

Lecture 3: Dynamic Programming

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Jun. 30th, 2022

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- Policy evaluation and policy improvement
- Policy iteration and value iteration

Markov Decision Process (MDP)

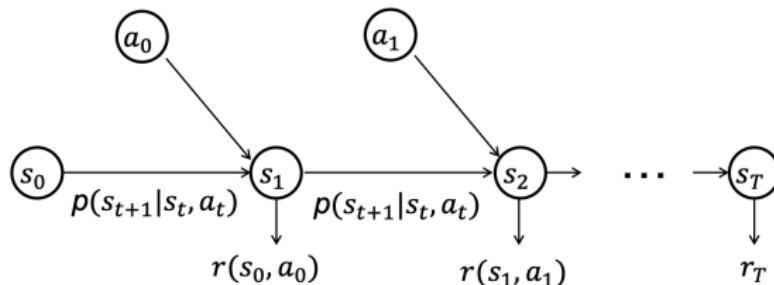
$$M = \langle S, A, T, R \rangle$$

S : State space state $s \in S$ (discrete/continuous)

A : Action space action $a \in A$ (discrete/continuous)

T : Transition operator $T_{i,j,k} = p(s_{t+1} = j | s_t = i, a_t = k)$

R : Reward function $R_{i,j,k} = r(s_{t+1} = j | s_t = i, a_t = k)$



Markov Decision Process (MDP)

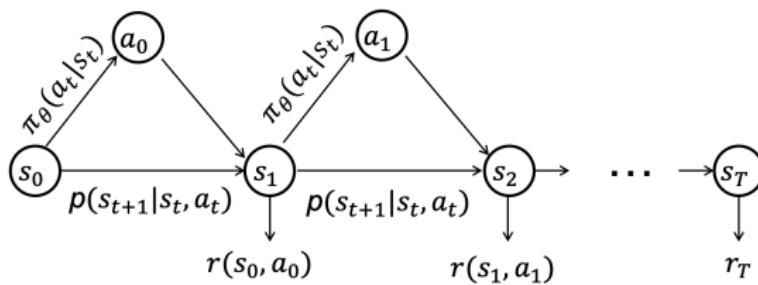
- A classical formalization of sequential decision making
 - Choosing different actions in different situations
 - Actions influence not just immediate rewards, but also **subsequent situations** through future rewards
 - Involve **delayed reward** and the need to tradeoff immediate and delayed reward
- A mathematically idealized form of the RL problem
 - Precise theoretical statements can be made
 - Key elements of the problem's mathematical structure, such as returns, value functions, Bellman equations, etc
 - A tension between breadth of applicability and mathematical tractability

The Goal of RL

- Find **optimal policies** to maximize cumulative reward

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} r(s_t, a_t) \right]$$

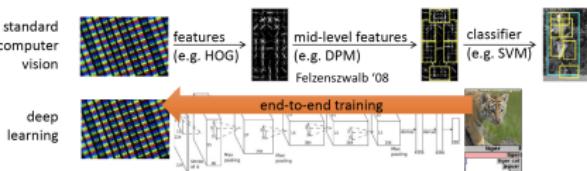
- In a **trial-and-error** manner
- A general **optimization** framework for sequential decision-making



Supervised learning vs. Sequential decision making

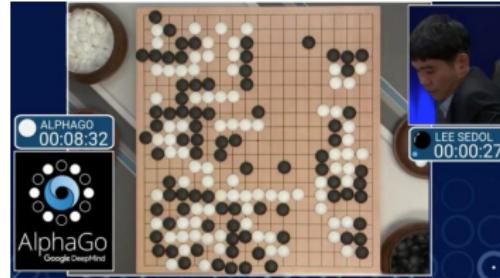
Supervised learning

- Samples are **independent and identically distributed (i.i.d.)**
- Given an input, map an optimal output

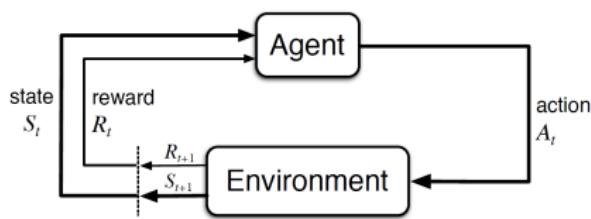


Reinforcement learning

- Samples are not i.i.d., **temporally co-related**
- Given an initial state, find a sequence of optimal actions



The agent-environment interface



- **Agent:** The learner, decision maker
- **Environment:** The thing it interact with, comprising everything outside the agent

At each time step $t = 0, 1, 2, \dots$, the agent...

- receives some representation of the environment's **state**, $S_t \in \mathcal{S}$
- on that basis, selects an **action**, $A_t \in \mathcal{A}(s)$
- one time step later, receives a numerical **reward**, $R_{t+1} \in \mathcal{R} \subset \mathbb{R}$
- finds itself in a new state, S_{t+1} (**transition function**)
- $S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3 \dots$

Dynamics of the MDP $p : \mathcal{S} \times \mathcal{R} \times \mathcal{S} \times \mathcal{A} \rightarrow [0, 1]$

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

$$\sum_{s' \in \mathcal{S}} \sum_{r \in \mathcal{R}} p(s', r | s, a) = 1, \quad \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$$

