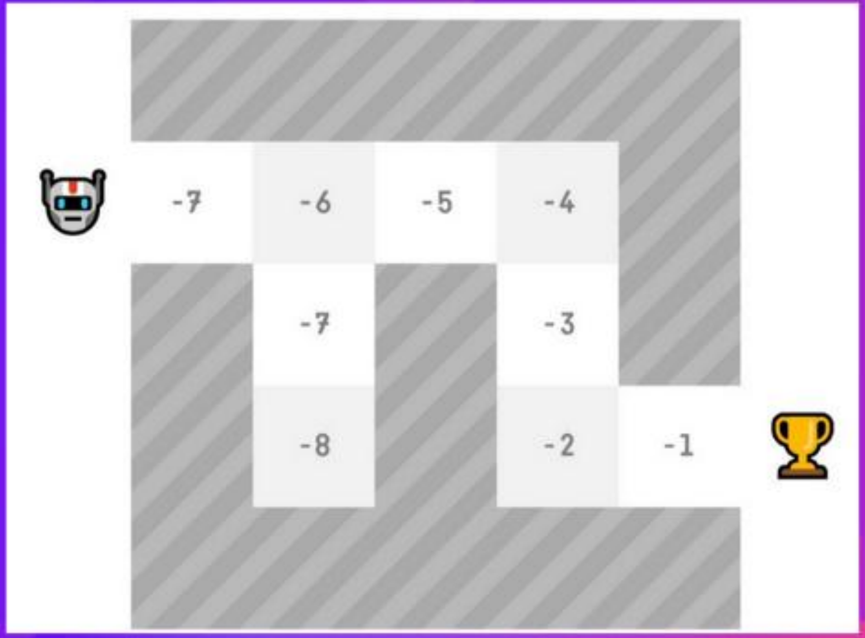
http://www.juyang.co/reinforcement-learning-ii-markov-decision-process-and-rl-agent

Two approaches to find optimal policy π^*:

Policy-Based methods: train the agent to learn which **action to take,** given a state.



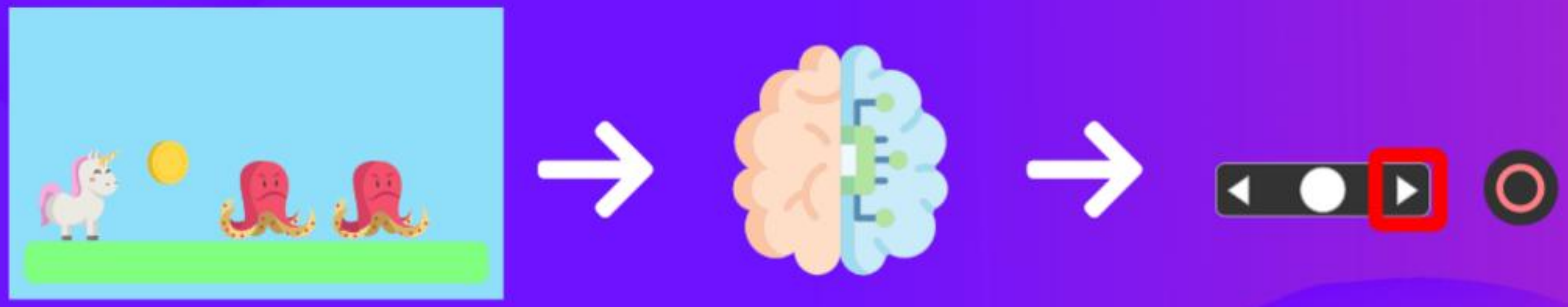
Value-Based methods: train the agent to learn which state **is more valuable** and take the action that **leads to it.**



Two approaches to find optimal policy π^*:

***Policy-Based methods*:**

- Train **directly the policy.**
- Our policy **is a Neural Network.**
- **No value function.**

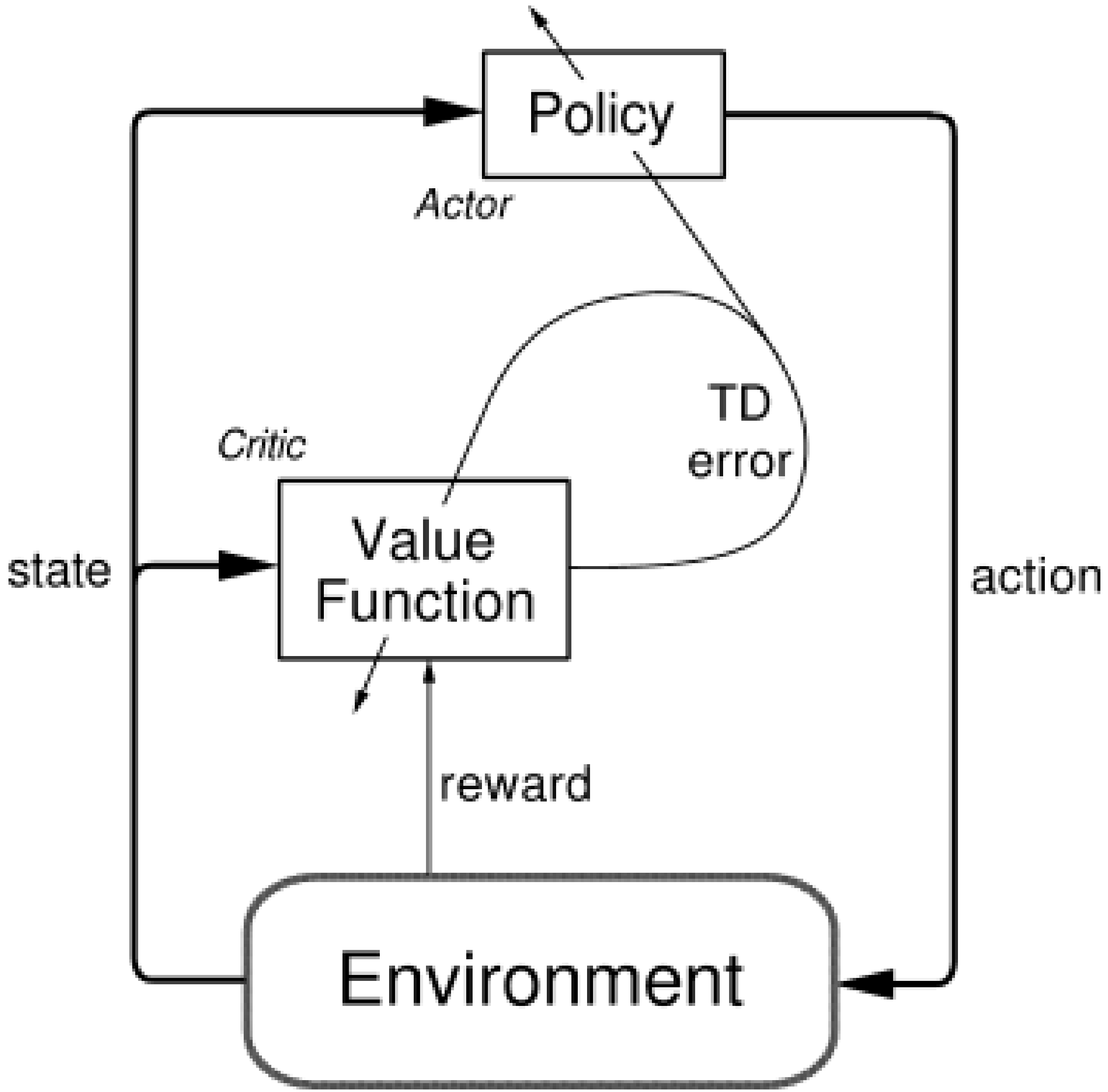


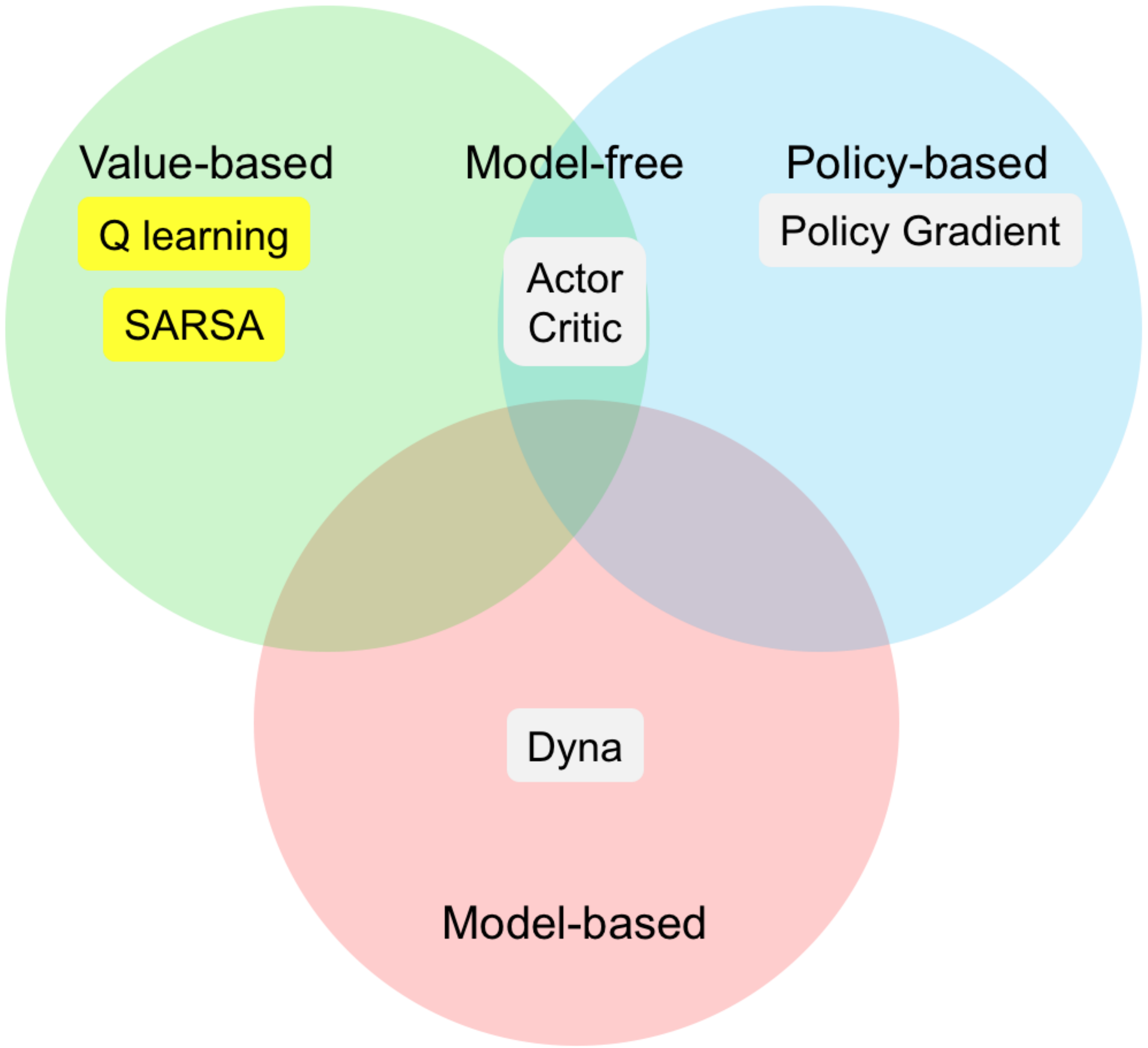
State → π(State) → Action

Two approaches to find optimal policy π^*:

***Value-Based methods*:**

- Don't train the policy.
- **Our policy is a function defined by hand.**
- Instead **train a value-function that is a Neural Network.**

