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Artificial Intelligence
Lecture 6:
Introduction to Reinforcement Learning

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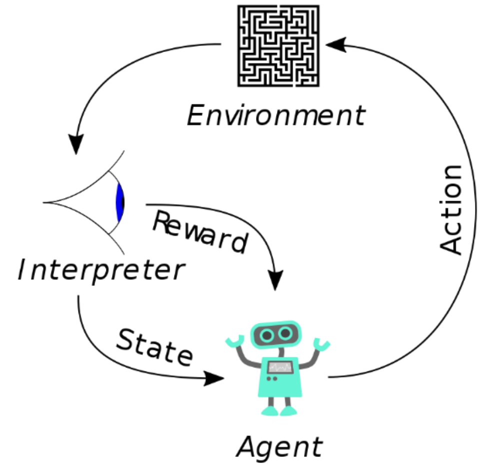
What is Reinforcement Learning?



- **Reinforcement Learning (RL)** is focused on goal-directed learning from interaction
- RL is learning what to do – how to map situations to actions – so as to maximize a numerical reward signal
  - The learner is not told which actions to take: it must discover which actions yield the most reward by trying them
  - Typically, actions may affect not only immediate reward but also the next situation and subsequent rewards
- The exploration-exploitation tradeoff
  - Agent must prefer actions that it knows to be effective – *exploit*
  - But to discover such actions, it has to try actions not selected before – *explore*

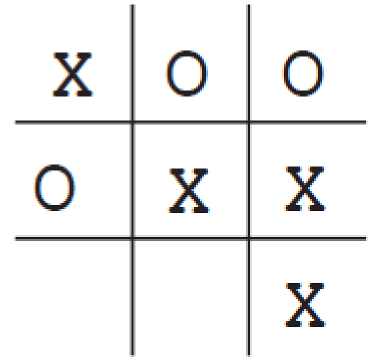
RL vs (Un)Supervised Learning

- Different from **supervised learning**
  - In interactive problems it is impractical to obtain examples of desired behavior
  - In uncharted territory, an agent must learn from its own experience
- Different from **unsupervised learning**
  - RL is trying to maximize a reward signal, not trying to find hidden structure in collections of unlabeled data

- RL explicitly considers the *whole* problem of a goal-directed agent interacting with an uncertain environment
  - Creating a behavior model while applying it in the environment

- RL is the closest form of ML to the kind of learning humans do

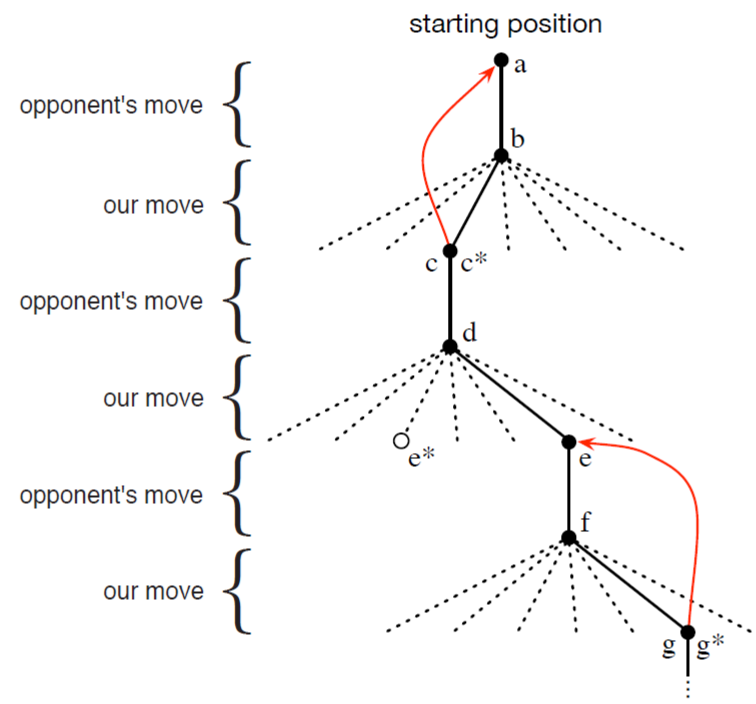
Learning to Play Tic-Tac-Toe



- Rule-based approach
  - Need to hardcode rules for each possible situations that might arise in a game
- Minimax
  - Assumes a particular way of playing by the opponent
- Dynamic programming can compute an optimal solution for any opponent
  - But requires as input a complete specification of that opponent (state/action probabilities)
- Can we obtain such information from experience?
  - Play many games against the opponent!

Learning to Play Tic-Tac-Toe

- States
  - Possible configurations of the board
- Actions
  - Possible moves to make
- Policy
  - Which action should I play in each state?
- Reward
  - How good was the chosen action?



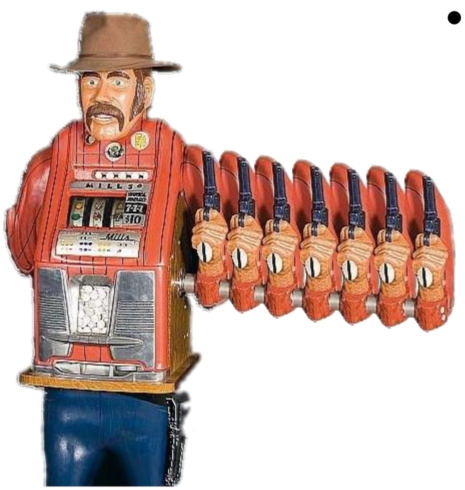
Elements of RL

- **Policy π**
  - How should the agent behave over time?
  - A policy is a (possibly stochastic) mapping from perceived states to actions
- **Reward signal r**
  - Defines the goal of the RL problem
  - On each time step, the environment sends a reward to the RL agent – the agent's goal is to maximize the total reward received over the long run
- **Value function v**
  - Specifies what is good in the long run
  - The value of a state is the total amount of reward an agent can expect to accumulate from that state onwards (it takes into account future rewards)

→ We seek actions that bring about states of highest value, not highest reward, because these actions obtain the greatest amount of reward over the long run

