



Reinforcement Learning

CS4246/CS5446

AI Planning and Decision Making

Sem 1, AY2021-22



Topics

- Reward Based Learning and Planning (22.1)
- Learning - Passive RL (22.2)
 - Monte Carlo learning: Direct utility estimation (22.2.1)
 - Adaptive dynamic programming (22.2.2)
 - Temporal difference learning (22.2.3)
- Planning - Active RL (22.3)
 - Active adaptive dynamic programming
 - Exploration vs exploitation (22.3.1)
 - Temporal difference Q-learning and SARSA (22.3.3)



Recall: Sequential Decision Problems

- What are sequential decision problems?
 - An agent's utility depends on a sequence of decisions
 - Incorporate utilities, uncertainty, and sensing
 - Search and planning problems are special cases
 - Decision (Planning) Models:
 - Markov decision process (MDP)
 - Partially observable Markov decision process (POMDP)
 - Reinforcement learning: sequential decision making + learning



Solving Sequential Decision Problems

- Decision (Planning) Problem or Model
 - Appropriate abstraction of states, actions, uncertain effects, goals (wrt costs and values or preferences), and time horizon + observations (through sensing)
- Decision Algorithm
 - Input: a problem
 - Output: a solution in the form of an optimal action sequence or policy over time horizon
- Decision Solution
 - An action sequence or solution from an initial state to the goal state(s)
 - An optional solution or action sequence; OR
 - An optimal policy that specifies “best” action in each state wrt to costs or values or preferences
 - (Optional) A goal state that satisfies certain properties

Recall: Decision Making under Uncertainty

- Decision Model:

- **Actions:** $a \in A$
- **Uncertain current state:** $s \in S$ with probability of reaching: $P(s)$
- **Transition model** of uncertain action outcome or effects:
 $P(s' | s, a)$ – probability that action a in state s reaches state s'
- **Outcome** of applying action a :
 $\text{Result}(a)$ – random variable whose values are outcome states
- **Probability of outcome state** s' , conditioning on that action a is executed:
 $P(\text{Result}(a) = s') = \sum_s P(s)P(s' | s, a)$
- **Preferences** captured by a **utility function**:
 $U(s)$ – assigns a single number to express the desirability of a state s

Recall: Markov Decision Process (MDP)

- Formally:

- An MDP $M \triangleq (S, A, T, R)$ consists of:
- A set S of states
- A set A of actions
- A transition function $T: S \times A \times S \rightarrow [0,1]$ such that:

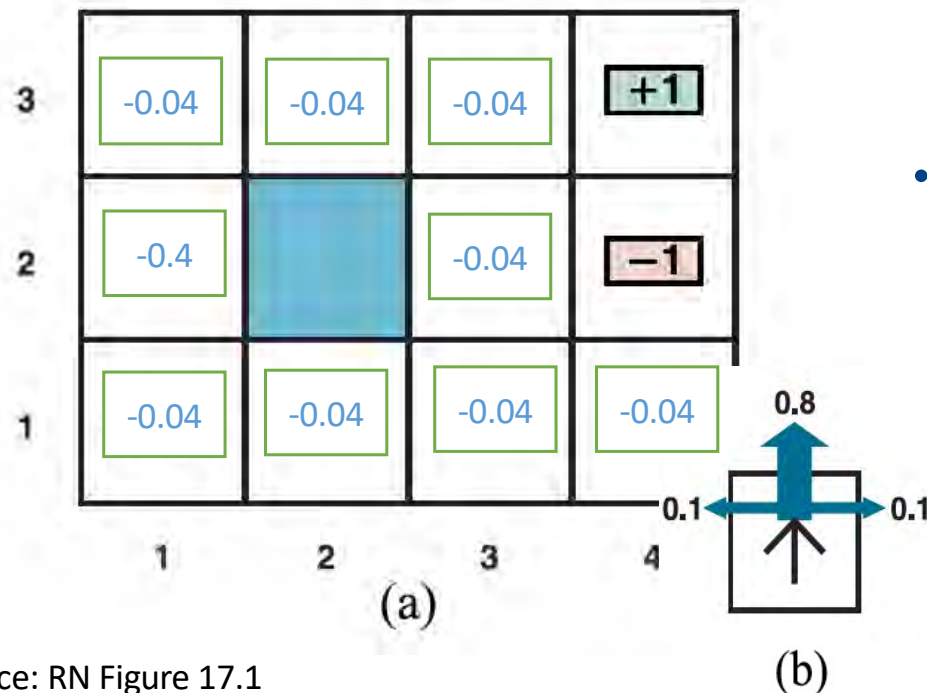
$$\forall s \in S, \forall a \in A: \sum_{s' \in S} T(s, a, s') = \sum_{s' \in S} P(s'|s, a) = 1$$

- A reward function $R: S \rightarrow \mathbb{R}$ or $R: S \times A \times S \rightarrow \mathbb{R}$

Solution is a policy – a function to recommend an action in each state: $\pi: S \rightarrow A$

