Model Free Control

Lecture 5

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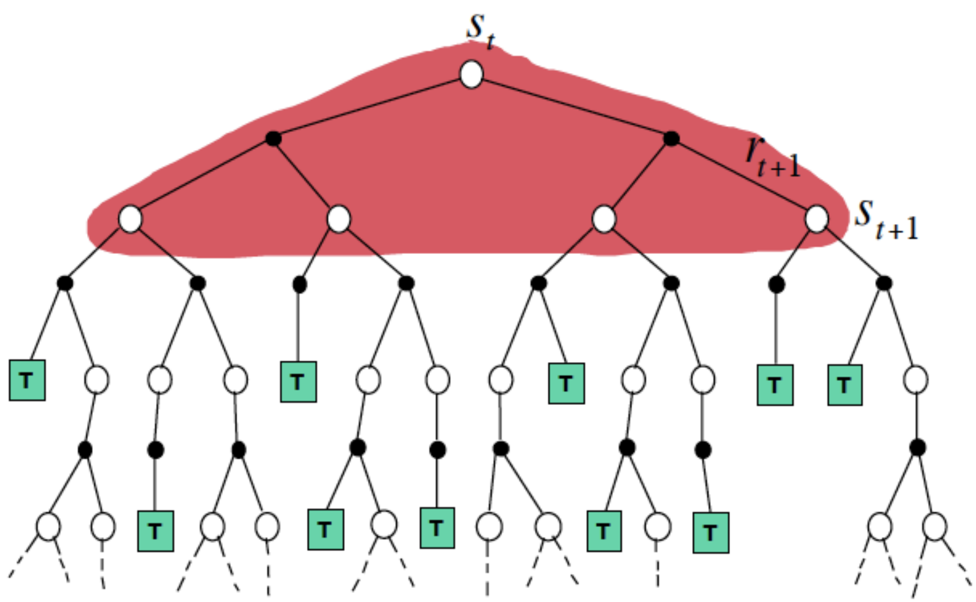
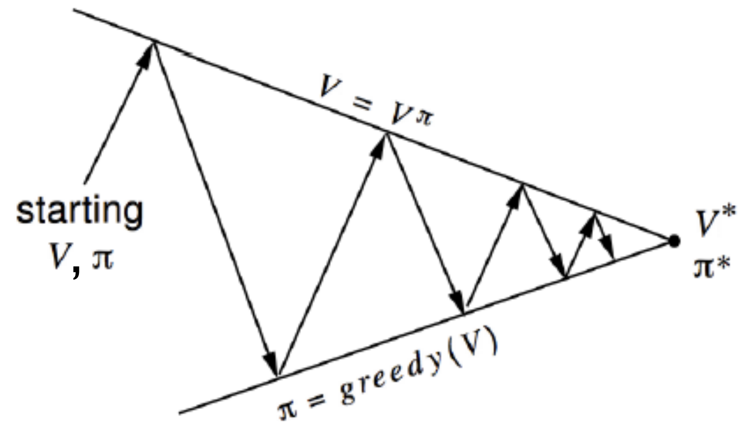
Model Based Policy Evaluation and Optimal Control (Lecture 3)

Model Based
Full Sweep
Full Backup



$$v_{k+1}(s) = \sum_{a \in \mathcal{A}} \pi(a|s) \left(\mathcal{R}_s^a + \gamma \sum_{s' \in \mathcal{S}} \mathcal{P}_{ss'}^a v_k(s') \right)$$

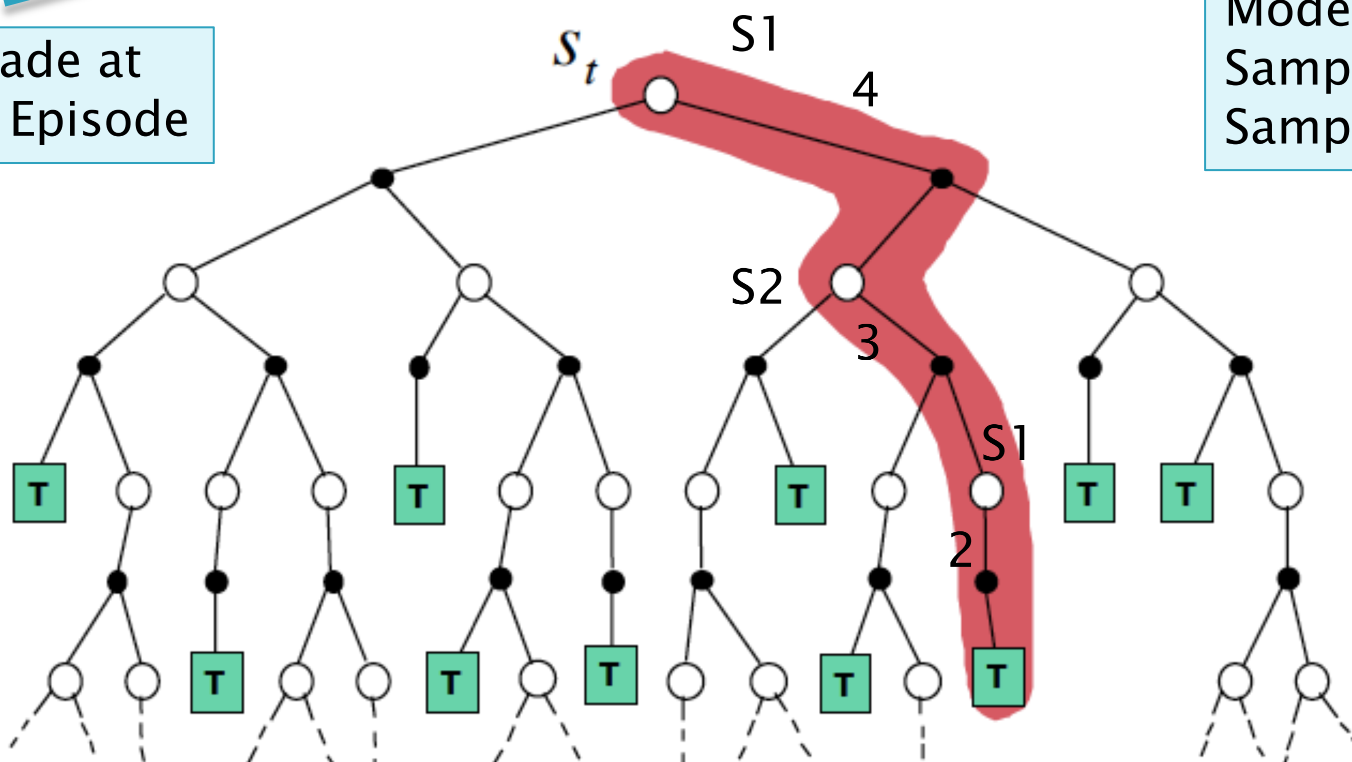


Full Policy Iteration
Generalized Policy Iteration

Model Free Policy Evaluation: Monte Carlo Learning (Lecture 4)