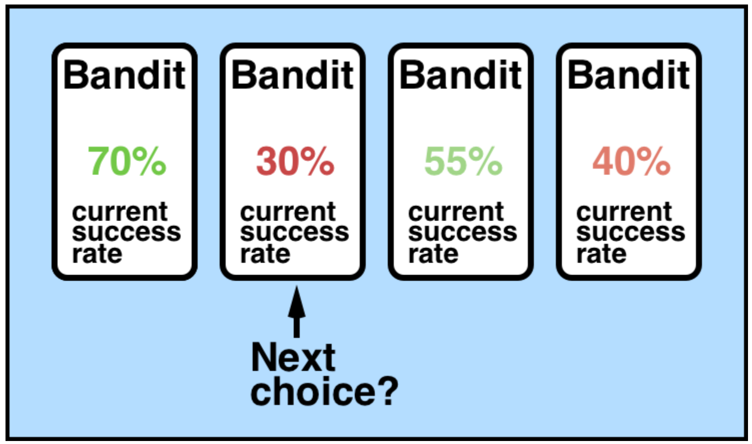
Bandit Problems

- A simple setting with a single state



- *K*-armed bandit problem
  - There are *k* different actions
  - After each action a numerical reward is received from a stationary probability distribution
  - Each action has a *value* – its expected or mean reward, not known by the agent: $q_*(a) \doteq \mathbb{E}[R_t | A_t = a]$
  - The agent *estimates*, at time step t, the value of an action a: $Q_t(a)$

Bandit Problems



- Selecting *greedy* actions (whose estimated value is greatest): exploiting
- Selecting non-greedy actions: exploring
  - Improve estimates of non-greedy actions' value
- Lower reward in the short run (during *exploration*), but higher in the long run – after discovering the best actions, we can *exploit* them many times

Estimating Action Values

- Sample average:

$$Q_t(a) \doteq \frac{\sum_{i=1}^{t-1} R_i \cdot 1_{A_i=a}}{\sum_{i=1}^{t-1} 1_{A_i=a}}$$

- Update rule:

$$Q_{n+1} = Q_n + \frac{1}{n}[R_n - Q_n]$$

$$\boxed{NewEstimate \leftarrow OldEstimate + StepSize[Target - OldEstimate]}$$

  - The target indicates a desirable direction in which to move
  - The *step-size* parameter changes from time step to time step

- Giving more weight to recent rewards – constant *step-size* parameter:

$$Q_{n+1} \doteq Q_n + \alpha[R_n - Q_n]$$

where $\alpha \in (0,1]$

Action Selection

- *Greedy* action selection (always exploits): $A_t \doteq \underset{a}{\operatorname{argmax}}\, Q_t(a)$

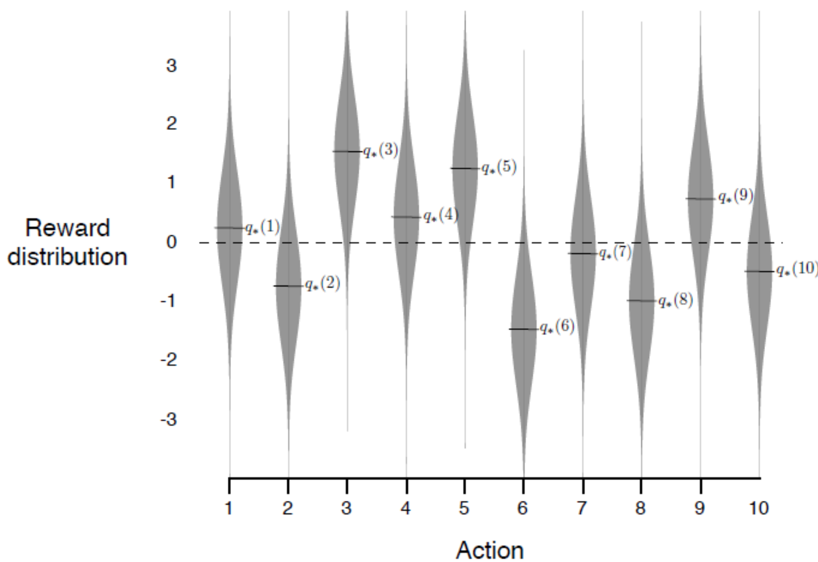
- *ε-greedy* action selection: behave greedily most of the time, but with small probability ε select randomly from among all the actions
  - $Q_t(a)$ will converge to $q_*(a)$ if a is selected sufficiently often

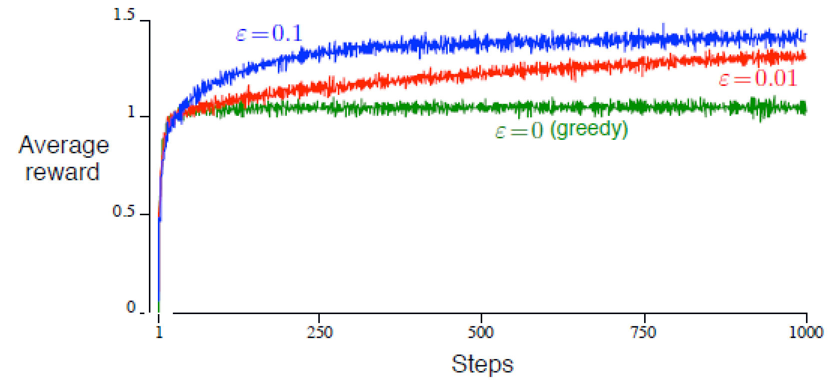
- *Soft-max* action selection (Boltzmann distribution):

