Reinforcement Learning

Lecture 4: Model-free Control

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Let‘s play Kahoot!

Kahoot!

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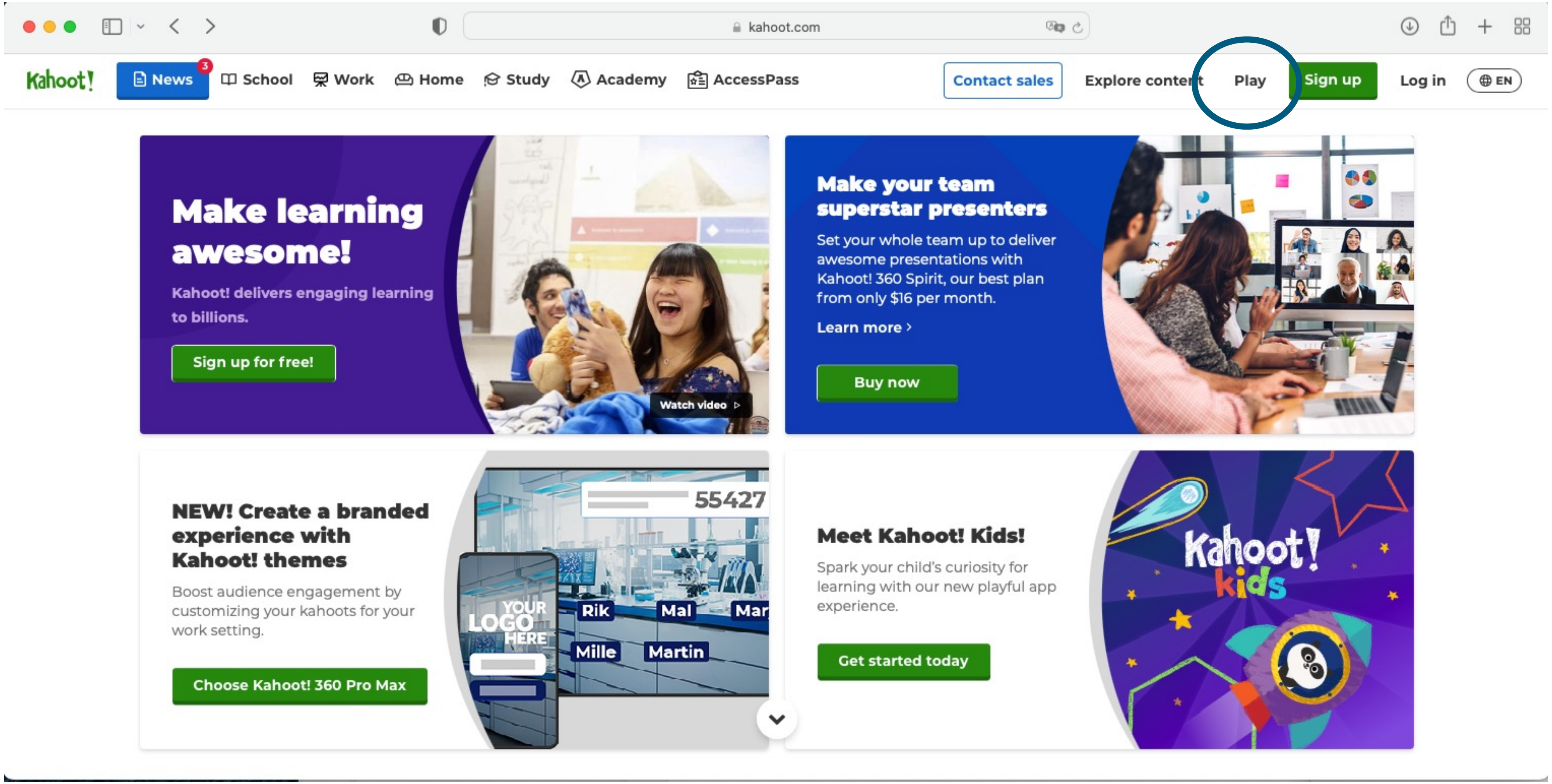

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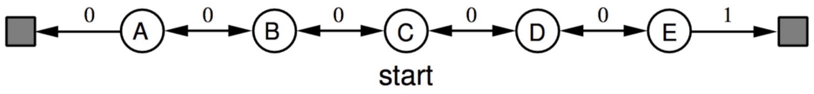
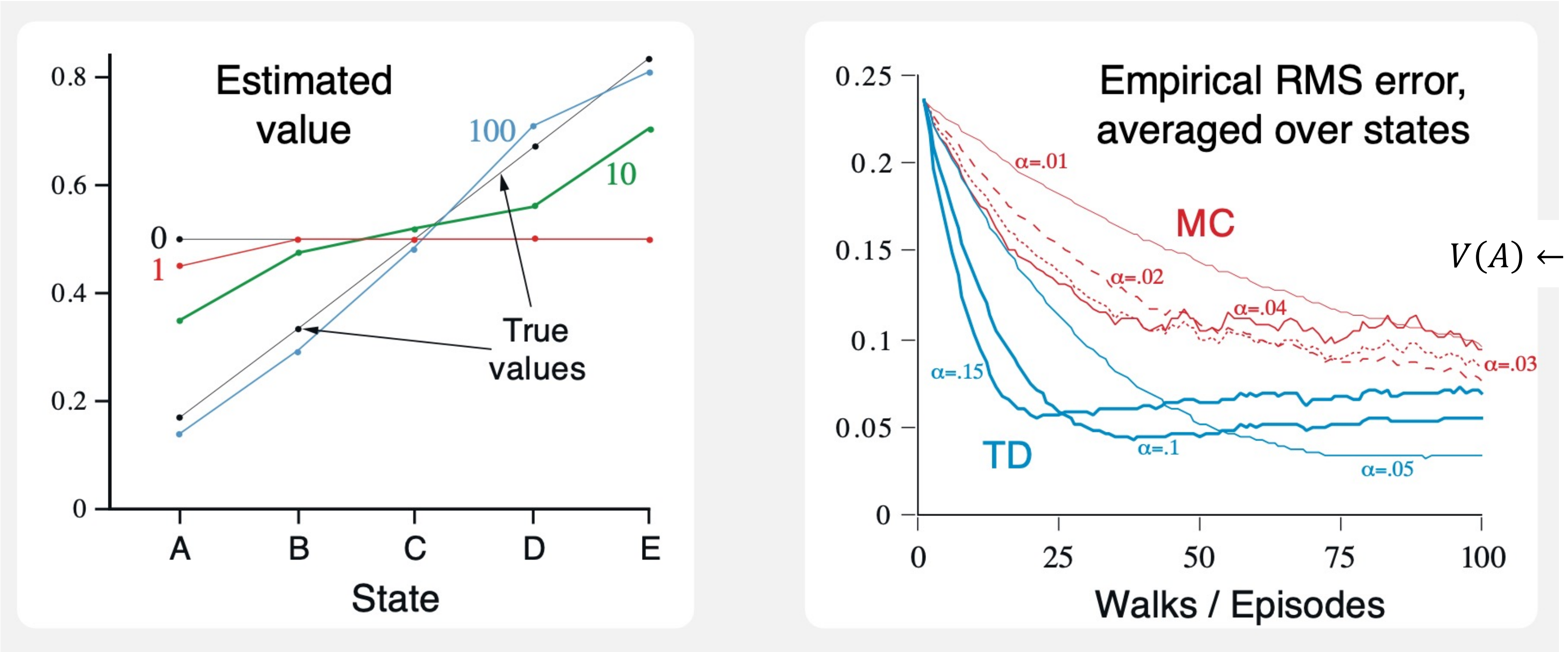
Recap



$\gamma = 1 \quad \alpha = 0.1$



$V(s_t) \leftarrow V(s_t) + 0.1\big(r_{t+1} + V(s_{t+1}) - V(s_t)\big)$

$V(A) \leftarrow V(A) + 0.1\big(0 + 0 - V((A)\big) = 0.9V \cdot (A) = 0.45$

Exercise 6.3 From the results shown in the left graph of the random walk example it appears that the first episode results in a change in only $V(\mathsf{A})$. What does this tell you about what happened on the first episode? Why was only the estimate for this one state changed? By exactly how much was it changed? □

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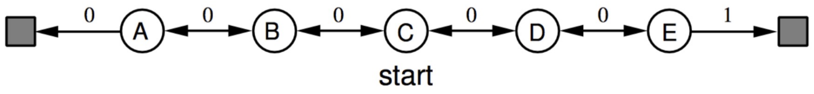
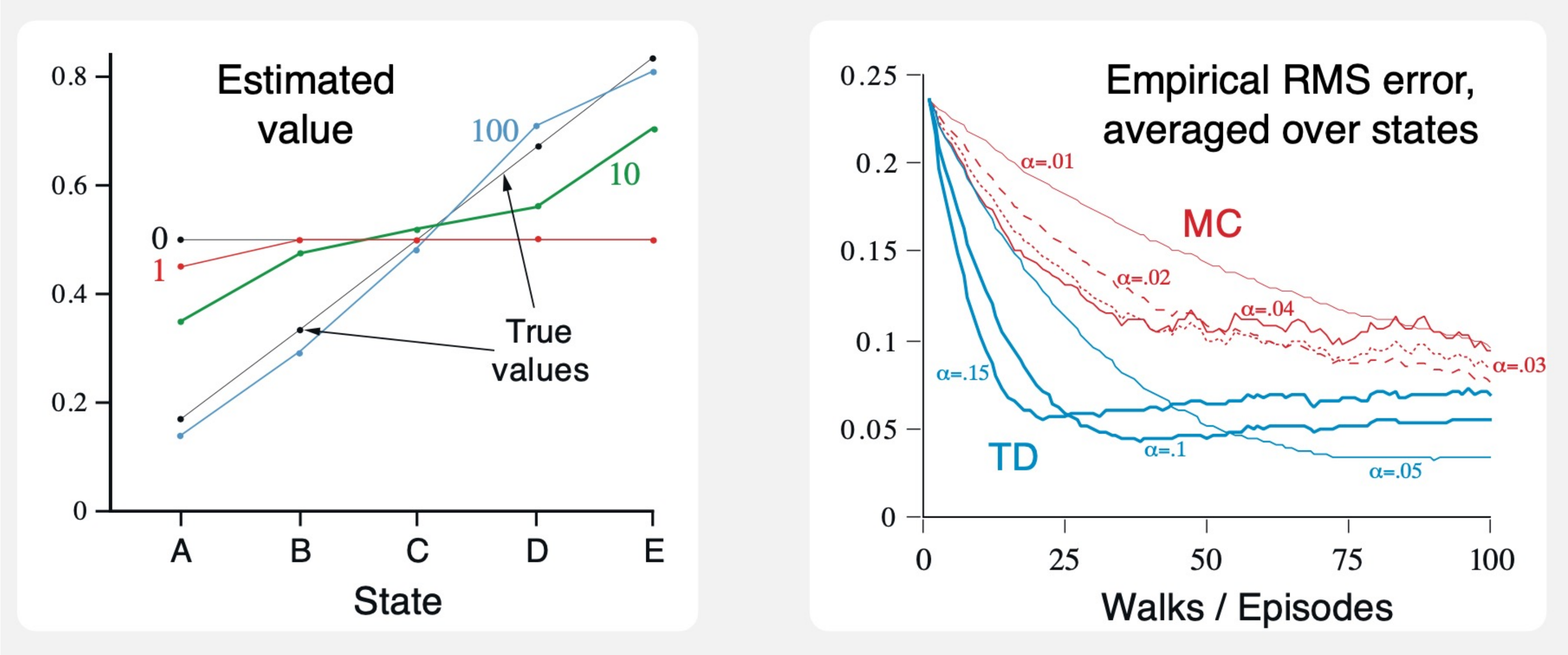
Recap





$\gamma = 1 \quad \alpha = 0.1$

What about $\alpha = \frac{1}{N(s)}$?