$$V(S_t) \leftarrow V(S_t) + \alpha\,(G_t - V(S_t))$$

Update made at end of an Episode



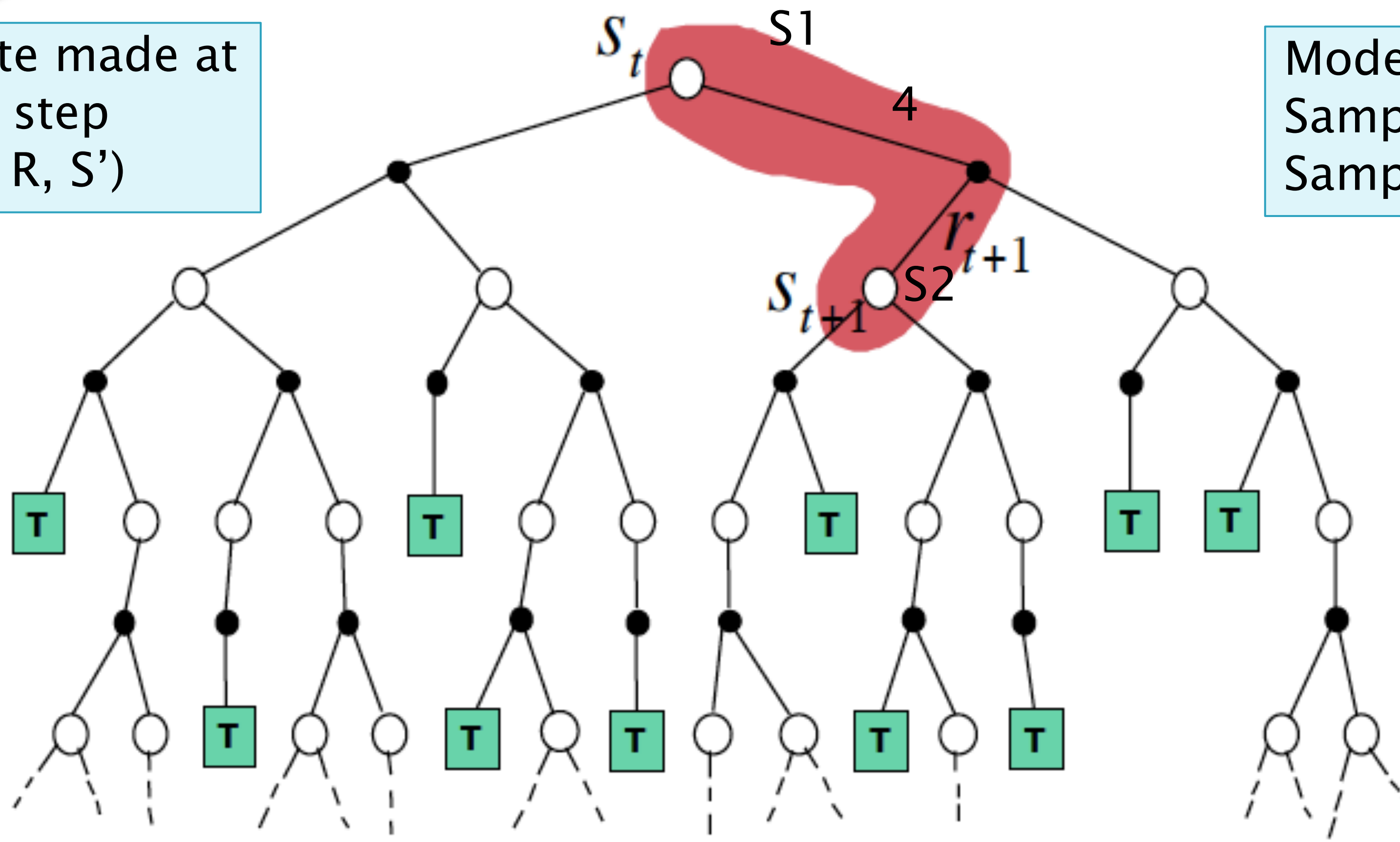
Model Free
Sample Sweep
Sample Backup

Instead of a Model, we now have sample episodes from the MDP

Model Free Policy Evaluation: Temporal-Difference (TD) Learning (Lecture 4)

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

Update made at every step (S, A, R, S')



Model Free
Sample Sweep
Sample Backup

Instead of a Model, we now have sample episodes from the MDP

The Next Step..

So Far: We have algorithms to find the Value Function v_π, given a policy π (with or without a model)

But: We are really interested in finding the Optimal Policy π_*

Model Free Reinforcement Learning

- Last lecture:
    - Model-free prediction
    - *Estimate* the value function of an *unknown* MDP

- This lecture:
    - Model-free control
    - *Optimise* the value function of an *unknown* MDP

Uses of Model-Free Control

Some example problems that can be modelled as MDPs

- Elevator
- Parallel Parking
- Ship Steering
- Bioreactor
- Helicopter
- Aeroplane Logistics
- Robocup Soccer
- Quake
- Portfolio management
- Protein Folding
- Robot walking
- Game of Go

❑ RL based on Human Feedback (RLHF)

For most of these problems, either:

- MDP model is unknown, but experience can be sampled
- MDP model is known, but is too big to use, except by samples

Model-free control can solve these problems

On and Off-Policy Learning

- On-policy learning
  - "Learn on the job"
  - Learn about policy π from experience sampled from π

Policy being used to generate episode is the same as the policy being learnt

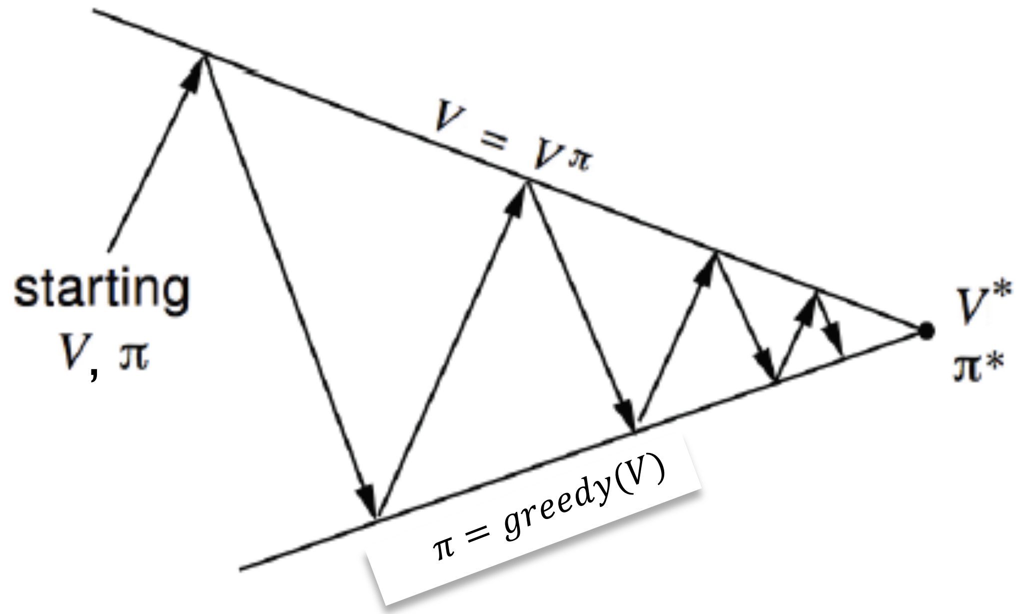
- Off-policy learning
  - "Look over someone's shoulder"
  - Learn about policy π from experience sampled from μ

Policy being used to generate episode is the different than the policy being learnt

