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Outline

- What is Reinforcement Learning (RL)
- Examples
- Defining an RL problem
  - Markov Decision Processes
- Solving an RL problem
  - Dynamic Programming
  - Monte Carlo methods
  - Temporal-Difference learning

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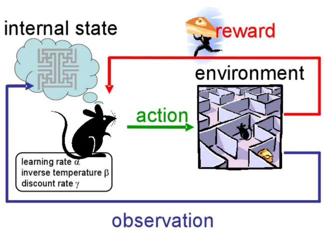
Reinforcement Learning (RL)

Learning (by operating in and interacting with the world [aka. environment]) to make good sequence of decisions under uncertainty



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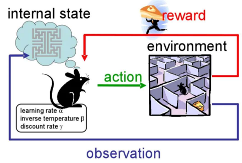
Reinforcement Learning (RL)



Learning (by operating in and interacting with the world [aka. environment]) to make good sequence of decisions under uncertainty

Repeat interactions with the world

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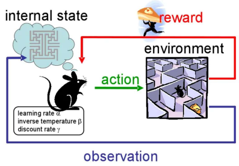
Reinforcement Learning (RL)



Learning (by operating in and interacting with the world [aka. environment]) to make good sequence of decisions under uncertainty

Rewards/Penalties for sequences of actions

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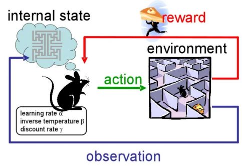
Reinforcement Learning (RL)

Don't know in advance how the world works



Learning (by operating in and interacting with the world [aka. environment]) to make good sequence of decisions under uncertainty

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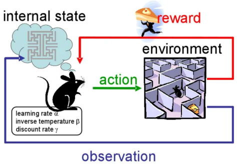
Reinforcement Learning (RL)



Learning (by operating in and interacting with the world [aka. environment]) to make good sequence of decisions under uncertainty

- The world can be dynamic
- Agent's actions are typically nondeterministic
- There can be other agents whose actions can be unpredictable

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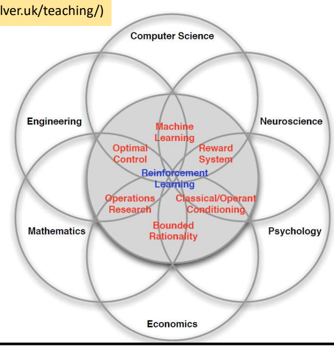
Source: David Silver (https://www.davidsilver.uk/teaching/)

Many faces of Reinforcement Learning



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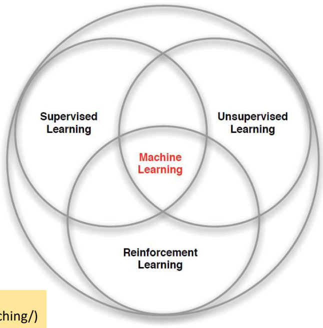
Branches of Machine Learning



Source: David Silver (https://www.davidsilver.uk/teaching/)

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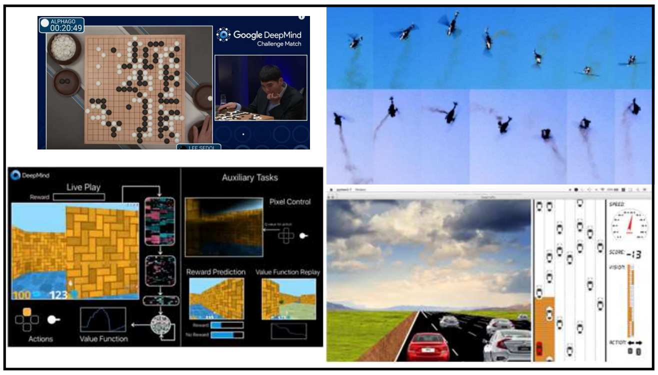

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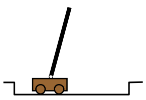
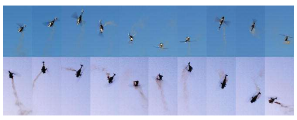
Other examples