Exercise 6.4 The specific results shown in the right graph of the random walk example are dependent on the value of the step-size parameter, α. Do you think the conclusions about which algorithm is better would be affected if a wider range of α values were used? Is there a different, fixed value of α at which either algorithm would have performed significantly better than shown? Why or why not? □

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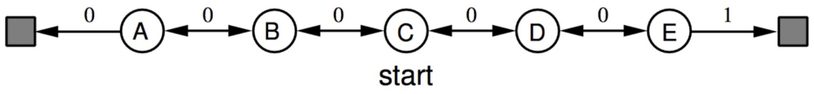
Recap



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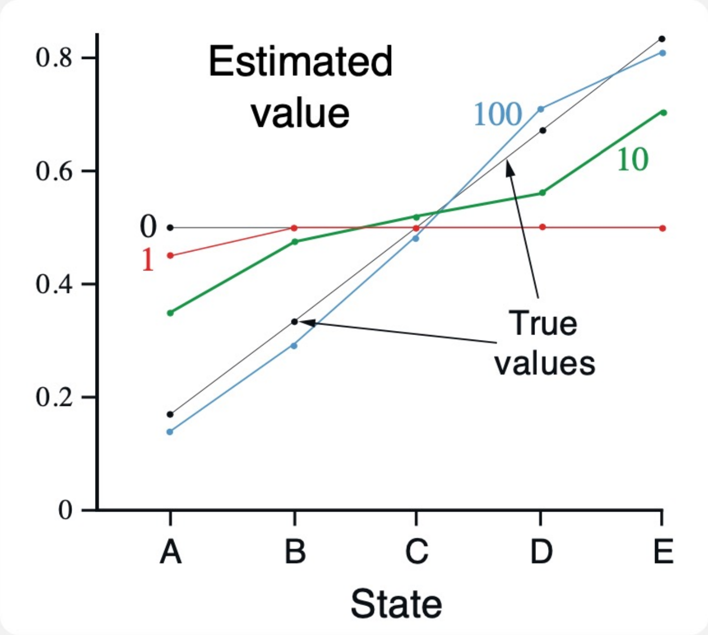
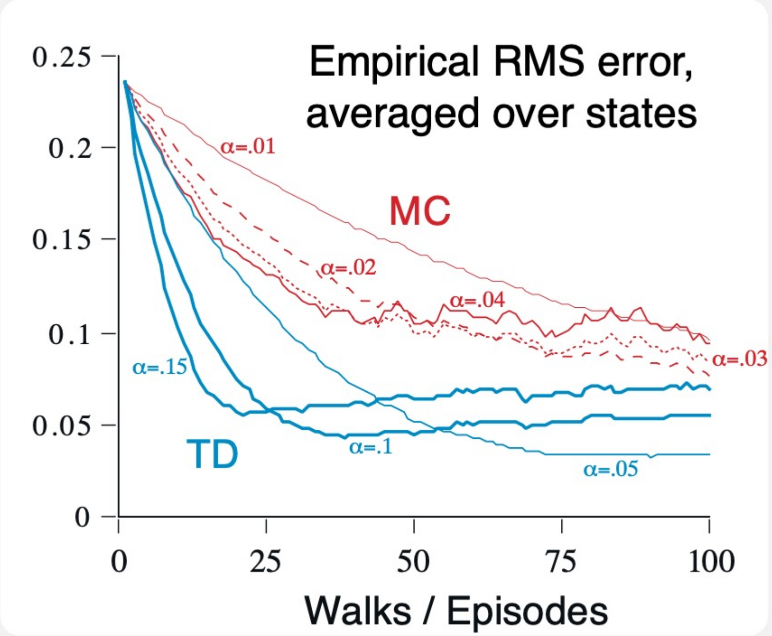
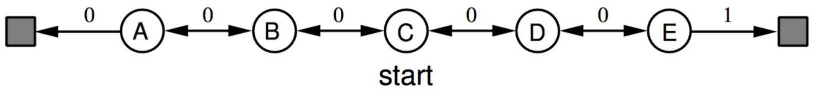
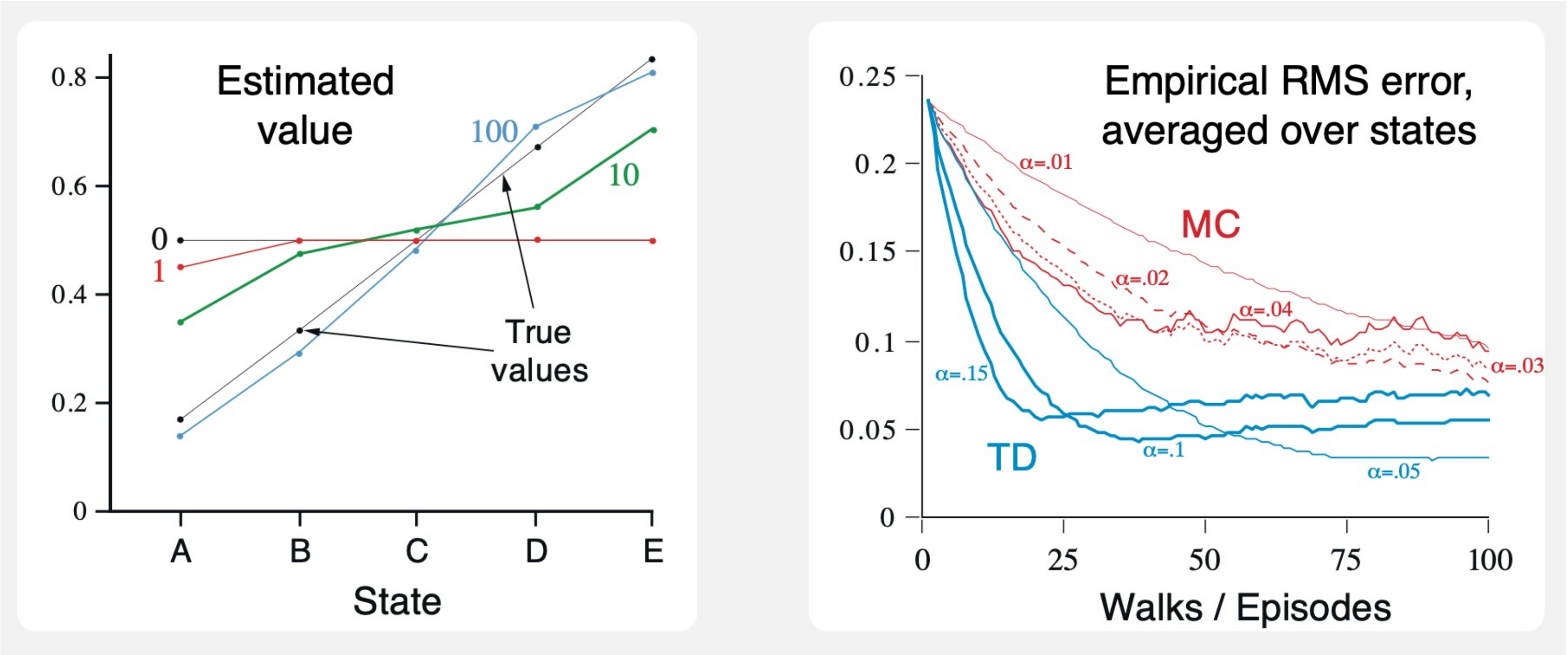




**Exercise 6.5* In the right graph of the random walk example, the RMS error of the TD method seems to go down and then up again, particularly at high α's. What could have caused this? Do you think this always occurs, or might it be a function of how the approximate value function was initialized? □

Recap





Exercise 6.6 In Example 6.2 we stated that the true values for the random walk example are $\frac{1}{6}, \frac{2}{6}, \frac{3}{6}, \frac{4}{6}$, and $\frac{5}{6}$, for states A through E. Describe at least two different ways that these could have been computed. Which would you guess we actually used? Why? □

$\gamma = 1 \quad \alpha = 0.1$

1. Value Iteration
2. e.g.: $V(D) = \frac{1}{2} \cdot V(C) + \frac{1}{2} \cdot V(E)$

5 equations, 5 unknowns → solve:

$$V(E) = \frac{V(D) + V(1)}{2}$$

$$V(D) = \frac{V(C) + V(E)}{2}$$

$$V(C) = \frac{V(B) + V(D)}{2}$$

$$V(B) = \frac{V(A) + V(C)}{2}$$

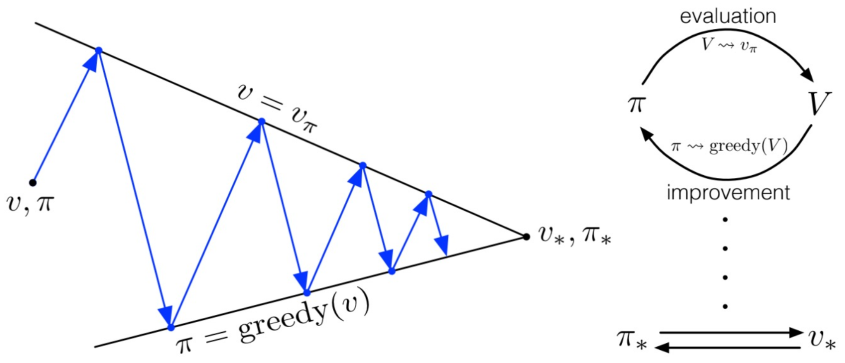
$$V(A) = \frac{0 + V(B)}{2}$$

Recap

Dynamic Programming

- Dynamic Programming (DP) methods to find optimal controllers
  - DP methods are guaranteed to find optimal solutions for Q and V in polynomial time (in number of states and actions) and are exponentially faster than direct search
  - Policy Iteration computes the value function under a given policy to improve the policy while value iteration directly works on the states
    - Perform sweeps through the state set
    - Implement the Bellman equation update
    - Use bootstrapping
  - Require complete and accurate model of the environment
  - Have limited applicability in practice…

    → as they need to know the dynamics of the environment!



Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

Recap

Monte Carlo and TD Methods

- So far: We know our MDP model $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$.
  - Planning by using dynamic programming
  - Solve a known MDP

- What if we don't know the model, i.e., $\mathcal{P}$ or $\mathcal{R}$ or both?

- We distinguish between 2 problems for unknown MDPs:

  - **Model-free Prediction:** Evaluate the future, given the policy π.
    (estimate the value function)

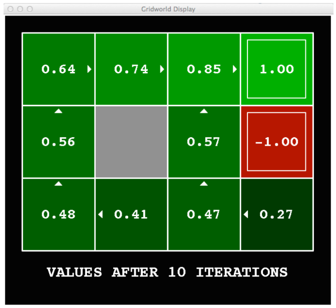
  - **Model-free Control:** Optimize the future by finding the best policy π.
    (optimize the value function)

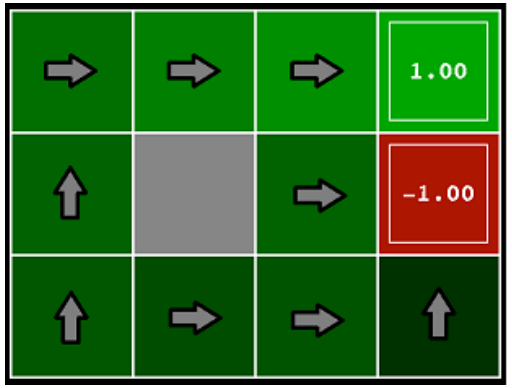
Recap

Monte Carlo and TD Methods

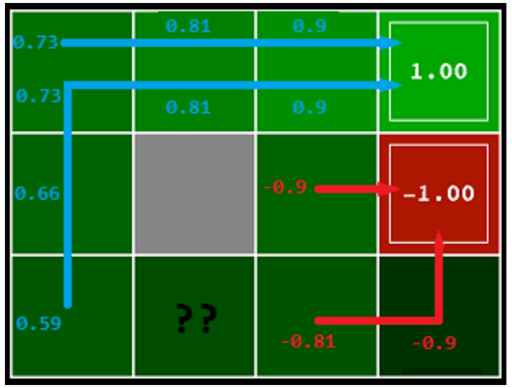
- Idea:
  - Use the samples to <u>estimate</u> the true V- and Q-value functions for the policy π

Remember:





Given Policy



Randomly select state and follow policy & Compute discounted return for each state

Average the values on each state

https://medium.com/@zsalloum/monte-carlo-in-reinforcement-learning-the-easy-way-564c53010511

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Recap

Monte Carlo and TD Methods

- TD(0) vs. MC Policy Evaluation
  - Goal: learn value function v_π online from experience when we follow policy π

- Simplest TD learning algorithm: TD(0)
- Update value **towards estimation $\hat{\boldsymbol{G}}$**:

$$V(s) \leftarrow V(s) + \alpha(\hat{\boldsymbol{G}} - V(s))$$

$$\hat{\boldsymbol{G}} = \boldsymbol{r} + \boldsymbol{\gamma V(s')}$$ (estimated return)

- $\hat{G}$ is called the TD target
- $\hat{G} - V(s)$ is called the TD error.

- Update $V(s)$ incrementally after each episode.
- For each state s with **actual return $\boldsymbol{G}$**:

$$N(s) \leftarrow N(s) + 1$$ (just increment visit counter)

$$V(s) \leftarrow V(s) + \frac{1}{N(s)}\left(\boldsymbol{G} - V(s)\right)$$ (update a bit → reduce error)

- In non-stationary problems, it can be useful to track a running mean, i.e., forget old episodes:

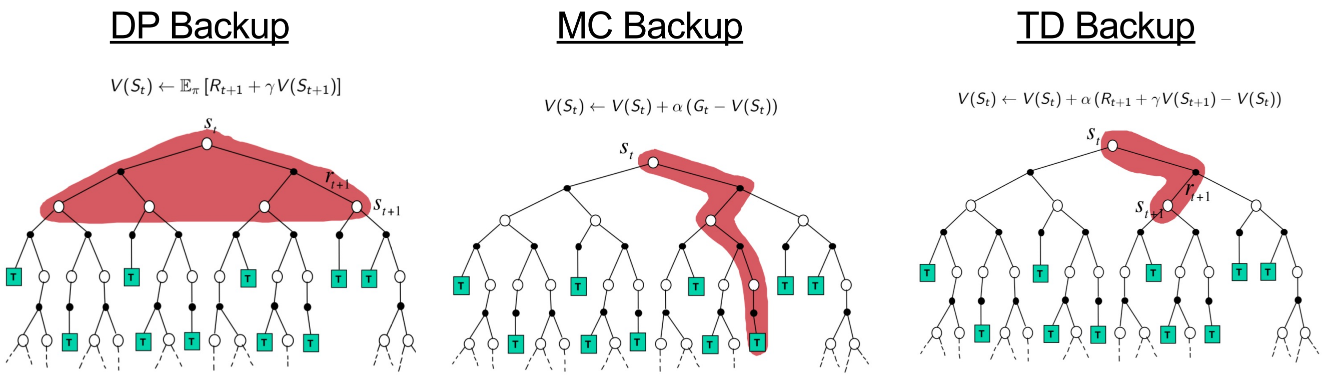
$$V(s) \leftarrow V(s) + \alpha\left(\boldsymbol{G} - V(s)\right).$$

$$NewEstimate \leftarrow OldEstimate + StepSize\,[Target - OldEstimate]$$

Recap

Monte Carlo and TD Methods

- Which one should I use? Does it make any difference?
  - Bias/Variance Trade-Off
  - MC has high variance, but zero bias
    - Good convergence (even with FA)
    - insensitive to initialization (no bootstrapping), simple to understand
  - TD has low variance, but some bias
    - TD(0) converges to $\pi_v(s)$ (be careful with FA: bias is a risk)
    - sensitive to initialization (because of the bootstrapping)
    - Usually more efficient in practice



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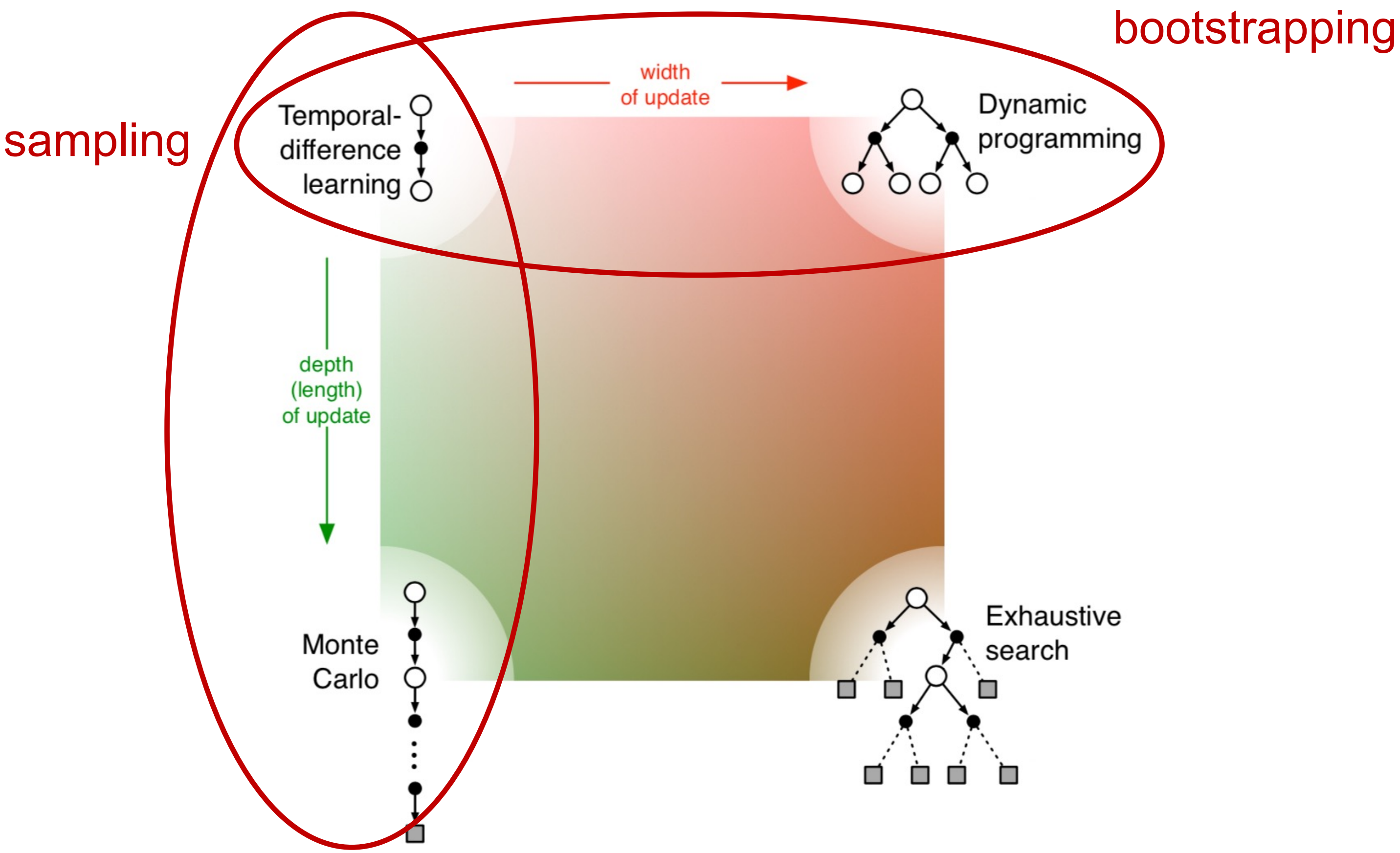
Recap