Monte Carlo Control

Generalized Policy Iteration

We computed v_π by using the Bellman Expectation Equation



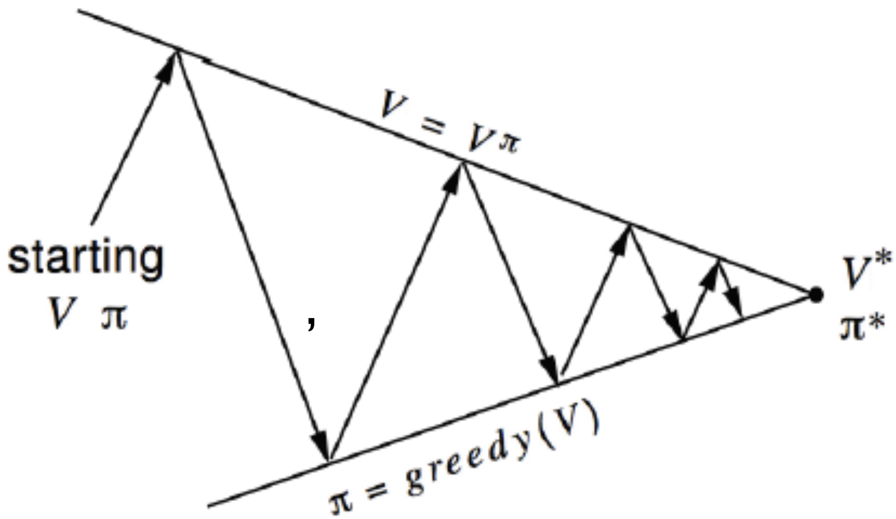
Policy evaluation Estimate $\boxed{V_\pi}$

e.g. Iterative policy evaluation

Policy improvement Generate $\pi' \geq \pi$

e.g. Greedy policy improvement

Generalized Policy Iteration with Monte Carlo Evaluation



Instead of using Bellman Expectation Equation to compute v_π, we are using Monte Carlo Policy evaluation to estimate V_π

Policy evaluation Monte-Carlo policy evaluation, $V = v_\pi$?

Policy improvement Greedy policy improvement?

What is wrong with this approach?

Model–Free Policy Iteration Using Action–Value Function

- Greedy policy improvement over $V(s)$ requires model of MDP

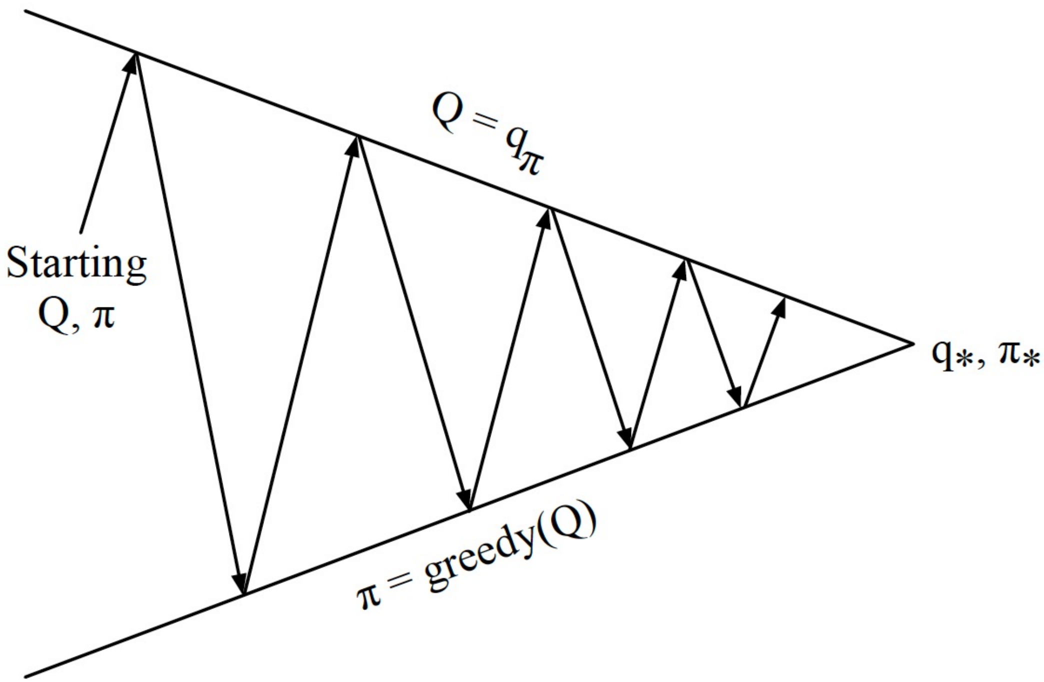
$$\pi'(s) = \underset{a \in \mathcal{A}}{\operatorname{argmax}} \left[\mathcal{R}_s^a + \sum \mathcal{P}_{ss'}^a V(s') \right]$$

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

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

Estimating V_π(s) is not enough, we need to estimate Q_π(s,a)

Generalized Policy Iteration with Action-Value Function



Evaluate new action VF Q_π(s,a)
Compute new policy

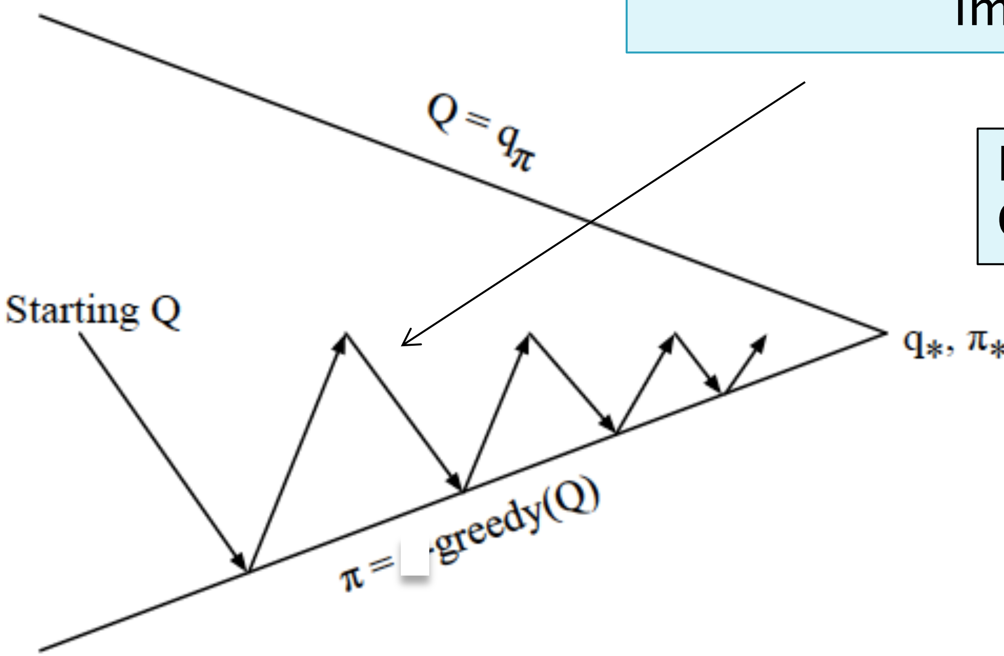
Policy evaluation Monte-Carlo policy evaluation, $Q = q_\pi$

Policy improvement Greedy policy improvement?

Generalized Policy Iteration with Action-Value Function

Run a single episode, and then immediately improve the Policy!