- Solution involves careful balancing of risk and reward

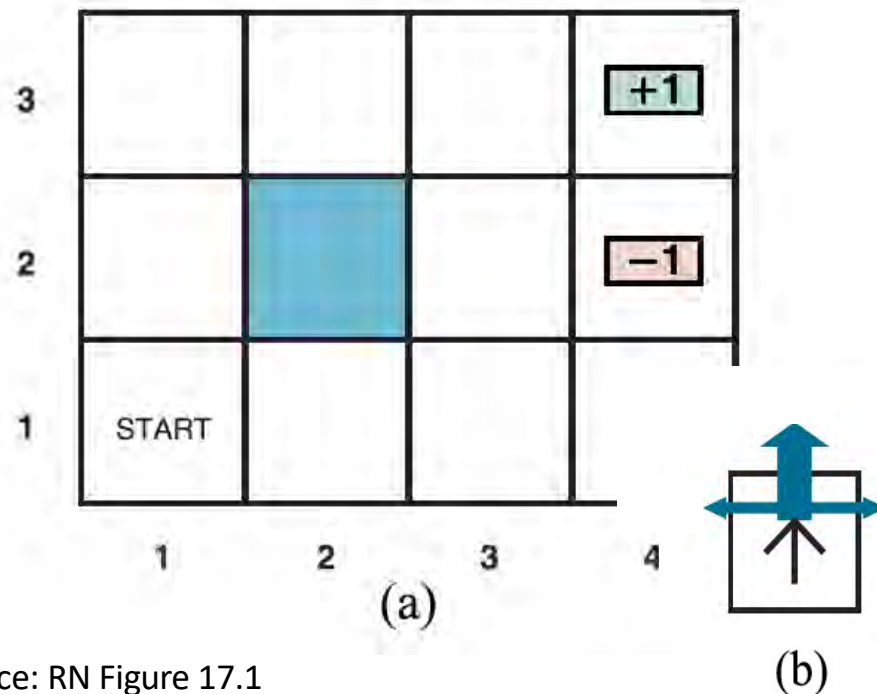
Example: Navigation in Grid World



Source: RN Figure 17.1

- Transition model:
 - Define (stochastic) outcome of each action
 - $P(s'|s, a)$ – probability of reaching state s' if action
- Reward model:
 - Define reward received for every transition
 - $R(s, a, s')$ – For every transition from s to s' via action a ; AND/OR
 - $R(s)$ – For any transition into state s
 - Rewards may be positive or negative, but bound by $\pm R_{max}ma$
 - Utility function depends on the sequence of states and actions – environment history – sum of rewards of the states in the sequence

Example: Navigation



- Transition model:
 - Unknown
- Reward model:
 - Unknown

Source: RN Figure 17.1

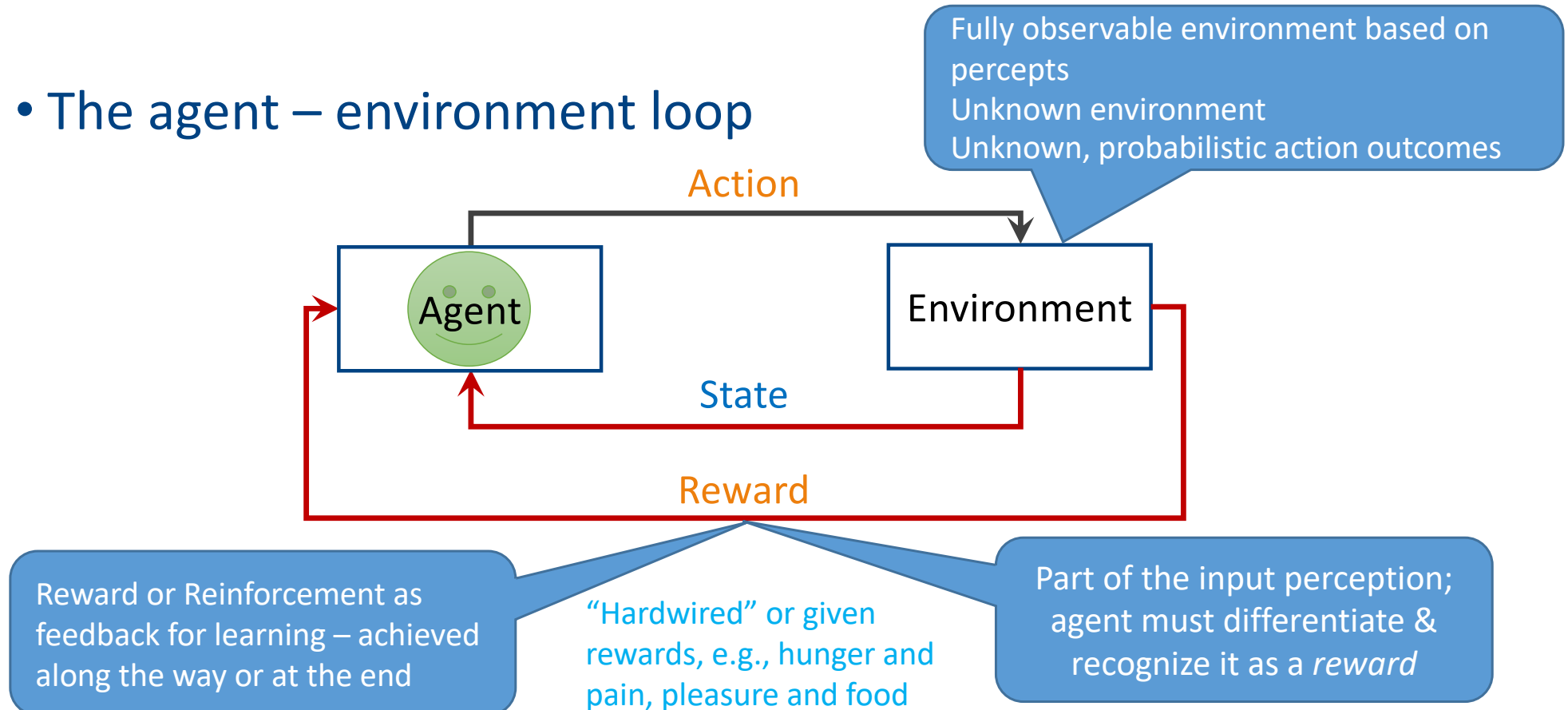


Reinforcement Learning

- Decision making in complex and uncertain environments
 - Learning to behave proficiently in unfamiliar environment, given only percepts and occasional rewards
 - E.g., playing chess, flying helicopter, exploring Mars, assisting elderly
- Assume:
 - Environment is a Markov Decision Process (MDP)
 - Optimal policy – policy that maximizes the expected total reward
- Reinforcement learning
 - Use observed rewards to learn an optimal policy for the environment
 - Often with no knowledge of the environment model or reward function
 - E.g., don't know the game rules, just play until Win/Loss declared
 - Would this for a good approach for an AI tutor?
 - Influences from psychology, neuroscience, operations research, and optimal control theory.