A Unified View of Prediction Algorithms



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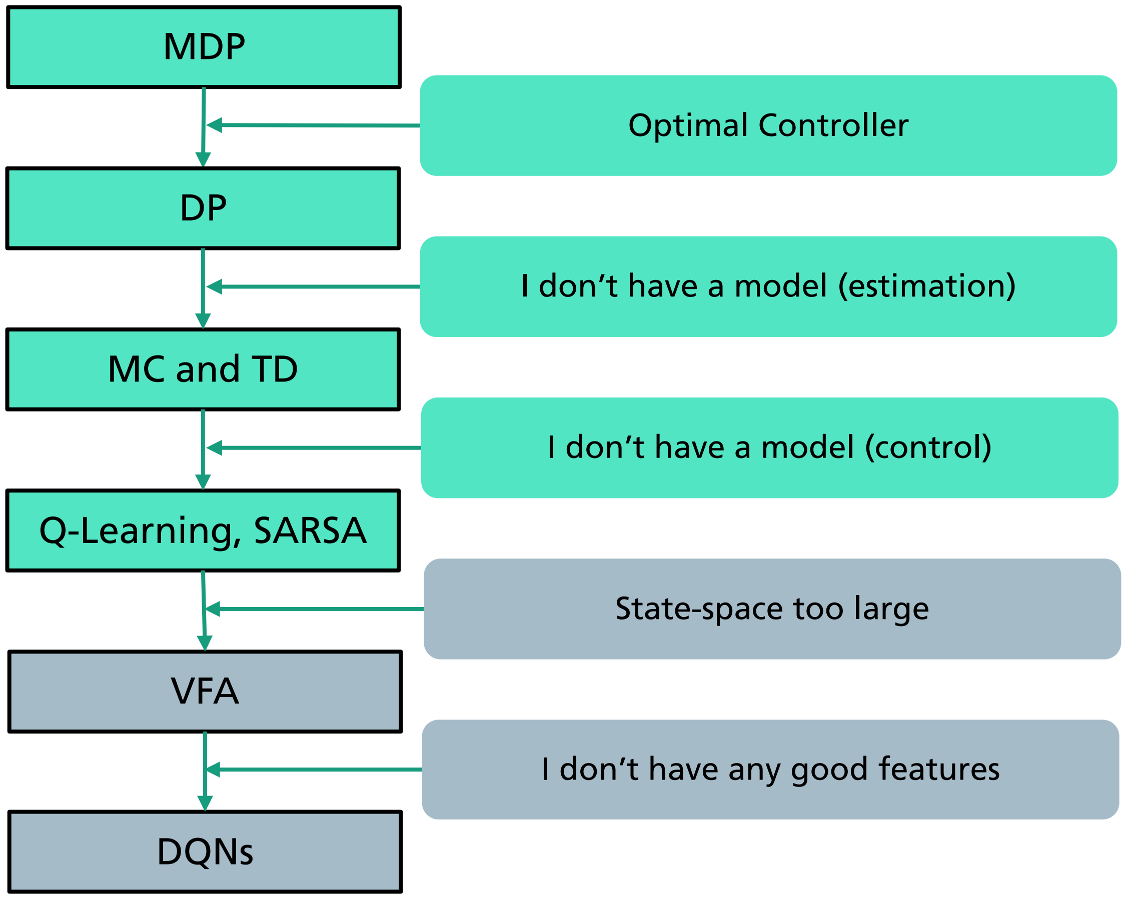
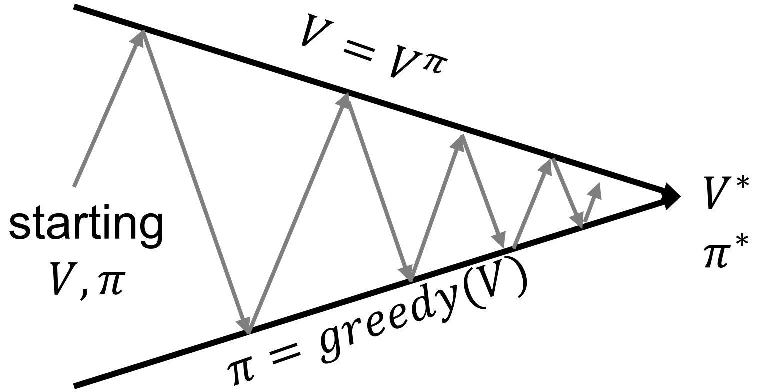
Overview


MDP
Optimal Controller
DP
I don’t have a model (estimation)
MC and TD
I don’t have a model (control)
Q-Learning, SARSA
State-space too large
VFA
I don’t have any good features
DQNs

Q-Learning and SARSA Algorithms

- The (model-free) control problem:
  - **Given** experience samples $s(s, a, r, s')$
  - **Learn** a close-to optimal policy π
- Simple idea:
  - If we have calculated the value function for a given policy π (e.g., from MC/TD policy evaluation from last week), we can use it for deriving a better policy π' through greedy policy improvement over $V(s)$



Policy Evaluation: Estimate $V = v_{\pi}$
e.g., Iterative Policy Evaluation

Policy Improvement: Generate $\pi' \geq \pi$
e.g., Greedy Policy Improvement

Q-Learning and SARSA Algorithms

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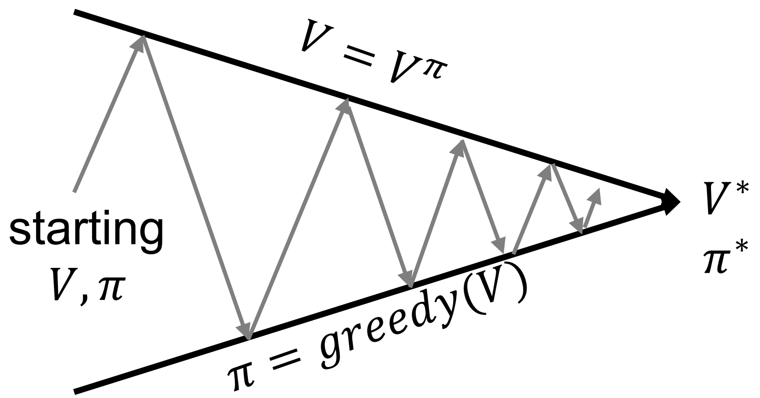

Policy Evaluation: Estimate $V = v_\pi$
e.g., Monte Carlo Policy Evaluation

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$$\pi'(\mathrm{s}) = \arg\max_{a \in A} \left\{ R(s,a) + \gamma \sum_{s' \in S} P(s'|s,a) V^{\pi}(s') \right\}, s \in S, V^{\pi'}(s) \geq V^{\pi}(s)$$

Requires a model!

  - Greedy policy improvement over $Q(s, a)$ is model-free

$$\pi'(\mathrm{s}) = \arg\max_{a \in A} Q(s,a)$$

Recap: Dynamic Programming

- How do we find optimal controllers for given (known) MDPs?
- Unfortunately, we need some definitions:
  - state-value function V for policy π

$$s \xrightarrow{\pi(s),\, R_0} S_1 \xrightarrow{\pi(S_1),\, R_1} S_2 \xrightarrow{\pi(S_2),\, R_2} S_3 \ldots\ S_{h-1} \xrightarrow{\pi(S_{h-1}),\, R_{h-1}} S_h$$

$$V^\pi(s) \triangleq Q^\pi(s, \pi(s)) = \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t R_t \mid S_0 = s\right].$$

  - state-action-value function Q for policy π

$$s \xrightarrow{a,\, R_0} S_1 \xrightarrow{\pi(S_1),\, R_1} S_2 \xrightarrow{\pi(S_2),\, R_2} S_3 \ldots\ S_{h-1} \xrightarrow{\pi(S_{h-1}),\, R_{h-1}} S_h$$

$$Q^\pi(s, a) = \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t R_t \mid S_0 = s, A_0 = a\right].$$

Recap: Dynamic Programming

- State-action-value function Q for policy π

$$s \xrightarrow{a, r_0} s_1 \xrightarrow{\pi(S_1), r_1} s_2 \xrightarrow{\pi(S_2), r_2} s_3 \ldots \; s_{h-1} \xrightarrow{\pi(s_{h-1}), r_{h-1}} s_h$$

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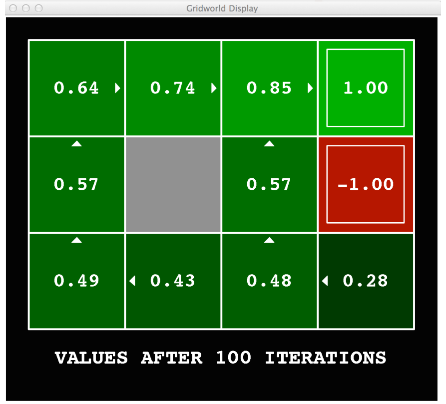

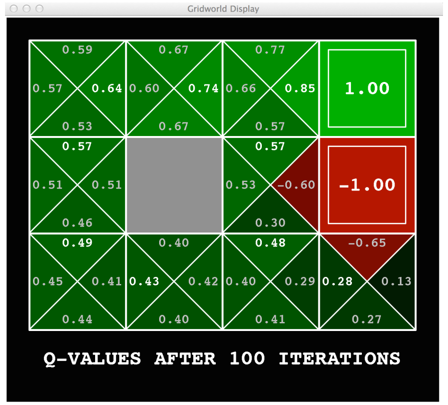

Recap: Dynamic Programming

- How do we find optimal controllers for given (known) MDPs?
- Unfortunately, we need some definitions:
  - Bellman Equation for Q, given policy π

$$s \xrightarrow{a,\mathcal{R}(s,a)} s' \xrightarrow{\pi(s'),\,R_1} S_2 \xrightarrow{\pi(S_2),\,R_2} S_3 \ldots\; S_{h-1} \xrightarrow{\pi(S_{h-1}),\,R_{h-1}} S_h$$

$$Q^{\pi}(s,a) = \underbrace{\mathcal{R}(s,a)}_{\text{first step}} + \underbrace{\gamma \sum_{s' \in \mathcal{S}} \mathcal{P}(s'|s,a)\, Q^{\pi}(s',\pi(s'))}_{\text{subsequent steps}}$$

Recap: Dynamic Programming

- How do we find optimal controllers for given (known) MDPs?
- Unfortunately, we need some definitions:
  - Bellman Optimality Equation for Q

$$s \xrightarrow{a,\,\mathcal{R}(s,a)} s' \xrightarrow{\pi^*(s'),\,R_1} S_2 \xrightarrow{\pi^*(S_2),\,R_2} S_3 \dots\; S_{h-1} \xrightarrow{\pi^*(S_{h-1}),\,R_{h-1}} S_h$$

$$Q^{\pi^*}(s,a) = \underbrace{\mathcal{R}(s,a)}_{\text{first step}} + \underbrace{\gamma \sum_{s' \in \mathcal{S}} \mathcal{P}(s'|s,a) \max_{a' \in \mathcal{A}} Q^{\pi^*}(s',a')}_{\text{subsequent steps}}$$