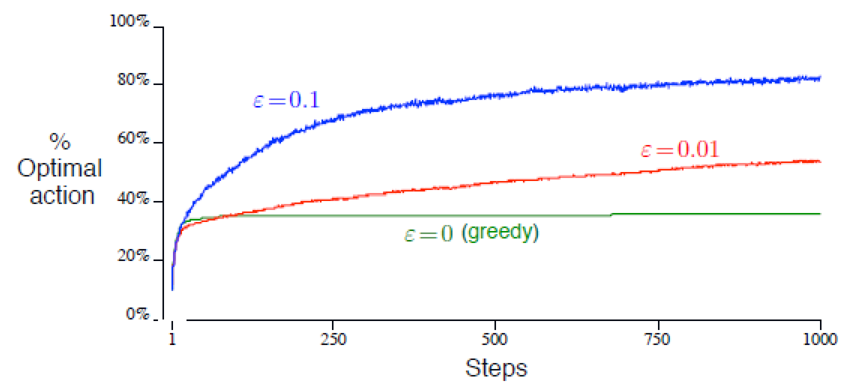
$$\Pr\{A_t = a\} \doteq \frac{e^{Q_t(a)/\tau}}{\sum_{b=1}^{k} e^{Q_t(b)/\tau}}$$

where τ is a temperature parameter: if high, actions will tend to be equiprobable; if low, action values matter more; if $\tau \to 0$, then we have greedy action selection

The 10-armed Testbed



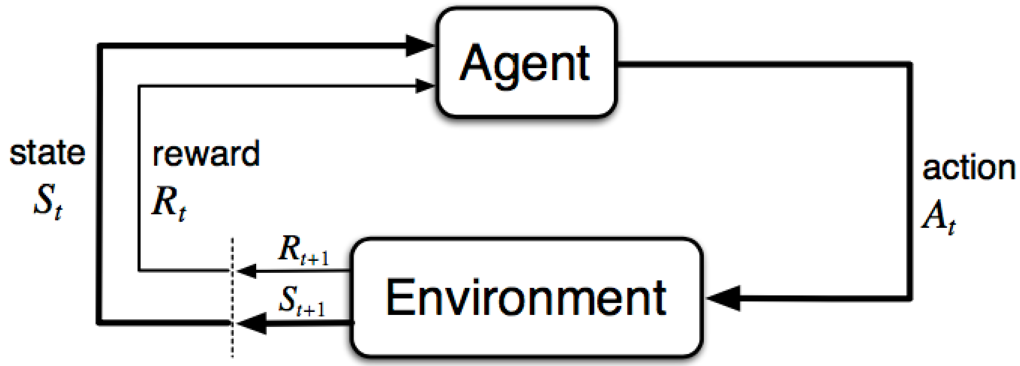




Markov Decision Processes

- In the general setting we have many states
- Markov Decision Processes (MDP) are a classical formalization of sequential decision making
  - Actions influence not just immediate rewards, but also subsequent situations (states) and thus future rewards
- In a finite MDP, there is a finite number of states, actions and rewards
- In MDPs we estimate the value $q_*(s, a)$

Agent-Environment Interface



- Dynamics of the MDP:

$$p(s', r | s, a) \doteq \Pr\{S_t = s', R_t = r \mid S_{t-1} = s, A_{t-1} = a\}$$

  - The probability of each possible value for s' and r depends only in the immediately preceding state s and action a
  - The state must include all relevant information about the past agent-environment interaction – Markov property

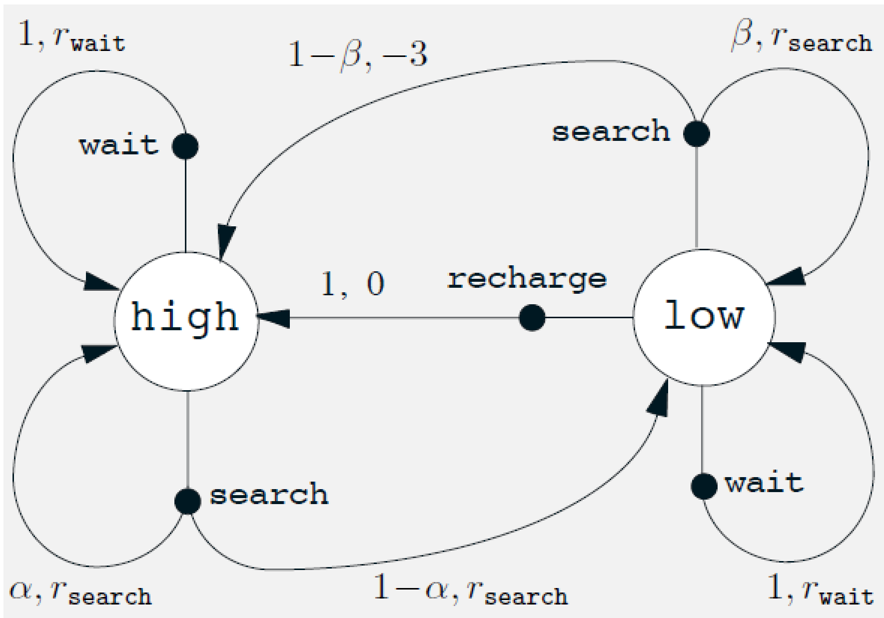
Example: Recycling Robot

- A robot has to decide whether it should (1) actively search for a can, (2) wait for someone to bring it a can, or (3) go to home base and recharge
- Searching is better (higher probability of getting a can) but runs down battery; if out of battery, the robot has to be rescued
- Decisions made on the basis of current energy level: high, low
- Reward is zero except when getting a can, and negative if out of battery

$$\mathcal{S} = \{high, low\}$$
$$\mathcal{A}(high) = \{search, wait\}$$
$$\mathcal{A}(low) = \{search, wait, recharge\}$$
$$r_{search} > r_{wait}$$

s	a	s'	$p(s' \mid s, a)$	$r(s, a, s')$
high	search	high	α	r_{search}
high	search	low	$1-\alpha$	r_{search}
low	search	high	$1-\beta$	-3
low	search	low	β	r_{search}
high	wait	high	1	r_{wait}
high	wait	low	0	-
low	wait	high	0	-
low	wait	low	1	r_{wait}
low	recharge	high	1	0
low	recharge	low	0	-