Reinforcement Learning

- The agent – environment loop



Types of RL Agents

- Reinforcement learning

- [PL] Passive Learning: Learning Utility functions
- [AL] Active Learning : Learning to Plan or Decide
- [MB] Model-based: Learn transition model to solve problem
- [MF] Model- free: Do not (need to) learn transition model to solve problem

- Passive learning agent

- Has a fixed policy that determines his behavior
- sf [policy evaluation](#) in policy iteration

- Active learning agent

- Must decide what actions to take
- sf [value iteration](#)



Passive Learning

Predict utility function (value function) of state given a fixed policy



Passive Learning

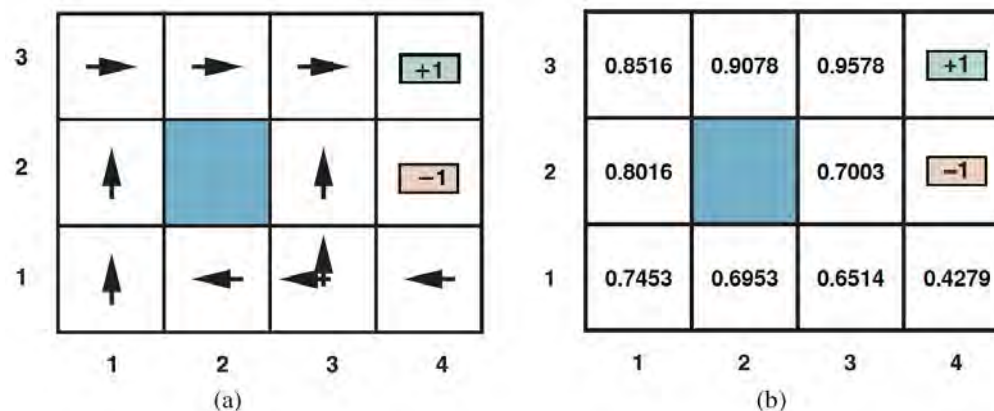
- Main idea

- Agent executes a set of trials in environment using policy π ; starts in (1,1) until reaches terminal state
- **Percepts** supply both **current state** and **reward** received in state
- Use reward information to learning expected utility $U^\pi(s)$ associated with each non-terminal state s

$$U^\pi(s) = E\left[\sum_{t=0}^{\infty} \gamma^t R(S_t)\right]$$

- where $R(s)$ is reward for a state s , S_t is a random variable indicating state reached at time t when executing policy π
 - **sf policy evaluation (in policy iteration)**
- Assume $\gamma = 1$ in examples that follow

Learning Utility Function

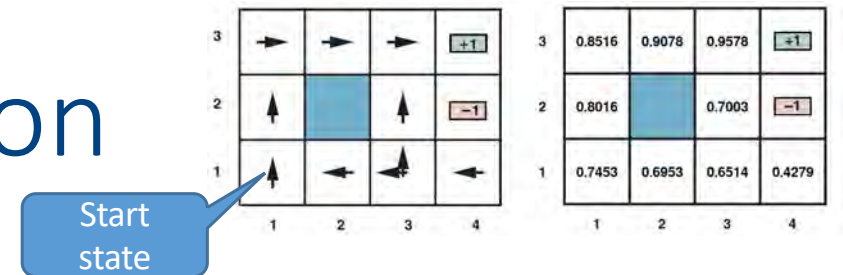


What are the percepts in each state?

Source: RN Figure 22.1

- The policy π is fixed:
 - Agent always executes $\pi(s)$ in state s
 - Goal: Learn utility function or value function $U^\pi(s)$ from observations
 - Unknown transition model, $P(s'|s, a)$
 - Unknown reward function, $R(s)$
- } If known, simply do policy evaluation!

Learning Utility Function



- Agent executes a series of trials using π , e.g.,
 - Trial 1: $(1, 1) \rightsquigarrow (1, 2) \rightsquigarrow (1, 3) \rightsquigarrow (1, 2) \rightsquigarrow (1, 3) \rightsquigarrow (2, 3) \rightsquigarrow (3, 3) \rightsquigarrow (4, 3) +1$
 - Trial 2: $(1, 1) \rightsquigarrow (1, 2) \rightsquigarrow (1, 3) \rightsquigarrow (2, 3) \rightsquigarrow (3, 3) \rightsquigarrow (3, 2) \rightsquigarrow (3, 3) \rightsquigarrow (4, 3) +1$
 - Trial 3: $(1, 1) \rightsquigarrow (2, 1) \rightsquigarrow (3, 1) \rightsquigarrow (3, 2) \rightsquigarrow (4, 2) -1$.
- Utility or value of a state:
 - Expected total reward from that state onwards
 - Also called **expected reward-to-go** / **expected return**
- Utility/value of s under π is:

$$U^\pi(s) = E \left[\sum_{t=0}^{\infty} \gamma^t R(S_t) | S_0 = s \right]$$

Assume
 $\gamma = 1$

Example: Monte Carlo Learning

$(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) +1$
 $(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (3, 2) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) +1$
 $(1, 1) \xrightarrow{-.04} (2, 1) \xrightarrow{-.04} (3, 1) \xrightarrow{-.04} (3, 2) \xrightarrow{-.04} (4, 2) -1$.

- Each trial provides a “sample” of expected return for each state visited
 - In the first trial, sample total reward:
 - For $(1,1) =$
 - For $(1,2) =$
 - Overall:
 - $U^\pi(1,1) =$
 - $U^\pi(1,2) =$

Monte Carlo Learning

$(1, 1) \xrightarrow{-0.04} (1, 2) \xrightarrow{-0.04} (1, 3) \xrightarrow{-0.04} (1, 2) \xrightarrow{-0.04} (1, 3) \xrightarrow{-0.04} (2, 3) \xrightarrow{-0.04} (3, 3) \xrightarrow{-0.04} (4, 3) +1$
 $(1, 1) \xrightarrow{-0.04} (1, 2) \xrightarrow{-0.04} (1, 3) \xrightarrow{-0.04} (2, 3) \xrightarrow{-0.04} (3, 3) \xrightarrow{-0.04} (3, 2) \xrightarrow{-0.04} (3, 3) \xrightarrow{-0.04} (4, 3) +1$
 $(1, 1) \xrightarrow{-0.04} (2, 1) \xrightarrow{-0.04} (3, 1) \xrightarrow{-0.04} (3, 2) \xrightarrow{-0.04} (4, 2) -1$.