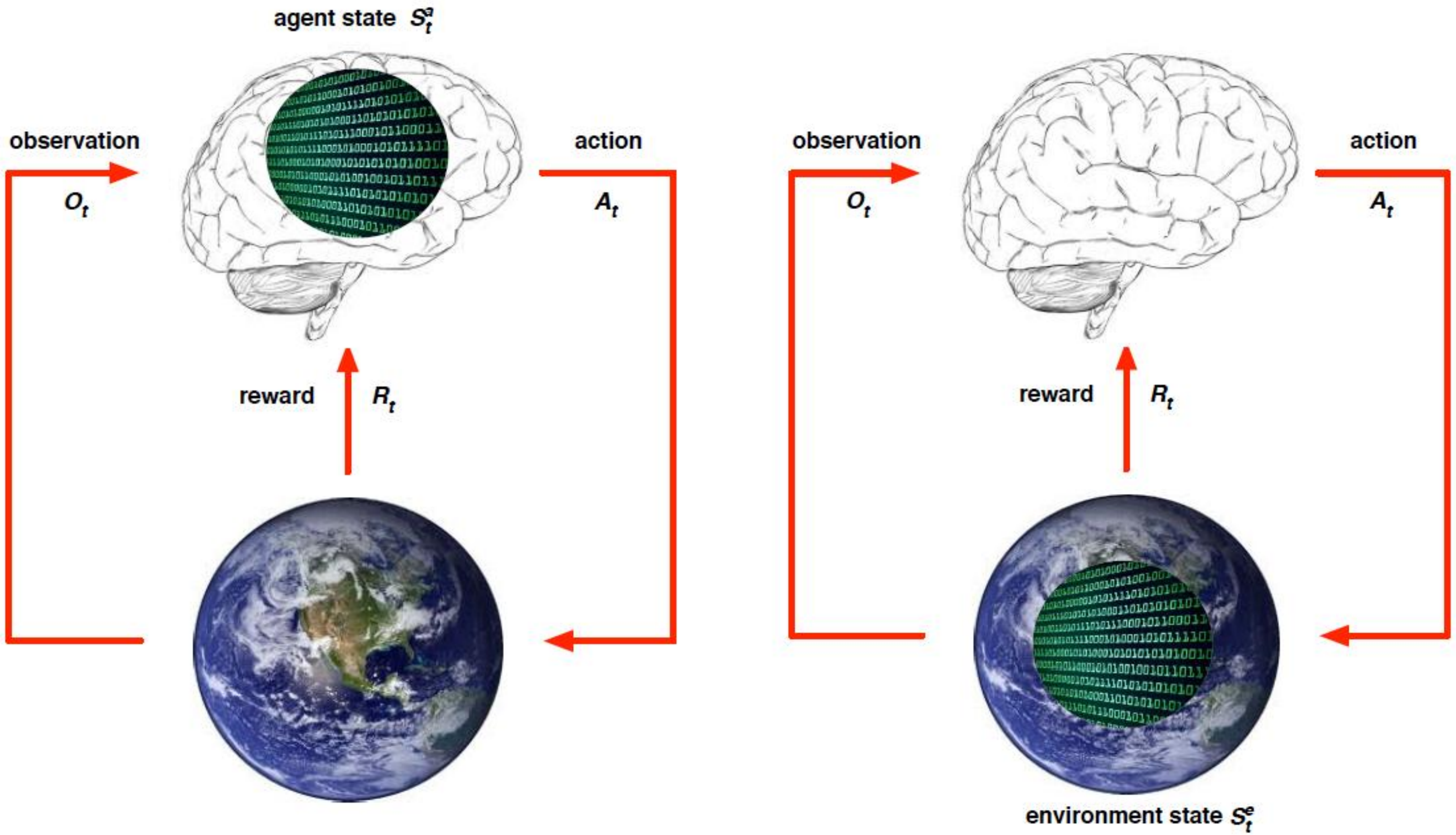

Policy
Actor
TD
error
Critic
Value
Function
state
action
reward
Environment


Value-based
Model-free
Policy-based
Q learning
SARSA
Actor Critic
Policy Gradient
Dyna
Model-based

WHAT WE HAVE LEARNED SO FAR?

- episodic vs continuing reinforcement learning
- offline vs online learning
- safe reinforcement learning
- on-policy vs off-policy vs offline reinforcement learning
- model-free vs model-base reinforcement learning
- exploration vs. exploitation dilemma
- credit assignment problem
- reward engineering problem
- generalization problem
- sample efficiency problem
- value-base vs policy-base vs actor-critic methods

MP, MRP, MDP



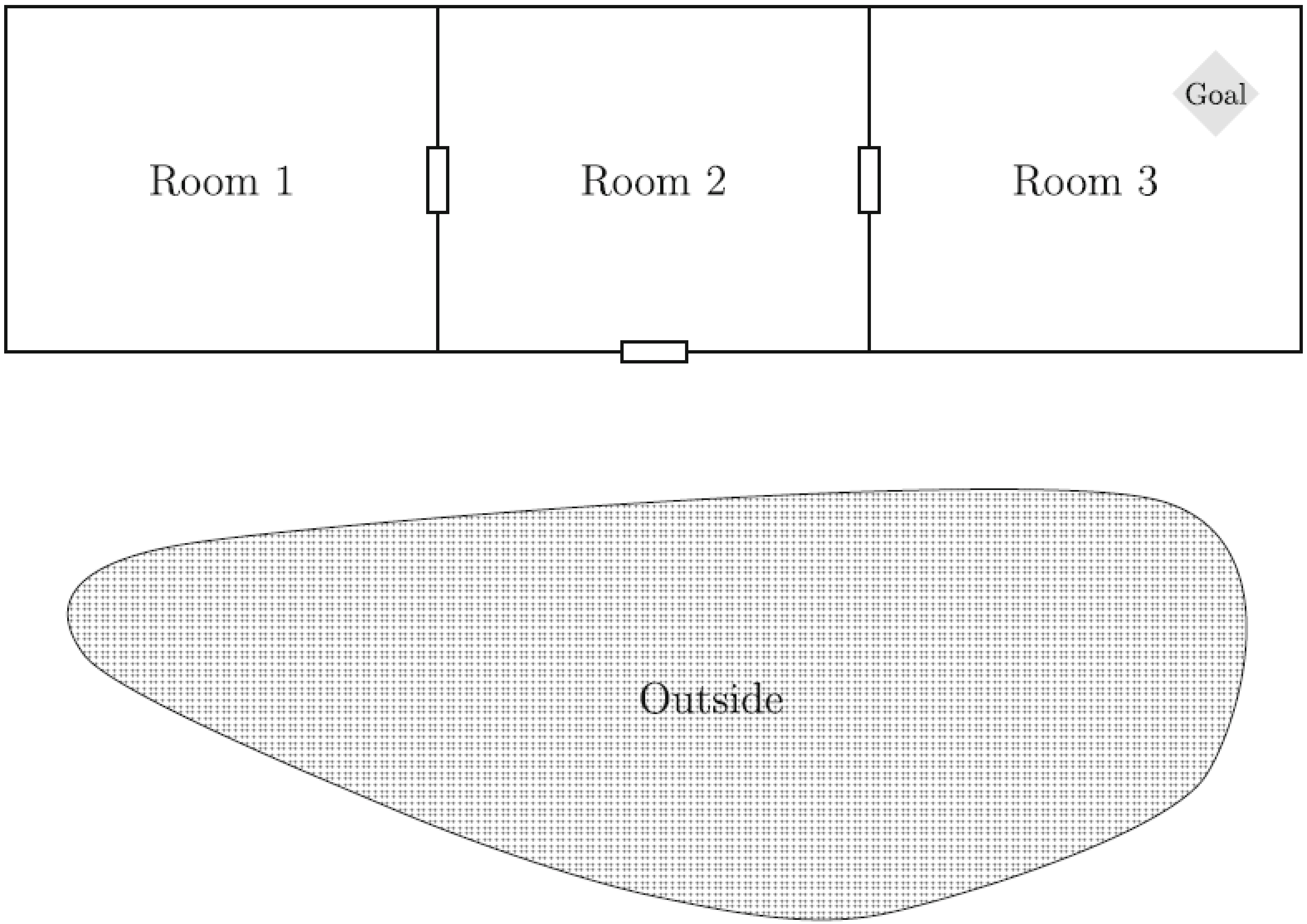
Introduction to RL by David Silver (DeepMind) [2015]

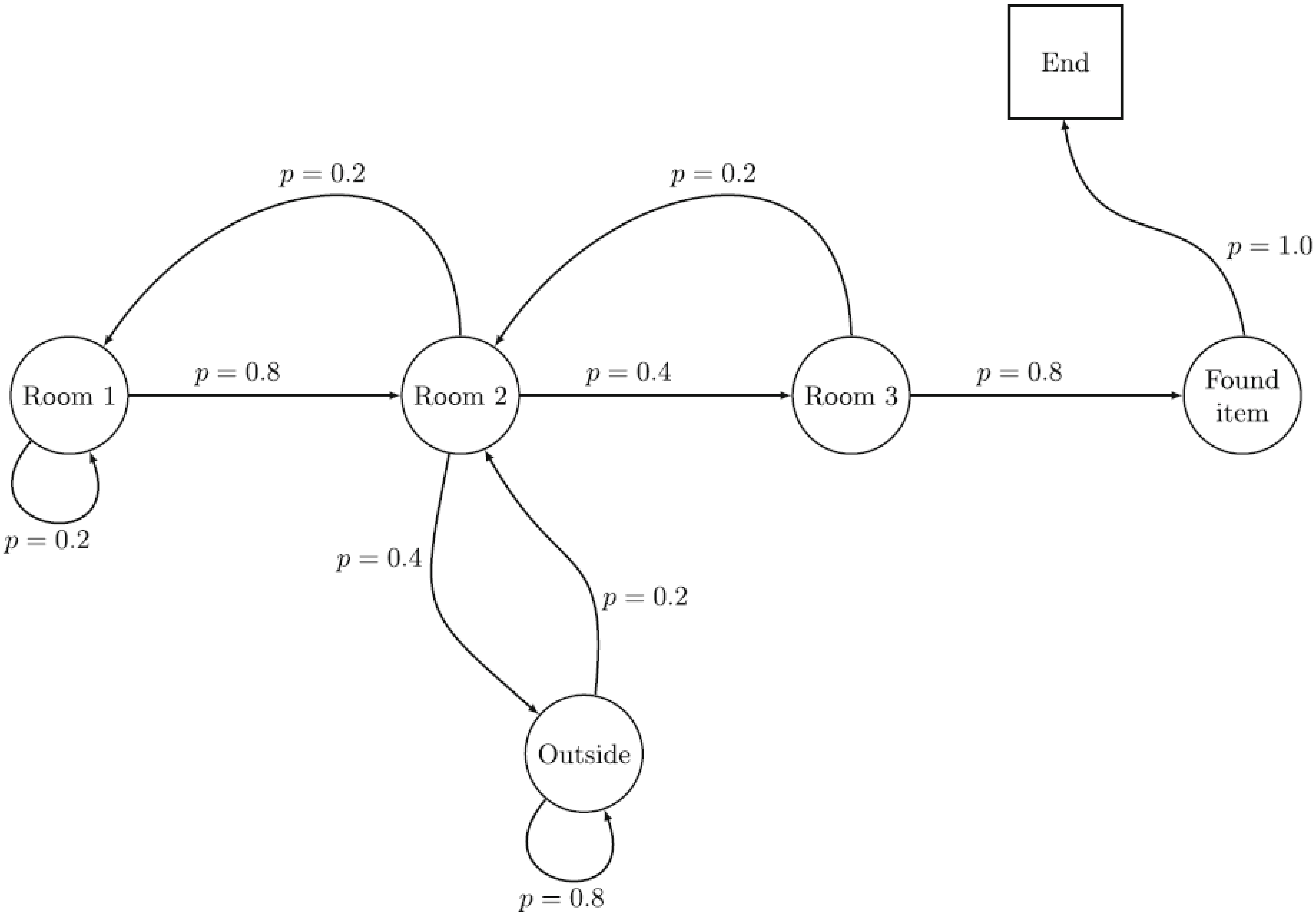
An information state (a.k.a. Markov state) contains all useful information from the history.