- pole-balancing
- helicopter [Andrew Ng]
- most teachers would not say "good" or "bad"
  - is reward "10" good or bad?
  - rewards could be delayed
- explore the environment and learn from experience
  - not just blind search, try to be smart about it



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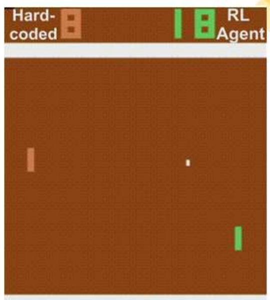
RL Agent playing atari Pong



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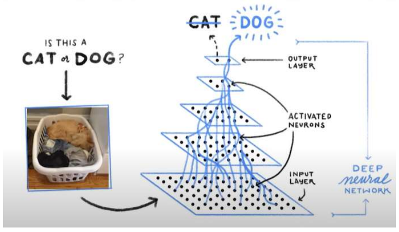
Is RL really necessary?

Would supervised learning do the job?



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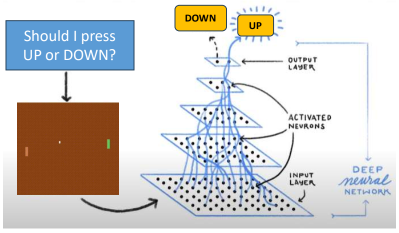
Is RL really necessary?

How about we turn it into a supervised learning problem?



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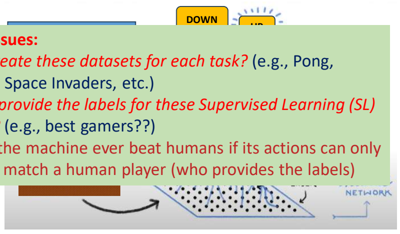
Is RL really necessary?

How about w… into a superv… learning prob…



Two major issues:

1. *How to create these datasets for each task?* (e.g., Pong, Breakout, Space Invaders, etc.)
2. *Who will provide the labels for these Supervised Learning (SL) datasets?* (e.g., best gamers??)
   2a. Will the machine ever beat humans if its actions can only (at best) match a human player (who provides the labels)

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Characteristics of Reinforcement Learning

What makes reinforcement learning different from other machine learning paradigms?

- There is no supervisor, only a *reward* signal
- Feedback is delayed, not instantaneous
- Time really matters (sequential, non i.i.d data)
- Agent's actions affect the subsequent data it receives

Source: David Silver (https://www.davidsilver.uk/teaching/)

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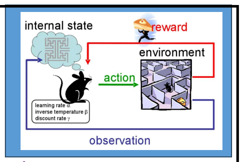
What is Reinforcement Learning



Learning (by operating in and interacting with the world [aka. environment]) to make good sequence of decisions under uncertainty

- Reward/Penalty
  - Reward function
  - Value function
- Sequential decision making
  - Policy
- Environment
  - States
  - Uncertainty
- Learning
  - Observation
  - Algorithms
  - Exploration vs Exploitation

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What is Reinforcement Learning - Reward

- Reward (at time *t*) R_t is a numerical feedback signal
- Indicates how well agent is doing at step *t*
- The agent's job is to maximise cumulative reward
  - Sequence of decisions → sequence of actions
- Rewards can be delayed
  - Delayed rewards can be "discounted"
  - See next slide on "Sequential decision making"

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What is Reinforcement Learning – Sequential decision making

- **Goal**: select actions to maximise total future reward
- Actions may have long term (i.e., delayed) consequences
- It may be better to sacrifice immediate reward to gain more long-term reward
  - Study (vs party) now
  - Contribute to your superannuation (less money to spend now vs retire comfortably)
  - Self-driving EV stops now to recharge (vs stranded in the middle of nowhere)

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Example - Robot in a room

			+100
			-100
START			

actions: UP, DOWN, LEFT, RIGHT

Deterministic vs Stochastic

- **reward** +100 at [4,3], -100 at [4,2] (and they are also terminal states)