Example: Recycling Robot



Goals and Rewards

- A reward signal is used to define the goal of the agent
  - Learning to walk: reward proportional to the robot's forward motion
  - Learning to Escape from a maze: reward -1 for any state prior to escape (encourage escaping as quickly as possible)
  - Learning to find empty cans for recycling: reward of 0 most of the time, +1 for each can collected
  - Learning to play checkers or chess: reward +1 for winning, -1 for losing, and 0 for drawing and nonterminal positions

- Provide rewards in such a way that by maximizing them the agent will also achieve our goal
  - The agent's goal is to maximize the cumulative reward it receives in the long run

→The reward signal is a way of communicating to the robot *what* you want it to achieve, not *how*

Returns and Episodes

- Agent wants to maximize expected return

$$G_t \doteq R_{t+1} + R_{t+2} + R_{t+3} + \cdots + R_T$$

- Episodic tasks: when the agent-environment interaction breaks naturally into subsequences – episodes
  - From a starting state to a terminal state
  - Followed by a reset to another starting state, chosen independently of how the previous episode ended

- Continuing tasks do not break naturally into identifiable episodes (*e.g.,* on-going process-control)
  - Problem with calculating G_t:
    - $T = \infty$
    - G_t could also be infinite (if rewards are positive at each time step)

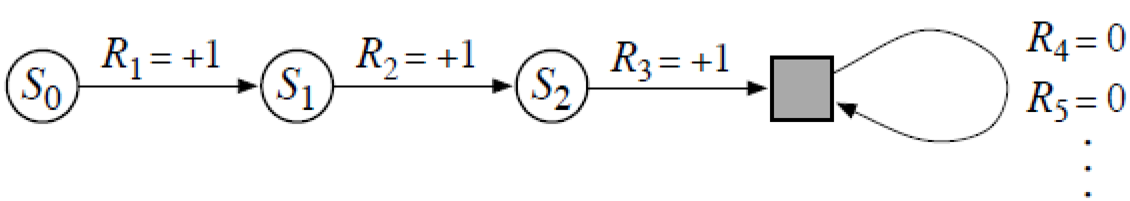
Returns and Episodes

- Adding discounting: agent wants to maximize expected discounted return

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

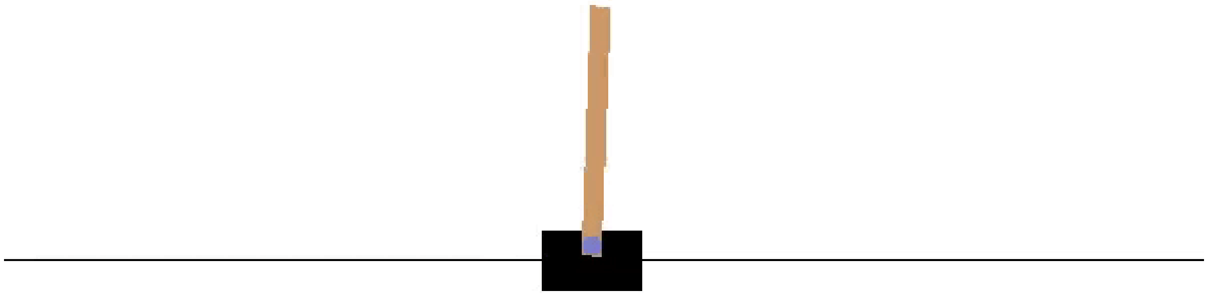
  - $0 \leq \gamma \leq 1$ is the discount rate
    - If $\gamma = 0$ the agent is "myopic" (only immediate reward matters)
    - As γ approaches 1, the agent becomes more farsighted (strongly considers future rewards)
  - G_t is now finite, even if summing an infinite number of terms

- Applicable also to episodic tasks, if we consider a final absorbing state:



Example: Pole Balancing

- Move a cart so as to keep a pole from falling over
  - Failure if the pole falls past a given angle or if the cart runs off the track
  - The pole is reset to vertical after each failure



- Episodic task: reward +1 except when failure
  - return is the number of steps until failure

- Continuing task, using discounting: reward –1 on each failure and 0 otherwise
  - return is $-\gamma^K$, where K is the number of steps before failure

Policies and Value Functions

- RL algorithms involve estimating value functions
  - How good (in terms of expected return) is it to be in a given state?
  - How good is it to perform a given action in a given state?

- Future rewards depend on the choice of actions
  - Value functions are defined with respect to policies (ways of acting)

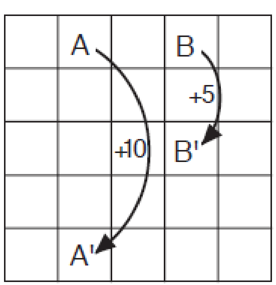
- Policy: a mapping from states to probabilities of selecting each possible action
  - $\pi(a|s) = \Pr(A_t = a|S_t = s)$

→RL methods specify how the policy (*i.e.*, the probability distribution over $a \in \mathcal{A}(s)$ for each $s \in \mathcal{S}$) is changed with experience

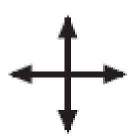
Policies and Value Functions

- State-value function $v_\pi(s)$
  - Expected return when starting in s and following π thereafter
  - $v_\pi(s) \doteq \mathbb{E}_\pi[G_t | S_t = s]$ (*Bellman equation*)
- Action-value function $q_\pi(s, a)$
  - Expected return when taking action a in state s, and following π thereafter
  - $q_\pi(s, a) \doteq \mathbb{E}_\pi[G_t | S_t = s, A_t = a]$
- The value functions v_π and q_π can be estimated from experience

- Example: using a random policy, with $\gamma = 0.9$:



Gridworld



Actions

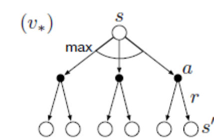
- Off-grid actions have no effect, with $r = -1$
- Any action from A gets to A', with $r = +10$
- Any action from B gets to B', with $r = +5$