- Main idea:

- Maintain running average of expected return for each state in a table
- Run infinitely many trials; value converges to true expected value
- Number of visits may be treated differently: e.g., first visit vs every visit
 - E.g., consider only 0.76 for (1,2); 0.84 is ignored
 - E.g., considers both 0.76 and 0.84 for (1,2)
 - Both converge to the true expected value in the limit

Monte Carlo Learning

Also called **Direct Utility Estimation**:

An instance of supervised learning - Each example has state as input and observed return (unbiased estimate) as output

$$((x_1, y_1), u_1), ((x_2, y_2), u_2), \dots, ((x_n, y_n), u_n)$$

where u_j is the measured utility of the j^{th} example

Very slow convergence:

Need to wait till the end of the episode before learning can begin

By ignoring constraints, searches much larger space, including utility functions that violate the Bellman equations for a fixed policy:

$$U^\pi(s) = \sum_{s'} P(s'|s, \pi(s)) [R(s, \pi(s), s') + \gamma U^\pi(s')]$$

Exercise

What is the Monte Carlo estimate of the value for state (1,1) after the trials shown?

$$\begin{aligned} (1,1) &\xrightarrow[-0.04]{Up} (1,2) \xrightarrow[-0.04]{Up} (1,3) \xrightarrow[-0.04]{Right} (1,2) \xrightarrow[-0.04]{Up} (1,3) \xrightarrow[-0.04]{Right} (2,3) \xrightarrow[-0.04]{Right} (3,3) \xrightarrow[+1]{Right} (4,3) \\ (1,1) &\xrightarrow[-0.04]{Up} (1,2) \xrightarrow[-0.04]{Up} (1,3) \xrightarrow[-0.04]{Right} (2,3) \xrightarrow[-0.04]{Right} (3,3) \xrightarrow[-0.04]{Right} (3,2) \xrightarrow[-0.04]{Up} (3,3) \xrightarrow[+1]{Right} (4,3) \\ (1,1) &\xrightarrow[-0.04]{Up} (1,2) \xrightarrow[-0.04]{Up} (1,3) \xrightarrow[-0.04]{Right} (2,3) \xrightarrow[-0.04]{Right} (3,3) \xrightarrow[-0.04]{Right} (3,2) \xrightarrow[-1]{Up} (4,2) \end{aligned}$$

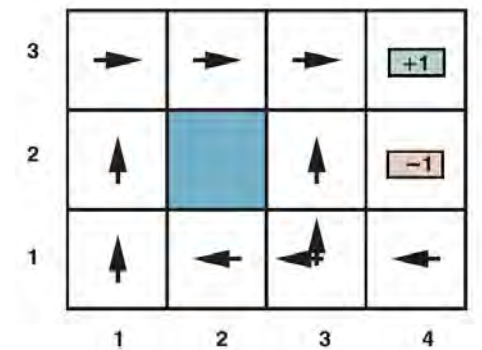
$$U^\pi(1,1) =$$

Example: Adaptive Dynamic Programming

$(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) \xrightarrow{+1}$
 $(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (3, 2) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) \xrightarrow{+1}$
 $(1, 1) \xrightarrow{-.04} (2, 1) \xrightarrow{-.04} (3, 1) \xrightarrow{-.04} (3, 2) \xrightarrow{-.04} (4, 2) \xrightarrow{-1}$.

What is the transition probability function from $s = (3, 3)$?

To compute:



Adaptive Dynamic Programming (ADP)

- Learn transition function T empirically through experience
 - Count action outcomes for each s, a
 - Normalize to give estimates of transition probabilities $P(s'|s, a)$
- Learn reward function $R(s, a, s')$ upon entering state s'
- Solve MDP with learned T
 - Given π , perform **policy evaluation** for all s :

$$U^\pi(s) = \sum_{s'} P(s'|s, \pi(s)) [R(s, \pi(s), s') + \gamma U^\pi(s')]$$

- Solve $|S|$ linear equations with $|S|$ unknowns in $O(|S|^3)$ time
- **Notes:**
 - Can learn $P(s'|s, a)$ using supervised learning
 - Exploits constraints among utilities of states

ADP-Learner

function PASSIVE-ADP-LEARNER(*percept*) **returns** an action

inputs: *percept*, a percept indicating the current state s' and reward signal r

persistent: π , a fixed policy

Using tabular representation { mdp , an MDP with model P , rewards R , actions A , discount γ
 U , a table of utilities for states, initially empty
 $N_{s'|s,a}$, a table of outcome count vectors indexed by state and action, initially zero
 s, a , the previous state and action, initially null

if s' is new **then** $U[s'] \leftarrow 0$

if s is not null **then**

- increment $N_{s'|s,a}[s, a][s']$
- $R[s, a, s'] \leftarrow r$
- add a to $A[s]$
- $\mathbf{P}(\cdot \mid s, a) \leftarrow \text{NORMALIZE}(N_{s'|s,a}[s, a])$
- $U \leftarrow \text{POLICYEVALUATION}(\pi, U, mdp)$
- $s, a \leftarrow s', \pi[s']$

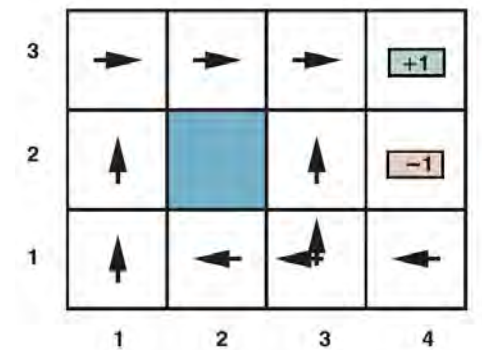
return a

Example: Temporal-Difference (TD) Learning

$(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) +1$
 $(1, 1) \xrightarrow{-.04} (1, 2) \xrightarrow{-.04} (1, 3) \xrightarrow{-.04} (2, 3) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (3, 2) \xrightarrow{-.04} (3, 3) \xrightarrow{-.04} (4, 3) +1$
 $(1, 1) \xrightarrow{-.04} (2, 1) \xrightarrow{-.04} (3, 1) \xrightarrow{-.04} (3, 2) \xrightarrow{-.04} (4, 2) -1$.