Evaluate new action VF Q_{π}(s,a)
Compute new policy



Every episode:

Policy evaluation Monte-Carlo policy evaluation, $Q \approx q_\pi$

Policy improvement -greedy policy improvement

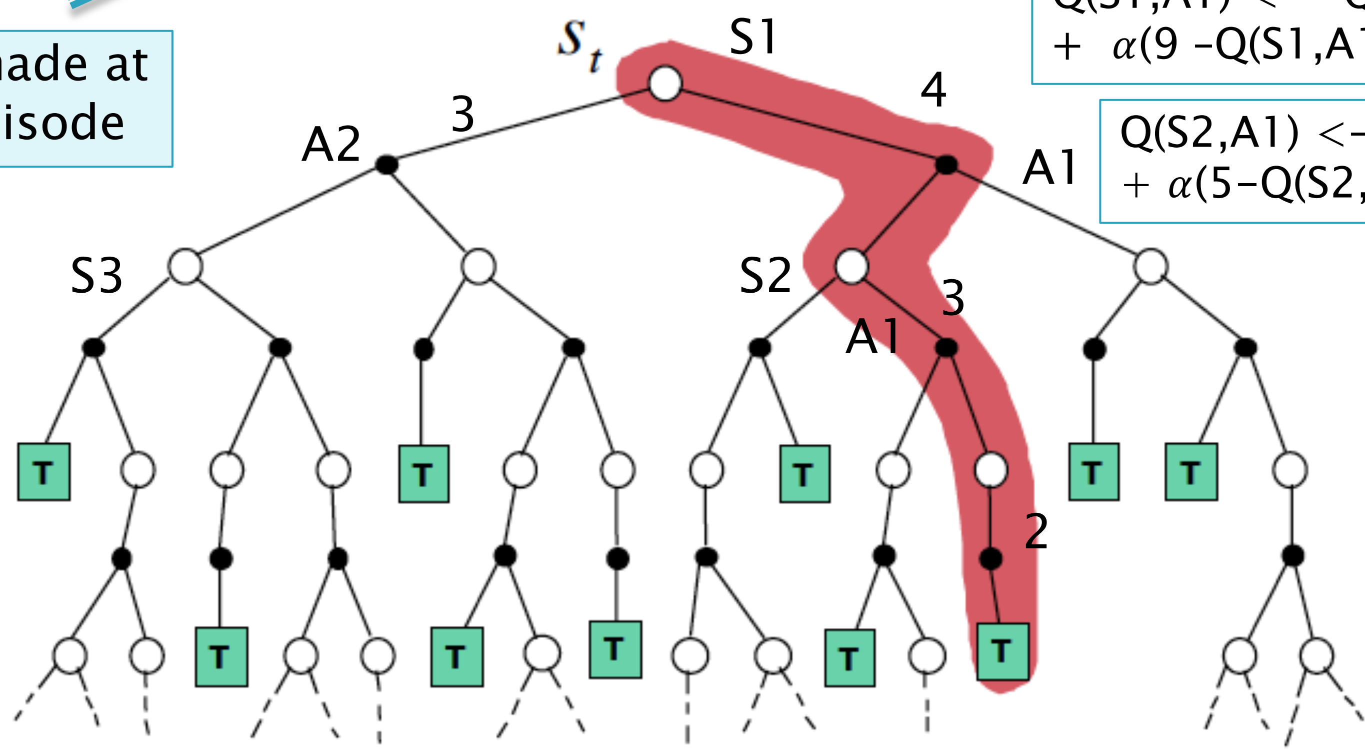
Monte Carlo Backup for Q

$$Q(S,A) \leftarrow Q(S,A) + \alpha(G - Q(S,A))$$

Update made at end of episode

Q(S1,A1) <-- Q(S1,A1) + α(9 -Q(S1,A1))

Q(S2,A1) <-- Q(S2,A1) + α(5−Q(S2,A1))

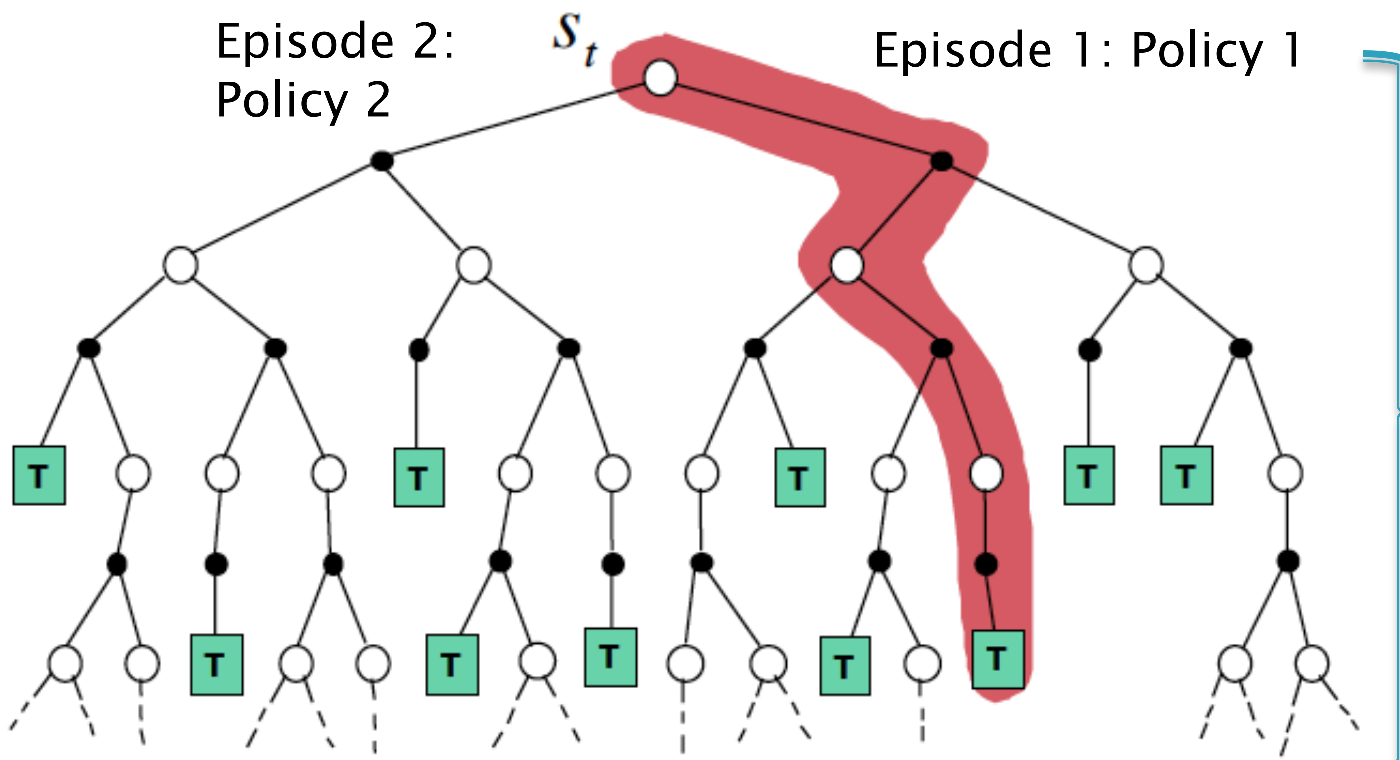


Q(S,A) Update => Policy Update
Policy changes at end of every episode

Another Problem:
How to ensure that every (S,A) pair is visited?