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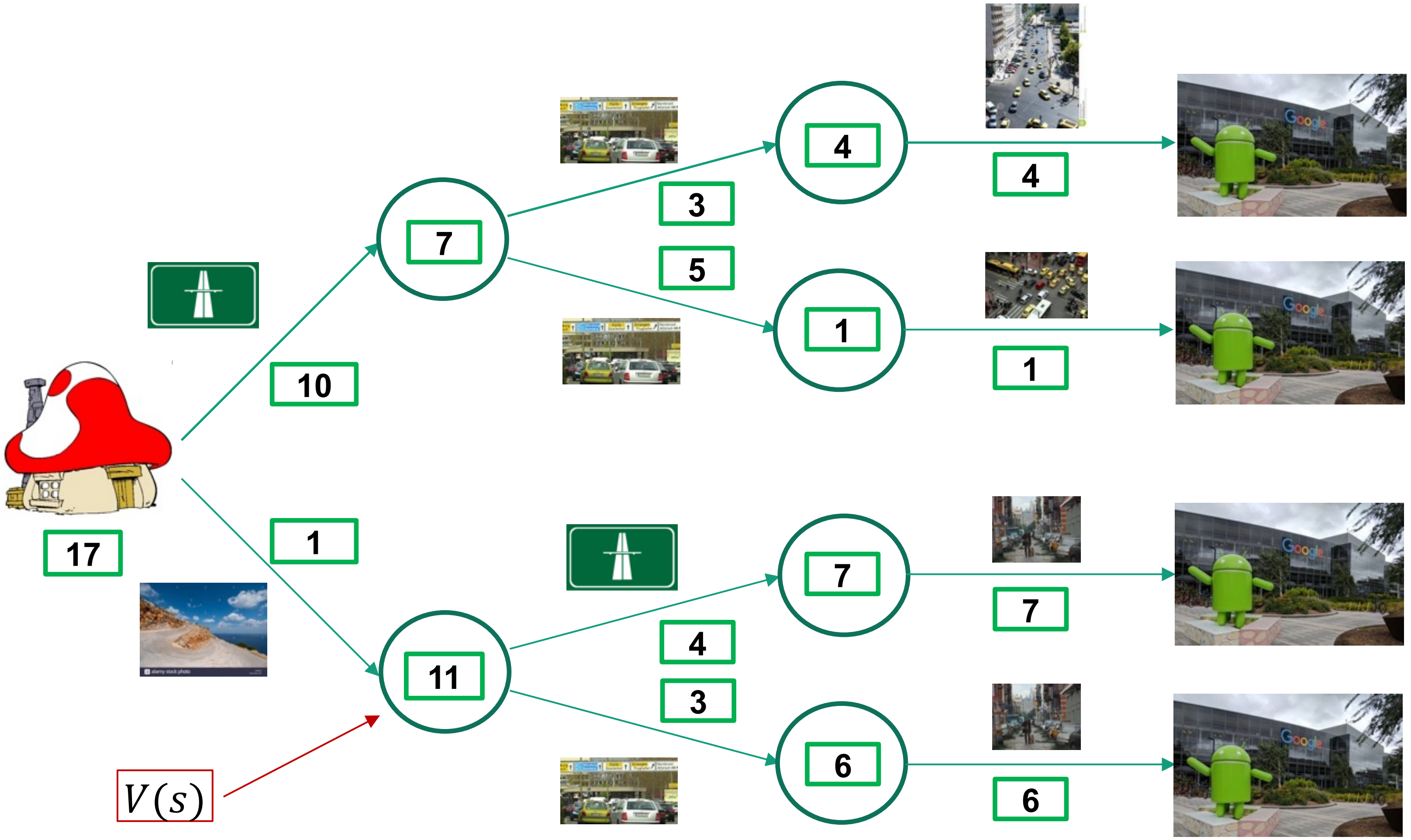
Recap: Dynamic Programming



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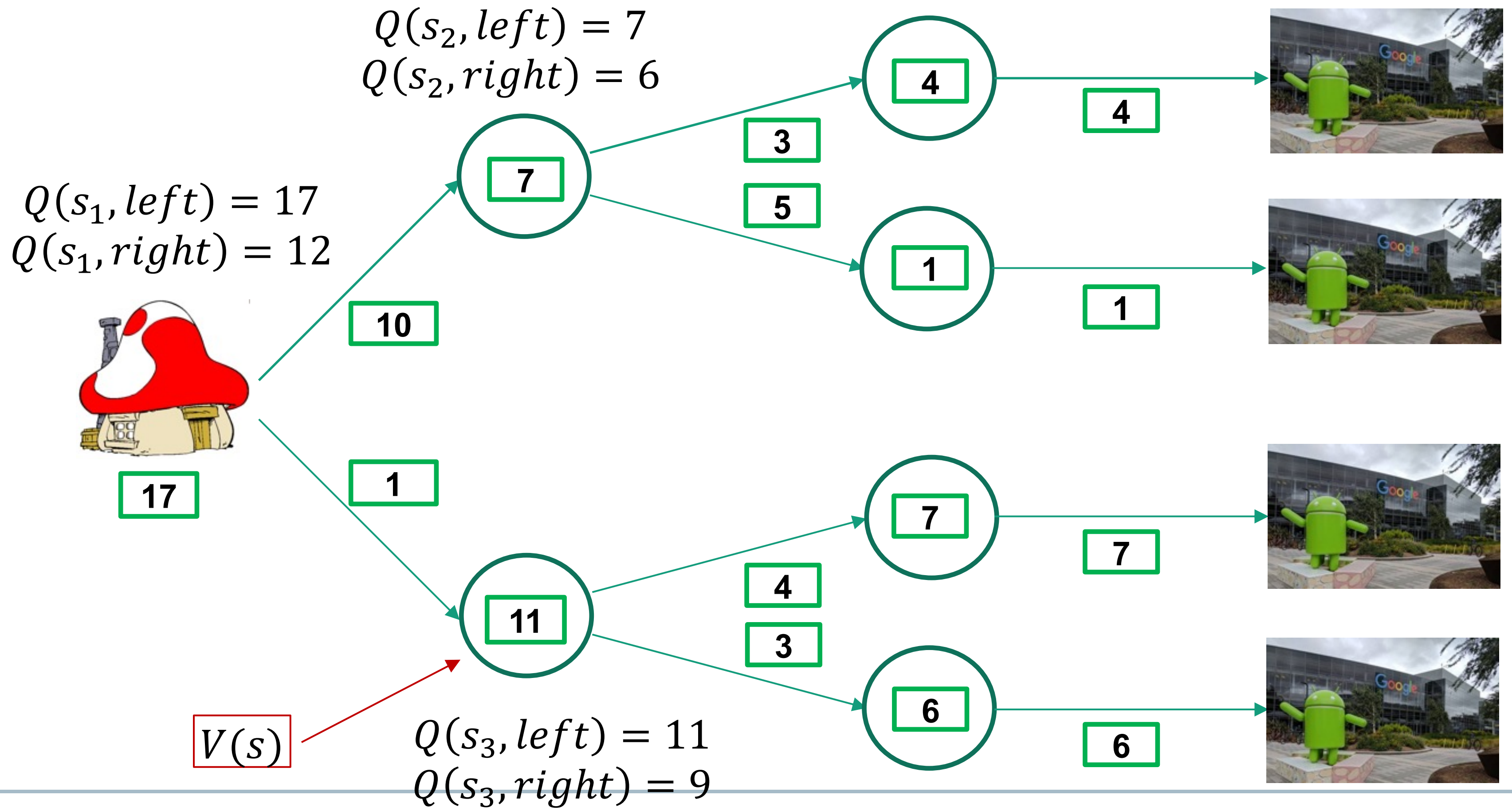

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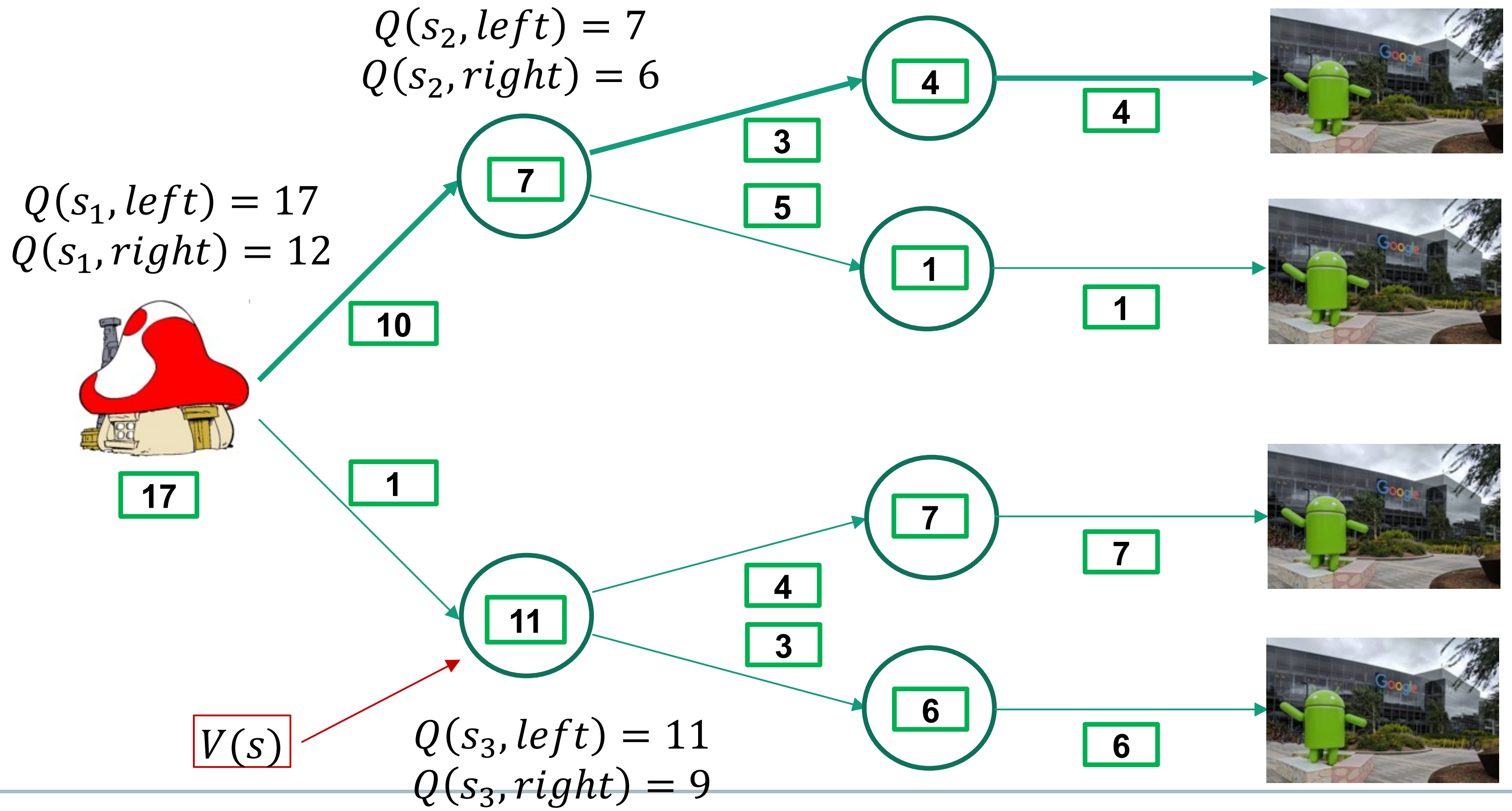