After first trial:

- $U^\pi(1,3) =$
- $U^\pi(2,3) =$
- In the long run, must obey:
 - $U^\pi(1,3) = -0.04 + U^\pi(2,3)$
- Hence:
 - $U^\pi(1,3) =$



Temporal Difference Learning (TD)

- Temporal difference learning (TD)

- For a transition from state s to s' , TD learning does:

$$U^\pi(s) \leftarrow U^\pi(s) + \alpha(R(s, \pi(s), s') + \gamma U^\pi(s') - U^\pi(s))$$

- where, α is the learning rate

- In TD learning:

- TD target: $R(s, \pi(s), s') + \gamma U^\pi(s')$

- TD term or error: $R(s, \pi(s), s') + \gamma U^\pi(s') - U^\pi(s)$

- TD term is error signal, update is intended to reduce error

- Increases $U^\pi(s)$ if $R(s, \pi(s), s') + \gamma U^\pi(s')$ is larger than $U^\pi(s)$; decreases otherwise
 - Converges if α decreases appropriately with the number of times the state has visited.

E.g., $\alpha(n) = O\left(\frac{1}{n}\right)$

Temporal-Difference (TD) Learning

- Main idea:

- Adjust utility estimates towards ideal (local) equilibrium with correct utility estimates
- In passive learning equilibrium is given by the Bellman equation for a fixed policy:

$$U_i(s) = \sum_{s'} P(s'|s, \pi_i(s)) [R(s, \pi_i(s), s') + \gamma U_i(s')]$$

- TD update:

- Involves only observed successor s' , average value of $U^\pi(s)$ will converge to correct value
- If learning rate α is changed from fixed parameter to decreasing function of increasing number of visits to a state, then $U^\pi(s)$ converges

- TD vs MC and ADP:

- Exploits more of the Bellman equation constraints than MC
- Does not need to learn the model (here refers to transition function T), unlike ADP

TD-Learner (Model-Free RL)

function PASSIVE-TD-LEARNER(*percept*) **returns** an action

inputs: *percept*, a percept indicating the current state s' and reward signal r

persistent: π , a fixed policy

s , the previous state, initially null

U , a table of utilities for states, initially empty

N_s , a table of frequencies for states, initially zero

if s' is new **then** $U[s'] \leftarrow 0$

if s is not null **then**

increment $N_s[s]$

$U[s] \leftarrow U[s] + \alpha(N_s[s]) \times (r + \gamma U[s'] - U[s])$

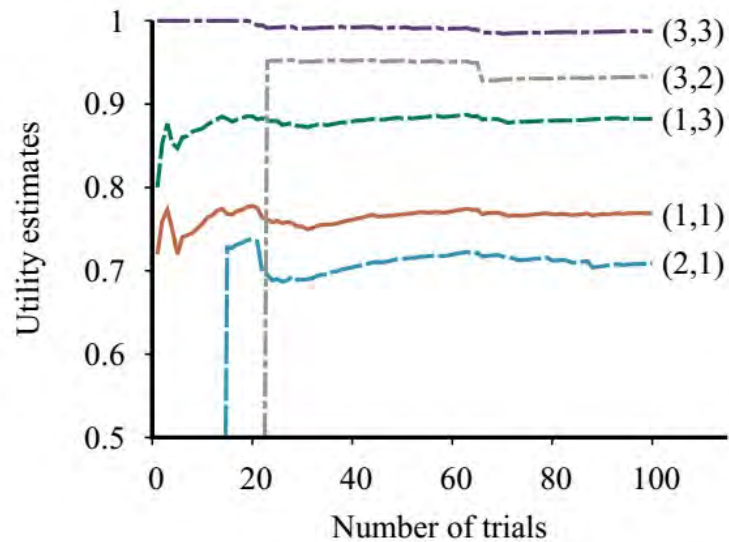
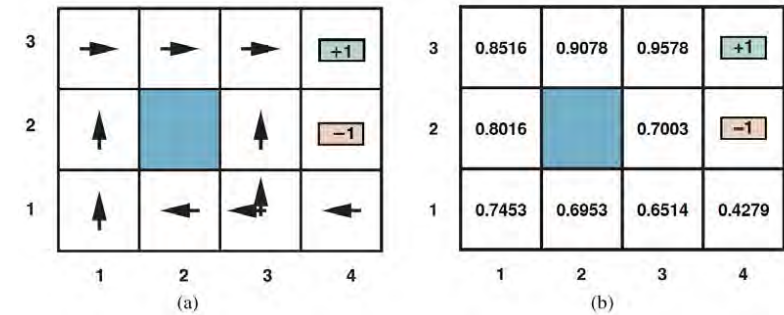
$s \leftarrow s'$

return $\pi[s']$

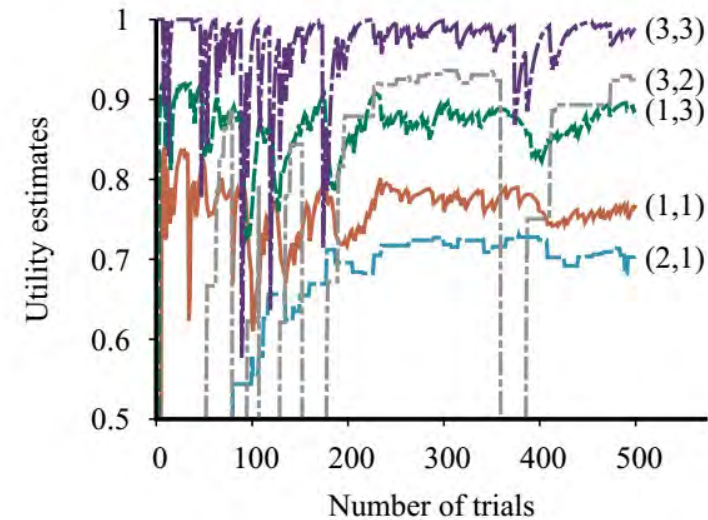
- TD needs only observed transitions to do the updates; no transition model is needed!
- Learn from every experience – update each time we experience s , $\pi(s)$, and s'

Source: RN Figure 22.4

Example: ADP vs TD



Adaptive Dynamic Programming



Temporal Difference Learning

Source: RN Figure 22.3 (a) and 22.5 (a)