Model Free Monte Carlo Control

$$Q(S, A) \leftarrow Q(S, A) + \alpha(G - Q(S, A))$$



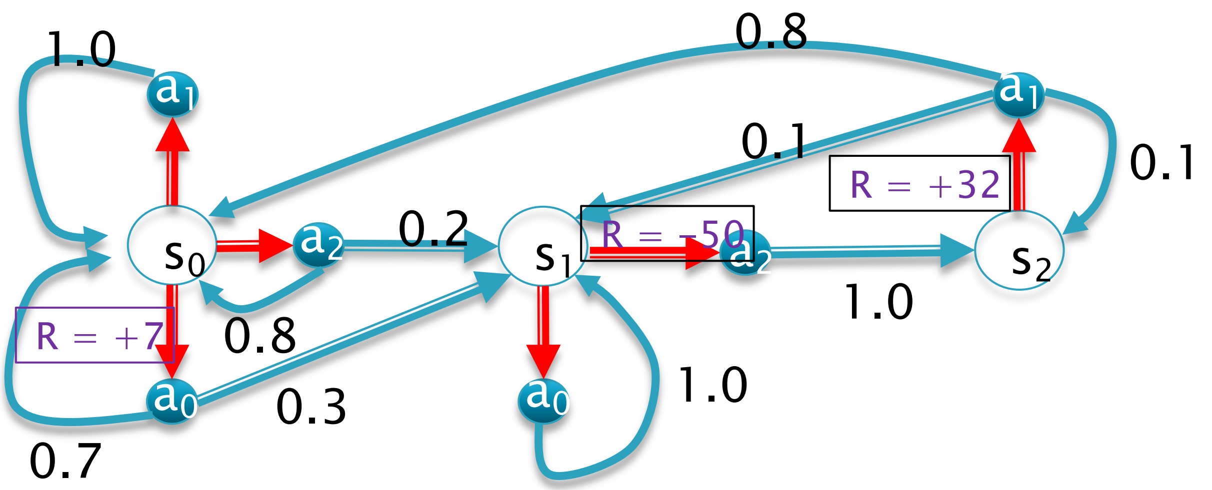
All of the Actions are chosen according to Policy π

Episode

0,0 → 1,2 (–50) → 2,1 (32) → 0,0 (7) → 0,0 (7) → 0,0 (7) →
0,0 → 1,2 (–50) → 2,1 (32) → 0,0

Policy Improvement Update made at end of an Episode

Example: Q(S,A) Evaluation



$\pi(s_0) = a_0$

$\pi(s_1) = a_2$

$\pi(s_2) = a_1$

```
policy_fire
States (+rewards): 0 1 (-50) 2 (40) 0 (10) 0 (10) 0 (10) 0 1 (-50) 2 (40) 0 ... Total rewards = -220
States (+rewards): 0 (10) 0 (10) 0 (10) 0 (10) 0 (10) 0 (10) 0 (10) 0 (10) 0 (10) 0 ... Total rewards = 40
States (+rewards): 0 (10) 0 (10) 0 (10) 0 1 (-50) 2 (40) 0 (10) 0 1 (-50) 2 (40) ... Total rewards = 160
States (+rewards): 0 (10) 0 (10) 0 (10) 0 (10) 0 (10) 0 1 (-50) 2 (40) 0 (10) 0 (10) ... Total rewards = 280
States (+rewards): 0 (10) 0 1 (-50) 2 1 (-50) 2 (40) 0 (10) 0 (10) 0 (10) 0 (10) ... Total rewards = 190
Summary: mean=122.2, std=134.956674, min=-340, max=490
```

0 → 1 (−50) → 2 (32) → 0 (7) → 0 (7) → 0 (7) → 0 → 1 (−50) → 2 (32) → 0 …

Estimating V

Estimating Q

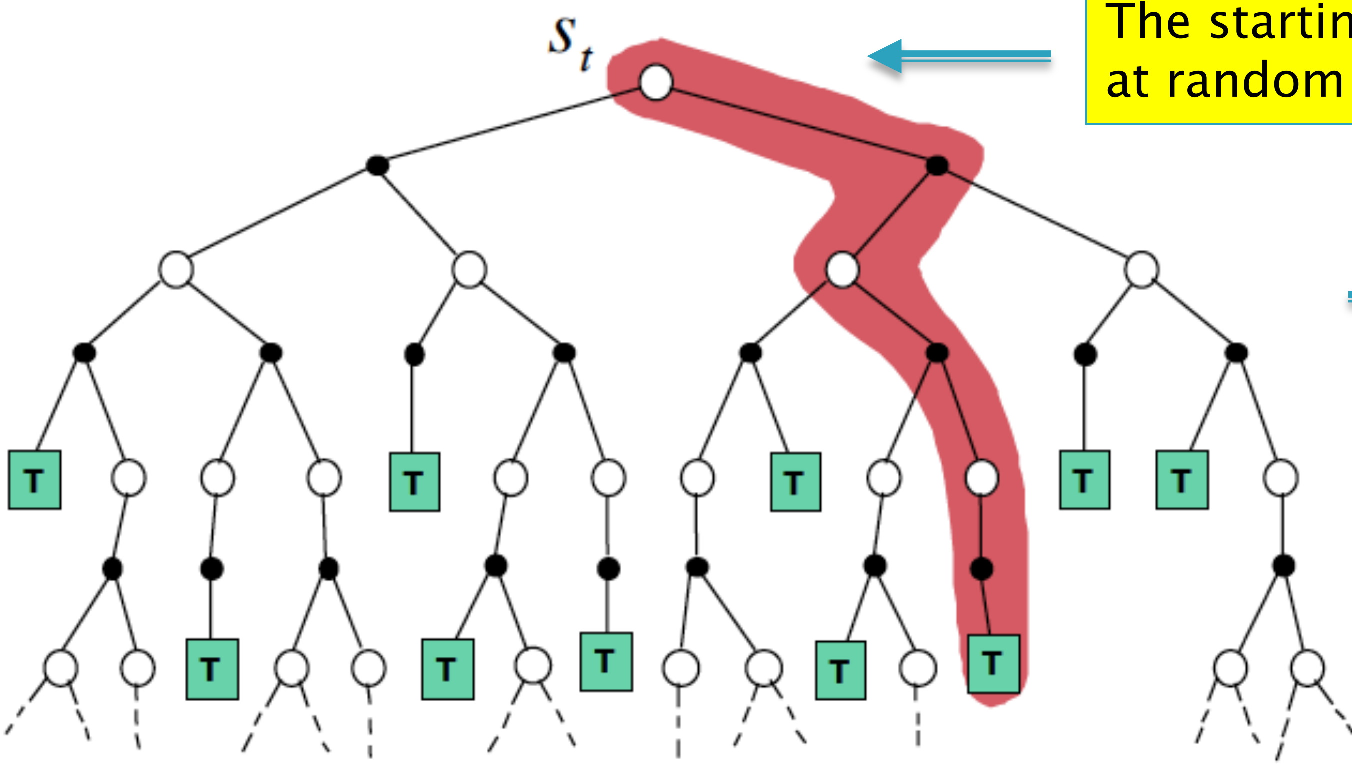
0,2 → 1,2 (−50) → 2,1 (32) → 0,0 (7) → 0,0 (7) → 0,0 (7) →
0,0 → 1,2 (−50) → 2,1 (32) → 0,0 …

Monte Carlo Backup for Action Value Functions with Exploring Starts

Update made at end of an Episode

$$Q(S,A) \leftarrow Q(S,A) + \alpha(G - Q(S,A))$$

The starting (S,A) is chosen at random for each episode



Rest of the Actions are chosen according to Policy π

Policy Improvement Update made at end of an Episode

Monte Carlo Control with Exploring Starts

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

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

Repeat forever:
    Choose $S_0 \in \mathcal{S}$ and $A_0 \in \mathcal{A}(S_0)$ s.t. all pairs have probability > 0
    Generate an episode starting from S_0, A_0, following π
    For each pair s, a appearing in the episode:
        $G \leftarrow$ the return that follows the first occurrence of s, a
        Append G to $Returns(s, a)$
        $Q(s, a) \leftarrow \text{average}(Returns(s, a))$
    For each s in the episode:
        $\pi(s) \leftarrow \arg\max_a Q(s, a)$

