

ST449 Artificial Intelligence and Deep Learning

Lecture 7

Dynamic programming and Monte Carlo methods



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<https://github.com/lse-st449/lectures>

Topics of this lecture

- Elementary solution methods:
 - Dynamic programming
 - Monte Carlo methods
- Next lecture: elementary solution methods cont'd
 - Temporal-difference learning

Dynamic programming (DP)

Dynamic Programming

- **Dynamic Programming (DP)**: a collection of algorithms used to compute optimal policies **given a perfect knowledge of the environment as a MDP**
- DP algorithms are rarely used directly in practice
- However, they provide a foundation for other solution methods
 - Other methods can be seen as trying to achieve the same but with less computation and without assuming a perfect knowledge of the environment

Our focus: finite MDPs

- Environment modeled by a **finite MDP**: finite state and action sets $S, A(s), s \in S$
- Dynamics specified by the **transition probabilities**

$$P_{s,s'}^a = \mathbf{Pr}[s_{t+1} = s' \mid s_t = s, a_t = a]$$

and the **immediate expected rewards** for actions and state transitions:

$$R_{s,s'}^a = \mathbf{E}[r_{t+1} \mid a_t = a, s_t = s, s_{t+1} = s']$$

- DP ideas can be applied also to problems with continuous state and action sets
 - A common approach is to use quantization

Bellman optimality equations

- The optimal state value function V^* satisfies:

$$V^*(s) = \max_a \sum_{s' \in S} P_{s,s'}^a [R_{s,s'}^a + \gamma V^*(s')], \text{ for } s \in S$$

- The optimal action value function Q^* satisfies:

$$Q^*(s, a) = \sum_{s' \in S} P_{s,s'}^a [R_{s,s'}^a + \gamma \max_{a'} Q^*(s, a')], \text{ for } s \in S, a \in A(s)$$

Policy evaluation

- **Policy evaluation**: computation of the state value function V^π for a given policy π
- Also referred to as **the prediction problem**
- For any given policy π , the existence and uniqueness of V^π are guaranteed whenever either
 - The discount rate satisfies $\gamma < 1$, or
 - Eventual termination is guaranteed from all states under policy π
- V^π is a solution of a system of $|S|$ linear equations with $|S|$ unknowns

Iterative policy evaluation

- Iterative policy evaluation: an iterative solution method that outputs a sequence of approximate state-value functions V_0, V_1, \dots
 - Initial value function V_0 is chosen arbitrarily subject to the constraint that at any terminal state it has value equal to 0
 - Iterative update rule:

$$\begin{aligned} V_{k+1}(s) &= \mathbf{E}_{\pi}[r_{t+1} + \gamma V_k(s_{t+1}) \mid s_t = s] \\ &= \sum_a \pi(s, a) \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V_k(s')] \quad \text{for } s \in S \end{aligned}$$

- The limit point of V_k as $k \rightarrow \infty$ is V^{π} under the same conditions that guarantee the existence of V^{π}

Iterative policy evaluation cont'd

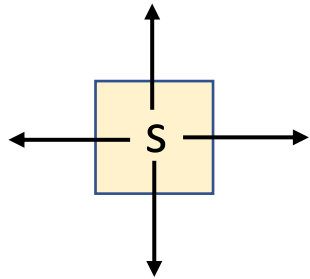
- The iterative policy evaluation in the previous slide is referred to as a **full backup iterative method**
 - In each time step, the state value function is updated based on the values of states evaluated in the previous time step
- An alternative backup method:
 - Updating the state value function at a state by using the most recent updates of the state value function at other states
 - Pseudo-code in the next slide

Iterative policy evaluation: pseudo-code

- **Input:** a policy π , θ (a small positive number)
- Initialization: $V(s) = 0$ for all $s \in S^+$
- **Repeat:**
 - $\Delta \leftarrow 0$
 - For each** $s \in S$:
 - $v \leftarrow V(s)$
 - $V(s) \leftarrow \sum_a \pi(s, a) \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V(s')]$
 - $\Delta = \max\{\Delta, |v - V(s)|\}$
- until** $\Delta < \theta$
- **Output:** V (approximation of V^π)

$S^+ := S \cup S^0$ where S^0 is the set of terminal states

Example: GridWorld



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



terminal state

- Undiscounted, episodic task
- Action set for state s : $A(s) = \{\text{up, down, right, left}\}$
- Action that would take the agent off the grid leave the state unchanged
- Rewards: for each transition, the reward of value -1

GridWorld: values of equiprobable random policy

$V^\pi(s)$:

0	-14 1	-20 2	-22 3
-14 4	-18 5	-20 6	-20 7
-20 8	-20 9	-18 10	-14 11
-20 12	-20 13	-14 14	0

Q1: What is the value of $Q^\pi(11, \text{down})$?