ADP vs TD/MC

- ADP
 - Learns the model and then solves for the value
- TD/MC
 - Don't need a model
 - Can work with measurements from real-world or simulator
- ADP
 - More data efficient
 - Requires less data from the real-world
- TD
 - Doesn't need to compute expectation
 - Computationally more efficient



Active Learning

Choose to act optimally based on prediction of utility or value of states
Exploration vs exploitation, Q-learning, SARSA



Active Learning

- Main ideas:

- T and R unknown; can choose any action a at each step
- Goal: Learn optimal policy π^* that obey the Bellman equations:

$$U(s) = \max_{a \in A(s)} \sum_{s'} P(s'|s, a) [R(s, a, s') + \gamma U(s')]$$

- In summary:

- Learner makes choices
- Tradeoff between exploration vs. exploitation:
- If learned \hat{T} is not the true T , optimal policy obtained using \hat{T} may be suboptimal wrt T , possibly incurring large **policy loss**

From Passive to Active ADP-Learner

function PASSIVE-ADP-LEARNER(*percept*) **returns** an action

inputs: *percept*, a percept indicating the current state s' and reward signal r

persistent: π , a fixed policy

π not fixed

mdp, an MDP with model P , rewards R , actions A , discount γ

U , a table of utilities for states, initially empty

$N_{s'|s,a}$, a table of outcome count vectors indexed by state and action, initially zero

s, a , the previous state and action, initially null

if s' is new **then** $U[s'] \leftarrow 0$

if s is not null **then**

increment $N_{s'|s,a}[s, a][s']$

$R[s, a, s'] \leftarrow r$

add a to $A[s]$

$\mathbf{P}(\cdot \mid s, a) \leftarrow \text{NORMALIZE}(N_{s'|s,a}[s, a])$

$U \leftarrow \text{POLICYEVALUATION}(\pi, U, mdp)$

$U \leftarrow \text{PolicyIteration}(\pi, U, mdp)$

$s, a \leftarrow s', \pi[s']$

return a

Reward
function R

Transition
function T

Exercise:

Is this a good reinforcement
learning algorithm?

- Replace POLICY-EVALUATION step by $\pi \leftarrow \text{POLICY-ITERATION}(mdp)$ above
- π is no longer fixed; changes as transitions & rewards are learned

Source: RN Figure 22.2



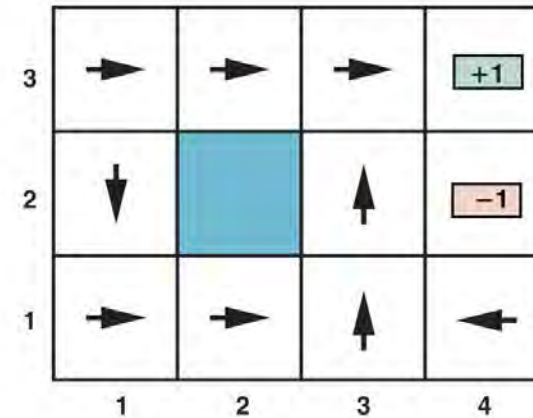
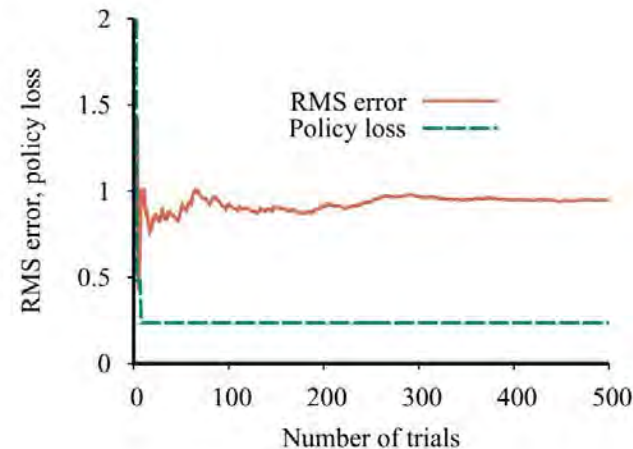
Active Adaptive Dynamic Programming

- For active-ADP:
 - Learn model T with outcome probabilities for all actions, not just for a fixed policy.
 - Learn utilities defined by optimal policy that obey the Bellman equation
 - Then, run VI or PI to determine optimal policy
 - Extract an optimal action by one-step look-ahead to maximize expected utility
- Note:
 - Learner has choice of actions
 - Actions don't just maximize rewards for given current learned model T , they also affect the percepts (states and rewards) received
 - Should learner then just execute action recommended by optimal policy? Why?

Greedy ADP Learner

RMS error in the utility estimates averaged over non-terminal states

Policy loss: $U^{\pi^*} - U^{\pi}$



- Resulting algorithm is greedy w.r.t the policy
- Policy resulting from executing action suggested by the learned model
 - Note, for e.g., at (2, 1) it goes right instead of left
 - Policy reasonable, but not optimal
- Agent is greedy – sometimes doesn't try better policies sufficiently after finding a suboptimal one



Exploration Vs Exploitation

- Actions in RL gain reward and help to learn a better model
 - By improving the model, better reward may potentially be obtained
- Need to trade off
 - **Exploration**: Choose action to learn the true model T (by affecting the states and rewards received) to receive greater rewards in future
 - **Exploitation**: Given current learned model T , choose action to maximize the reward (as reflected in current utility estimates)
- Main questions:
 - How to balance exploration and exploitation to maximize long-term expected rewards?
 - When to “stop” learning the model?
- **With greater understanding, less exploration is necessary!**



Greedy in the Limit of Infinite Exploration

- GLIE: A scheme for balancing exploration and exploitation
 - Try each action in each state an unbounded number of times to avoid a finite probability of missing an optimal action
 - Eventually become greedy so that it is optimal w.r.t the true model
- GLIE-based schemes for forcing exploration in RL:
 - ϵ -greedy exploration
 - Choose the greedy action with probability $(1 - \epsilon)$
 - Choose a random action with probability ϵ
 - GLIE based ϵ -greedy eventually converges to the optimal, but can be slow
 - One solution: lower ϵ over time (e.g., $\epsilon = \frac{1}{t}$)
 - Another solution: use exploration functions!