How to Avoid the Exploring Starts Assumption

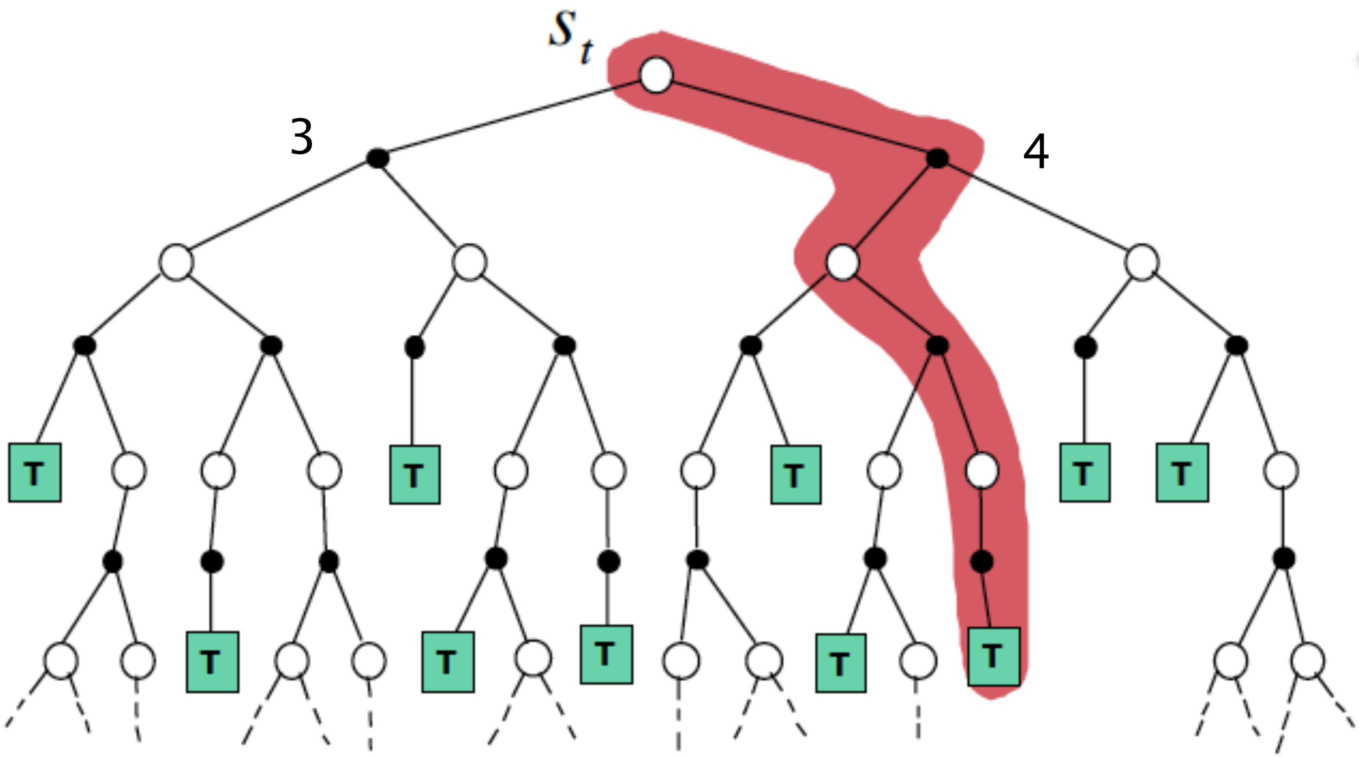
The initial State and Action may not be under our control

General Strategy: Continue to select all possible Actions (even during an episode)

But: The agent is supposed to follow Policy π.

Idea: Randomize the Policy!

$$Q(S,A) \leftarrow Q(S,A) + \alpha(G - Q(S,A))$$



All of the Actions are chosen according to Policy π'

π' is a Random Policy

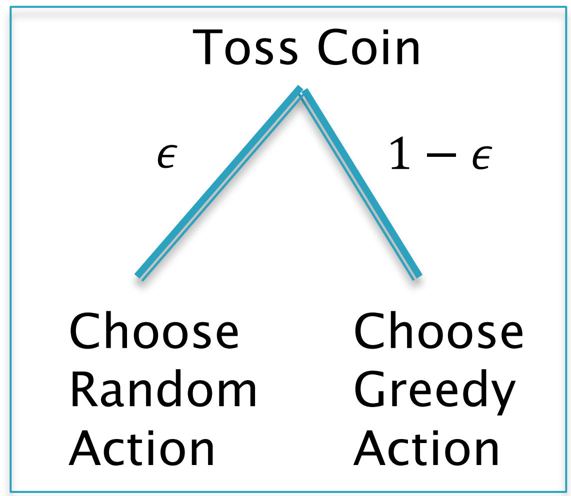
Policy Improvement Update made at end of an Episode

ε –Greedy Exploration

- Simplest idea for ensuring continual exploration
- All m actions are tried with non-zero probability
- With probability $1 - \epsilon$ choose the greedy action
- With probability ϵ choose an action at random

$$\pi(a|s) = \begin{cases} \epsilon/m + 1 - \epsilon & \text{if } a^* = \underset{a \in \mathcal{A}}{\operatorname{argmax}}\ Q(s,a) \\ \epsilon/m & \text{otherwise} \end{cases}$$

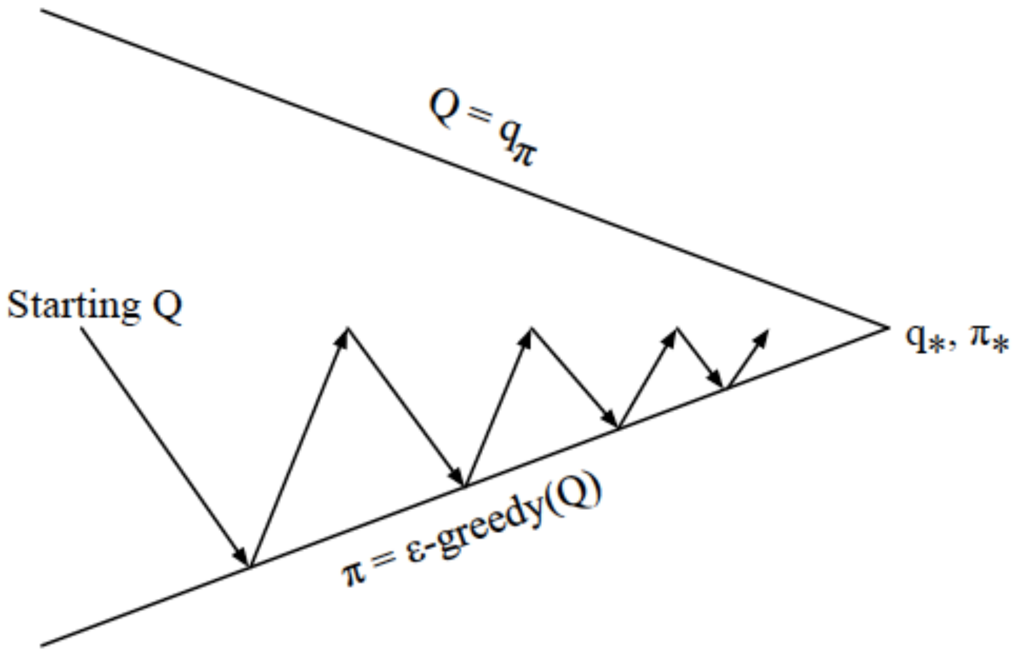
Works very well in practice
Guarantees that you continue to explore everything
Guarantees that you improve your policy