- The probabilities given by p completely characterize the environment's dynamics
- **Markov Property**
 - The probability of each possible value for S_t and R_t depends only on the immediately preceding state S_{t-1} and action A_{t-1} , not at all on earlier states and actions
 - $p(S_t, R_t | S_{t-1}, A_{t-1}) = p(S_t, R_t | S_{t-1}, A_{t-1}, S_{t-2}, A_{t-2}, S_{t-3}, A_{t-3}, \dots)$
- Recall supervised learning $p(X_i | X_j) = 0$

Dynamics of the MDP $p : \mathcal{S} \times \mathcal{R} \times \mathcal{S} \times \mathcal{A} \rightarrow [0, 1]$

- The probabilities given by p completely **characterize the environment's dynamics**

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

- **Reward Hypothesis** – by R. S. Sutton
 - That all of what we mean by goals and purposes can be well thought of as the maximization of the expected value of the cumulative sum of a received scalar signal (called reward).
- The agent's goal: maximize the total amount of reward it receives
 - $\text{maximize } J(\pi) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t r_{t+1} \right]$
 - Maximize not immediate reward, but **cumulative reward in the long run**

Episodes and returns

- The subsequence of the agent-environment interaction, **episodes**
 - $S_t, A_t, R_{t+1}, S_{t+1}, A_{t+1}, R_{t+2}, \dots, S_{T-1}, A_{T-1}, R_T, S_T$
 - Each episode ends in a special state called the terminal state, S_T
- We seek to maximize the **expected return**, G_t , the reward sequence
 - $G_t = R_{t+1} + R_{t+2} + \dots + R_T$
 - Episodic tasks

Discount rate $\gamma \in [0, 1]$

- Infinite case, $T = \infty$
- Assume that: $0 \leq R_{min} \leq R \leq R_{max} \leq \infty$
- Without discount factor: unbounded

$$\begin{aligned} G_t &= R_t + R_{t+1} + R_{t+2} + \dots \\ &\geq R_{min} + R_{min} + R_{min} + \dots \\ &= \infty \end{aligned}$$

- With discount factor: bounded

$$\begin{aligned} G_t &= R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots \\ &\leq R_{max} + \gamma R_{max} + \gamma^2 R_{max} + \dots \\ &= \frac{R_{max}}{1 - \gamma} \end{aligned}$$

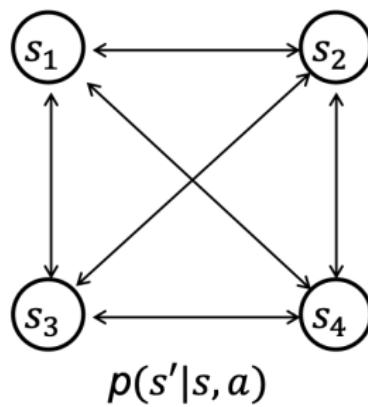
Discount rate $\gamma \in [0, 1]$

- The expected **discounted** return
 - $G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} \dots = \sum_{k=1}^{\infty} \gamma^k R_{t+k+1}$
- The discount rate determines the present value of future rewards: a reward received k time steps in the future is worth only γ^{k-1} times what it would be worth if it were received immediately
- $\gamma \rightarrow 0$, the agent is “myopic”, only maximizing immediate rewards
 - Akin to supervised learning that maximizes the log-likelihood of each sample, $\log p(y_i|x_i)$
- $\gamma \rightarrow 1$, the agent is “farsighted”, taking future rewards into account
- Returns at successive time steps are related to each other

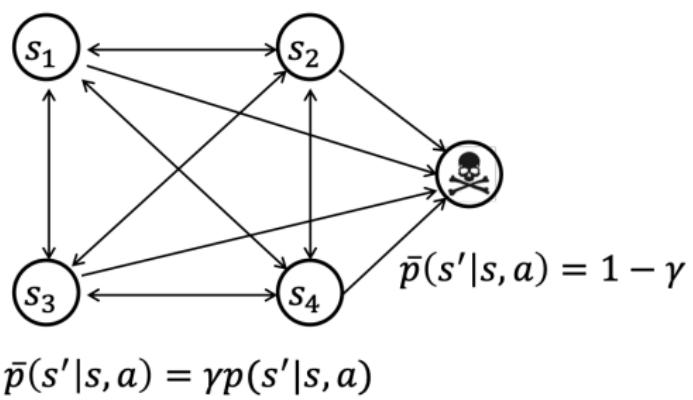
$$\begin{aligned} G_t &= R_{t+1} + \gamma(R_{t+2} + \gamma R_{t+3} + \gamma^2 R_{t+4} + \dots) \\ &= R_{t+1} + \gamma G_{t+1} \end{aligned}$$

γ changes the MDP

Without discount:



With discount:



Policies and value functions

- **Policy:** $\pi(a|s)$, a mapping from states to probabilities of selecting each possible action

- $\sum_a \pi(a|s) = 1$

- e.g., for a given state s_1 , four possible actions

$$p(a_1) = 0.1, p(a_2) = 0.3, p(a_3) = 0.2, p(a_4) = 4$$

- **Value functions:** function of states or state-action pairs

- State-value function $V_\pi(s)$: Estimate how good it is for the agent to be in a given state

- Action-value function $Q_\pi(s, a)$: Estimate how good it is to perform a given action in a given state

- “How good”: defined in expected future rewards, i.e., expected return

- Depend on what actions to take, defined w.r.t. particular ways of acting, called **policies**, π