Definition

A state S_t is Markov if and only if

$$\mathbb{P}[S_{t+1} \mid S_t] = \mathbb{P}[S_{t+1} \mid S_1, ..., S_t]$$


Goal
Room 1
Room 2
Room 3
Outside



The Art of Reinforcement Learning (Michael Hu)

A Markov chain can be defined as a tuple of $(\mathcal{S}, \mathcal{P})$

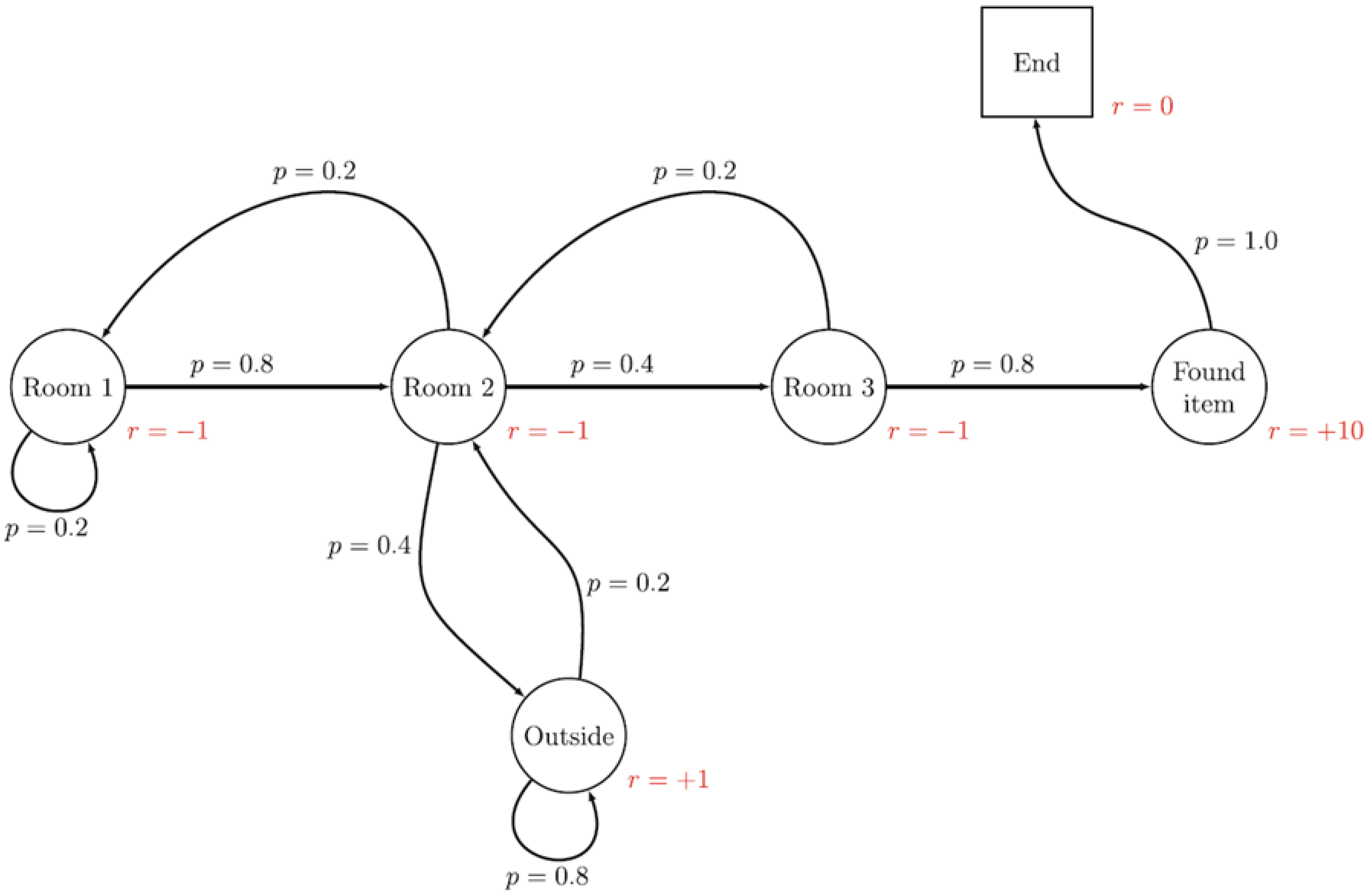
- $\mathcal{S}$ is a finite set of states called the state space.

$$\mathcal{P} = \begin{array}{l} \\ \text{Room 1} \\ \text{Room 2} \\ \text{Room 3} \\ \text{Outside} \\ \text{Found item} \\ \text{End} \end{array} \begin{array}{c} \begin{array}{cccccc} \text{Room 1} & \text{Room 2} & \text{Room 3} & \text{Outside} & \text{Found item} & \text{End} \end{array} \\ \begin{pmatrix} 0.2 & 0.8 & 0 & 0 & 0 & 0 \\ 0.2 & 0 & 0.4 & 0.4 & 0 & 0 \\ 0 & 0.2 & 0 & 0 & 0.8 & 0 \\ 0 & 0.2 & 0 & 0.8 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1.0 \\ 0 & 0 & 0 & 0 & 0 & 1.0 \end{pmatrix} \end{array}$$

- Episode 1: (Room 1, Room 2, Room 3, Found item, End)
- Episode 2: (Room 3, Found item, End)
- Episode 3: (Room 2, Outside, Room 2, Room 3, Found item, End)
- Episode 4: (Outside, Outside, Outside, $\ldots$)

We can define the Markov reward process as a tuple $(\mathcal{S}, \mathcal{P}, \mathcal{R})$

- $\mathcal{S}$ is a finite set of states called the state space.
- $\mathcal{P}$ is the dynamics function (or transition model) of the environment, where $P(s'|s) = P\Big[S_{t+1} = s' \Bigm| S_t = s\Big]$ specify the probability of environment transition into successor state s' when in current state s.
- $\mathcal{R}$ is a reward function of the environment. $R(s) = \mathbb{E}\Big[R_t \Bigm| S_t = s\Big]$ is the reward signal provided by the environment when the agent is in state s.

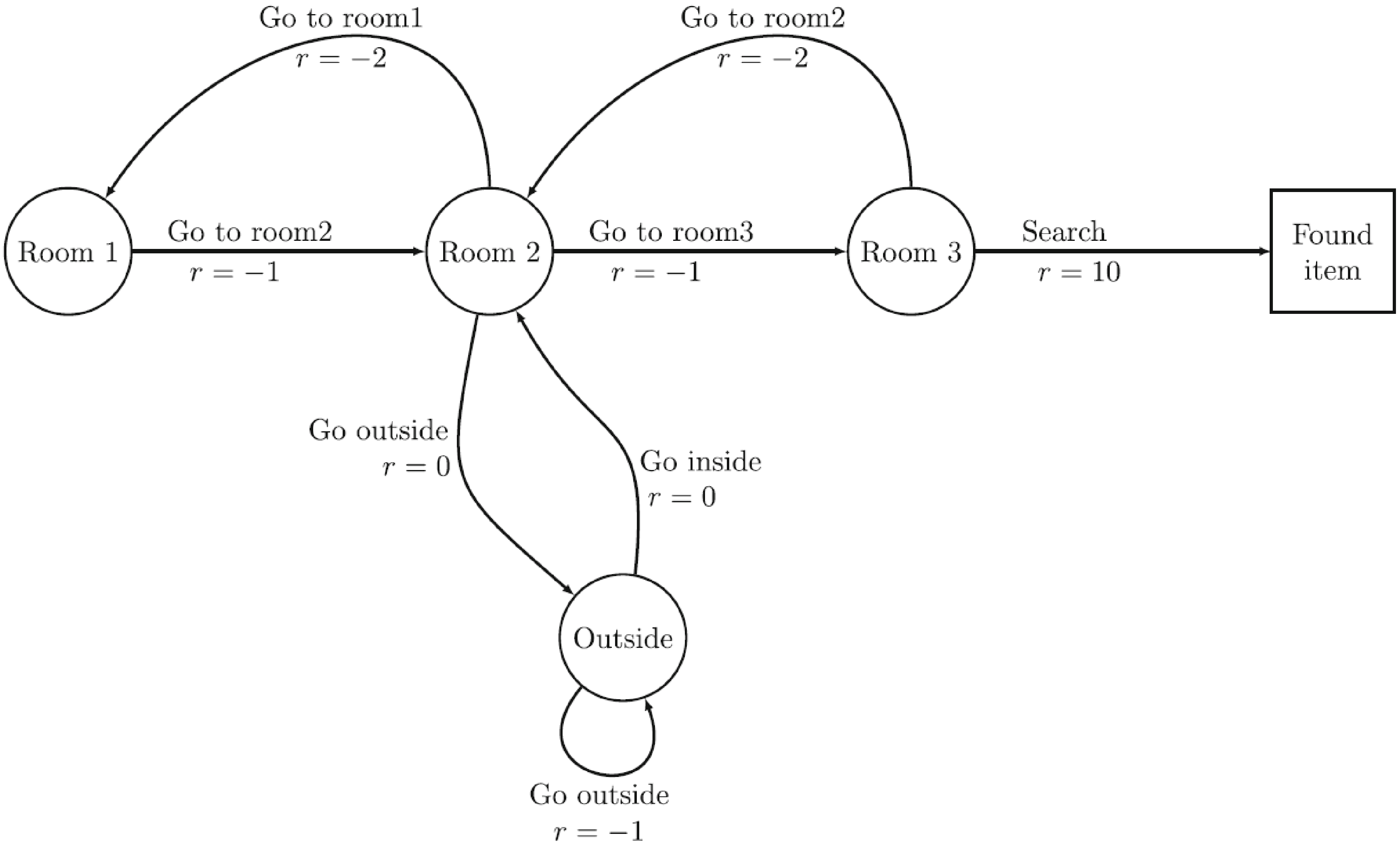


The Art of Reinforcement Learning (Michael Hu)

- Episode 1: (Room 1, Room 2, Room 3, Found item, End)
  Total rewards $= -1 - 1 - 1 + 10 + 0 = 7.0$
- Episode 2: (Room 3, Found item, End)
  Total rewards $= -1 + 10 = 9.0$
- Episode 3: (Room 2, Outside, Room 2, Room 3, Found item, End)
  Total rewards $= -1 + 1 - 1 - 1 + 10 + 0 = 8.0$
- Episode 4: (Outside, Outside, Outside ...)
  Total rewards $= 1 + 1 + \cdots = \infty$

We can define the MDP as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R})$:

- $\mathcal{S}$ is a finite set of states called the state space.
- $\mathcal{A}$ is a finite set of actions called the action space.
- $\mathcal{P}$ is the dynamics function (or transition model) of the environment, where $P(s'|s,a) = P\left[S_{t+1} = s' \,\middle|\, S_t = s, A_t = a\right]$ specify the probability of environment transition into successor state s' when in current state s and take action a.
- $\mathcal{R}$ is a reward function of the environment; $R(s,a) = \mathbb{E}\left[R_t \,\middle|\, S_t = s, A_t = a\right]$ is the reward signal provided by the environment when the agent is in state s and taking action a.