Q2: What is the value of $Q^\pi(7, \text{down})$?

Value function evaluation

By symmetry:

0	1 v_1	2 v_2	3 v_3
4 v_1	5 v_5	6 v_6	7 v_2
8 v_2	9 v_6	10 v_5	11 v_1
12 v_3	13 v_2	14 v_1	0

Bellman optimality equation:

$$v_1 = \frac{1}{4}(-1 + v_2) + \frac{1}{4}(-1 + v_5) + \frac{1}{4}(-1 + 0) + \frac{1}{4}(-1 + v_1)$$

$$v_2 = \frac{1}{4}(-1 + v_3) + \frac{1}{4}(-1 + v_6) + \frac{1}{4}(-1 + v_1) + \frac{1}{4}(-1 + v_2)$$

$$v_3 = \frac{1}{4}(-1 + v_3) + \frac{1}{4}(-1 + v_2) + \frac{1}{4}(-1 + v_2) + \frac{1}{4}(-1 + v_3)$$

$$v_5 = \frac{1}{4}(-1 + v_6) + \frac{1}{4}(-1 + v_6) + \frac{1}{4}(-1 + v_1) + \frac{1}{4}(-1 + v_1)$$

$$v_6 = \frac{1}{4}(-1 + v_2) + \frac{1}{4}(-1 + v_5) + \frac{1}{4}(-1 + v_5) + \frac{1}{4}(-1 + v_2)$$

$$\Rightarrow (v_1, v_2, v_3, v_5, v_6) = (-14, -20, -22, -18, -20)$$

GridWorld: optimal value and policy

0	-1	-2	-3
-1	-2	-3	-2
-2	-3	-2	-1
-3	-2	-1	0

	←	←	↙
↑	↖	↕	↓
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GridWorld: optimal value and policy (cont'd)

0	v_1 1	v_2 2	v_3 3
v_1 4	v_5 5	v_6 6	v_2 7
v_2 8	v_6 9	v_5 10	v_1 11
v_3 12	v_2 13	v_1 14	0

Bellman's optimality equations:

- 1 $v_1 = \max\{-1 + v_2, -1 + v_5, -1 + 0, -1 + v_1\}$
- 2 $v_2 = \max\{-1 + v_3, -1 + v_6, -1 + v_1, -1 + v_2\}$
- 3 $v_3 = \max\{-1 + v_3, -1 + v_2, -1 + v_2, -1 + v_3\}$
- 5 $v_5 = \max\{-1 + v_6, -1 + v_6, -1 + v_1, -1 + v_1\}$
- 6 $v_6 = \max\{-1 + v_2, -1 + v_5, -1 + v_5, -1 + v_2\}$

- 1 $\Rightarrow v_1 = -1$

&

- 2 $\Rightarrow v_2 = -2$

...

Policy improvement

- The policy improvement theorem: suppose that π and π' are two deterministic policies such that

$$Q^{\pi}(s, \pi'(s)) \geq V^{\pi}(s) \text{ for all } s \in S \quad (\text{C})$$

Then π' must be as good as, or better, than π , i.e.

$$V^{\pi'}(s) \geq V^{\pi}(s) \text{ for all } s \in S \quad (\text{R})$$

Moreover, if the inequality in (C) is strict for at least one state, then the inequality in (R) must be strict for at least one state

Proof of the policy improvement theorem

- $V^\pi(s) \leq Q^\pi(s, \pi'(s))$
 $= \mathbf{E}_{\pi'}[r_{t+1} + \gamma V^\pi(s_{t+1}) \mid s_t = s]$
 $\leq \mathbf{E}_{\pi'}[r_{t+1} + \gamma Q^\pi(s_{t+1}, \pi'(s_{t+1})) \mid s_t = s]$
 $= \mathbf{E}_{\pi'}[r_{t+1} + \gamma r_{t+2} + \gamma^2 V^\pi(s_{t+2}) \mid s_t = s]$
 \vdots
 $= \mathbf{E}_{\pi'}[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots \mid s_t = s]$
 $\leq V^{\pi'}(s)$