- RL = estimate value functions + estimate policies + estimate both

Value functions

- V_π , the **state-value function** for policy π

$$V_\pi(s) = \mathbb{E}_\pi[G_t | S_t = s] = \mathbb{E}_\pi \left[\sum_{k=1}^{\infty} \gamma^k R_{t+k+1} | S_t = s \right], \forall s \in \mathcal{S}$$

- Q_π , the **action-value function** for policy π

$$\begin{aligned} Q_\pi(s, a) &= \mathbb{E}_\pi[G_t | S_t = s, A_t = a] \\ &= \mathbb{E}_\pi \left[\sum_{k=1}^{\infty} \gamma^k R_{t+k+1} | S_t = s, A_t = a \right], \forall s \in \mathcal{S}, a \in \mathcal{A}(s) \end{aligned}$$

Relationship between state- and action-value functions

$$V_\pi(s) = \mathbb{E}_\pi \left[\sum_{k=1}^{\infty} \gamma^k R_{t+k+1} | S_t = s \right]$$

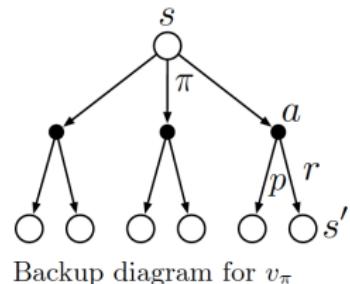
$$Q_\pi(s, a) = \mathbb{E}_\pi \left[\sum_{k=1}^{\infty} \gamma^k R_{t+k+1} | S_t = s, A_t = a \right]$$

$$\begin{aligned} V_\pi(s) &= \mathbb{E}_\pi \left[\sum_{k=1}^{\infty} \gamma^k R_{t+k+1} | S_t = s \right] \\ &= \sum_a \pi(a|s) \mathbb{E}_\pi \left[\sum_{k=1}^{\infty} \gamma^k R_{t+k+1} | S_t = s, A_t = a \right] \\ &= \sum_a \pi(a|s) Q_\pi(s, a) = \mathbb{E}_{a \sim \pi(a|s)} [Q_\pi(s, a)] \end{aligned}$$

A fundamental property: Bellman equation

$$\begin{aligned}V_{\pi}(s) &= \mathbb{E}_{\pi}[G_t | S_t = s] = \mathbb{E}_{\pi}[R_{t+1} + \gamma G_{t+1} | S_t = s] \\&= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a) [r + \gamma \mathbb{E}_{\pi}[G_{t+1} | S_{t+1} = s']] \\&= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a) [r + \gamma V_{\pi}(s')]\end{aligned}$$

- Average over all the possibilities, weighting each by its probability of occurring
- Express the relationship between the value of a state and the values of its successor states
- Transfer value information back to a state from its successor states



Example: Gridworld

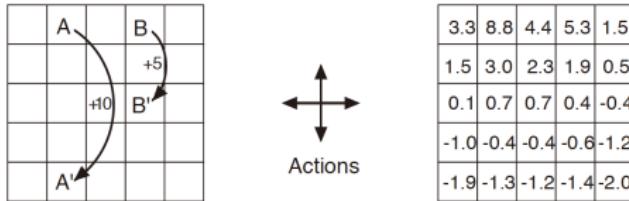


Figure 3.3: Gridworld example: exceptional reward dynamics (left) and state-value function for the equiprobable random policy (right).

$$V_\pi(s) = \sum_a \pi(a|s)[r + \gamma V_\pi(s')]$$

- Actions that would take the agent off the grid leave its location unchanged, but also result in $r = -1$, otherwise $r = 0$
- From state A , all four actions yield $r = 10$ and take the agent to A'
- From state B , all actions yield $r = 5$ and the agent to B'

Optimal policies and optimal value functions

- RL tasks: find a policy that achieves a lot of reward over the long run
- Value functions define a partial ordering over policies
 - $\pi \geq \pi'$ if and only if $V_\pi(s) \geq V_{\pi'}(s), \forall s \in \mathcal{S}$
- At least one policy that is better than or equal to all other policies, i.e., **optimal policy**
- Optimal policies, π_* , share the same **optimal value function**

$$V_*(s) = \max_{\pi} V_{\pi}(s), \quad \forall s \in \mathcal{S}$$

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

$$Q_*(s, a) = \mathbb{E}[R_{t+1} + \gamma V_*(S_{t+1}) | S_t = s, A_t = a]$$

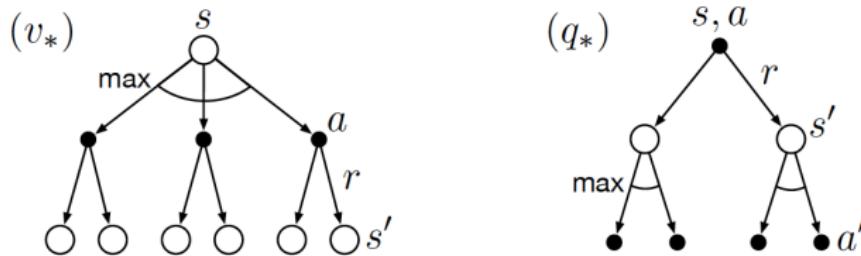
Bellman optimality equation

$$\begin{aligned}V_*(s) &= \max_a Q_{\pi_*}(s, a) \\&= \max_a \mathbb{E}_{\pi_*}[G_t | S_t = s, A_t = a] \\&= \max_a \mathbb{E}_{\pi_*}[R_{t+1} + \gamma G_{t+1} | S_t = s, A_t = a] \\&= \max_a \mathbb{E}[R_{t+1} + \gamma V_*(S_{t+1}) | S_t = s, A_t = a] \\&= \max_a \sum_{s',r} p(s', r | s, a) [r + \gamma V_*(s')]\end{aligned}$$