Recap: Dynamic Programming

- How do we find optimal controllers for given (known) MDPs?
- Unfortunately, we need some definitions:
  - Greedy Policy Improvement over Q

$$\pi'(s) = \underset{a \in \mathcal{A}}{\operatorname{argmax}}\, Q^{\pi}(s,a)$$

$$\forall s \in \mathcal{S}, \qquad Q^{\pi'}\big(s, \pi'(s)\big) \geq Q^{\pi}\big(s, \pi(s)\big)$$

  - Greedy Policy Improvement over V

$$\pi'(s) = \underset{a \in \mathcal{A}}{\operatorname{argmax}} \left\{ \mathcal{R}(s,a) + \gamma \sum_{s' \in \mathcal{S}} \mathcal{P}(s'|s,a)\, V^{\pi}(s') \right\}$$

$$\forall s \in \mathcal{S}, \qquad V^{\pi'}(s') \geq V^{\pi}(s')$$

Q-Learning and SARSA Algorithms

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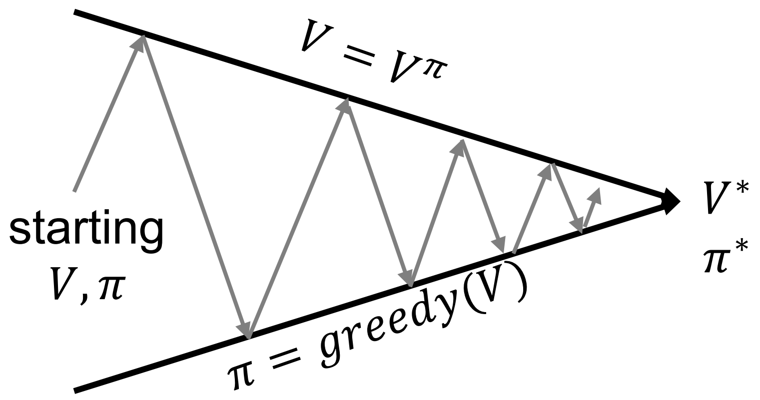

Policy Evaluation: Estimate $V = v_\pi$
e.g., Monte Carlo Policy Estimation

Policy Improvement: Generate $\pi' \geq \pi$
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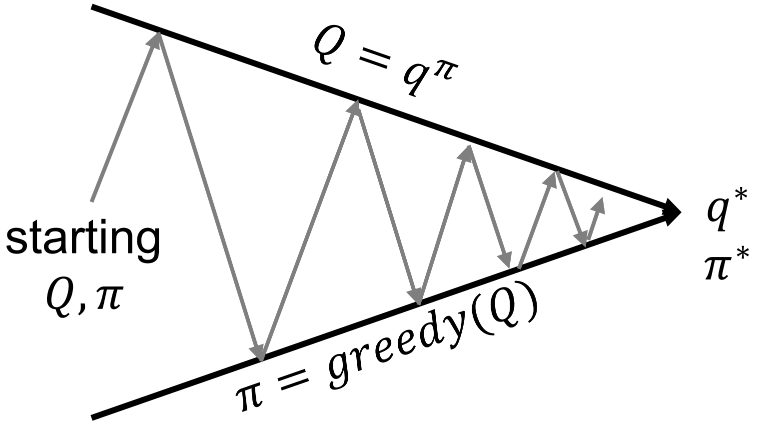

Policy Evaluation: Estimate $Q = q_{\pi}$
e.g., Monte Carlo Policy Evaluation

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Q-Learning and SARSA Algorithms

- Idea: your agent should not be afraid of trying something new ☺

thanks to @bomboclaater

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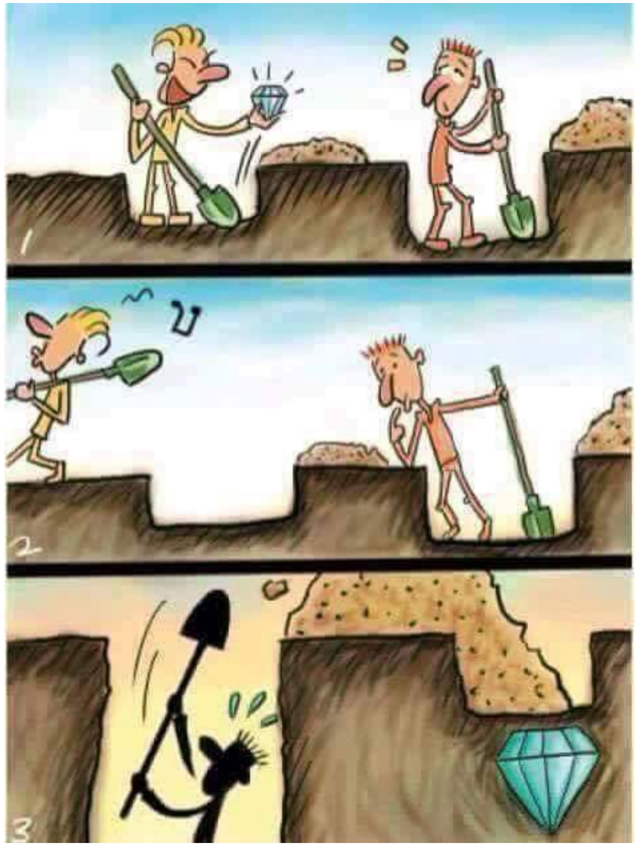
Q-Learning and SARSA Algorithms

Exploration vs. Exploitation



https://medium.com/deep-math-machine-learning-ai/ch-12-1-model-free-reinforcement-learning-algorithms-monte-carlo-sarsa-q-learning-65267cb8d1b4

Q-Learning and SARSA Algorithms

Exploration vs. Exploitation

"Behind one door is tenure - behind the other is flipping burgers at McDonald's."

- There are two doors in front of you.
- You open the left door and get reward 0
  $V(left) = 0$
- You open the right door and get reward +1
  $V(right) = +1$
- You open the right door and get reward +3
  $V(right) = +2$
- You open the right door and get reward +2
  $V(right) = +2$

$\vdots$

- Are you sure you've chosen the best door?

David Silver: Lectures on Reinforcement Learning. UCL Course on RL. 2015.

Q-Learning and SARSA Algorithms

- Greedy policy improvement problems:
  - Executes the best action according to the estimated value function
  - Non-optimal initial choices may disorient exploration
  - Areas of the state space remain unexplored!
- Solution: ε-greedy exploration
  - Seems simplistic but very difficult to do better in practice!
  - Either take the best action or explore the action space
  - ε = “probability of exploration”
  - It can be proven that any ε-greedy policy π' is an improvement over the ε-greedy policy π, $v_{\pi'}(s) \geq v_{\pi}(s)$

See “David Silver: Lectures on Reinforcement Learning. UCL Course on RL. 2015.” Lecture 5 on Control, slide 12 for a proof on this

- GLIE MC Control:

$$N(S_t, A_t) \leftarrow N(S_t, A_t) + 1 \quad Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \frac{1}{N(S_t, A_t)} \left(G_t - Q(S_t, A_t)\right)$$

  - Improve policy based on new action-value function ($\varepsilon \leftarrow \frac{1}{k}, \pi \leftarrow \varepsilon$-greedy$(Q)$)
  - Converges to the optimal action-value function $Q(S_t, A_t) \rightarrow q_*(s, a)$

Q-Learning and SARSA Algorithms

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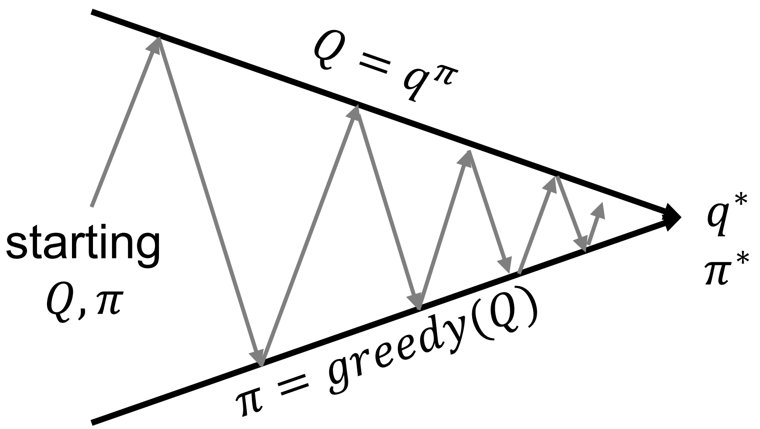

Policy Evaluation: Estimate $Q = q_\pi$
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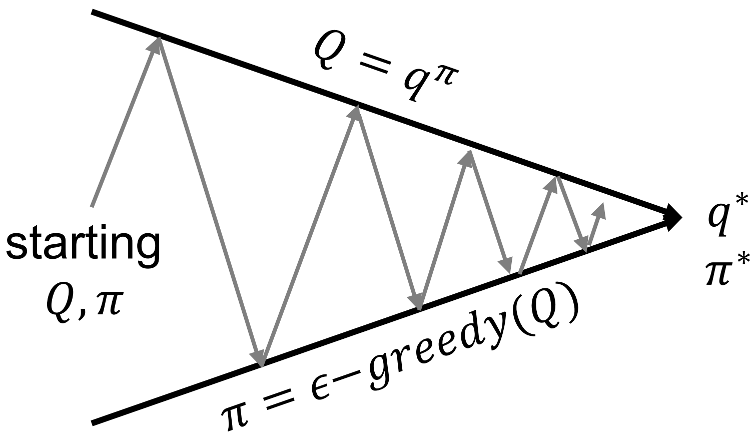

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Q-Learning and SARSA Algorithms

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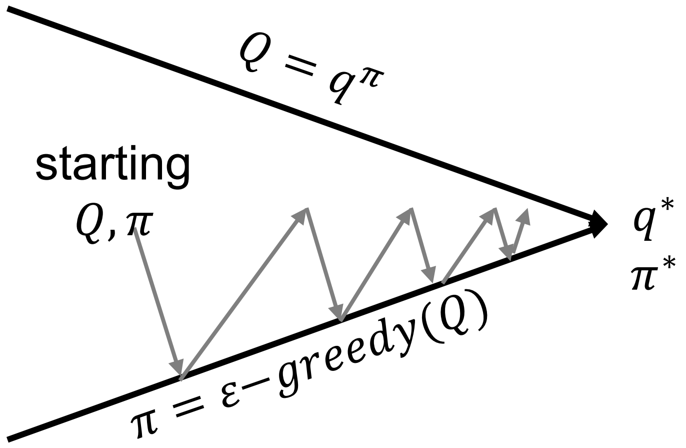