Exploration and Exploitation

- *Exploration* finds more information about the environment
- *Exploitation* exploits known information to maximise reward
- It is usually important to explore as well as exploit

Generalized Policy Iteration with Action-Value Function and ϵ Greedy Exploration



Every episode:

Policy evaluation Monte-Carlo policy evaluation, $Q \approx q_\pi$

Policy improvement ϵ-greedy policy improvement

On–Policy First Visit MC Control with ε Greedy Policies

On-policy first-visit MC control (for ε-soft policies), estimates $\pi \approx \pi_*$

Initialize, for all $s \in \mathcal{S}$, $a \in \mathcal{A}(s)$:
  $Q(s,a) \leftarrow$ arbitrary
  $Returns(s,a) \leftarrow$ empty list
  $\pi(a|s) \leftarrow$ an arbitrary ε-soft policy

Repeat forever:
  (a) Generate an episode using π
  (b) For each pair s, a appearing in the episode:
    $G \leftarrow$ the return that follows the first occurrence of s, a
    Append G to $Returns(s,a)$
    $Q(s,a) \leftarrow \text{average}(Returns(s,a))$
  (c) For each s in the episode:
    $A^* \leftarrow \arg\max_a Q(s,a)$ (with ties broken arbitrarily)
    For all $a \in \mathcal{A}(s)$:
$$\pi(a|s) \leftarrow \begin{cases} 1 - \varepsilon + \varepsilon/|\mathcal{A}(s)| & \text{if } a = A^* \\ \varepsilon/|\mathcal{A}(s)| & \text{if } a \neq A^* \end{cases}$$

On Policy: Policy being used to generate episode is the same as the policy being learnt

Example: Monte Carlo

$\alpha = 0.8, \gamma = 1$

- **Given the following episode:**

(s1,a0) (r = 3) → (s0,a0) (r = 2) → (s2,a1) (r = -1) → (s0,a0)

assume that the Q values in the starting iteration are given by the following table:

Q(s,a)	a0	a1
s0	2	-1
s1	4	3
s2	0	5

(d) Monte Carlo $\quad Q(S,A) \leftarrow Q(S,A) + \alpha(G - Q(S,A))$

$q(s_1, a_0) = 4 + 0.8 \times ((3+2-1) - 4) = 4$

$q(S_0, a_0) = 2 + 0.8 \times ((2-1) - 2) = 1.2$

$q(S_2, a_1) = 5 + 0.8 \times (-1-5) = 0.2$

ε –Greedy Policy Improvement

Is the ε greedy policy π' actually better than the old policy π?

Theorem

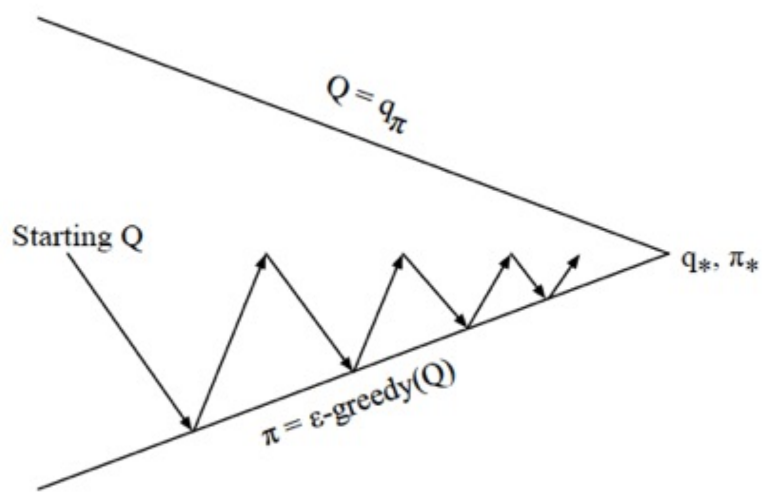
For any ϵ-greedy policy π, the ϵ-greedy policy π' with respect to q_π is an improvement, $v_{\pi'}(s) \geq v_\pi(s)$

$$
\begin{aligned}
v_{\pi'}(s) &= \sum_{a \in \mathcal{A}} \pi'(a|s) q_\pi(s, a) \\
&= \epsilon/m \sum_{a \in \mathcal{A}} q_\pi(s, a) + (1 - \epsilon) \max_{a \in \mathcal{A}} q_\pi(s, a) \\
&\geq \epsilon/m \sum_{a \in \mathcal{A}} q_\pi(s, a) + (1 - \epsilon) \sum_{a \in \mathcal{A}} \frac{\pi(a|s) - \epsilon/m}{1 - \epsilon} q_\pi(s, a) \\
&= \sum_{a \in \mathcal{A}} \pi(a|s) q_\pi(s, a) = v_\pi(s)
\end{aligned}
$$

Therefore from policy improvement theorem, $v_{\pi'}(s) \geq v_\pi(s)$

One More Problem …

- We know that the Optimal Policy is NOT Random
- We need a way to gradually reduce the randomness in the Policy



Solution: GLIE

Definition

Greedy in the Limit with Infinite Exploration (GLIE)

- All state-action pairs are explored infinitely many times,

$$\lim_{k \to \infty} N_k(s, a) = \infty$$

- The policy converges on a greedy policy,

$$\lim_{k \to \infty} \pi_k(a|s) = \mathbf{1}(a = \operatorname*{argmax}_{a' \in \mathcal{A}} Q_k(s, a'))$$

True for epsilon greedy

Policy eventually becomes greedy

- For example, ϵ-greedy is GLIE if ϵ reduces to zero at $\epsilon_k = \frac{1}{k}$

GLIE Monte-Carlo Control

- Sample kth episode using π: $\{S_1, A_1, R_2, ..., S_T\} \sim \pi$
- For each state S_t and action A_t in the episode,