- The value of a state under an optimal policy must equal the expected return for the best action from that state

Bellman optimality equation

$$\begin{aligned} Q_*(s, a) &= \mathbb{E}[R_{t+1} + \gamma \max_{a'} Q_*(S_{t+1}, a') | S_t = s, A_t = a] \\ &= \sum_{s', r} p(s', r | s, a) [r + \gamma \max_{a'} Q_*(s', a')] \end{aligned}$$

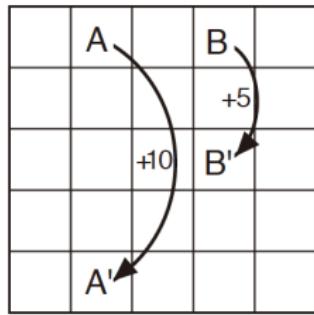


$$V_*(s) = \max_a \sum_{s', r} p(s', r | s, a) [r + \gamma V_*(s')]$$

Determine optimal policies from optimal value functions

- For V_* : a one-step search
 - Actions that appear best after one-step search will be optimal actions
- For Q_* : no need to do a one-step-ahead search
 - $a_* = \arg \max_a Q_*(s, a)$
 - The optimal action-value function allows optimal actions to be selected without having to know anything about possible successor states and their values, i.e., without having to know anything about the environment's dynamics

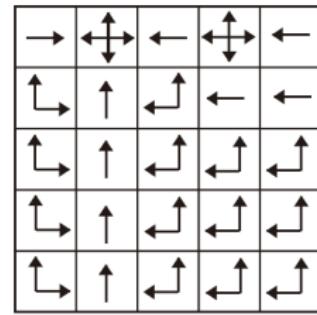
Example: Gridworld



Gridworld

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_*

Figure 3.6: Optimal solutions to the gridworld example.

- State transition function - dynamics of the MDP
- Episodes and returns
 - The discount rate
- Policies and value functions
 - State-value functions, action-value functions
 - Their relationships
 - Bellman equation
- Optimal policies and value functions
 - Bellman optimality equation

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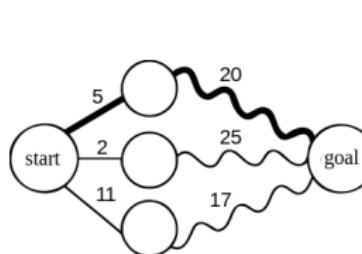
1 Finite Markov Decision Processes

2 Dynamic Programming

- Policy evaluation and policy improvement
- Policy iteration and value iteration

Dynamic Programming (DP)

- It refers to simplifying a complicated problem by breaking it down into simpler sub-problems in a **recursive** manner.

- Finding the shortest path in a graph using optimal substructure
 - A straight line: a single edge, a wavy line: a shortest path
 - The bold line: the overall shortest path from start to goal
- 

Dynamic Programming (DP)

- A collection of algorithms that can be used to compute optimal policies given a perfect model of the environment (MDP)
 - Of limited utility in RL both because of their assumption of a perfect model and because of their great computational expense
 - Important theoretically, provide an essential foundation for the understanding of RL methods
 - **RL methods can be viewed as attempts to achieve much the same effect as DP**, only with less computation and without assuming a perfect model of the environment

Policy evaluation (Prediction)

- Compute the state-value function V_π for an arbitrary policy π

$$\begin{aligned}V_\pi(s) &= \mathbb{E}_\pi[G_t | S_t = s] \\&= \mathbb{E}_\pi[R_{t+1} + \gamma G_{t+1} | S_t = s] \\&= \sum_a \pi(a|s) \sum_{s'} \sum_r p(s', r | s, a) [r + \gamma \mathbb{E}_\pi[G_{t+1} | S_{t+1} = s']] \\&= \sum_a \pi(a|s) \sum_{s', r} p(s', r | s, a) [r + \gamma V_\pi(s')]\end{aligned}$$

- If the environment's dynamics are completely known
 - In principle, the solution is a straightforward computation

Iterative policy evaluation

- Consider a sequence of approximate value functions V_0, V_1, V_2, \dots
 - The initial approximation, V_0 , is chosen arbitrarily
- Use the **Bellman equation** for V_π as an update rule

$$\begin{aligned}V_{k+1}(s) &= \mathbb{E}_\pi[R_{t+1} + \gamma V_k(S_{t+1})|S_t = s] \\&= \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a)[r + \gamma V_k(s')]\end{aligned}$$

- $V_k = V_\pi$ is a fixed point for this update rule
 - The sequence $\{V_k\}$ converges to V_π as $k \rightarrow \infty$ under the same conditions that guarantee the existence of V_π

Iterative policy evaluation

Iterative Policy Evaluation, for estimating $V \approx v_\pi$

Input π , the policy to be evaluated

Algorithm parameter: a small threshold $\theta > 0$ determining accuracy of estimation

Initialize $V(s)$, for all $s \in \mathcal{S}^+$, arbitrarily except that $V(\text{terminal}) = 0$