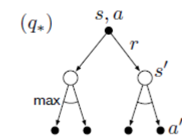
3.3	8.8	4.4	5.3	1.5
1.5	3.0	2.3	1.9	0.5
0.1	0.7	0.7	0.4	-0.4
-1.0	-0.4	-0.4	-0.6	-1.2
-1.9	-1.3	-1.2	-1.4	-2.0

v_π

Optimal Policy and Value Function

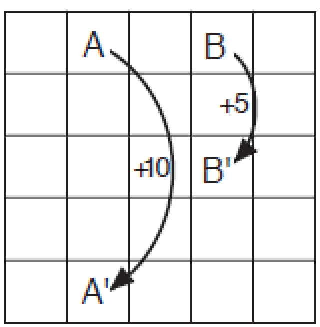
- Optimal policy π_*: expected return is greater than any other policy
  - Optimal state-value function: $v_*(s) \doteq \max_{\pi} v_\pi(s)$
  - Optimal action-value function: $q_*(s,a) \doteq \max_{\pi} q_\pi(s,a)$



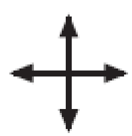


- Once we know v_* or q_*, the optimal policy is greedy

- Example:



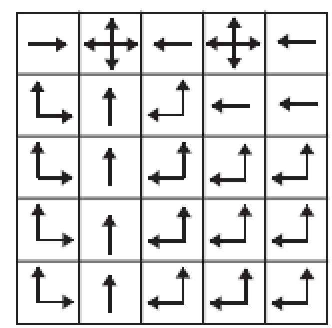
Gridworld



Actions

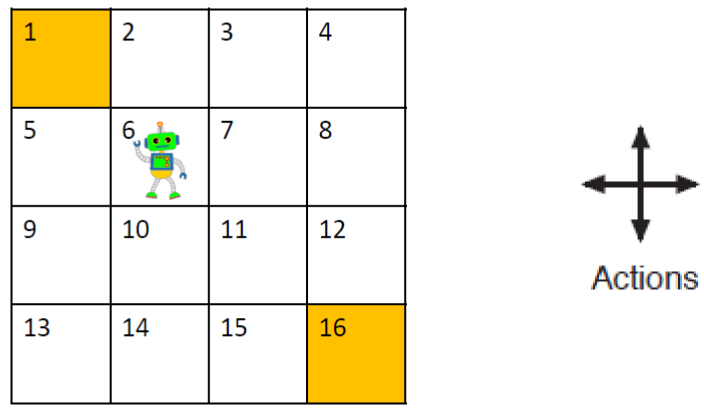
22.0	24.4	22.0	19.4	17.5
19.8	22.0	19.8	17.8	16.0
17.8	19.8	17.8	16.0	14.4
16.0	17.8	16.0	14.4	13.0
14.4	16.0	14.4	13.0	11.7

v_*



π_*

Example Grid World



- A bot is required to traverse a grid of 4×4 dimensions to reach its goal (1 or 16)
- There are 2 terminal states (1 and 16) and 14 non-terminal states (2 to 15)
- Each step is associated with a reward of -1
- Consider a random policy: at every state, the probability of every action {up, down, left, right} is 0.25
- Initialize v_1 for the random policy with all 0s

Example Grid World: Policy Evaluation

- Turning Bellman equation into an update:

$$v_{k+1}(s) \doteq \mathbb{E}_\pi[R_{t+1} + \gamma v_k S_{t+1} \, | S_t = s]$$

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

$$\begin{aligned} v_1(6) &= \sum_{a \in \{u,d,l,r\}} \pi(a|6) \sum_{s',r} p(s',r|6,a)[r + \gamma v_0(s')] \\ &= \sum_{a \in \{u,d,l,r\}} \underbrace{\pi(a|6)}_{=0.25\ \forall a} \sum_{s'} p(s'|6,a)[\underbrace{r}_{=-1} + \gamma \underbrace{v_0(s')}_{=0\ \forall s'}] \\ &= 0.25 * \{-p(2|6,u) - p(10|6,d) - p(5|6,l) - p(7|6,r)\} \\ &= 0.25 * \{-1 - 1 - 1 - 1\} \\ &= -1 \end{aligned}$$

$$\Rightarrow v_1(6) = -1$$

- For non-terminal states, $v_1(s) = -1$
- For terminal states, $p(s'|s,a) = 0$ (and hence $v_k(1) = v_k(6) = 0$, for all k)

$v_1 =$

0.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	0.0

Example Grid World: Policy Evaluation

- Step 2, with discount factor $\gamma = 1$

$$v_2(6) = \sum_{a \in \{u,d,l,r\}} \underbrace{\pi(a|6)}_{= 0.25\ \forall a} \sum_{s'} p(s'|6,a)[\underbrace{r}_{=-1} + \gamma \underbrace{v_1(s')}_{= \begin{cases} -1, s' \in S \\ 0, s' \in S^+ \setminus S \end{cases}}]$$

$$= 0.25 * \{p(2|6,u)[-1-\gamma] + p(10|6,d)[-1-\gamma] + p(5|6,l)[-1-\gamma] + p(7|6,r)[-1-\gamma]\}$$

$$\overset{\gamma=1}{=} 0.25 * \{-2-2-2-2\}$$

$$= -2$$

- For all red states, $v_2(s) = -2$

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

- For the other states (2, 5, 12, 15):

$$v_2(2) = \sum_{a \in \{u,d,l,r\}} \underbrace{\pi(a|2)}_{= 0.25\ \forall a} \sum_{s'} p(s'|2,a)[\underbrace{r}_{=-1} + \gamma \underbrace{v_1(s')}_{= \begin{cases} -1, s' \in S \\ 0, s' \in S^+ \setminus S \end{cases}}]$$

$$= 0.25 * \{p(2|2,u)[-1-\gamma] + p(6|2,d)[-1-\gamma] + p(1|2,l)[-1-\gamma * 0] + p(3|2,r)[-1-\gamma]\}$$