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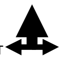
Example - Robot in a room

			+100
			-100
START			

actions: UP, DOWN, LEFT, RIGHT

UP

80% move UP
10% move LEFT
10% move RIGHT



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Example - Robot in a room

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			-100
START			

actions: UP, DOWN, LEFT, RIGHT

UP

80% move UP
10% move LEFT
10% move RIGHT

- **reward** +100 at [4,3], -100 at [4,2] (and they are also terminal states)
- **reward** -4 for each step

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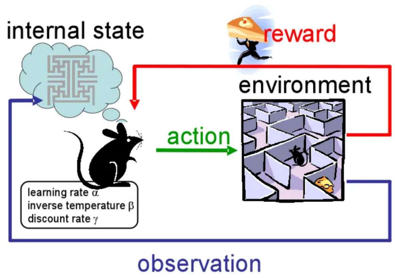
RL agent & Environment



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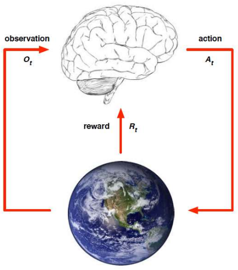
Agent and Environment

Source: David Silver (https://www.davidsilver.uk/teaching/)



- At each step t the agent:
  - Executes action A_t
  - Receives observation O_t
  - Receives scalar reward R_t
- The environment:
  - Receives action A_t
  - Emits observation O_{t+1}
  - Emits scalar reward R_{t+1}
- t increments at env. step

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History and State

Source: David Silver (https://www.davidsilver.uk/teaching/)

- The history is the sequence of observations, actions, rewards

$$H_t = O_1, R_1, A_1; \dots, A_{t-1}; O_t, R_t$$

- i.e. all observable variables up to the current time t
- What happens next depends on the history:
  - The agent selects actions
  - The environment selects observations/rewards
- State is the information used to determine what happens next
- i.e., state is a function of the history:

$$S_t = f(H_t)$$

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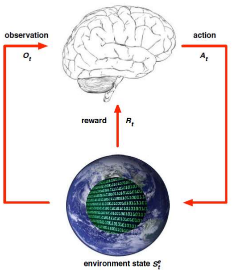
Environment State

Source: David Silver (https://www.davidsilver.uk/teaching/)



- The environment state S^e_t is the environment's private representation
- The environment state is not usually visible to the agent
- Even if S^e_t is visible, it may contain irrelevant information

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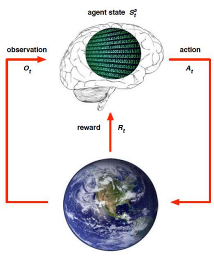
Agent State

Source: David Silver (https://www.davidsilver.uk/teaching/)



- The agent state S^a_t is the agent's internal representation (of the environment)
- i.e. whatever information the agent uses to pick the next action
- It can be any function of the history:

$$S^a_t = f(H_t)$$

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Information State

Source: David Silver (https://www.davidsilver.uk/teaching/)

- 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

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

- i.e., "*The future is independent of the past given the present*"
- Existing RL algorithms assumes that the agent state S^a_t is Markov.

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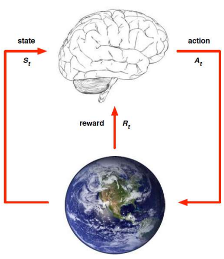
Fully Observable Environment

Source: David Silver (https://www.davidsilver.uk/teaching/)



- Full observability: agent directly observes environment state

$$O_t = S^a_t = S^e_t$$

- Agent state = environment state = information state
- Formally, this is a Markov Decision Process (MDP)

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Partially Observable Environment

Source: David Silver (https://www.davidsilver.uk/teaching/)

- Partial observability: agent indirectly observes environment with its sensors:
  - Its sensors can be incomplete
  - Its sensors can be noisy
  - There are other agents who have private information not available to the RL agent (e.g., agent playing card games, warfare, etc.)
- Now agent state ≠ environment state
- Formally this is a partially observable Markov decision process (POMDP)
- Agent must construct its own state representation S^a_t:
  - e.g. Complete (observable) history: $S^a_t = H_t$