- $\mathcal{S}$ = {Room 1, Room 2, Room 3, Outside, Found item}
- $\mathcal{A}$ = {Go to room1, Go to room2, Go to room3, Go outside, Go inside, Search}
- $\mathcal{R}$ = {−1, −2, +1, 0, +10}

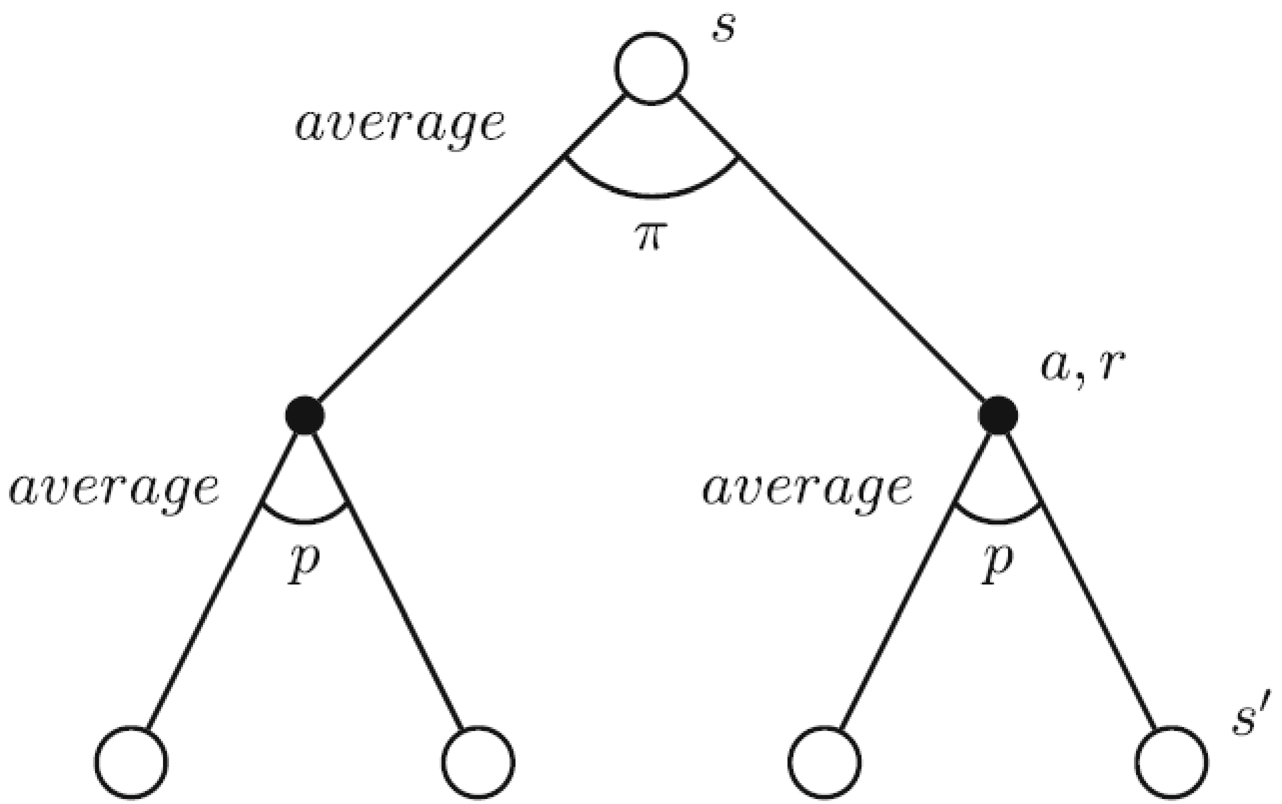
The Art of Reinforcement Learning (Michael Hu)

$$
\mathcal{P} = \begin{array}{r} \\ \text{Go to room1} \\ \text{Go to room2} \\ \text{Go to room3} \\ \text{Go outside} \\ \text{Go inside} \\ \text{Search} \end{array}
\begin{array}{c} \begin{array}{ccccc} \text{Room 1} & \text{Room 2} & \text{Room 3} & \text{Outside} & \text{Found item} \end{array} \\
\begin{pmatrix} 1.0 & 0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 0 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \end{pmatrix} \end{array}
$$

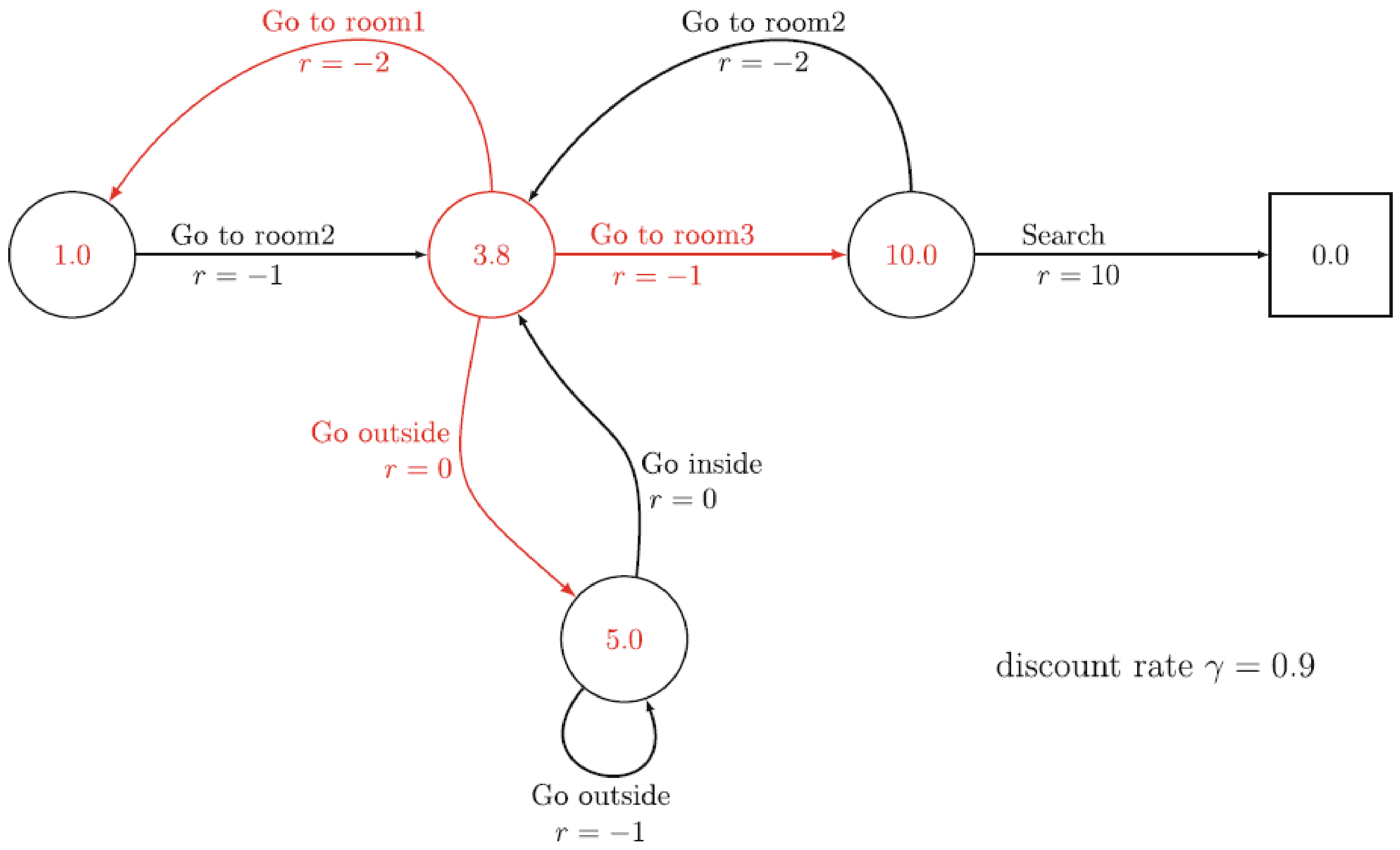
$$
\mathcal{P} = \begin{array}{r} \\ \text{Go to room1} \\ \text{Go to room2} \\ \text{Go to room3} \\ \text{Go outside} \\ \text{Go inside} \\ \text{Search} \end{array}
\begin{array}{c} \begin{array}{ccccc} \text{Room 1} & \text{Room 2} & \text{Room 3} & \text{Outside} & \text{Found item} \end{array} \\
\begin{pmatrix} 0.6 & 0 & 0 & 0.4 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 0 & 0.2 & 0.8 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0.0 & 0 \end{pmatrix} \end{array}
$$

$$V_\pi(s) = \mathbb{E}_\pi\Big[G_t \;\Big|\; S_t = s\Big], \quad \text{for all } s \in \mathcal{S}$$

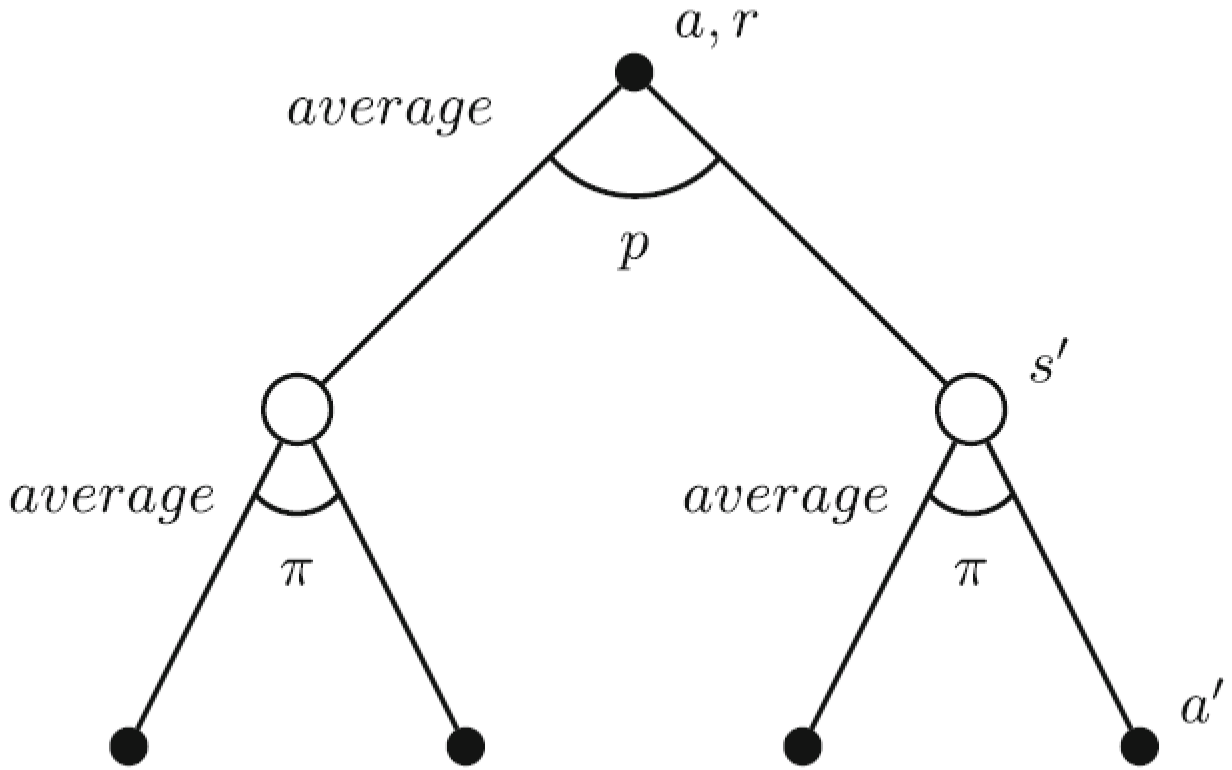
$$Q_\pi(s, a) = \mathbb{E}_\pi\Big[G_t \;\Big|\; S_t = s, A_t = a\Big], \quad \text{for all } s \in \mathcal{S}, a \in A$$



$$
\begin{aligned}
V_\pi(s) &= \mathbb{E}_\pi\Big[G_t \;\Big|\; S_t = s\Big] \\
&= \sum_{a \in A} \pi(a|s) \left[R(s,a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s,a) V_\pi(s') \right], \quad \text{for all } s \in \mathcal{S}
\end{aligned}
$$