Loop:

$$\Delta \leftarrow 0$$

Loop for each $s \in \mathcal{S}$:

$$v \leftarrow V(s)$$

$$V(s) \leftarrow \sum_a \pi(a|s) \sum_{s',r} p(s',r|s,a) [r + \gamma V(s')]$$

$$\Delta \leftarrow \max(\Delta, |v - V(s)|)$$

until $\Delta < \theta$

- The updates as being done in a **sweep** through the state space

Example: Gridworld

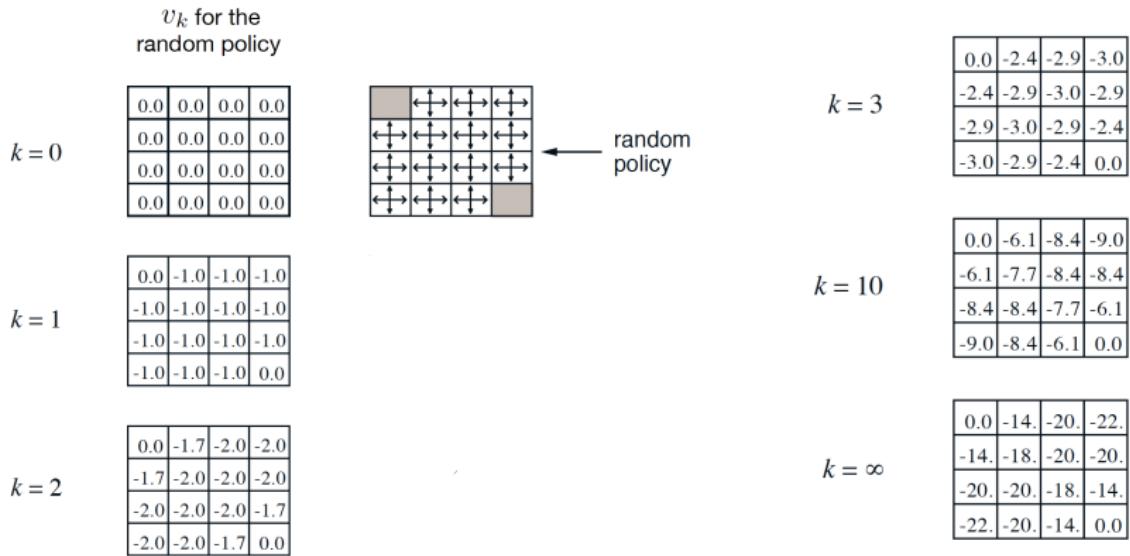


	1	2	3
4	5	6	7
8	9	10	11
12	13	14	

$$R_t = -1 \text{ on all transitions}$$

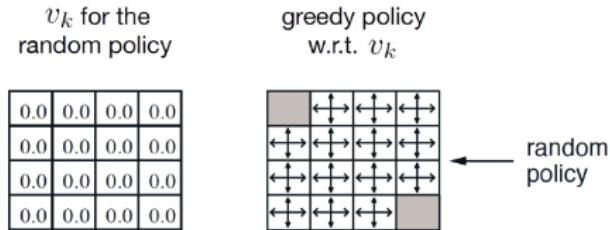
- Four actions deterministically case the corresponding state transitions
 - e.g., $p(6, -1|5, \text{right}) = 1, p(7, -1|7, \text{right}) = 1$
 - $p(10, r|5, \text{right}) = 0, \forall r \in \mathcal{R}$
- Test: If every action will succeed in the next state with probability 90%, then what are the state transition probabilities?
 - $p(6, -1|5, \text{right}) = ? \quad p(5, -1|5, \text{right}) = ? \quad p(5, 0|5, \text{right}) = ?$

The agent follows the equiprobable random policy



- The final estimate is in fact V_π
 - The negation of the expected number of steps from that state until termination

Tests...



- Write the value function V_π for two sweeps
 - Case I: a random policy, $R_t = 1$ when transitioning to the right bottom cell, $R_t = 0$ on all other transitions
 - Case II: $R_t = -1$ on all transitions, a policy that always goes to right

Policy improvement

- Our reason for computing the value function for a policy is to help **find better policies**
 - We have determined the value function V_π for policy π
 - we would like to know whether or not we should change the policy to deterministically choose an action $a \neq \pi(s)$
 - We know how good it is to follow the current policy from s , e.g., V_π , but would it be better or worse to change to the new policy, π' ?
- Consider selecting a in s and thereafter following the existing policy π

$$\begin{aligned} Q_\pi(s, a) &= \mathbb{E}[R_{t+1} + \gamma V_\pi(S_{t+1}) | S_t = s, A_t = a] \\ &= \sum_{s',r} p(s', r | s, a) [r + \gamma V_\pi(s')] \end{aligned}$$

- If $Q_\pi(s, a) \geq V_\pi(s)$?

Policy improvement theorem

- Let π and π' be any pair of deterministic policies such that,

$$Q_\pi(s, \pi'(s)) \geq V_\pi(s), \quad \forall s \in \mathcal{S}.$$

Then the policy π' must be as good as, or better than, π .