$$\overset{\gamma=1}{=} 0.25 * \{-2-2-1-2\}$$

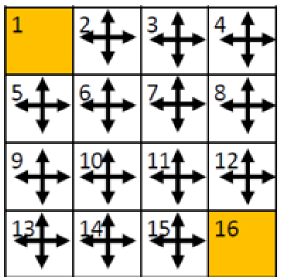
$$= -1.75$$

$$\Rightarrow v_2(2) = -1.75$$

$v_2 =$

0.0	-1.7	-2.0	-2.0
-1.7	-2.0	-2.0	-2.0
-2.0	-2.0	-2.0	-1.7
-2.0	-2.0	-1.7	0.0

Example Grid World: Policy Evaluation



Random policy

$k = 0$

0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0

$k = 1$

0.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	-1.0
-1.0	-1.0	-1.0	0.0

$k = 2$

0.0	-1.7	-2.0	-2.0
-1.7	-2.0	-2.0	-2.0
-2.0	-2.0	-2.0	-1.7
-2.0	-2.0	-1.7	0.0

$k = 3$

0.0	-2.4	-2.9	-3.0
-2.4	-2.9	-3.0	-2.9
-2.9	-3.0	-2.9	-2.4
-3.0	-2.9	-2.4	0.0

...

$k = 10$

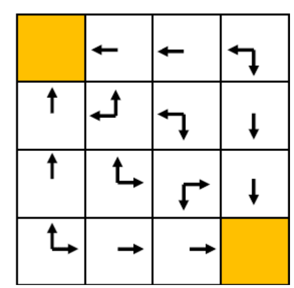
0.0	-6.1	-8.4	-9.0
-6.1	-7.7	-8.4	-8.4
-8.4	-8.4	-7.7	-6.1
-9.0	-8.4	-6.1	0.0

...

$k = \infty$

0.0	-14.	-20.	-22.
-14.	-18.	-20.	-20.
-20.	-20.	-18.	-14.
-22.	-20.	-14.	0.0

$\leftarrow v_\pi$



Optimal policy

Approximation

- Optimal policies are computationally costly to find – we can only approximate
  - In tasks with small, finite state sets: tabular methods
  - Otherwise: function approximation using a more compact parameterized function representation (*e.g.* using neural networks)

→The online nature of RL allows us to *put more effort into learning to make decisions for frequently encountered states*

Temporal-Difference Learning

- TD methods update estimates based on immediately observed reward and state

- Update rule:

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

- Because TD bases its update in part on an existing estimate, it is a *bootstrapping* method

Tabular TD(0) for estimating v_π

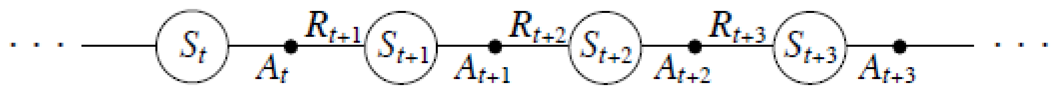
Input: the policy π to be evaluated
Algorithm parameter: step size $\alpha \in (0, 1]$
Initialize $V(s)$, for all $s \in \mathcal{S}^+$, arbitrarily except that $V(terminal) = 0$

Loop for each episode:
    Initialize S
    Loop for each step of episode:
        $A \leftarrow$ action given by π for S
        Take action A, observe R, S'
        $V(S) \leftarrow V(S) + \alpha[R + \gamma V(S') - V(S)]$
        $S \leftarrow S'$
    until S is terminal

Temporal-Difference Learning

- TD vs Dynamic Programming methods
  - TD methods do not require a model of the environment's dynamics (rewards and next-state probability distributions)
- TD vs Monte Carlo methods
  - TD methods are naturally implemented in an online, fully incremental fashion, while MC methods must wait until the end of an episode
    - Useful if episodes are very long, or in continuing tasks (that have no episodes at all)
- Usually, TD methods converge faster than MC methods on stochastic tasks

Sarsa: On-policy TD Control



- Update rule:

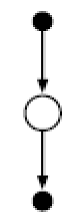
$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)]$$

  - This rule uses every element of the quintuple of events $(S_t, A_t, R_{t+1}, S_{t+1}, A_{t+1})$

Sarsa (on-policy TD control) for estimating $Q \approx q_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(terminal, \cdot) = 0$

Loop for each episode:
    Initialize S
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Loop for each step of episode:
        Take action A, observe R, S'
        Choose A' from S' using policy derived from Q (e.g., ε-greedy)
        $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma Q(S', A') - Q(S, A)\big]$
        $S \leftarrow S'$; $A \leftarrow A'$;
    until S is terminal



Sarsa

- Converges to optimal policy and action-value function if all state-action pairs are visited infinitely and policy converges to greedy (*e.g.* using ε-greedy with $\varepsilon = 1/t$)

Q-learning: Off-policy TD Control

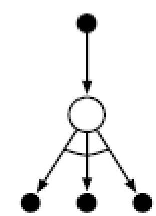
- Update rule:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\right]$$

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Algorithm parameters: step size $\alpha \in (0, 1]$, small $\varepsilon > 0$
Initialize $Q(s, a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, arbitrarily except that $Q(\mathit{terminal}, \cdot) = 0$

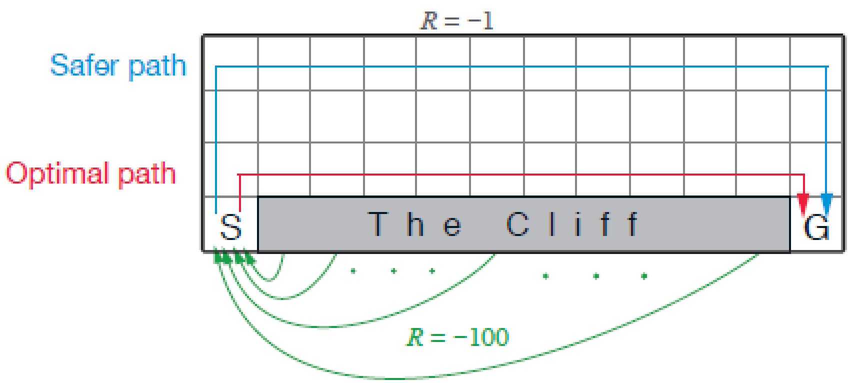
Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Take action A, observe R, S'
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
    $S \leftarrow S'$
  until S is terminal