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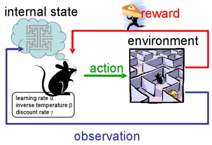
RL Agents – Making decisions and Learning



- Major Components of an RL Agent:
  - **Policy**: (Mandatory) agent's behaviour function
  - **Value function**: (Optional) how good is each state and/or action
  - **Model**: (Optional) agent's representation of the environment

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Robot in a room (or, Mouse in a maze)

			+100
			-100
START			

actions: UP, DOWN, LEFT, RIGHT

UP

80%	move UP
10%	move LEFT
10%	move RIGHT

- **reward** +100 at [4,3] (the **cheese**), -100 at [4,2] (the **trap**)
- **reward** -4 for each step
- For an MDP, the states consist of the whole maze (i.e., agent having a bird's-eye view of the maze)
- what's the strategy to achieve max reward?

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Is this a solution?

→	→	→	+100
↑			-100
↑			

- only if actions are deterministic
  - not in this case (actions are stochastic)
- Solution is a policy
  - **Policy**: mapping from each state to an action

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Which policy?

→	→	→	+100
↑		↑	-100
↑	→	↑	←

→	→	→	+100
↑		→	-100
→	→	→	↑

→	→	→	+100
↑		↑	-100
↑	←	←	←

- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a \mid s) = P[A_t = a \mid S_t = s]$

Note: Deterministic policy ≠ Deterministic environment

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RL algorithms - Value function

- Assume for a moment that the environment is DETERMINISTIC, **optimal policy**:

→	→	→	+100
↑		↑	-100
↑	→	↑	←

- We can calculate (recursively from the terminal states) the following **value function**:

88	92	96	+100
84		92	-100
80	84	88	84

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RL algorithms - Value function

- Value function is a prediction of future reward
- Used to evaluate the goodness/badness of states
- And therefore to select between actions
- Example:

$$v_\pi(s) = \mathbb{E}_\pi \left[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + ... \mid S_t = s \right]$$

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What about STOCHASTIC environments!

Optimal policy: - **WHY?**

→	→	→	+100
↑		↑	-100
↑	←	←	←

UP

80% move UP
10% move LEFT
10% move RIGHT

Can you calculate the value function?

HINT: It is the *expected value* based on the probabilistic outcomes of the action taken in each cell!

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Reward for each step: -120

→	→	→	+100
↑		→	-100
→	→	→	↑

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Reward for each step: -10

→	→	→	+100
↑		↑	-100
↑	→	↑	←

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Reward for each step: -4

→	→	→	+100
↑		↑	-100
↑	←	←	←

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Reward for each step: -1

→	→	→	+100
↑		←	-100
↑	←	←	↓

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Reward for each step: +1

↓	←	←	+100
↓		←	-100
←	←	←	↓

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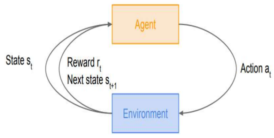
Markov Decision Process (MDP) - Model

- set of states S, set of actions A, initial state s_0
- transition model P(s'|s,a)
  - P([1,2] | [1,1], up) = 0.8
- reward function r(s)
  - r([4,3]) = +100



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Categorizing RL agents (1)

Source: David Silver (https://www.davidsilver.uk/teaching/)

- Value Based
  - No Policy (Implicit)
  - Value Function
- Policy Based
  - Policy
  - No Value Function
- Actor Critic
  - Policy
  - Value Function

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Categorizing RL agents (2)

Source: David Silver (https://www.davidsilver.uk/teaching/)

- Model Free
  - Policy and/or Value Function
  - No Model
- Model Based
  - Policy and/or Value Function
  - Model

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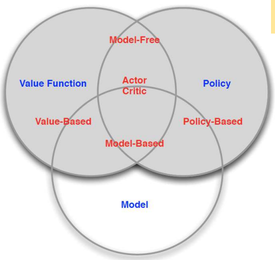
RL Agent Taxonomy