Greedy policy improvement

- Greedy policy π' for any given policy π is given by

$$\pi'(s) = \operatorname{argmax}_a Q^\pi(s, a), \text{ for all } s \in S$$

- Greedy policy selects the best action in **one step lookahead**
- The greedy policy meets the conditions of the policy improvement theorem, thus it is as good as, or better than, the original policy

Greedy policy improvement cont'd

- Note that:

$$\begin{aligned}\pi'(s) &= \operatorname{argmax}_a Q^\pi(s, a) \\ &= \operatorname{argmax}_a \mathbf{E}[r_{t+1} + \gamma V^\pi(s_{t+1}) \mid s_t = s, a_t = a] \\ &= \operatorname{argmax}_a \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V^\pi(s')]\end{aligned}$$

- If π' is as good as but not better than π , then $V^\pi = V^{\pi'} \Rightarrow V^{\pi'}$ satisfies the Bellman optimality equation $\Rightarrow \pi$ and π' are optimal
- Policy improvement yields a strictly better policy, except when the original policy is already optimal

Policy iteration

- **Policy iteration**: an iterative method that alternates between

(E) policy evaluation

(I) policy improvement

- $\pi_0 \rightarrow V^{\pi_0} \rightarrow \pi_1 \rightarrow V^{\pi_1} \rightarrow \dots \rightarrow \pi^* \rightarrow V^*$

- A finite MDP has a finite number of policies

\Rightarrow the policy iteration method must converge in a finite number of steps

Policy iteration: pseudo-code

Initialization: $V(s) \in \mathbf{R}$, $\pi(s) \in A(s)$ arbitrary for all $s \in S$

Repeat:

$\Delta \leftarrow 0$

For each $s \in S$:

$v \leftarrow V(s)$

$V(s) \leftarrow \sum_{s'} P_{s,s'}^{\pi(s)} [R_{s,s'}^{\pi(s)} + \gamma V(s')]$

$\Delta = \max\{\Delta, |v - V(s)|\}$

until $\Delta < \theta$

$\text{polycystable} \leftarrow \text{True}$

For each $s \in S$:

$b \leftarrow \pi(s)$

$\pi(s) = \operatorname{argmax}_a \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V(s')]$

If $b \neq \pi(s)$ **then** $\text{polycystable} \leftarrow \text{False}$

If polycystable , **then** return, **else** go to policy evaluation

policy evaluation

policy improvement

Value iteration

- Drawbacks of the policy iteration method:
 - Each iteration requires executing policy evaluation which requires multiple iterations (sweeps through the state space)
 - This can be computationally inefficient
- Value iteration idea: evaluate **only one step** in the policy evaluation

$$\begin{aligned} V_{k+1}(s) &= \max_a \mathbf{E}[r_{t+1} + \gamma V_k(s_{t+1}) | s_t = s, a_t = a] \\ &= \max_a \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V_k(s')] \end{aligned}$$

- The sequence V_0, V_1, \dots converges to V^* under the same conditions that guarantee the existence of V^*

Value iteration: pseudo-code

- Initialization: $V(s) = 0$ for all $s \in S^+$

- Repeat:

$\Delta \leftarrow 0$

For each $s \in S$:

$v \leftarrow V(s)$

$V(s) \leftarrow \max_a \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V(s')]$

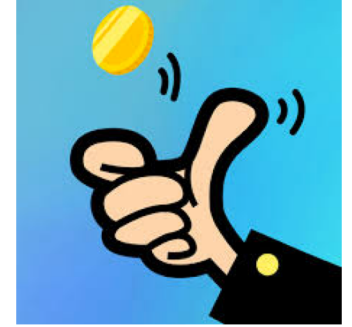
$\Delta = \max\{\Delta, |v - V(s)|\}$

until $\Delta < \theta$

- Output: deterministic policy π given by

$$\pi(s) = \operatorname{argmax}_a \sum_{s'} P_{s,s'}^a [R_{s,s'}^a + \gamma V(s')] \text{ for all } s \in S$$