Optimism

- Alternatively, balance exploration and exploitation using greedy action selection w.r.t an **optimistic estimate** of the utility, $U^+(s)$
- One way to construct $U^+(s)$ is to use an **exploration function** $f(u, n)$ with the following update:

$$U^+(s) \leftarrow \max_a f \left(\sum_{s'} P(s'|s, a) [R(s, a, s') + \gamma U^+(s)], N(s, a) \right)$$

- Where, $N(s, a)$ is the number of times action a has been tried in state s



Exploration Functions

- When to explore:
 - Random actions: explore a fixed amount
 - Better idea: explore areas where “badness” has not been established
- Exploration function: f
 - Takes a value estimate (u) and a count (n), and returns an optimistic utility $f(u, n)$
 - Determines how greed (preference for high values of u) is traded off against curiosity (preference for actions that have not been tried often with low n)
 - f should be increasing in u and decreasing in n (form is not important)

Example: Exploration Functions

- An exploration function $f(u, n)$ that is increasing with u and decreasing with n :

$$f(u, n) = \begin{cases} R^+ & \text{if } n < N_e \\ u & \text{otherwise} \end{cases}$$

Where:

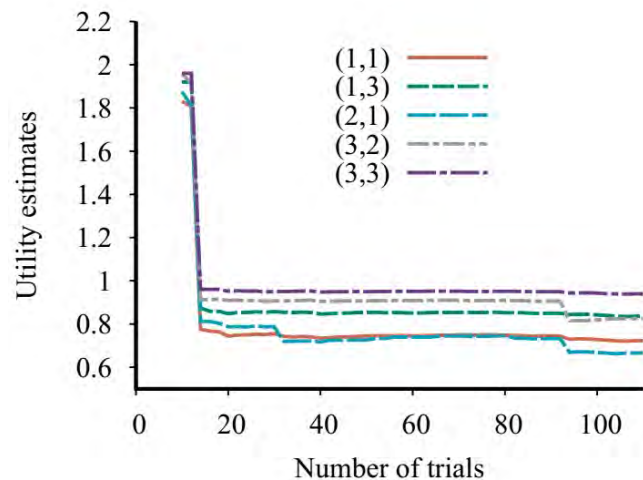
- R^+ is an optimistic estimate of the best possible reward
- N_e is the parameter

Agent tries each state-action pairs N_e times

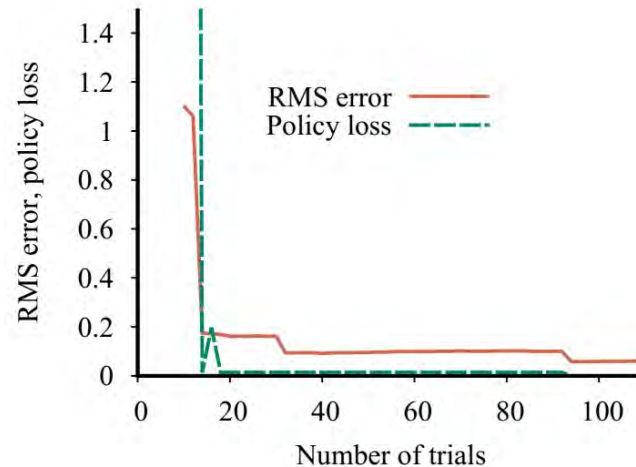
- **Example: RMAX [1]**
 - Works well for small problems, has guarantees

[1] Brafman, R.I. and M. Tennenholtz, *R-max - a general polynomial time algorithm for near-optimal reinforcement learning*. J. Mach. Learn. Res., 2003. **3**(null): p. 213–231.

Example: Navigation in Grid World

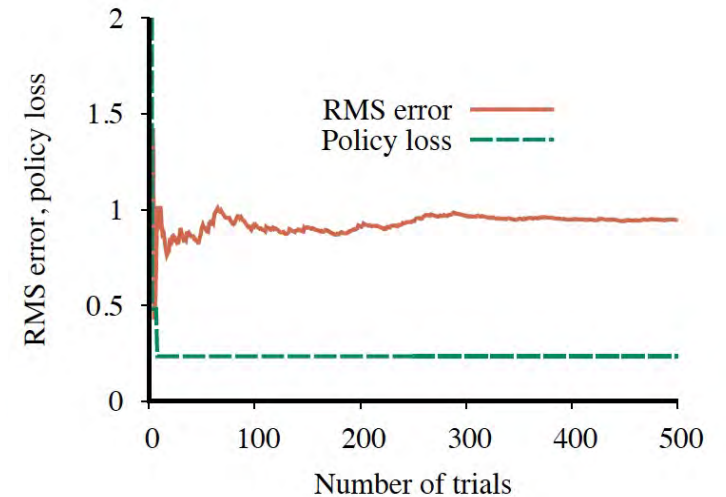


(a)



(b)

Exploring ADP



(a)

Greedy ADP

- Exploring ADP using exploration function with: $R^+ = 2, N_e = 5$

Source: RN Figure 22.6 (a) 22.7 (a) and (b)

Q-Learning: Learning Action-Utility Functions

- **Q-function – Action-utility function $Q(s, a)$**

- Expected total discounted reward if action a is taken in state s
- Q-functions (also called **Q-values**) are related to utilities by: $U(s) = \max_a Q(s, a)$

- **Q-Learning**

- **Model-free** learning: Agent can act optimally knowing Q -function; no need for look-ahead based on a transition model
- The Bellman equation for Q -functions:

$$Q(s, a) = \sum_{s'} P(s'|s, a) [R(s, a, s') + \gamma \max_{a'} Q(s', a')]$$

- Uses TD update to learn action-utility functions or Q-functions:

$$Q(s, a) \leftarrow Q(s, a) + \alpha [R(s, a, s') + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

TD Term or Error

Q-learning: Active TD Learning

function Q-LEARNING-AGENT(*percept*) **returns** an action

inputs: *percept*, a percept indicating the current state s' and reward signal r

persistent: Q , a table of action values indexed by state and action, initially zero