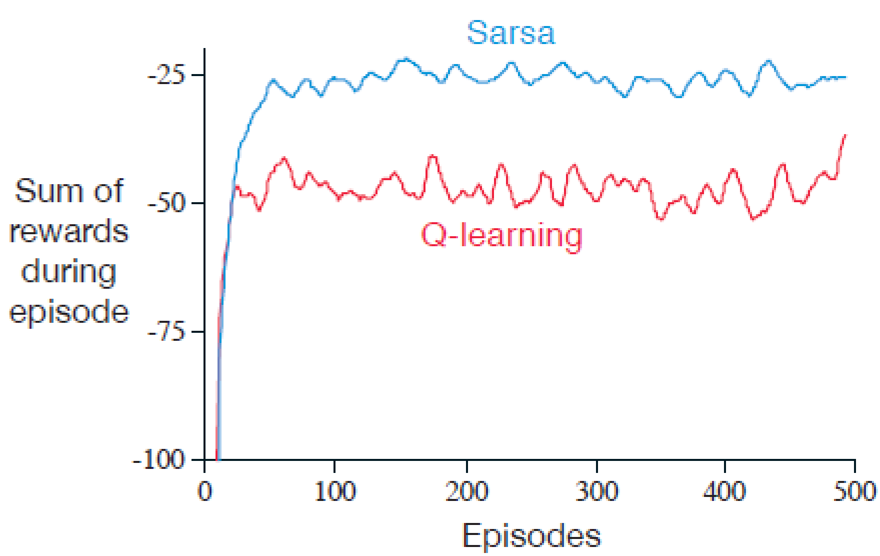


Q-learning

- The learned action-value function Q directly approximates q_*, independently of the policy being followed

Example: Cliff Walking



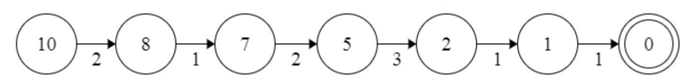


- Sarsa and Q-learning with ε-greedy action selection ($\varepsilon = 0.1$)
  - Q-learning learns values for the optimal policy
  - Sarsa takes action selection into account and learns the longer but safer path
  - Given exploration, Q-learning occasionally falls off the cliff, hence the lower online performance
- If ε is gradually reduced, both methods converge to the optimal policy

Quiz: The Toothpick Game

- 10 toothpicks
- 2 players take 1, 2 or 3 in turn
- Avoid last toothpick
  - $r(0) = +1$ $r(1) = -1$ $r(n) = 0, n > 1$

- Using Q-learning with $\alpha = 0.5$ and $\gamma = 0.9$, which values of $Q(s, a)$ change in each of the following episodes? (Consider only self-actions, shown in **bold**.)
  - Actions: **2**-1-**2**-3-**1**-1 (States: **10**-8-**7**-5-**2**-1-**0**)
  - Actions: **2**-2-**1**-3-**1**-1 (States: **10**-8-**6**-5-**2**-1-**0**)
  - Actions: **1**-3-**1**-3-**1**-1 (States: **10**-9-**6**-5-**2**-1-**0**)



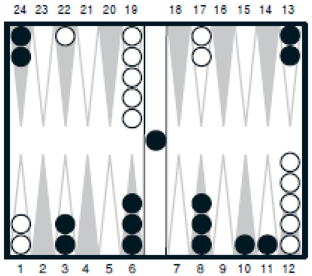
- After such updates, does the agent win when starting in state 10 and following a greedy policy, assuming the opponent always takes as much toothpicks as it can?

RL Algorithms

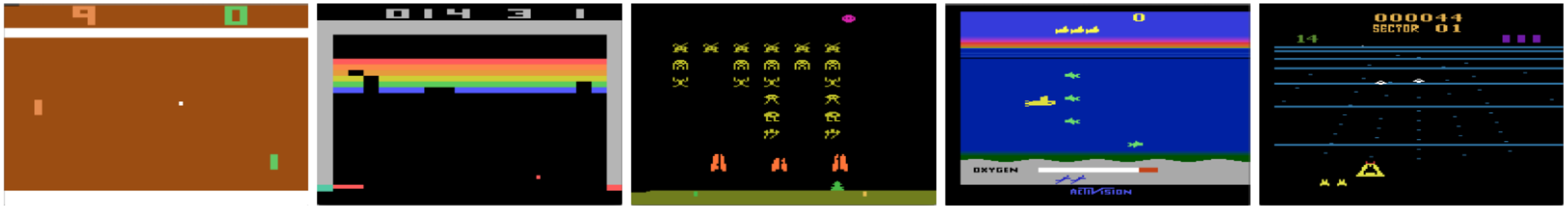
Algorithm	Description	Policy	Action Space	State Space
Monte Carlo	Every visit to Monte Carlo	Either	Discrete	Discrete
Q-learning	State–action–reward–state	Off-policy	Discrete	Discrete
SARSA	State–action–reward–state–action	On-policy	Discrete	Discrete
Q-learning - Lambda	Q-learning with eligibility traces	Off-policy	Discrete	Discrete
SARSA - Lambda	SARSA with eligibility traces	On-policy	Discrete	Discrete
DQN [Mnih et al., 2013]	Deep Q Network	Off-policy	Discrete	Continuous
DDPG [Lillicrap et al., 2016]	Deep Deterministic Policy Gradient	Off-policy	Continuous	Continuous
A3C [Mnih et al., 2016]	Asynchronous Advantage Actor-Critic	On-policy	Continuous	Continuous
NAF [Gu et al., 2016]	Q-Learning with Normalized Advantage Functions	Off-policy	Continuous	Continuous
TRPO [Schulman et al., 2015]	Trust Region Policy Optimization	On-policy	Continuous	Continuous
PPO [Schulman et al., 2017]	Proximal Policy Optimization	On-policy	Continuous	Continuous
TD3 [Fujimoto et al., 2018]	Twin Delayed Deep Deterministic Policy Gradient	Off-policy	Continuous	Continuous
SAC [Haarnoja et al., 2018]	Soft Actor-Critic	Off-policy	Continuous	Continuous