Example: Gambler's problem

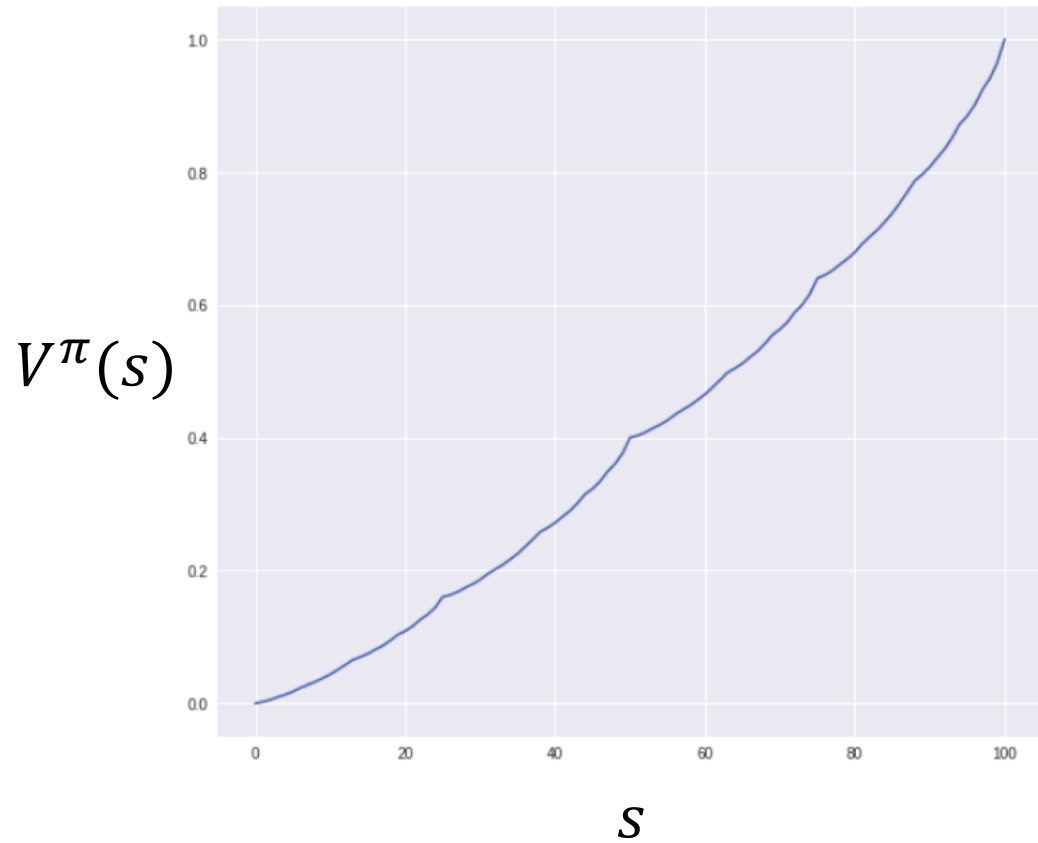


- A gambler makes bets on the outcomes of a sequence of coin flips
 - The gambler must decide for each coin flip what portion of his capital to stake
- **If outcome of the coin flip = heads then:**
 - The gambler **wins** as much money as he has staked on this flip
- **else**
 - The gambler **loses** his stake
- The game ends when the gambler reaches his goal of **\$100** or **loses by running out of money**