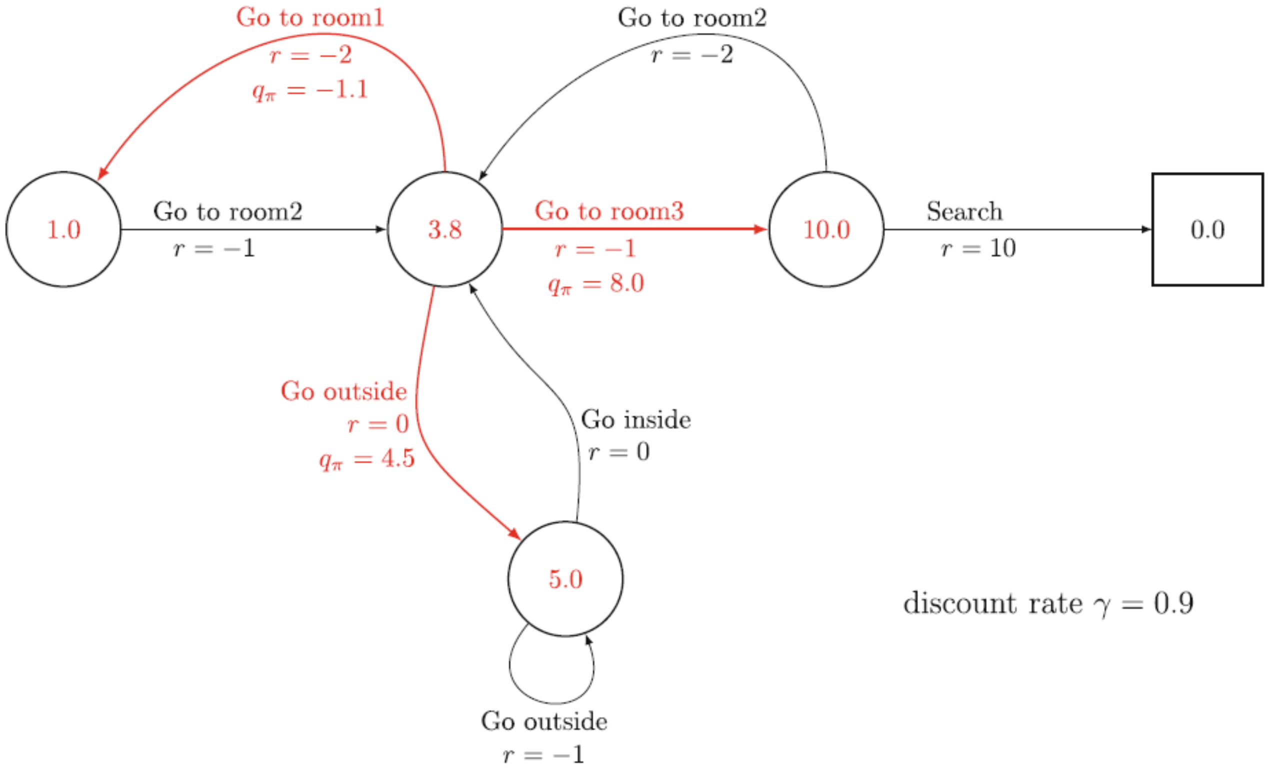


$$V_\pi(Room\ 2) = 0.33 * (-2 + 0.9 * 1.0) + 0.33 * (-1 + 0.9 * 10.0)$$
$$+ 0.33 * (0 + 0.9 * 5.0)$$
$$= 0.33 * -1.1 + 0.33 * 8 + 0.33 * 4.5$$
$$= 3.76$$



$$Q_\pi(s,a) = \mathbb{E}_\pi\Big[G_t \;\Big|\; S_t = s, A_t = a\Big]$$

$$= R(s,a) + \gamma \sum_{s' \in \mathcal{S}} P(s'|s,a) \sum_{a' \in A} \pi(a'|s') Q_\pi(s',a'), \quad \text{for all } s \in \mathcal{S}, a \in A$$



discount rate $\gamma = 0.9$

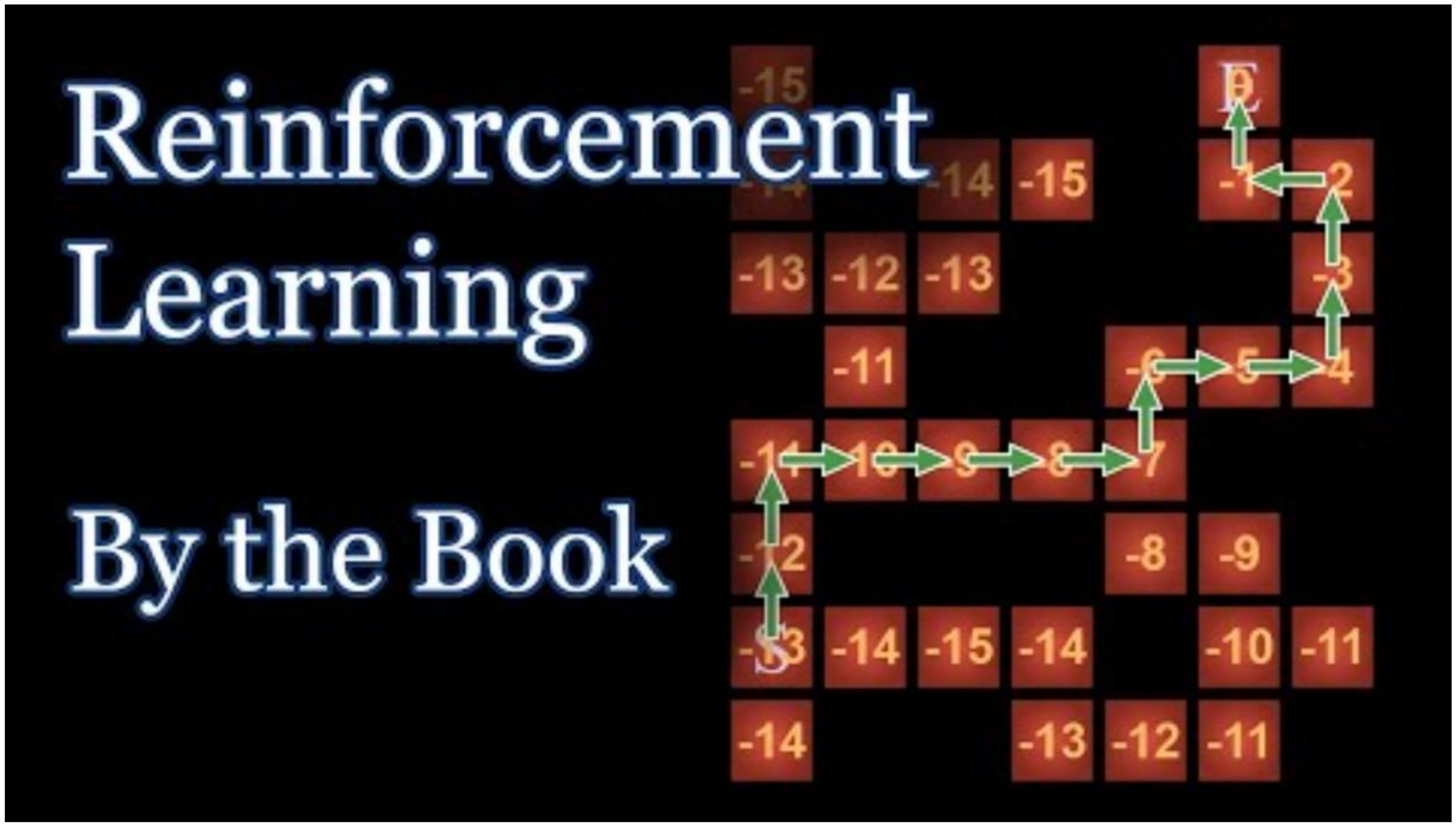
$$Q_\pi(Room\ 2,\ Go\ to\ room1) = -2 + 0.9 * 1.0$$
$$= -1.1$$

$$Q_\pi(Room\ 2,\ Go\ to\ room3) = -1 + 0.9 * 10.0$$
$$= 8.0$$

$$Q_\pi(Room\ 2,\ Go\ outside) = 0 + 0.9 * 5.0$$
$$= 4.5$$

$$V_\pi(Room\ 2) = 0.33 * -1.1 + 0.33 * 8 + 0.33 * 4.5$$
$$= 3.76$$

WATCH THE FOLLOWING VIDEO



https://www.youtube.com/watch?v=NFo9v_yKQXA

How to solve
full RL problem?

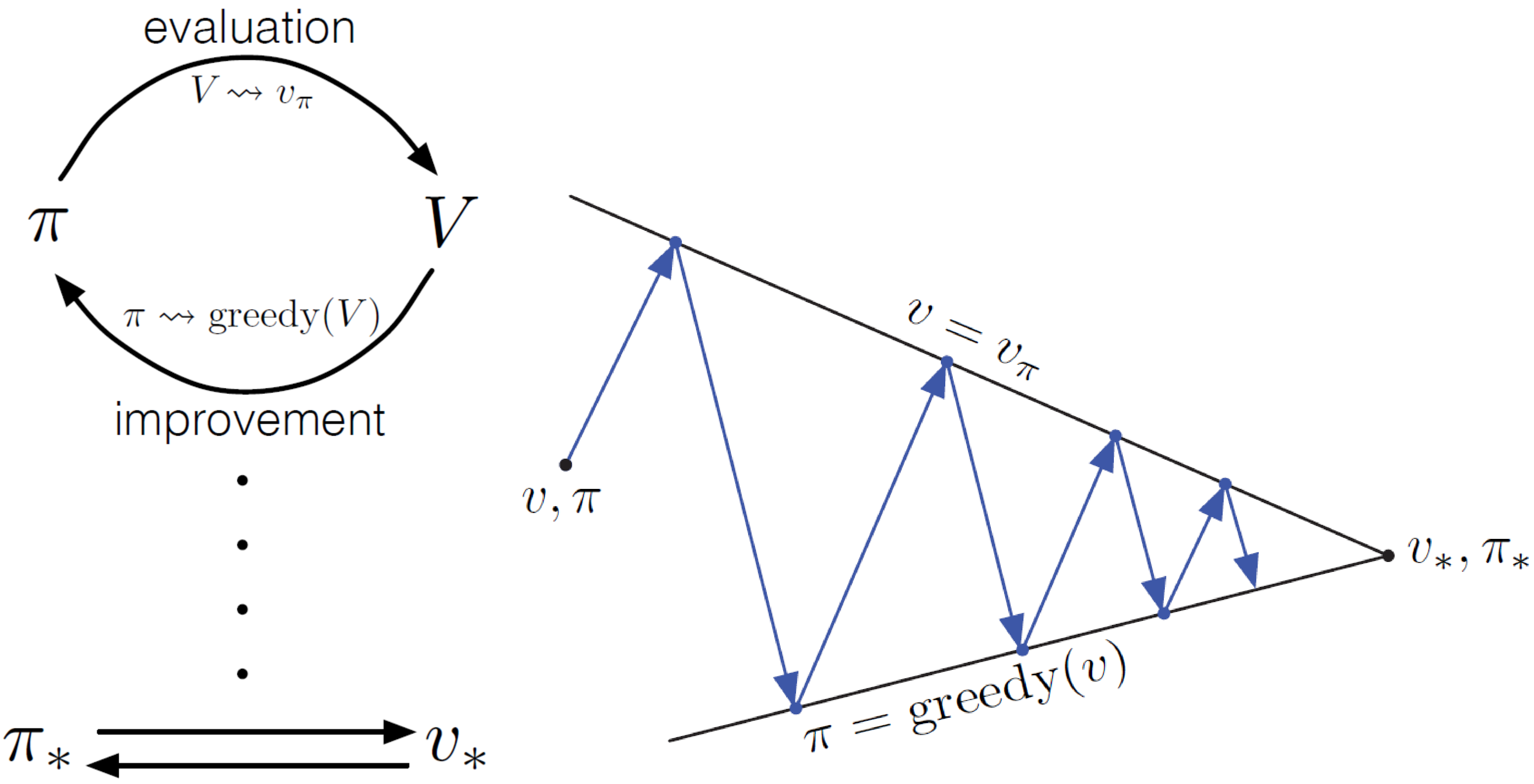
When we have:

$$P(s', r|s, a) = \mathbb{P}[S_{t+1} = s', R_{t+1} = r|S_t = s, A_t = a]$$

OPTIMAL VALUE AND POLICY

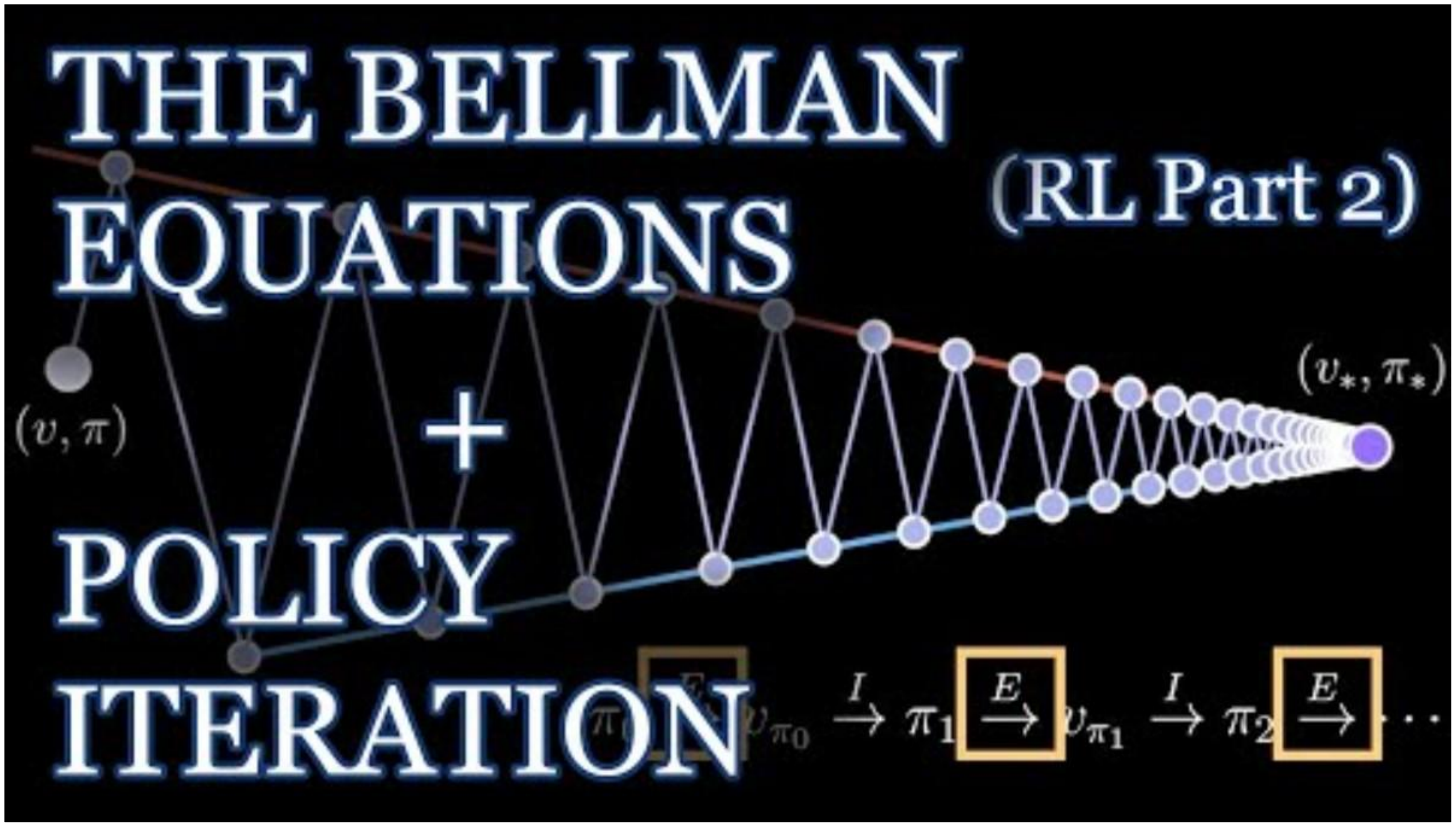
$$Q_*(s,a) = \max_{\pi} Q_\pi(s,a), \quad \text{for all } s \in \mathcal{S}, a \in \mathcal{A}$$

$$\pi_*(a|s) = \begin{cases} 1, & \text{if} \quad a = \arg\max_{a \in A} Q_*(s,a) \\ 0, & \text{otherwise} \end{cases}$$



Reinforcement Learning: An Introduction (Richard S. Sutton and Andrew G. Barto)

WATCH THE FOLLOWING VIDEO



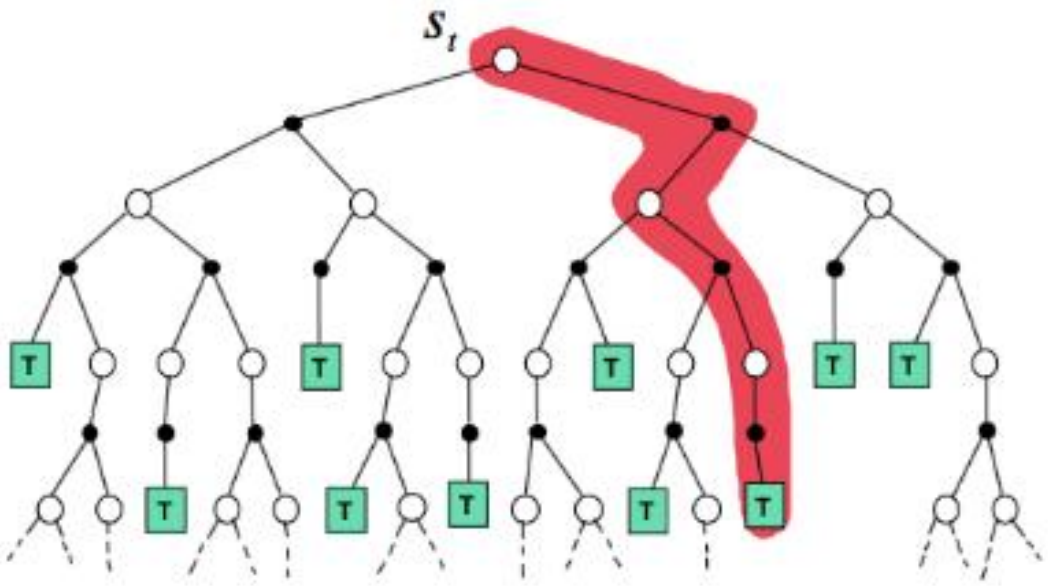
https://www.youtube.com/watch?v=_j6pvGEchWU

When we don’t have:

$$\cancel{P(s', r|s, a) = \mathbb{P}[S_{t+1} = s', R_{t+1} = r|S_t = s, A_t = a]}$$

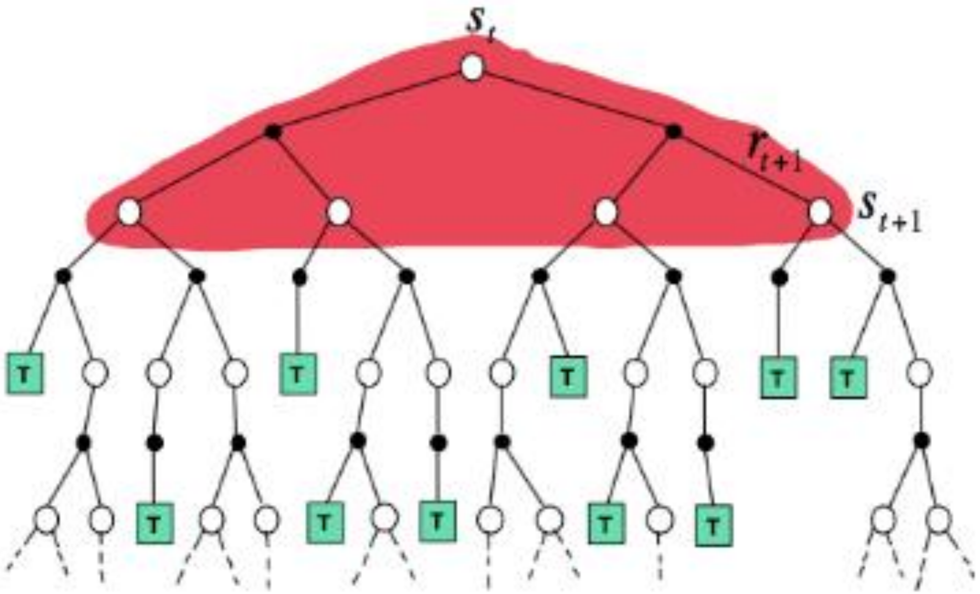
Monte-Carlo

$$V(S_t) \leftarrow V(S_t) + \alpha\,(G_t - V(S_t))$$



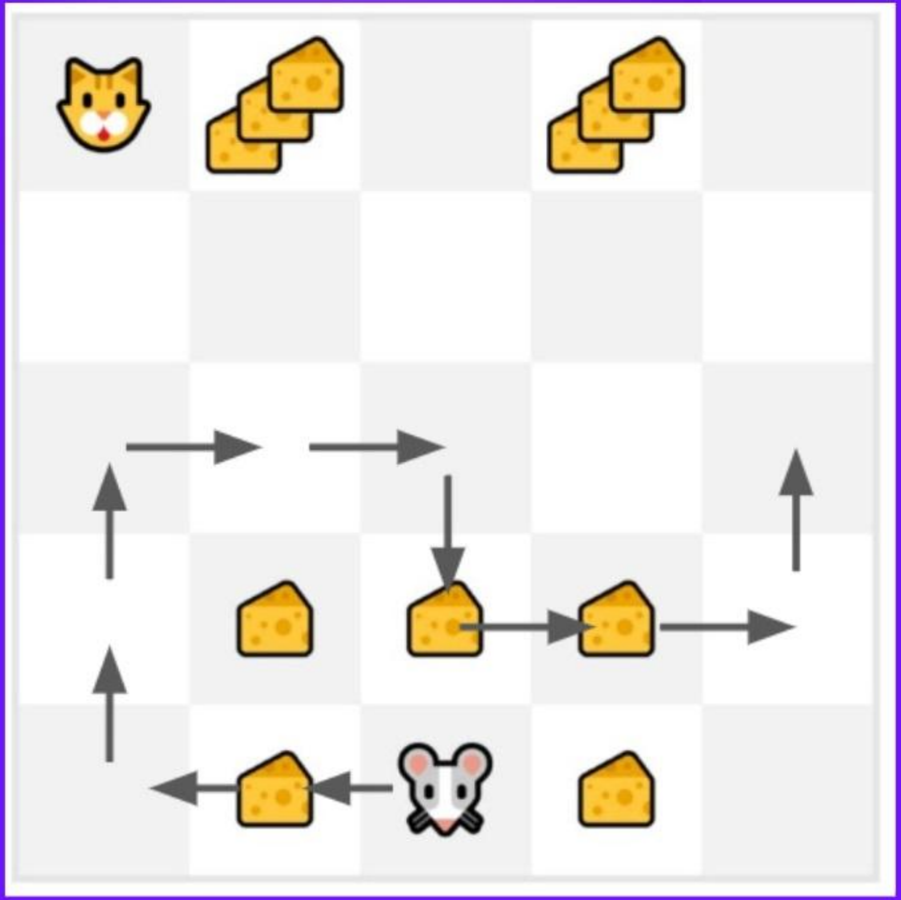
Dynamic Programming

$$V(S_t) \leftarrow \mathbb{E}_\pi\,[R_{t+1} + \gamma V(S_{t+1})]$$



Lin, Baihan. "Reinforcement learning and bandits for speech and language processing: Tutorial, review and outlook." *Expert Systems with Applications* 238 (2024): 122254.

Monte Carlo Approach:



- **Calculate the return Gt.**

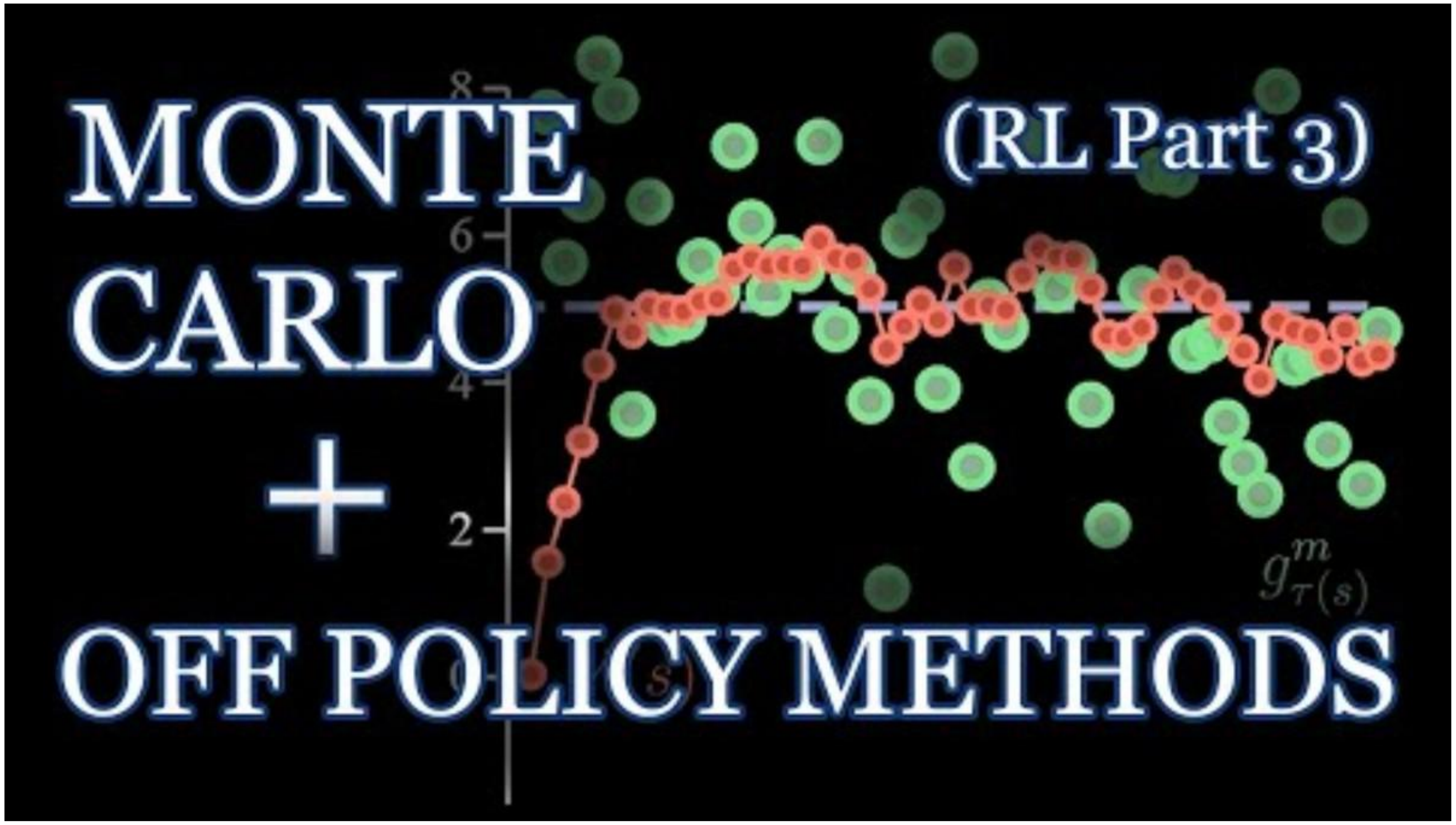
Gt = Rt+1 + Rt+2 + Rt+3…
Gt = 1 + 0 + 0 + 0+ 0 + 0 + 1 + 1+ 0 + 0
Gt= 3