Source: David Silver (https://www.davidsilver.uk/teaching/)



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Computing return from rewards

- episodic (vs. continuing) tasks
  - "game over" after N steps
  - optimal policy depends on N; harder to analyze
- additive rewards
  - $V(s_0, s_1, \ldots) = r(s_0) + r(s_1) + r(s_2) + \ldots$
  - infinite value for continuing tasks
- discounted rewards (γ < 1)
  - $V(s_0, s_1, \ldots) = r(s_0) + \gamma^* r(s_1) + \gamma^{2*} r(s_2) + \ldots$
  - value bounded if rewards bounded

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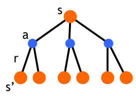
Value functions

- state value function: $V^\pi(s)$
  - expected return when starting in *s* and following π
- state-action value function: $Q^\pi(s,a)$
  - expected return when starting in *s*, performing *a*, and following π
- For a fixed policy π, the utility function obey the **Bellman equation**:

$V^\pi(s) = r(s) + \gamma \sum_{s'} P(s' \mid s, \pi(s)) * V^\pi(s')$



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Value functions

- state value function: $V^\pi(s)$
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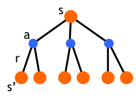

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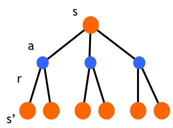
Optimal value functions

- there's a set of *optimal* policies
  - V^π defines the value of policy for every state $s \in S$
  - Then, there is a single optimal value for each state $s \in S$

$$V^*(s) = \max_\pi V^\pi(s)$$

- Bellman optimality equation
  - $V^*(s) = r(s) + \gamma * \max_{a \in A(s)} \sum_{s'} P(s' \mid s, a) * V^*(s')$
  - system of n non-linear equations
  - solve for $V^*(s)$
  - easy to extract the optimal policy π^*
- having $Q^*(s,a)$ makes it even simpler: $\pi^*(s) = \arg\max_a Q^*(s,a)$



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Dynamic programming (DP)

- main idea
  - If an action in a situation/state cause something (really) good/bad to happen immediately then we **"know"** the **"goodness"** of that action (given that state) and the **"value"** of that state!
  - need a **perfect** model of the environment (aka. **Model-based RL**)
- two main components
  (of "Policy iteration algorithm")
  - policy evaluation: compute V^π from π
  - policy improvement: improve π based on V^π
  - start with an arbitrary policy
  - repeat evaluation/improvement until convergence

			+100
			-100
START			

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Policy iteration

- Initialise V and policy π' for all $s \in S$

$\pi = \pi'$

For all $s \in S$: (concurrent update ☺)

$V(s) = r(s) + \gamma \sum_{s'} P(s' \mid s, \pi(s)) * V(s')$

For all $s \in S$:

$\pi'(s) = \arg\max_{a \in A(s)} \sum_{s'} P(s' \mid s, a) * V(s')$

Repeat until $\pi = \pi'$

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Policy iteration

- Initialise V and policy π' for all s∈S

$\pi = \pi'$

For all s∈S: (concurrent update ☺)

V(s) = r(s) + γ$\sum_{s'}$ P(s' | s, π(s))*V(s')

Question: If the state-action value function Q(s,a) is maintained, how does the algorithm look?

For all

π'(s) = arg max$_{a \in A(s)}$ $\sum_{s'}$ P(s' | s, a)*V(s')

Repeat until $\pi = \pi'$

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Using DP

- The algorithm only works for an MDP, where:
  - The set of all states S is known
  - A transition model P(s' | s, a) is known for all s', s ∈S and all a ∈A
  - A reward function r(s) is known for all states s ∈S
- Reinforcement learning does not always have those luxuries!
  - transitions and rewards usually not available
    - Learning to walk, fly an aircraft, playing games with incomplete info such as poker
  - how to explore the environment to learn about states you may not known prior
    - Mars rover
  - how to update the policy as transition model and the reward function are being updated based on the leaner's experience