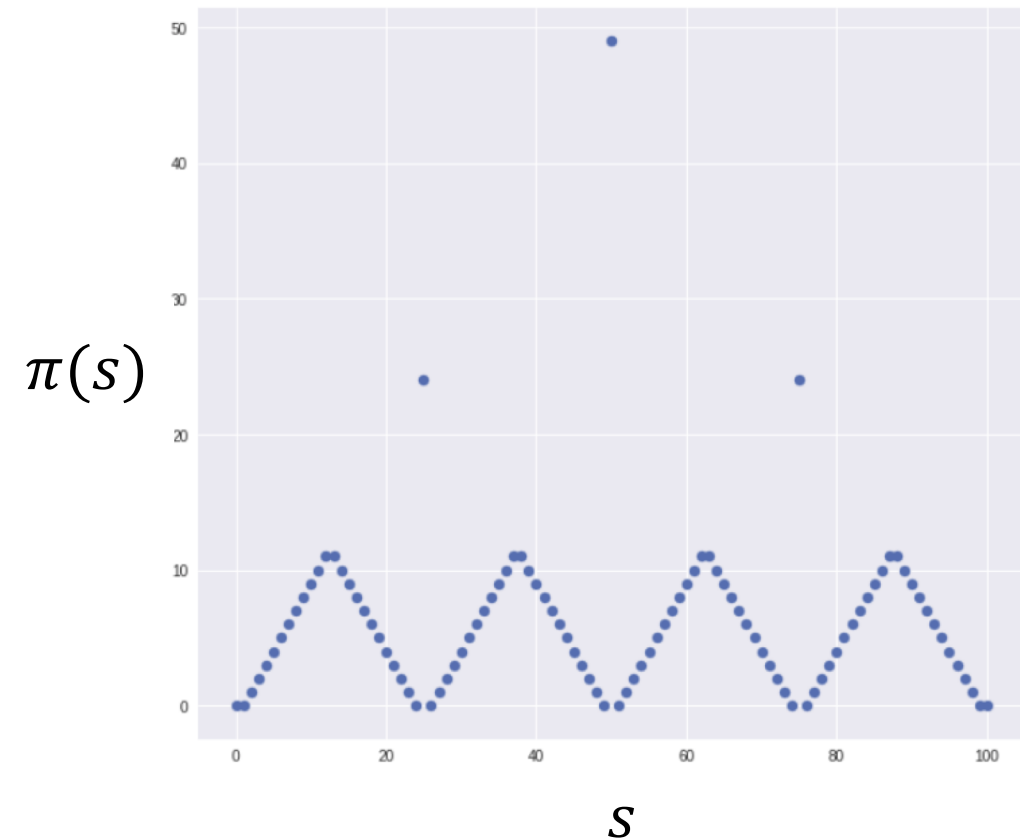
Gambler's problem cont'd

- Formulated as an undiscounted, episodic, finite MDP problem
- State set: $S = \{1, 2, \dots, 99\}$, $S^+ = S \cup \{0, 100\}$
- Action sets: $A(s) = \{1, 2, \dots, \min\{s, 100 - s\}\}$ for $s \in S$
- $\Pr[\text{outcome of coin flip is heads}] = p$ (known parameter)
- Exercise (seminar session):
 - Show value function for different iterations
 - Show the optimal policy

Gambler's problem cont'd



Optimal value function



Optimal policy

Asynchronous DP

- Drawback of standard DP method:
 - Requires operations over the entire state set of the MDP
 - For large state sets this can be computationally expensive
- **Asynchronous DP**: backups up values in any order using whatever values of other states are available
 - Convergence guaranteed provided each state is visited with a positive rate
- Asynchronous DP algorithms referred to as **distributed DP algorithms**
 - Implementation in multiprocessor systems with communication delays between processors

Monte Carlo methods

Monte Carlo methods

- **Monte Carlo (MC) methods for reinforcement learning:** learning methods for solving the RL problem based on **averaging sample returns**
 - Estimating value functions and discovering optimal policies
 - Not assuming a perfect model of the environment
 - Based only on experience: sample sequences of states, actions and rewards from online or simulated interactions with an environment
- Defined for episodic tasks to ensure well-defined returns
- **Incremental methods in an episode-by-episode sense**
 - Estimates of value functions and policies are updated only upon the completion of an episode
 - Different from **step-by-step incremental methods** (next lecture)

MC policy evaluation

- Suppose our goal is to estimate $V^\pi(s)$, the value of a state s for a given policy π , given a set of episodes obtained by following π and passing through state s
- Types of visits to states:
 - A visit to s : each occurrence of state s in an episode
 - First visit to s : each first occurrence of s in an episode
- Types of MC methods:
 - The every-visit MC method: $V^\pi(s)$ estimated by the average of the returns following **each visit** to s in a set of episodes
 - The first-visit MC method: $V^\pi(s)$ estimated by the average of the returns following **each first visit** to s in an episode of a set of episodes
- The every-visit and first-visit MC methods are similar but have different theoretical properties
 - Q: Can you think of a fundamental difference between the two methods?

The first-visit MC method: pseudo code

- **Initialization:**

$\pi \leftarrow$ policy to be evaluated

$V \leftarrow$ an arbitrary state-value function

$\text{Returns}(s) \leftarrow$ an empty list, for all $s \in S$

- **Repeat:**

Generate an episode using policy π

For each distinct s appearing in the episode:

$R \leftarrow$ return following the first occurrence of s

Append R to $\text{Returns}(s)$

$V(s) \leftarrow \text{average}(\text{Returns}(s))$

Backup diagram

- Backup diagram for MC estimation of V^π shows states **sampled** in one episode



- Unlike to the DP backup diagram that shows only **one-step transitions**

Some pros and cons of MC methods

- Pros:

- Estimating the value of a single state is independent of the number of states
- One can generate many sample episodes starting from a given state to estimate the value of this state