Policy improvement theorem

$$\begin{aligned} V_\pi(s) &\leq Q_\pi(s, \pi'(s)) \\ &= \mathbb{E}[R_{t+1} + \gamma V_\pi(S_{t+1}) | S_t = s, A_t = \pi'(s)] \\ &= \mathbb{E}_{\pi'}[R_{t+1} + \gamma V_\pi(S_{t+1}) | S_t = s] \\ &\leq \mathbb{E}_{\pi'}[R_{t+1} + \gamma Q_\pi(S_{t+1}, \pi'(S_{t+1})) | S_t = s] \\ &= \mathbb{E}_{\pi'}[R_{t+1} + \gamma \mathbb{E}_{\pi'}[R_{t+2} + \gamma V_\pi(S_{t+2}) | S_{t+1}, A_{t+1} = \pi'(S_{t+1})] | S_t = s] \\ &= \mathbb{E}_{\pi'}[R_{t+1} + \gamma R_{t+2} + \gamma^2 V_\pi(S_{t+2}) | S_t = s] \\ &\leq \mathbb{E}_{\pi'}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 V_\pi(S_{t+3}) | S_t = s] \\ &\leq \dots \\ &\leq \mathbb{E}_{\pi'}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \gamma^3 R_{t+4} + \dots | S_t = s] \\ &= V_{\pi'}(s) \end{aligned}$$

Policy improvement

- Consider the new **greedy** policy, π' , selecting at each state the action that appears best according to $Q_\pi(s, a)$

$$\begin{aligned}\pi'(s) &= \arg \max_a Q_\pi(s, a) \\ &= \arg \max_a \mathbb{E}[R_{t+1} + \gamma V_\pi(S_{t+1}) | S_t = s, A_t = a] \\ &= \arg \max_a \sum_{s'} p(s', r | s, a) [r + \gamma V_\pi(s')]\end{aligned}$$

- The process of making a new policy that improves on an original policy, by making greedy w.r.t. the value function of the original policy, is called **policy improvement**
 - The greedy policy **meets the conditions of the policy improvement theorem**

Proof

- Note that $\pi(a|s) \in [0, 1]$, $\sum_a \pi(a|s) = 1$

$$\begin{aligned} V_{\pi'}(s) &= \max_a \sum_{s'} p(s', r|s, a)[r + \gamma V_{\pi}(s')] \\ &\geq \sum_a \pi(a|s) \sum_{s'} p(s', r|s, a)[r + \gamma V_{\pi}(s')] \end{aligned}$$

Policy improvement

- Suppose the new policy π' is as good as, but not better than, the old policy π , then $V_{\pi'} = V_{\pi}$

$$\begin{aligned}V_{\pi'}(s) &= \max_a \mathbb{E}[R_{t+1} + \gamma V_{\pi'}(S_{t+1}) | S_t = s, A_t = a] \\&= \max_a \sum_{s',r} p(s',r|s,a) [r + \gamma V_{\pi'}(s')]\end{aligned}$$

- The same as the **Bellman optimality equation**
- Both π and π' must be optimal policies
- Policy improvement must give us a strictly better policy except when the original policy is already optimal

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Policy iteration

- Using policy improvement theorem, we can obtain a sequence of monotonically improving policies and value functions

- E: Policy Evaluation, I: Policy Improvement

$$\pi_0 \xrightarrow{E} V_{\pi_0} \xrightarrow{I} \pi_1 \xrightarrow{E} V_{\pi_1} \xrightarrow{I} \pi_2 \xrightarrow{E} \dots \xrightarrow{I} \pi_* \xrightarrow{E} V_*$$

- This process is guaranteed to converge to an optimal policy and optimal value function in a finite number of iterations
 - Each policy is guaranteed to be a strictly improvement over the previous one unless it is already optimal
 - A finite MDP has only a finite number of policies

Policy iteration

Policy Iteration (using iterative policy evaluation) for estimating $\pi \approx \pi_*$

1. Initialization

$V(s) \in \mathbb{R}$ and $\pi(s) \in \mathcal{A}(s)$ arbitrarily for all $s \in \mathcal{S}$

2. Policy Evaluation

Loop:

$$\Delta \leftarrow 0$$

Loop for each $s \in \mathcal{S}$:

$$v \leftarrow V(s)$$

$$V(s) \leftarrow \sum_{s',r} p(s',r|s,\pi(s)) [r + \gamma V(s')]$$

$$\Delta \leftarrow \max(\Delta, |v - V(s)|)$$

until $\Delta < \theta$ (a small positive number determining the accuracy of estimation)

3. Policy Improvement

policy-stable \leftarrow true

For each $s \in \mathcal{S}$:

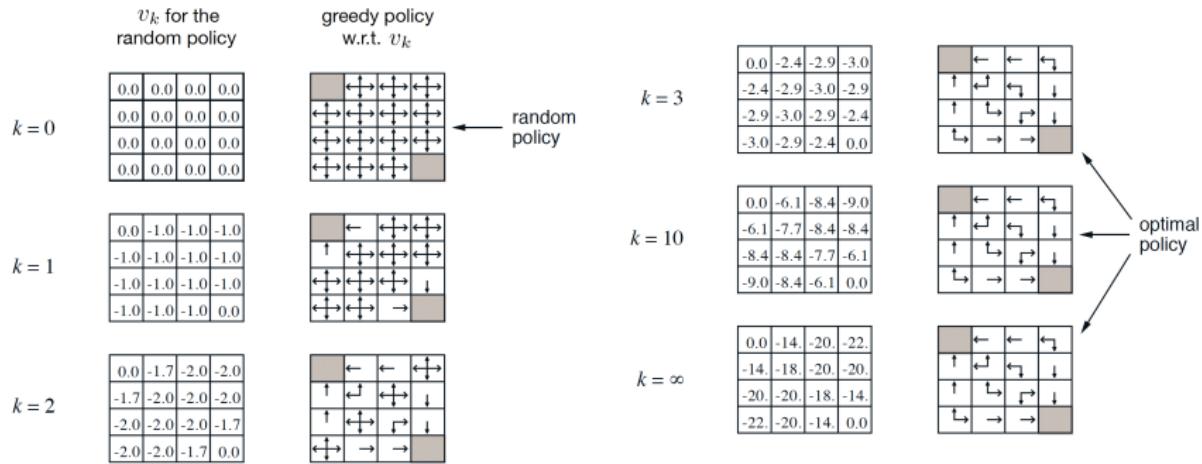
$$\text{old-action} \leftarrow \pi(s)$$

$$\pi(s) \leftarrow \operatorname{argmax}_a \sum_{s',r} p(s',r|s,a) [r + \gamma V(s')]$$