- **We can now update V(S0).**

$$V(S_t) \leftarrow V(S_t) + \alpha[G_t - V(S_t)]$$

New V(S0) = V(S0) + lr * [Gt-V(S0)]
New V(S0) = 0 + 0.1 * [3 –0]
New V(S0) = 0.3

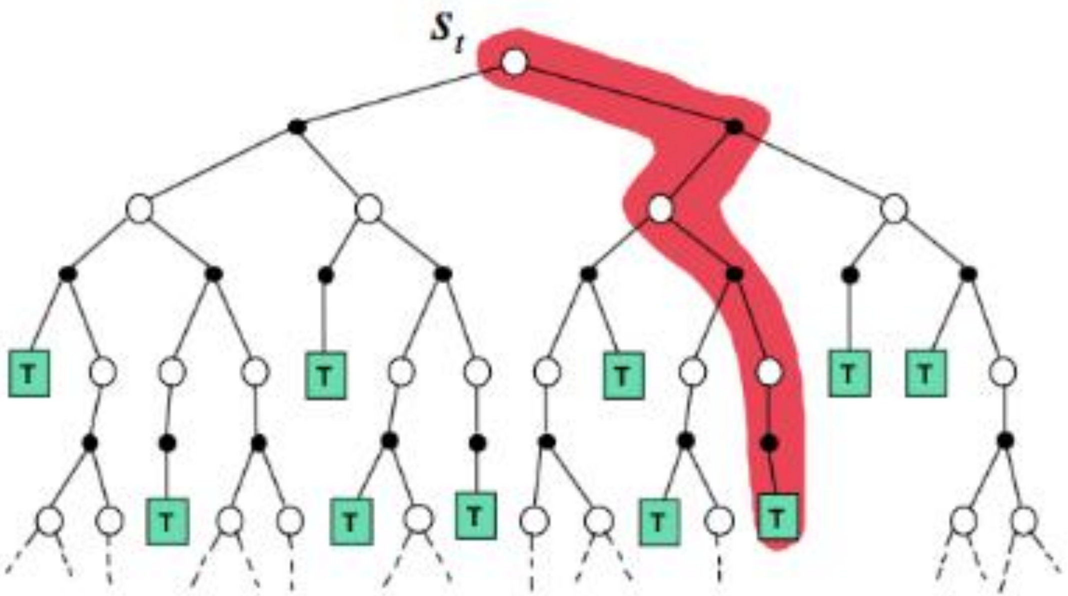
WATCH THE FOLLOWING VIDEO



https://www.youtube.com/watch?v=bpUszPiWM7o

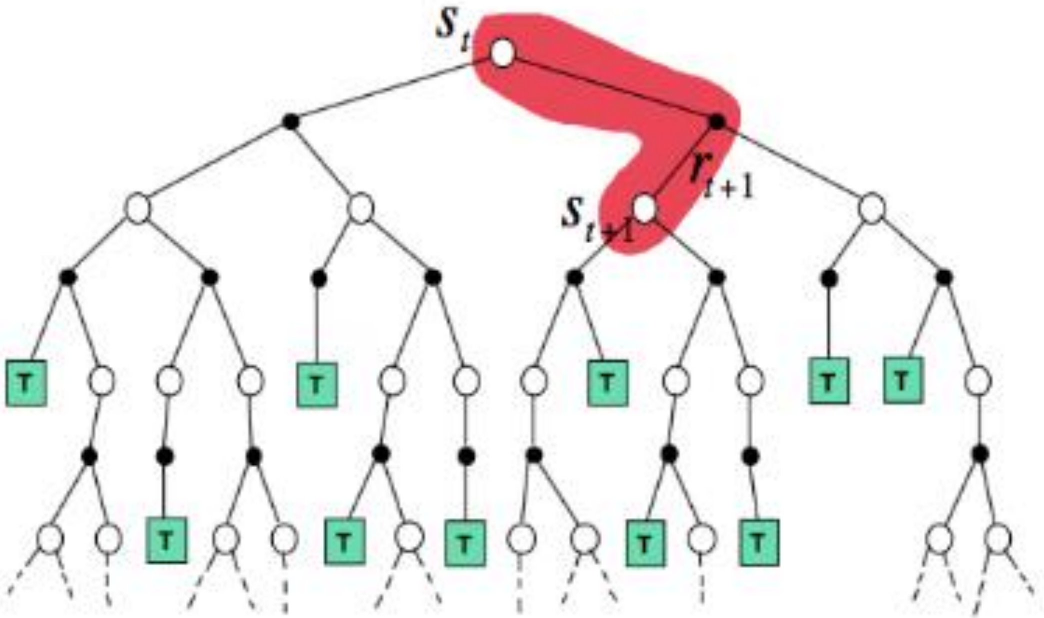
Monte-Carlo

$$V(S_t) \leftarrow V(S_t) + \alpha\,(G_t - V(S_t))$$



Temporal-Difference

$$V(S_t) \leftarrow V(S_t) + \alpha\,(R_{t+1} + \gamma V(S_{t+1}) - V(S_t))$$



https://cs.stanford.edu/people/karpathy/reinforcejs/gridworld_td.html

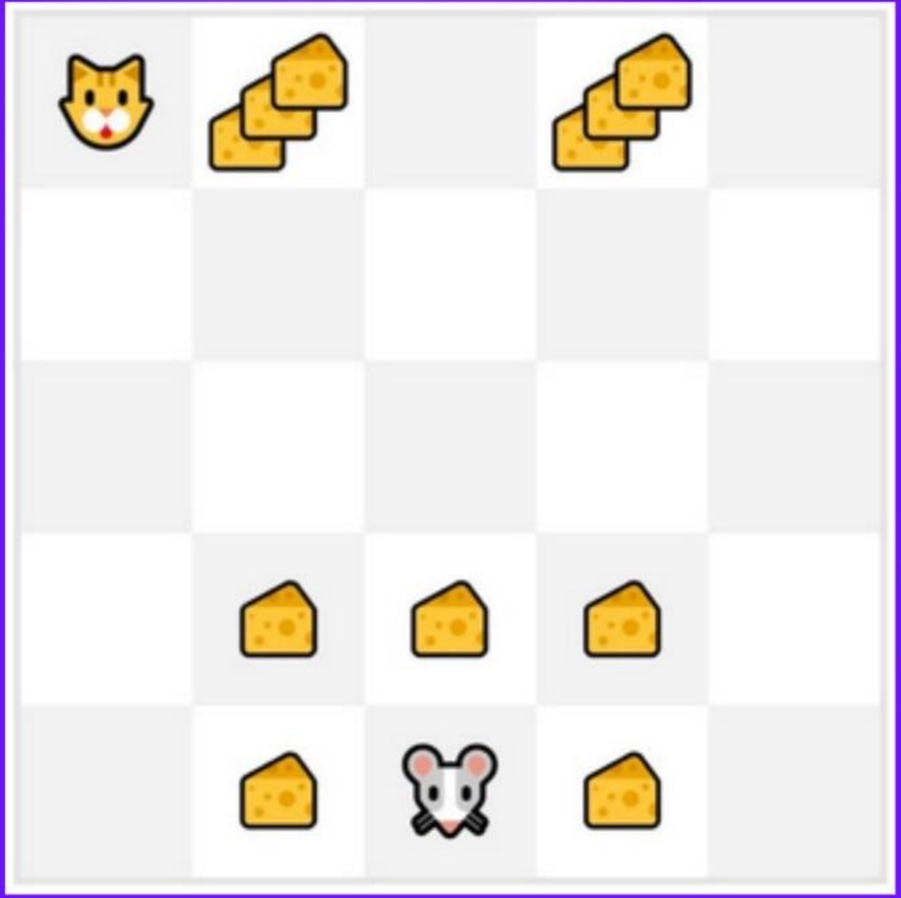
Lin, Baihan. "Reinforcement learning and bandits for speech and language processing: Tutorial, review and outlook." *Expert Systems with Applications* 238 (2024): 122254.

TD Learning Approach:

***Temporal Difference Learning*:** learning at **each time step.**

$$\underbrace{V(S_t)}_{\text{New value of state t}} \leftarrow \underbrace{V(S_t)}_{\text{Former estimation of value of state t}} + \underbrace{\alpha}_{\text{Learning Rate}}[\underbrace{\underbrace{R_{t+1}}_{\text{Reward}} + \underbrace{\gamma V(S_{t+1})}_{\text{Discounted value of next state}}}_{\text{TD Target}} - \underbrace{V(S_t)}_{}]$$

TD Approach:



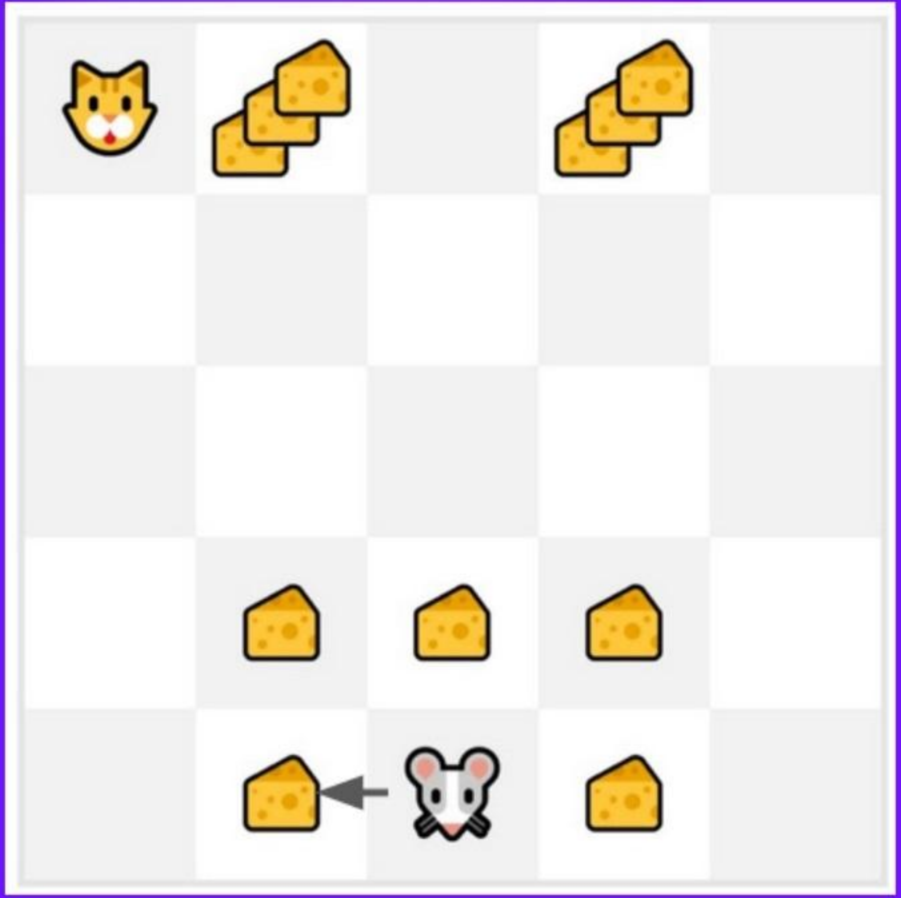
At the end of one step (State, Action, Reward, Next State):