- Cons:

- Incremental updates on an episode-by-episode basis which introduces delays
- Alternative methods allow for step-by-step incremental updates
 - Time-difference learning methods (discussed in next lecture)

MC estimation of action values

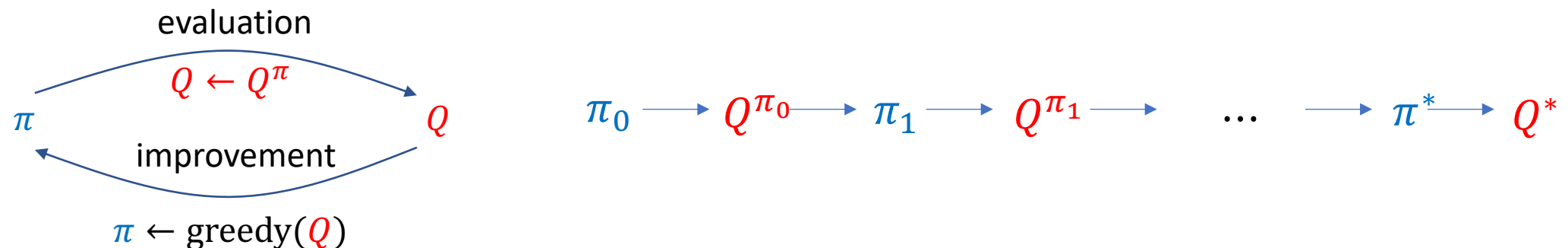
- Given a model, state values are sufficient to find a policy
 - Simply look one-step ahead and choose an action that leads to the best combination of reward and next state
- Without a model, state values are insufficient to find a policy
 - We need to explicitly estimate the value of each action to find a policy
- Primary goal of MC methods: estimate optimal action value function Q^*
- The estimates can be defined analogously to estimating the state value function
 - E.g. the first-visit MC method

MC estimation of action values (cont'd)

- **Issue**: many state-action pairs may never be visited under a policy
 - E.g. if π is a deterministic policy, only one action-state pair is observed for each distinct state
 - Need to maintain exploration !
- Two approaches to ensuring continual exploration:
 - **Exploring starts**: the first step of each episode starts at a state-action pair and every such pair has non-zero probability of being selected at the start
 - **Stochastic policies**: use policies that ensure a non-zero probability of selecting each action from the set of available actions in each given state

MC control

- **MC control**: using MC estimation to approximate optimal policies
- Basic idea: use **generalized policy iteration**
 - Repeatedly alter the value function estimate to more closely approximate the value function of the current policy
 - Repeatedly improve the policy estimate wrt the current value function
- MC version of the standard policy iteration:



MC control with exploring starts

- **Initialization:** for all $s \in S, a \in A(s)$
 $Q(s, a) \leftarrow \text{arbitrary}$
 $\pi(s) \leftarrow \text{arbitrary}$
 $\text{Returns}(s, a) \leftarrow \text{empty list}$
- **Repeat:**
 Generate an episode using exploring starts and policy π

 For each pair (s, a) appearing in the episode:
 $R \leftarrow \text{return following the first occurrence of } (s, a)$
 Append R to $\text{Returns}(s, a)$
 $Q(s, a) \leftarrow \text{average}(\text{Returns}(s, a))$

 For each s in the episode:
 $\pi(s) \leftarrow \text{argmax}_a Q(s, a)$

On-policy vs off-policy control methods

- **On-policy methods**: attempt to evaluate or improve the policy that is **used to make decisions**
- **Off-policy methods**: attempt to evaluate a policy by **observing episodes generated by using a different policy**

Soft policies

- In on-policy control methods, policy π is usually a soft policy:

$$\pi(s, a) > 0 \text{ for all } s \in S \text{ and } a \in A(s)$$

- A policy π is said to be an ϵ -soft policy if

$$\pi(s, a) \geq \frac{\epsilon}{|A(s)|} \text{ for all } s \in S \text{ and } a \in A(s)$$

- ϵ -greedy policy: chose an action with maximum estimated action value with probability $1 - \epsilon$, and otherwise select an action at random
 - Any non-greedy action is selected with probability $\geq \epsilon/|A(s)|$
 - Greedy action is selected with probability $1 - \epsilon + \epsilon/|A(s)|$