If $\text{old-action} \neq \pi(s)$, then *policy-stable* \leftarrow false

If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$; else go to 2

Policy iteration often converges in very few iterations



- The final estimate is in fact v_π
 - The negation of the expected number of steps from that state until termination
 - The last policy is guaranteed only to be an improvement over the random policy, but in this case it, and all policies after the third step of policy evaluation, are optimal

Value iteration

Policy Iteration (using iterative policy evaluation) for estimating $\pi \approx \pi_*$

1. Initialization

$V(s) \in \mathbb{R}$ and $\pi(s) \in \mathcal{A}(s)$ arbitrarily for all $s \in \mathcal{S}$

2. Policy Evaluation

Loop:

$$\Delta \leftarrow 0$$

Loop for each $s \in \mathcal{S}$:

$$v \leftarrow V(s)$$

$$V(s) \leftarrow \sum_{s',r} p(s',r|s,\pi(s)) [r + \gamma V(s')]$$

$$\Delta \leftarrow \max(\Delta, |v - V(s)|)$$

until $\Delta < \theta$ (a small positive number determining the accuracy of estimation)

3. Policy Improvement

policy-stable \leftarrow true

For each $s \in \mathcal{S}$:

$$old-action \leftarrow \pi(s)$$

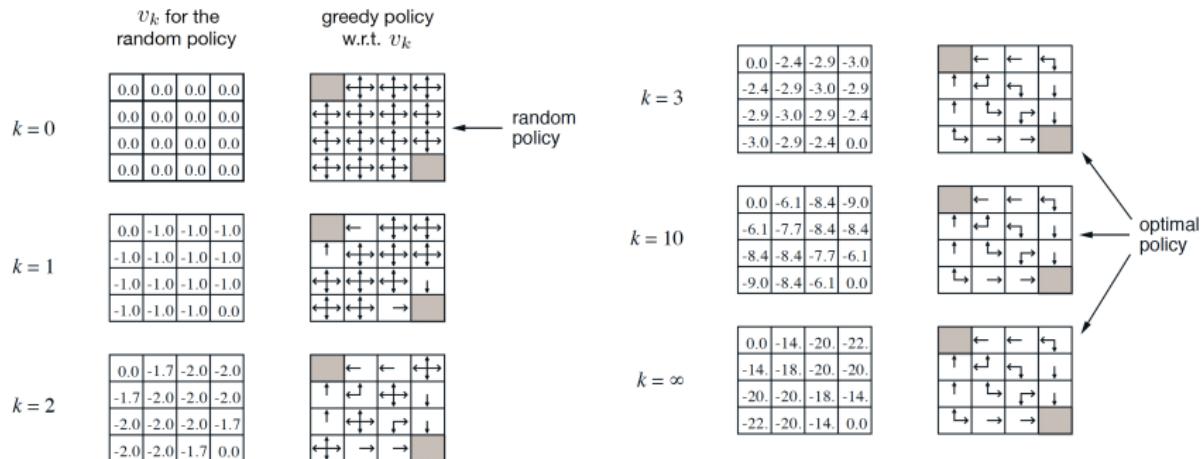
$$\pi(s) \leftarrow \operatorname{argmax}_a \sum_{s',r} p(s',r|s,a) [r + \gamma V(s')]$$

If $old-action \neq \pi(s)$, then *policy-stable* \leftarrow false

If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$; else go to 2

- Each policy iteration involves policy evaluation, which may be a protracted iterative computation **requiring multiple sweeps through the state set**

Truncate policy evaluation?



- Policy evaluation iterations beyond the first three have no effect on the corresponding greedy policy

Value iteration = Truncate policy evaluation for one sweep

- In policy iteration, stop policy evaluation after just one sweep

$$V_{k+1}(s) = \sum_{s',r} p(s',r|s, \pi_k(s)) [r + \gamma V_k(s')]$$

$$\pi_{k+1}(s) = \arg \max_a \sum_{s',r} p(s',r|s, a) [r + \gamma V_{k+1}(s')]$$

- Combine into one operation, called **value iteration** algorithm

$$V_{k+1}(s) = \max_a \sum_{s',r} p(s',r|s, a) [r + \gamma V_k(s')]$$

- For arbitrary V_0 , the sequence $\{V_k\}$ converges to V_* under the same conditions that guarantee the existence of V_*