RL in Games

- TD-Gammon [Tesauro, 1995]
  - Neural Network trained with self-play reinforcement learning

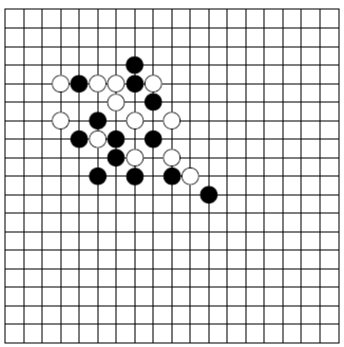


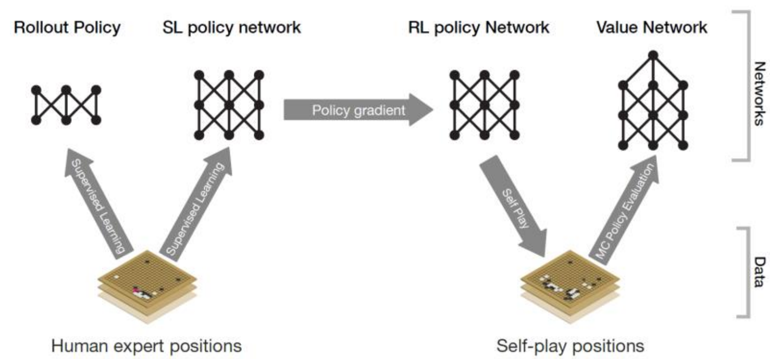
- Atari 2600 Games [DeepMind, 2013]
  - Learn control policies directly from high-dimensional sensory input using reinforcement learning
  - Input is raw pixels and output is a value function estimating future rewards



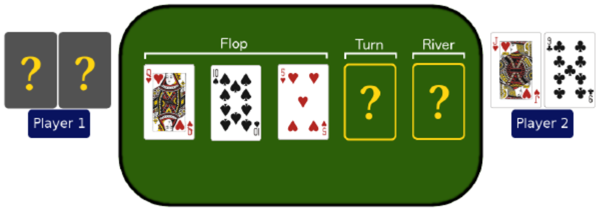
RL in Games

- AlphaGo [Google DeepMind, 2016]
  - Convolutional Neural Networks trained with human expert data
  - Deep Reinforcement Learning with fictitious self-play



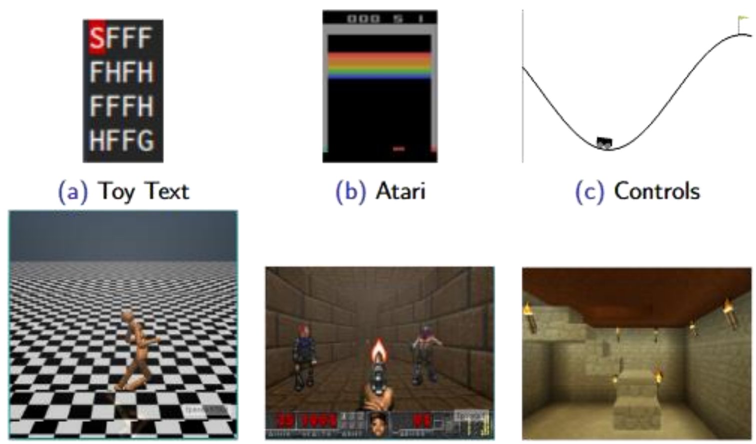


- Poker: Heads-Up Limit Texas Hold'em – NFSP [UCL, 2016]
  - Deep Reinforcement Learning with fictitious self-play
  - No prior knowledge



OpenAI Gym

- Gym is a toolkit for developing and comparing reinforcement learning algorithms
- The gym library is a collection of test problems with a shared interface — environments — that you can use to work out your RL algorithms

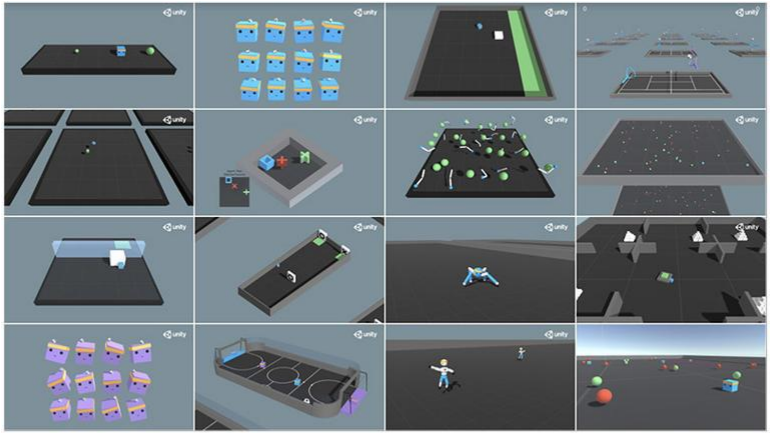


(a) Toy Text (b) Atari (c) Controls
(d) MuJoCo (e) Doom (f) Minecraft

- OpenAI Baselines is a set of high-quality implementations of RL algorithms
  - See also Stable Baselines

Unity ML-Agents

- With Unity Machine Learning Agents (ML-Agents), you teach intelligent agents through a combination of deep reinforcement learning and imitation learning



Further Reading

- Sutton, R. S. and Barto, A. G. (2018). *Reinforcement Learning – An Introduction*, 2nd ed., The MIT Press: Chap. 1-3, 6

- Simple Tutorial Videos for Deep RL:

  Introduction on Reinforcement Learning and Deep RL:

  https://www.youtube.com/watch?v=JgvyzIkgxF0

  PPO – Proximal Policy Optimization (PPO):

  https://www.youtube.com/watch?v=5P7I-xPq8u8

Conclusions

- RL enables to learn intelligent behavior in complex environments
- Large number of algorithms and approaches
- Amazing results in vintage Atari Games
- Stunning results of AlphaGo and AlphaZero
- Very promising results in Robotics
- Very fast evolution in the last few years