An ϵ -soft on-policy MC control algorithm

- **Initialization:** for all $s \in S, a \in A(s)$
 $Q(s, a) \leftarrow$ arbitrary
 $\pi(s) \leftarrow$ arbitrary ϵ -soft policy
 $\text{Returns}(s, a) \leftarrow$ empty list
- **Repeat:**
Generate an episode using policy π
For each pair (s, a) appearing in the episode:
 $R \leftarrow$ return following the first occurrence of (s, a)
 Append R to $\text{Returns}(s, a)$
 $Q(s, a) \leftarrow \text{average}(\text{Returns}(s, a))$

 For each s in the episode:
 $a^* \leftarrow \operatorname{argmax}_a Q(s, a)$
 For each $a \in A(s)$:

$$\pi(s, a) \leftarrow \begin{cases} 1 - \epsilon + \epsilon \frac{1}{|A(s)|} & \text{if } a = a^* \\ \epsilon \frac{1}{|A(s)|} & \text{if } a \neq a^* \end{cases}$$

Improvement guarantees

- Suppose π is any ϵ -soft policy and π' is the ϵ -greedy policy wrt Q^π
- Fact: $Q^\pi(s, \pi'(s)) \geq V^\pi(s)$ for all $s \in S$
- By the policy improvement theorem: $V^{\pi'}(s) \geq V^\pi(s)$ for all $s \in S$

Off-policy MC control

- The policy used to generate behavior (**behavior policy**) may be different to the policy used for evaluation and improvement (**estimation policy**)
- An advantage of off-policy MC methods: the estimation policy may be deterministic (e.g. greedy) while the behavior policy can continue to sample all auctions
- The key point: **evaluating one policy while following another**

Evaluating one policy while following another

- Suppose episodes are generated by following policy π' while we want to estimate V^π or Q^π for a given policy π such that $\pi \neq \pi'$
- Requirement: $\pi(s, a) > 0 \Rightarrow \pi'(s, a) > 0$ for all $s \in S, a \in A(s)$
- How can we construct an estimate of $V^\pi(s)$ using returns, states, and actions observed under policy π' ?

Estimating the value function

- N := the number of episodes
- $T_i(s)$:= first time step at which state s is visited in episode i , otherwise infinity
- T_i := the number of steps in episode i
- $R_i(s)$:= reward from the first visit to state s in episode i
- $N_s(N)$:= number of episodes with at least one visit of state s

- **Estimator:** $\hat{V}_N^{\pi'}(s) = \frac{1}{N_s(N)} \sum_{i=1}^N R_i(s) \mathbf{1}_{\{T_i(s) < T_i\}}$

- By the law of large numbers,

$$\lim_{N \rightarrow \infty} \hat{V}_N^{\pi'}(s) = \frac{\mathbf{E}[R_1(s) \mathbf{1}_{\{T_1(s) < T_1\}}]}{\mathbf{Pr}[T_1(s) < T_1]} = \mathbf{E}[R_1(s) \mid T_1(s) < T_1]$$

Estimating the value function (cont'd)

- By the definition of the MDP environment:

$$\mathbf{E}[R_1(s) \mid T_1(s) < T_1] = \sum_{(s,a) \in \Pi} \left(\prod_{k=t_1(s)}^{t_1-1} \pi'(s_k, a_k) P_{s_k, s_{k+1}}^{a_k} \right) \left(\sum_{k=t_1(s)}^{t_1-1} R_{s_k, s_{k+1}}^{a_k} \right)$$

where Π contains pairs of sequences $\mathbf{s} = (s_{t_1(s)}, \dots, s_{t_1})$ and $\mathbf{a} = (a_{t_1(s)}, \dots, a_{t_1-1})$

- To have an estimator of $V^\pi(s)$ in the equation above we would like to have $\pi(s_k, a_k)$ instead of $\pi'(s_k, a_k)$

- Use the estimator:
$$\hat{V}_N^\pi(s) = \frac{\sum_{i=1}^N \frac{p_i^\pi(s)}{p_i^{\pi'}(s)} R_i(s) \mathbf{1}_{\{T_i(s) < T_i\}}}{\sum_{i=1}^N \mathbf{1}_{\{T_i(s) < T_i\}}}$$

where $p_i^\varphi(s) := \prod_{k=T_i(s)}^{T_i-1} \varphi(s_k, a_k) P_{s_k, s_{k+1}}^{a_k}$ for a policy φ

Estimating the value function (cont'd)