Value iteration

- Bellman optimality equation

$$V_*(s) = \max_a \sum_{s',r} p(s',r|s,a)[r + \gamma V_*(s')]$$

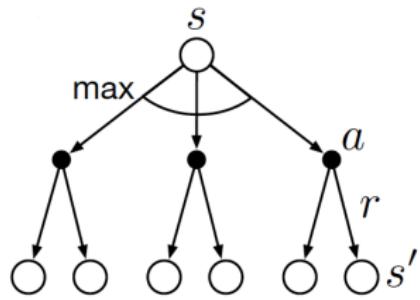
- Value iteration

$$V_{k+1}(s) = \max_a \sum_{s',r} p(s',r|s,a)[r + \gamma V_k(s')]$$

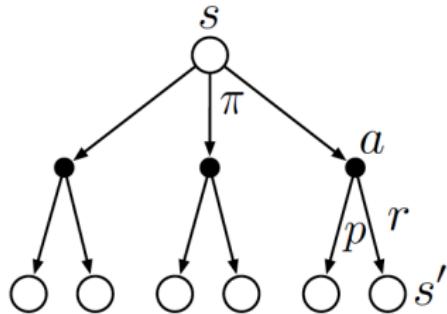
- Turn **Bellman optimality equation** into an update rule
- Directly **approximate the optimal state-value function**, V_*

Value iteration vs. policy evaluation

Backup diagram for value iteration



Backup diagram for policy evaluation



- Use Bellman optimality equation as update rule
- Approximate the optimal state-value function V_*

- Use Bellman equation as update rule
- Approximate the state-value function of a given policy V_π

Value iteration algorithm

Value Iteration, for estimating $\pi \approx \pi_*$

Algorithm parameter: a small threshold $\theta > 0$ determining accuracy of estimation
Initialize $V(s)$, for all $s \in \mathcal{S}^+$, arbitrarily except that $V(\text{terminal}) = 0$

Loop:

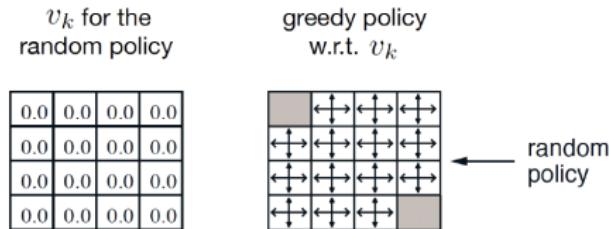
```
| Δ ← 0
| Loop for each  $s \in \mathcal{S}$ :
|    $v \leftarrow V(s)$ 
|    $V(s) \leftarrow \max_a \sum_{s',r} p(s',r|s,a) [r + \gamma V(s')]$ 
|   Δ ← max(Δ, |v - V(s)|)
until Δ < θ
```

Output a deterministic policy, $\pi \approx \pi_*$, such that

$$\pi(s) = \operatorname{argmax}_a \sum_{s',r} p(s',r|s,a) [r + \gamma V(s')]$$

- One sweep = one sweep of policy evaluation + one sweep of policy improvement

Tests...



- Write the value function $V(s), \forall s$ for two sweeps, using the value iteration algorithm
 - $R_t = 1$ when transitioning to the right bottom cell, $R_t = 0$ on all other transitions

Properties of dynamic programming

- **Bootstrapping:** Update estimates on the basis of other estimates
 - Estimate the values of states based on estimates of the values of successor states
- **Model-based:** Require the accurate model of the environment
 - The complete probability distributions of all possible transitions, $p(s', r|s, a)$

Algorithms	Bootstrapping?	Model-based?
Dynamic programming	Yes	Yes
Monte Carlo methods	No	No
Temporal-difference learning	Yes	No

Why is DP fundamental and important?

- Important theoretically, provide an essential **foundation** for the understanding of RL methods
- RL methods can be viewed as attempts to **achieve much the same effect** as DP, only with less computation and without assuming a perfect model of the environment

Why is DP fundamental and important?

PHYSICAL SCIENCES



Fast reinforcement learning with generalized policy updates

André Barreto, Shaobo Hou, Diana Borsa, David Silver, and Doina Precup

PNAS first published August 17, 2020 <https://doi.org/10.1073/pnas.1907370117>

Edited by David L. Donoho, Stanford University, Stanford, CA, and approved July 9, 2020 (received for review July 20, 2019)

Generalized Policy Updates

From the discussion above, one can see that an important branch of the field of RL depends fundamentally on the notions of policy evaluation and policy improvement. We now discuss generalizations of these operations.

Definition 3. “Generalized policy evaluation” (GPE) is the computation of the value function of a policy π on a set of tasks \mathcal{R} .

Definition 4. Given a set of policies Π and a task r , “generalized policy improvement” (GPI) is the definition of a policy π' such that

$$Q_r^{\pi'}(s, a) \geq \sup_{\pi \in \Pi} Q_r^{\pi}(s, a) \text{ for all } (s, a) \in \mathcal{S} \times \mathcal{A}. \quad [5]$$

- Policy evaluation
 - Use Bellman equation as the update rule
 - Guaranteed to converge
- Policy improvement
 - Make greedy w.r.t. the value function of the original policy
- Policy iteration
 - Alternate between policy evaluation and policy improvement steps
- Value iteration
 - Truncate policy evaluation for one sweep
 - Use Bellman optimality equation as the update rule

Learning objectives of this lecture

You should be able to...

- Know elements of finite MDPs, the agent-environment interface
- (Discounted) returns and episodes, policies and value functions, Bellman (optimality)
- Understand and be able to use dynamic programming
- Know policy evaluation and policy improvement, policy iteration and value iteration

References

- Chapter 3: Finite Markov Decision Processes, Chapter 4: Dynamic Programming, *Reinforcement Learning: An Introduction*, 2nd Edition
 - <http://202.119.32.195/cache/2/03/incompleteideas.net/5b682cef88335157bc5542267cf3f442/RLbook2018.pdf>

THE END