Every episode:

Policy Evaluation: Estimate $Q \approx q_{\pi}$
e.g., Monte Carlo Policy Evaluation

Policy Improvement: Generate $\pi' \geq \pi$
e.g., ϵ-greedy Policy Improvement over Q

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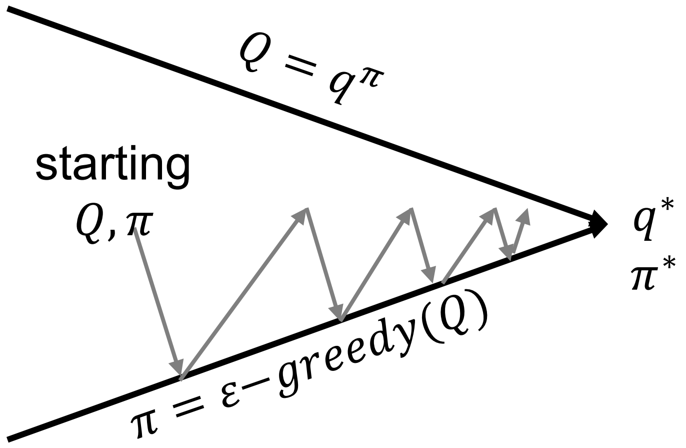
Q-Learning and SARSA Algorithms

- Greedy policy improvement problems:
  - Executes the best action according to the estimated value function
  - Non-optimal initial choices may disorient exploration
  - Areas of the state space remain unexplored!
- Solution: ε-greedy exploration



Every time step:

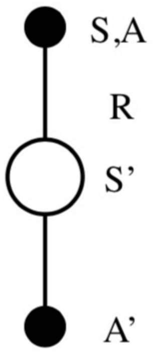
Policy Evaluation: Estimate $Q \approx q_{\pi}$
e.g., SARSA

Policy Improvement: Generate $\pi' \geq \pi$
e.g., ϵ-greedy Policy Improvement over Q

Q-Learning and SARSA Algorithms

SARSA algorithm (on-policy control)

- Apply TD to $Q(s, a)$
- Use ε-greedy policy improvement
- Update at every time-step



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 $Q(terminal, \cdot) = 0$

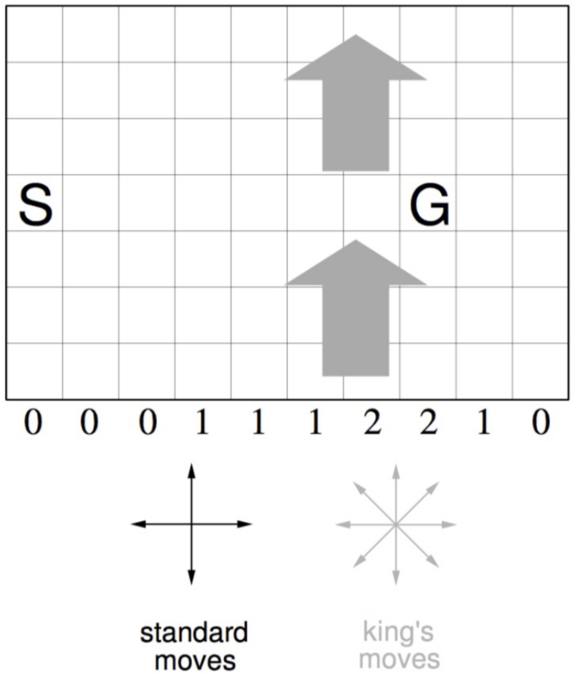
Loop for each episode:
  Initialize S
  Choose A from S using policy derived from Q (e.g., ε-greedy)
  Loop for each step of episode:
    Take action A, observe R, S'
    Choose A' from S' using policy derived from Q (e.g., ε-greedy)
    $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma Q(S', A') -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

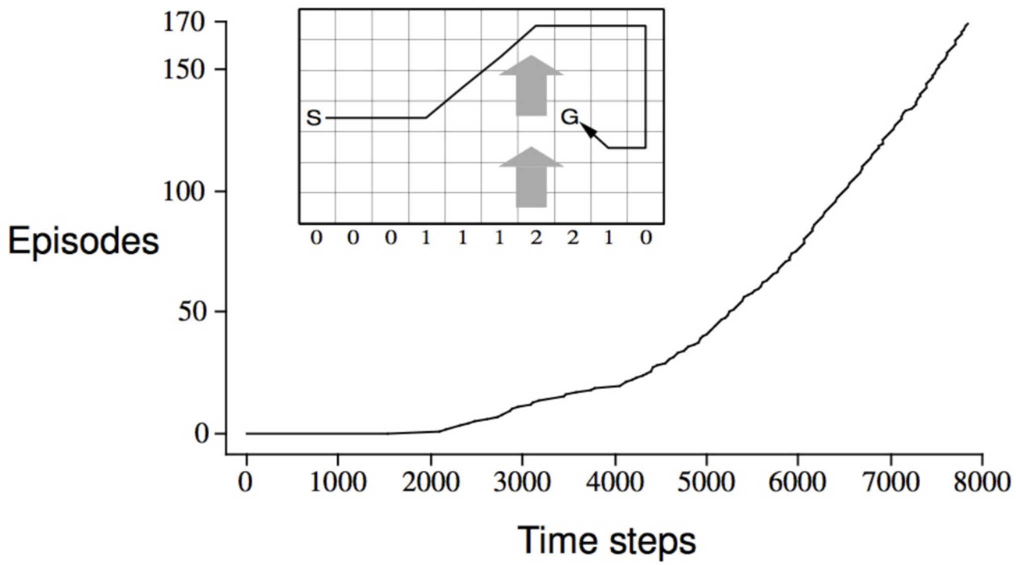
Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

Q-Learning and SARSA Algorithms

SARSA algorithm (on-policy control)

- Example: Windy Gridworld
  - Reward: -1 per time step; no discount





Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

Q-Learning and SARSA Algorithms

SARSA algorithm (on-policy control)

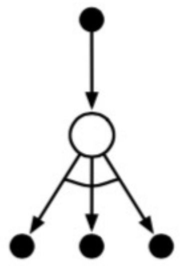
Pros & Cons

+ **Processes each sample immediately**
+ **Minimal update cost per sample**
- Poses constraints on sample collection (on-policy)
- Requires a huge number of samples
- Requires careful schedule for the learning rate
- Makes minimal use of each sample
- The ordering of samples influences the outcome
- Exhibits instabilities under approximate representations
- Requires careful handling on the policy greediness

Q-Learning and SARSA Algorithms

Q-Learning algorithm (off-policy control)

- Evaluate one policy while following another
- Can re-use experience gathered from old policies



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 $Q(terminal, \cdot) = 0$

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

Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

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Q-Learning and SARSA Algorithms

Q-Learning algorithm (off-policy control)

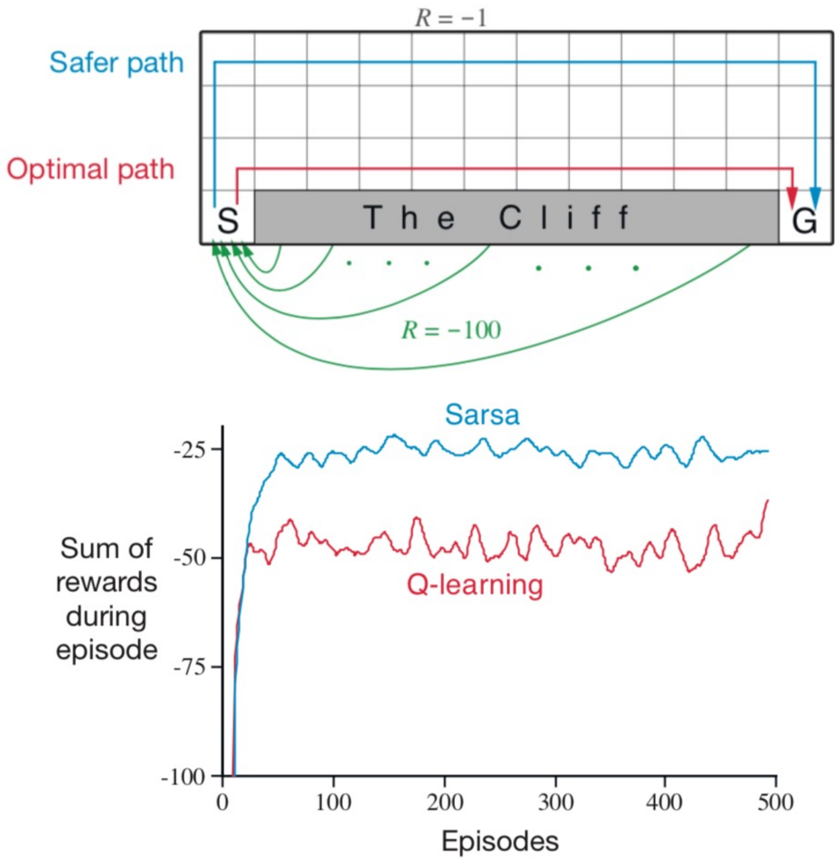
Pros and Cons

+ **Processes each sample immediately**
+ **Minimal update cost per sample**
+ **Poses no constraints on sample collection (off-policy)**
- Requires a huge number of samples
- Requires careful schedule for the learning rate
- Makes minimal use of each sample
- The ordering of samples influences the outcome
- Exhibits instabilities under approximate representations

Q-Learning and SARSA Algorithms

- Example: Cliff Walking
  - Every transition has reward of -1, falling off the cliff gives a reward of -100 and ends the episode
  - No discounting
  - Assume we use ε-greedy (0.1) for SARSA and Q-Learning, no decay.