- $\lim_{N \rightarrow \infty} \hat{V}_N^{\pi}(s) = \frac{\mathbf{E}[R_1(s) \mathbf{1}_{\{T_1(s) < T_1\}}]}{\Pr[T_1(s) < T_1]} = \mathbf{E} \left[\frac{p_1^{\pi}(s)}{p_1^{\pi'}(s)} R_1(s) \mid T_1(s) < T_1 \right]$

- Now, note that (as desired):

$$\begin{aligned} & \mathbf{E} \left[\frac{p_1^{\pi}(s)}{p_1^{\pi'}(s)} R_1(s) \mid T_1(s) < T_1 \right] \\ &= \sum_{(s,a) \in \Pi} \left(\prod_{k=t_1(s)}^{t_1-1} \pi'(s_k, a_k) P_{s_k, s_{k+1}}^{a_k} \right) \frac{\left(\prod_{k=t_1(s)}^{t_1-1} \pi(s_k, a_k) P_{s_k, s_{k+1}}^{a_k} \right)}{\left(\prod_{k=t_1(s)}^{t_1-1} \pi'(s_k, a_k) P_{s_k, s_{k+1}}^{a_k} \right)} \left(\sum_{k=t_1(s)}^{t_1-1} R_{s_k, s_{k+1}}^{a_k} \right) \\ &= \sum_{(s,a) \in \Pi} \left(\prod_{k=t_1(s)}^{t_1-1} \pi(s_k, a_k) P_{s_k, s_{k+1}}^{a_k} \right) \left(\sum_{k=t_1(s)}^{t_1-1} R_{s_k, s_{k+1}}^{a_k} \right) \end{aligned}$$

No need to know the environment

- The important point for the estimator $\hat{V}_N^\pi(s)$ is that it **does not require knowledge of the environment**
- The ratio of the weights depends only on the policies:

$$\frac{p_i^\pi(s)}{p_i^{\pi'}(s)} = \prod_{k=T_i(s)}^{T_i-1} \frac{\pi(s_k, a_k)}{\pi'(s_k, a_k)}$$

- The random reward $R_i(s)$ is observable

Alternative notation

- In the book, the estimator is defined equivalently but using different notation by considering only the episodes in which state s is visited (we only collect a sample of the reward in these episodes)
- The estimator $\hat{V}_N^{\pi}(s)$ can be written as

$$V(s) = \frac{\sum_{j=1}^{n_s} \frac{p_j(s)}{p'_j(s)} R_j(s)}{\sum_{j=1}^{n_s} \frac{p_j(s)}{p'_j(s)}}$$

where n_s is the number of episodes in which state s is visited and $p_j(s) = p_{i_s(j)}^{\pi}(s)$ and $p'_j(s) = p_{i'_s(j)}^{\pi'}(s)$ where $i_s(j)$ is the index of the episode in the sequence of all episodes for which state s occurred for the j -th time in an episode

An off-policy MC control algorithm

- **Initialization:** for all $s \in S, a \in A(s)$:

$Q(s, a) \leftarrow$ arbitrary

$N(s, a) \leftarrow 0$ // numerator of $Q(s, a)$

$D(s, a) \leftarrow 0$ // denominator of $Q(s, a)$

$\pi \leftarrow$ an arbitrary deterministic policy

- **Repeat:**

Select a policy π' and use it to generate an episode:

$S_0, a_0, r_1, S_1, a_1, r_2, \dots, S_{T-1}, a_{T-1}, r_T, S_T$

$\tau \leftarrow$ latest time at which $a_\tau \neq \pi(s_\tau)$

For each pair (s, a) appearing at the episode at τ or later:

$t \leftarrow$ time of the first occurrence of (s, a) at $t \geq \tau$

$w \leftarrow \prod_{k=t+1}^{T-1} \frac{1}{\pi'(s_k, a_k)}$

$N(s, a) \leftarrow N(s, a) + wR_t$

$D(s, a) \leftarrow D(s, a) + w$

$Q(s, a) \leftarrow \frac{N(s, a)}{D(s, a)}$

For each $s \in S$:

$\pi(s) = \operatorname{argmax}_a Q(s, a)$

References

- R. S. Sutton and A. G. Barto, Reinforcement Learning, Chapters 4 and 5, 1998

Seminar exercises

- Iterative policy evaluation: Gridworld problem
- Value iteration: Gambler's problem
- Monte Carlo prediction: Black Jack example
- Monte Carlo control: Black Jack example