- We have Rt+1 and St+1
- We update V(St):
    - **We estimate Gt** by adding Rt+1 and the discounted value of next state.
      TD target : Rt+1 + gamma * V(St+1)

$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

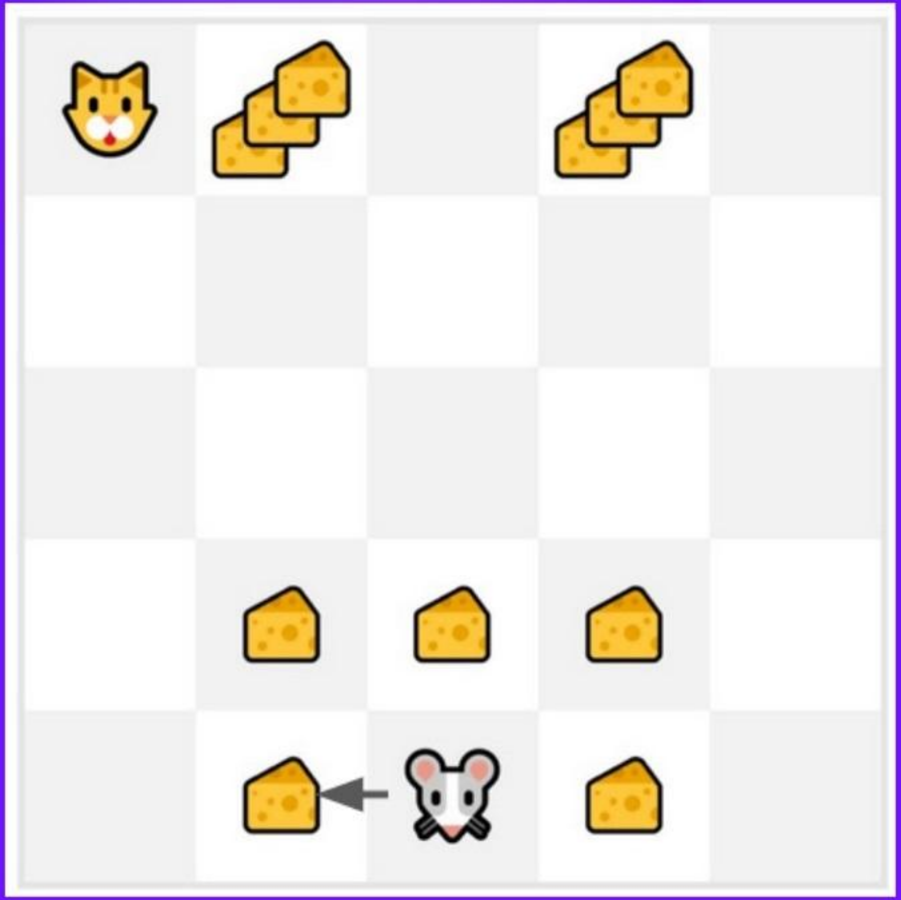
Now we **continue to interact with this environment** with our updated value function. By running more and more steps, **the agent will learn to play better and better.**

TD Approach:



- We just started to train our Value function **so it returns 0 value for each state.**
- Learning rate (lr) is 0.1 and our discount rate is 1 **(no discount)**
- Our mouse, **explore the environment** and take a random action: going left.
- It gets **a +1 reward (cheese).**

TD Approach:



- **We can now update V(S0):**

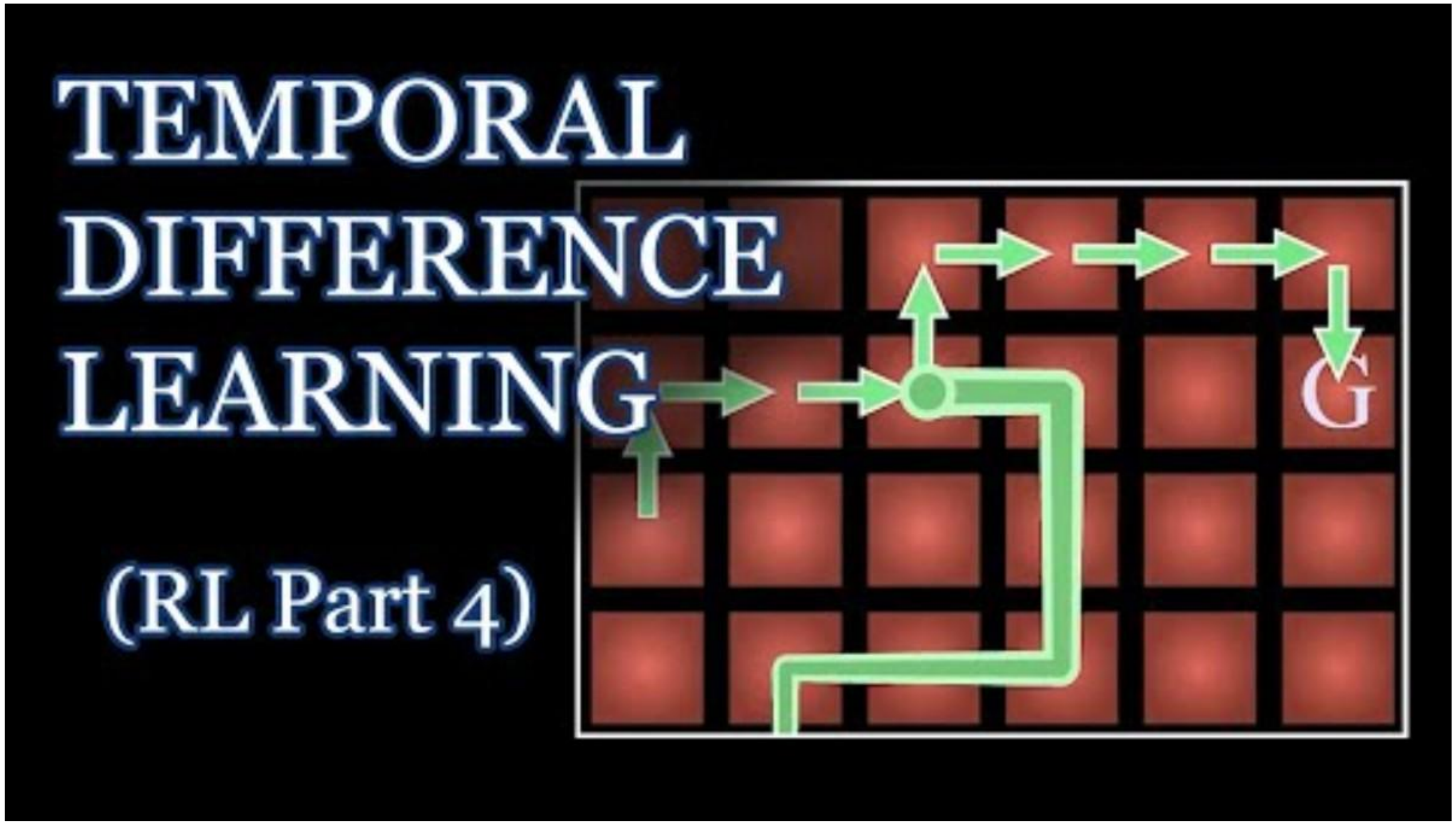
$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

New V(S0) = 0 + 0.1 * [1 + 1 * 0–0]
The new V(S0) = 0.1

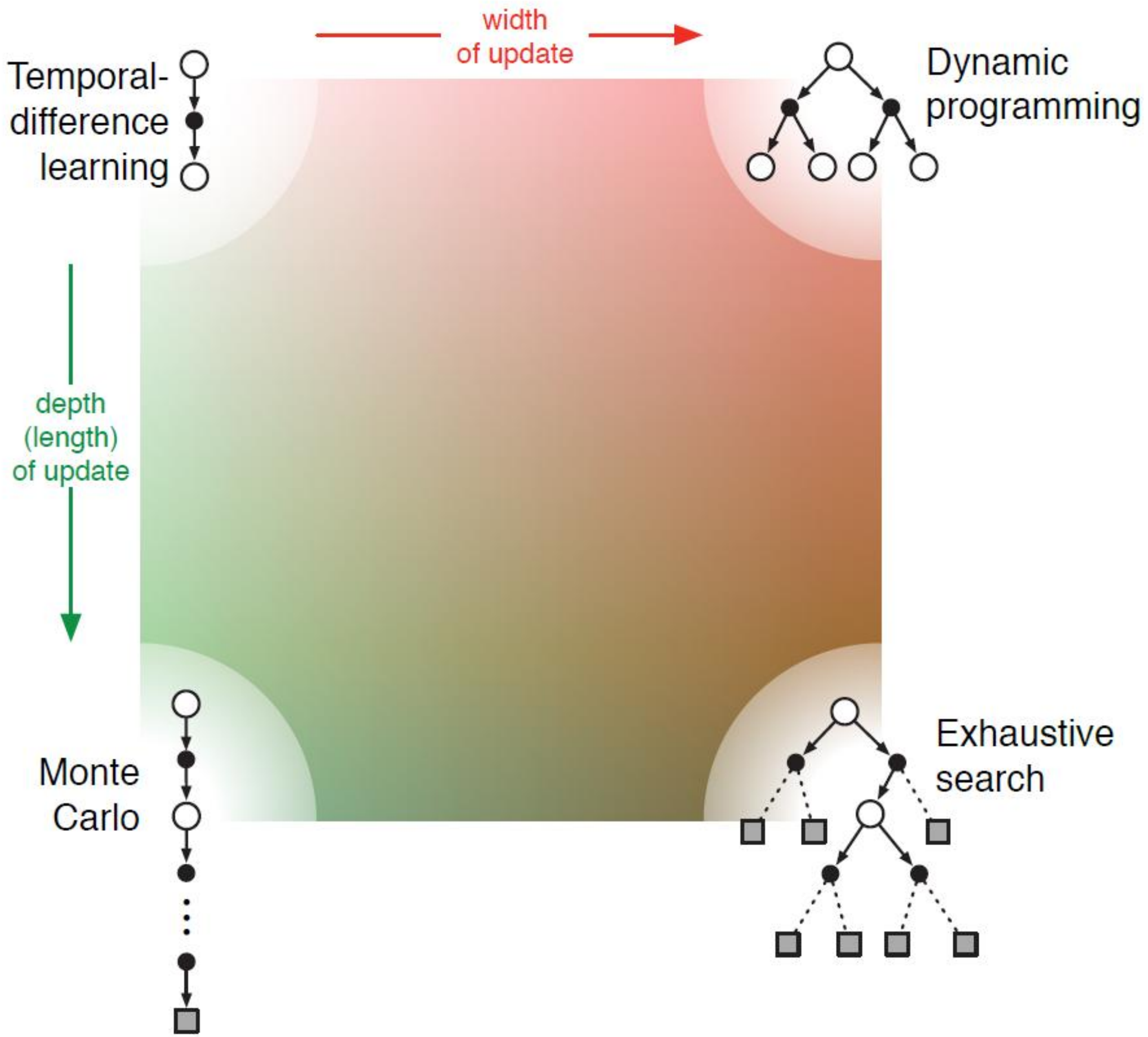
So we just updated our **value function for State 0.**

Now **we continue to interact with this environment with our updated value function.**

WATCH THE FOLLOWING VIDEO



https://www.youtube.com/watch?v=AJiG3ykOxmY



Reinforcement Learning: An Introduction (Richard S. Sutton and Andrew G. Barto)