- SARSA chooses the safe route, because SARSA incorporates the current policy (ε-greedy)
- Q-Learning chooses the optimal path (and falls of the cliff using the ε-greedy)



Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

Model-free Control: Remarks

Monte Carlo Control

- We only studied TD-based control in this lecture.
- Note: there is also an MC-based way to do control:
  (see Sutton and Barto's RL book pp. 97 – 103)

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

Initialize:
    $\pi(s) \in \mathcal{A}(s)$ (arbitrarily), for all $s \in \mathcal{S}$
    $Q(s,a) \in \mathbb{R}$ (arbitrarily), for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$
    $Returns(s,a) \leftarrow$ empty list, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$

Loop forever (for each episode):
    Choose $S_0 \in \mathcal{S}$, $A_0 \in \mathcal{A}(S_0)$ randomly such that all pairs have probability > 0
    Generate an episode from S_0, A_0, following π: $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$
    $G \leftarrow 0$
    Loop for each step of episode, $t = T-1, T-2, \ldots, 0$:
        $G \leftarrow \gamma G + R_{t+1}$
        Unless the pair S_t, A_t appears in $S_0, A_0, S_1, A_1 \ldots, S_{t-1}, A_{t-1}$:
            Append G to $Returns(S_t, A_t)$
            $Q(S_t, A_t) \leftarrow \text{average}(Returns(S_t, A_t))$
            $\pi(S_t) \leftarrow \arg\max_a Q(S_t, a)$

Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.

Off-policy vs. On-policy

Exercise 6.11 Why is Q-learning considered an *off-policy* control method? □

Q-Learning vs. SARSA with greedy policy

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

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 $Q(terminal, \cdot) = 0$

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

Exercise 6.12 Suppose action selection is greedy. Is Q-learning then exactly the same algorithm as Sarsa? Will they make exactly the same action selections and weight updates? □

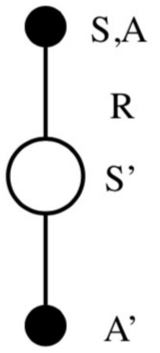
Q-Learning vs. SARSA

- Q-Learning estimates the return (total discounted future reward) for state-action pairs assuming a greedy policy (although it may follow an explorative policy)
- Instead, SARSA estimates the return for state-action pairs assuming the current policy (that it also follows)
- If the current policy is also a greedy policy, then the distinction disappears.
- SARSA will also get to the Q-Learning result if we decay ε (carefully!)

Q-Learning vs. SARSA

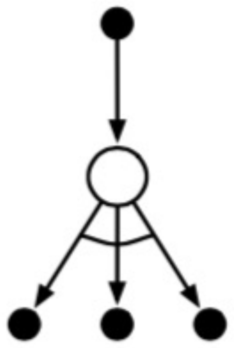
SARSA algorithm (on-policy control)

+ Processes each sample immediately
+ Minimal update cost per sample
- Requires a huge number of samples
- Requires careful schedule for the learning rate
- Makes minimal use of each sample
- The ordering of samples influences the outcome
- Exhibits instabilities under approximate representations
- Poses constraints on sample collection (on-policy)
- Requires careful handling on the policy greediness



Q-Learning algorithm (off-policy control)

+ Processes each sample immediately
+ Minimal update cost per sample
+ Poses no constraints on sample collection (off-policy)
- Requires a huge number of samples
- Requires careful schedule for the learning rate
- Makes minimal use of each sample
- The ordering of samples influences the outcome
- Exhibits (even more) instabilities under approximate representations



Double Q-Learning

Double Q-learning, for estimating $Q_1 \approx Q_2 \approx q_*$

Algorithm parameters: step size $\alpha \in (0,1]$, small $\varepsilon > 0$
Initialize $Q_1(s,a)$ and $Q_2(s,a)$, for all $s \in \mathcal{S}^+, a \in \mathcal{A}(s)$, such that $Q(terminal, \cdot) = 0$

Loop for each episode:
  Initialize S
  Loop for each step of episode:
    Choose A from S using the policy ε-greedy in $Q_1 + Q_2$
    Take action A, observe R, S'
    With 0.5 probabilility:

$$Q_1(S,A) \leftarrow Q_1(S,A) + \alpha\Big(R + \gamma Q_2\big(S', \arg\max_a Q_1(S',a)\big) - Q_1(S,A)\Big)$$

    else:

$$Q_2(S,A) \leftarrow Q_2(S,A) + \alpha\Big(R + \gamma Q_1\big(S', \arg\max_a Q_2(S',a)\big) - Q_2(S,A)\Big)$$

    $S \leftarrow S'$
  until S is terminal

Double Q-Learning

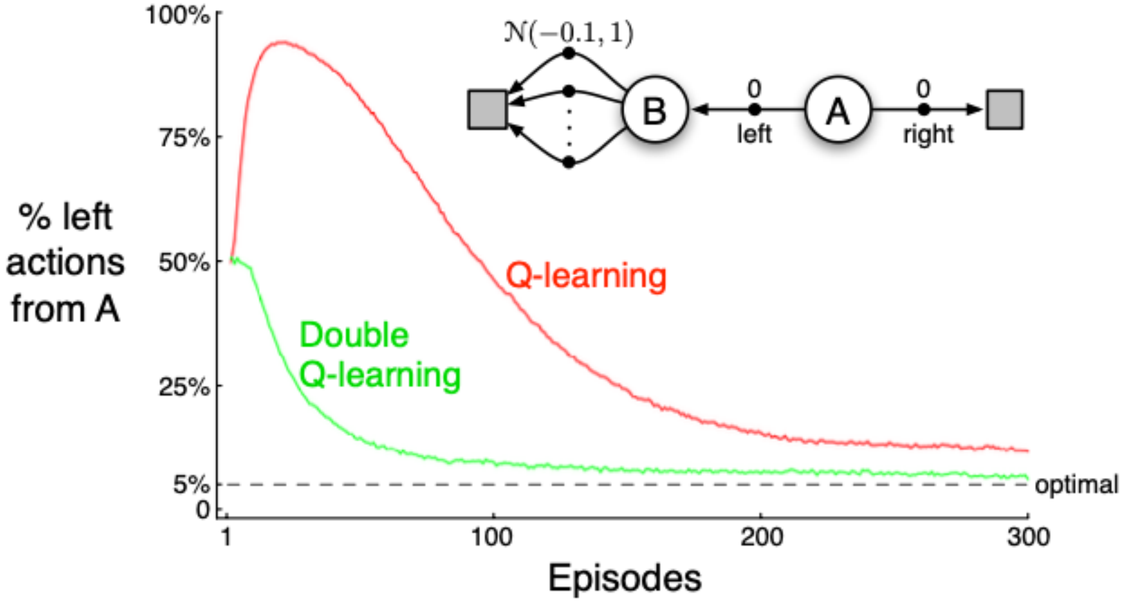


Figure 6.5: Comparison of Q-learning and Double Q-learning on a simple episodic MDP (shown inset). Q-learning initially learns to take the left action much more often than the right action, and always takes it significantly more often than the 5% minimum probability enforced by ε-greedy action selection with $\varepsilon = 0.1$. In contrast, Double Q-learning is essentially unaffected by maximization bias. These data are averaged over 10,000 runs. The initial action-value estimates were zero. Any ties in ε-greedy action selection were broken randomly.

Teaser: Alphastar

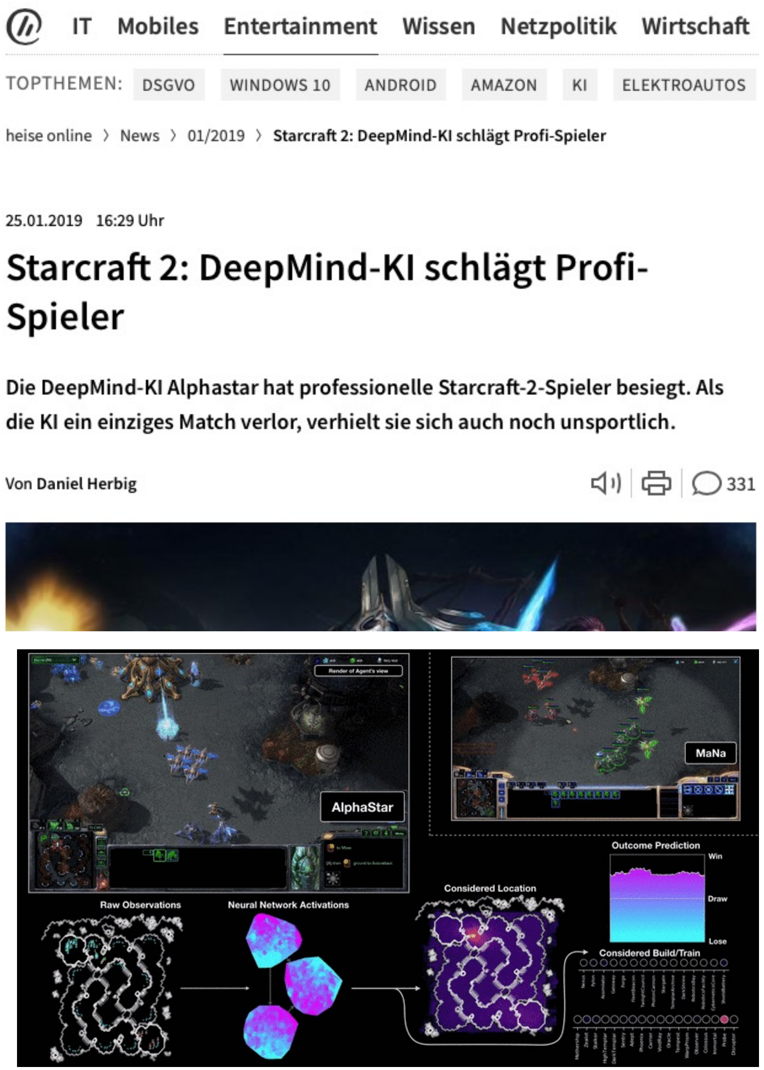
Challenge:

- Game theory: many „good“ strategies
- Imperfect information: crucial information is hidden
- Long-term planning: early actions pay off much later
- Real time: continual to game clock
- Large action space: hierarchical action space

Solution:

- Many nice tricks ☺
- LSTMs, autoregressive policy heads with pointer networks, multi-agent centralized value baselines, …
- It is really about population modelling!

More Info:
https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/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25.01.2019 16:29 Uhr

Starcraft 2: DeepMind-KI schlägt Profi-Spieler

Die DeepMind-KI Alphastar hat professionelle Starcraft-2-Spieler besiegt. Als die KI ein einziges Match verlor, verhielt sie sich auch noch unsportlich.

Von Daniel Herbig 331

Fraunhofer IIS

References

Books:

- Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.
- Bellman, R.E. 1957. Dynamic Programming. Princeton University Press.

Lectures:

- UC Berkeley CS188 Intro to AI. http://ai.berkeley.edu/lecture_slides.html
- UCL Course on RL. http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html
- Advanced Deep Learning and Reinforcement Learning (UCL + DeepMind). http://www.cs.ucl.ac.uk/current_students/syllabus/compgi/compgi22_advanced_deep_learning_and_reinforcement_learning
- Pieter Abbeel: CS 188 Introduction to Artificial Intelligence. Fall 2018

Blogs etc.:

- https://cs.stanford.edu/people/karpathy/reinforcejs/gridworld_td.html