N_{sa} , a table of frequencies for state–action pairs, initially zero

s, a , the previous state and action, initially null

TD Update

if s is not null **then**

increment $N_{sa}[s, a]$

$Q[s, a] \leftarrow Q[s, a] + \alpha(N_{sa}[s, a])(r + \gamma \max_{a'} Q[s', a'] - Q[s, a])$

$s, a \leftarrow s', \operatorname{argmax}_{a'} f(Q[s', a'], N_{sa}[s', a'])$

return a

Exploration function

TD Term or Error

- TD Q-learning does not need a transition model, $P(s'|s, a)$ for learning or action selection



SARSA

- State-Action-Reward-State-Action (SARSA):

- Uses TD for prediction (evaluation) and ϵ -greedy for action selection

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R(s, a, s') + \gamma Q(s', a') - Q(s, a)]$$

where a' is the action taken at state s'

- Note:

- Rule is applied at the end of each quintuple (s, a, r, s', a')
- With appropriately decreasing ϵ , SARSA converges to the optimal policy



Off-Policy and On-Policy Learning

- Q -learning update rule:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left(R(s, a, s') + \gamma \max_{a'} Q(s', a') - Q(s, a) \right)$$

- SARSA update rule:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left(R(s, a, s') + \gamma Q(s', a') - Q(s, a) \right)$$

- Q -learning is off-policy – Target of Q -learning uses the max over possible actions a' at s'
 - Doesn't need the actual action in the next state in the update
 - Can converge to the optimal policy even when trained off-policy
 - Needs appropriately decaying α
 - Each action is taken in each state infinitely often
- SARSA is on-policy – Target uses Q -function from the policy that is running
 - Using Q -function from another state-action pair will give incorrect target value



Q-Learning vs SARSA

- Similarities:

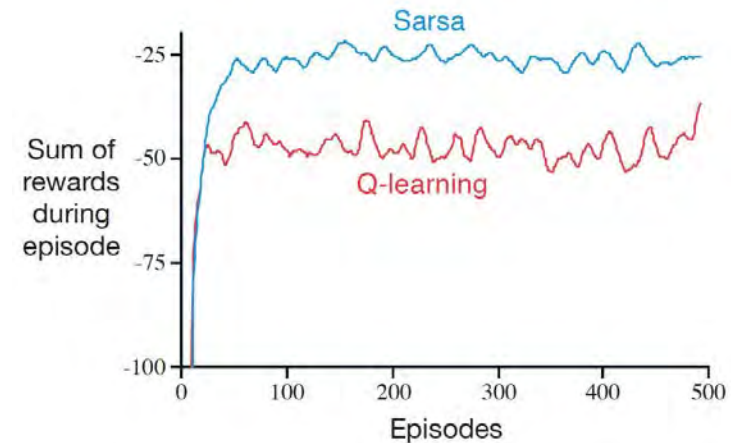
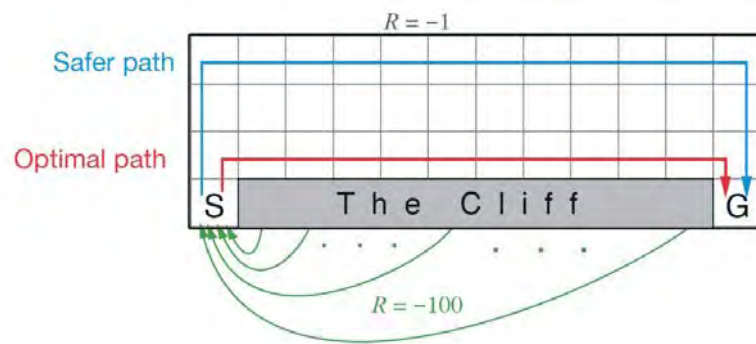
- If agent is greedy and always takes action with the best Q -function: the two are identical
- Both converge slowly as local updates do not enforce consistency among all the Q -functions via model

- Differences:

- Q -learning backs up Q -function from the best action in s'
- SARSA waits until an action is taken and backs up Q -function for that action
- If exploration yields a negative reward: SARSA penalizes the action, Q -learning does not

Example: Cliff Walking

From Sutton & Barto



Source: SB: Example 6.6

- Actions: left, right, up, down
- Reward: -1 for each step; -100 if you fall off
- SARSA & Q -learning used with ϵ -greedy; $\epsilon = 0.1$
 - Why does SARSA outperform Q -learning?
 - What happens if GLIE exploration is used?



Summary: Reinforcement Learning

- **Passive Learning – fixed policy**
 - [MB/MF] Monte-Carlo prediction (MC): Direct utility estimation
 - [MB] Adaptive dynamic programming (ADP)
 - [MF] Temporal difference methods (TD)
- **Active Learning – optimal policy**
 - [MB] Active Adaptive dynamic programming (ADP)
 - [MF] Active Temporal Difference methods (TD)
 - Q-Learning
 - SARSA



Applications of Reinforcement Learning

- **Game playing**
 - Checkers (1959, 1967)
 - Backgammon (TD-Gammon 1992)
 - Atari Games (2015)
 - Go (2019)
 - Starcraft II: <https://youtu.be/gEyBzcPU5-w>
 - DOTA2 (2019)
- **Robotic control**
 - Cart-pole balancing problem (inverted pendulum) (1968)
 - Helicopter flight (2001, 2004, ...)
 - Rover in unfamiliar place (planet) ...
 - Autonomous robot navigation: <https://youtu.be/KyA2uTIQfxw>
- **Potential real world applications:**
 - Power grid management
 - Generate product recommendations
 - Cargo management
 - Diagnosis and treatment of infectious disease
 - Drug discovery
 - Assistive care and education
 - ...



Homework

- Readings:
 - RN: 22.1, 22.2. 22.3.1, 22.3.2
 - *SB*: 6.2, 6.4, 6.5 (Optional)
- Some classical papers and recent surveys on RL
(Journal articles publicly available online or through NUS Library e-Resources)
 - L. P. Kaelbling, M. L. Littman, & A. W. Moore. [Reinforcement Learning: A Survey](#). JAIR, 4:237-285, 1996
 - Wirth, C., et al., [A survey of preference-based reinforcement learning methods](#). J. Mach. Learn. Res., 2017. **18**(1): p. 4945–4990.