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Monte Carlo methods

- don't need full knowledge of environment (aka. Model free RL)
  - just experience, or
  - simulated experience
- but similar to DP
  - policy evaluation, policy improvement
- **averaging sample returns**
  - defined only for **episodic tasks**

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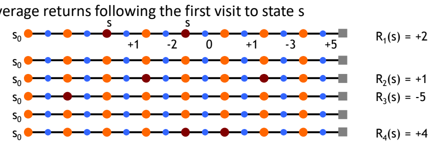
Monte Carlo policy evaluation

- want to estimate V^{π}(s)
  - = expected return starting from s and following π
  - estimate as average of observed returns in state s
- first-visit MC
  - average returns following the first visit to state s



V^{π}(s) ≈ (2 + 1 - 5 + 4)/4 = 0.5

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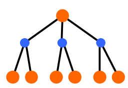
Monte Carlo control

- V^{π} not enough for policy improvement
  - need exact model of environment
- estimate Q^{π}(s,a)



$$\pi'(s) = \arg\max_a Q^{\pi}(s,a)$$

- MC control
  - update after each episode $\pi_0 \rightarrow^E Q^{\pi_0} \rightarrow^I \pi_1 \rightarrow^E Q^{\pi_1} \rightarrow^I \ldots \rightarrow^I \pi^* \rightarrow^E Q^*$
- non-stationary environment

$$V(s_t) \leftarrow V(s_t) + \alpha\,[R_t - V(s_t)]$$

- a problem
  - greedy policy won't explore all actions

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Maintaining exploration

- deterministic/greedy policy won't explore all actions
  - don't know anything about the environment at the beginning
  - need to try all actions to find the optimal one
- maintain exploration
  - use *soft* policies instead: π(s,a)>0 (for all s,a)
    - i.e., the policy does not simply return an action for each state, it returns a probability distribution over the action space for each state
- ε-greedy policy
  - with probability 1-ε perform the optimal/greedy action
  - with probability ε perform a random action
  - will keep exploring the environment
  - slowly move it towards greedy policy: ε -> 0

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Summary of Monte Carlo

- don't need model of environment
  - averaging of sample returns
  - only for episodic tasks
- learn from sample episodes or simulated experience
- can concentrate on "important" states
  - don't need a full sweep
- need to maintain exploration
  - use soft policies

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Outline

- examples
- defining an RL problem
  - Markov Decision Processes
- solving an RL problem
  - Dynamic Programming
  - Monte Carlo methods
  - Temporal-Difference learning

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Temporal Difference Learning

- combines ideas from MC and DP
  - like MC: learn directly from experience (don't need a model)
  - like DP: learn from values of successors
  - works for continuous tasks, usually faster than MC
- constant-alpha MC:
  - have to wait until the end of episode to update

$$V(s_t) \leftarrow V(s_t) + \alpha \left[R_t - V(s_t)\right]$$

- simplest TD
  - update after every step, based on the successor

$$V(s_t) \leftarrow V(s_t) + \alpha \left[r_{t+1} + \gamma V(s_{t+1}) - V(s_t)\right]$$

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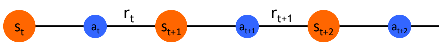
Sarsa

- again, need Q(s,a), not just V(s)



$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)\right]$$

- control
  - start with a random policy
  - update Q and π after each step
  - again, need ε-soft policies

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The RL Intro book

Richard Sutton, Andrew Barto
Reinforcement Learning,
An Introduction

http://www.cs.ualberta.ca/~sutton/book/the-book.html

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Summary

- Reinforcement learning
  - use when need to make decisions in uncertain environment
- solution methods
  - dynamic programming
    - need complete model
  - Monte Carlo
  - time-difference learning (Sarsa, Q-learning)
- most work
  - algorithms simple
  - need to design features, state representation, rewards

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Where to start?

- You need an environment (to build your RL agent)
- The OpenAI Gym provides a good starting point with some pre-defined environments and also allow you to define your own environment:
- https://towardsdatascience.com/reinforcement-learning-with-openai-d445c2c687d2

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