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

- Improve policy based on new action-value function

$$\epsilon \leftarrow 1/k$$
$$\pi \leftarrow \epsilon\text{-greedy}(Q)$$

Theorem

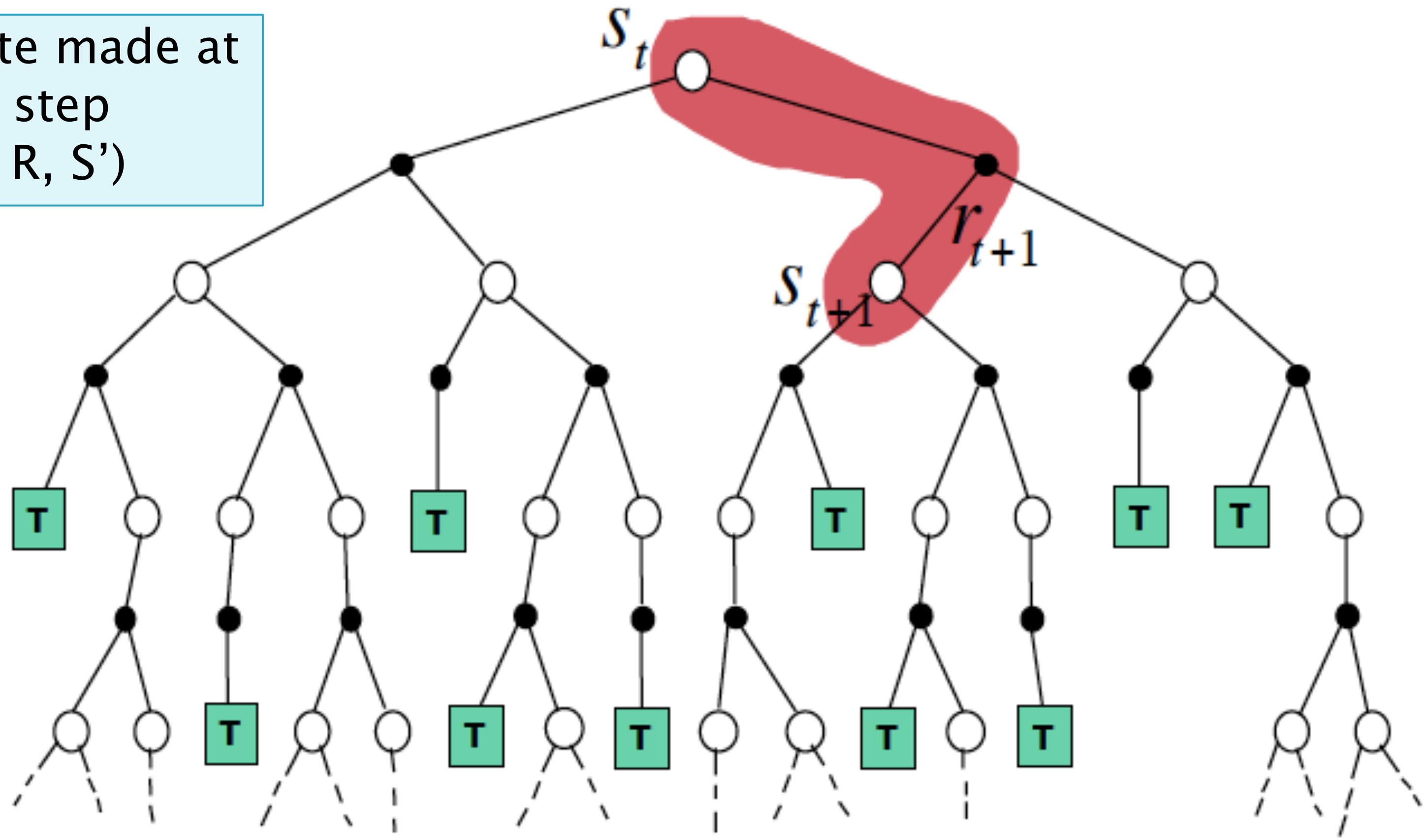
GLIE Monte-Carlo control converges to the optimal action-value function, $Q(s, a) \rightarrow q_*(s, a)$

On Policy TD Control: The SARSA Algorithm

Recall: Temporal-Difference (TD) Learning

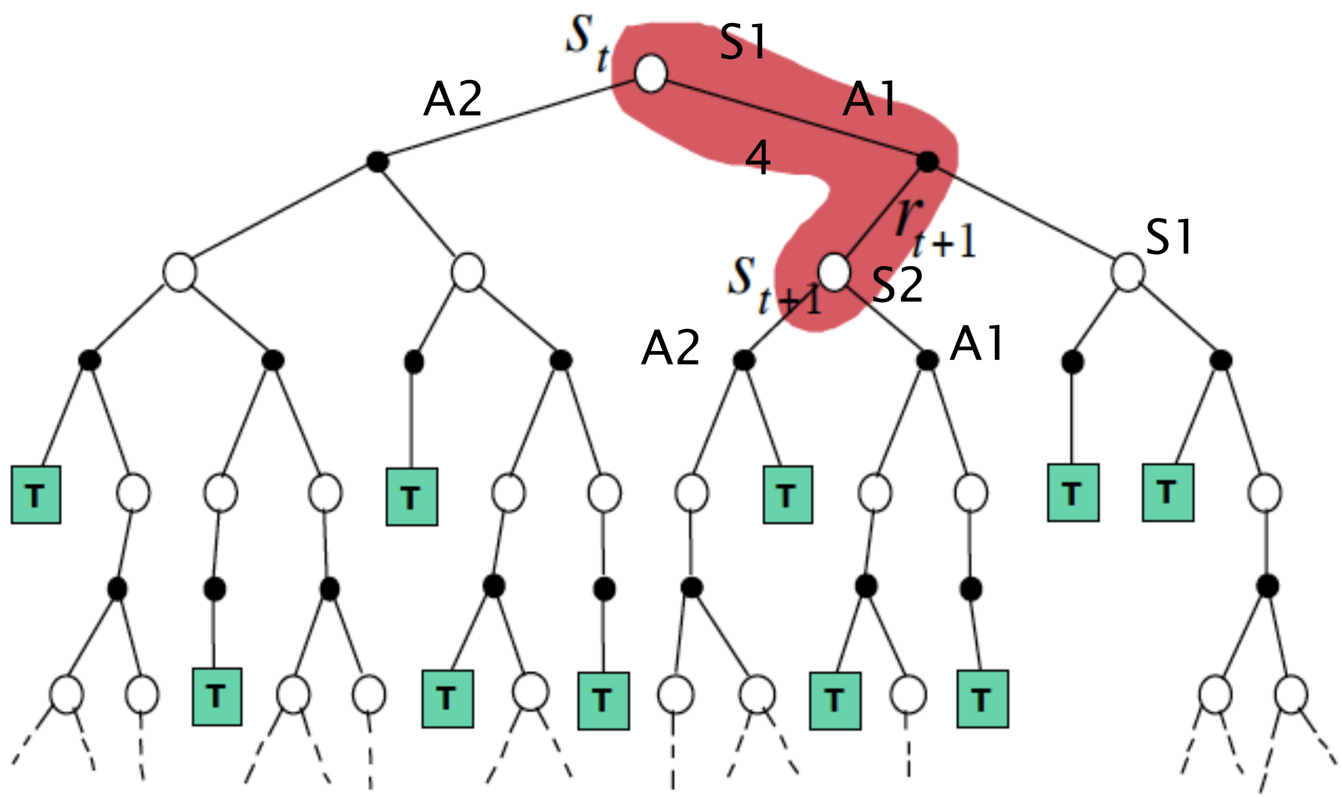
$$V(S_t) \leftarrow V(S_t) + \alpha \left(R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \right)$$

Update made at every step (S, A, R, S')



Model Free On Policy Temporal-Difference Algorithm: SARSA

$$Q(S,A) \leftarrow Q(S,A) + \alpha \left(R + \gamma Q(S',A') - Q(S,A) \right)$$

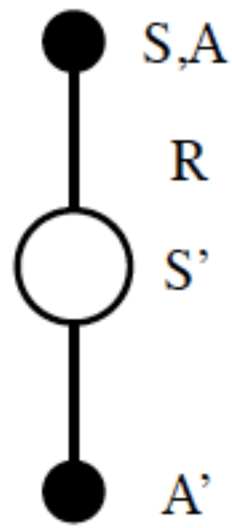


Actions are chosen according to Policy $\pi 1$

Actions are chosen according to Improved Policy π

Policy Improvement Update made after each step!

Updating Q Functions with SARSA



Start from (S,A)

Sample S'

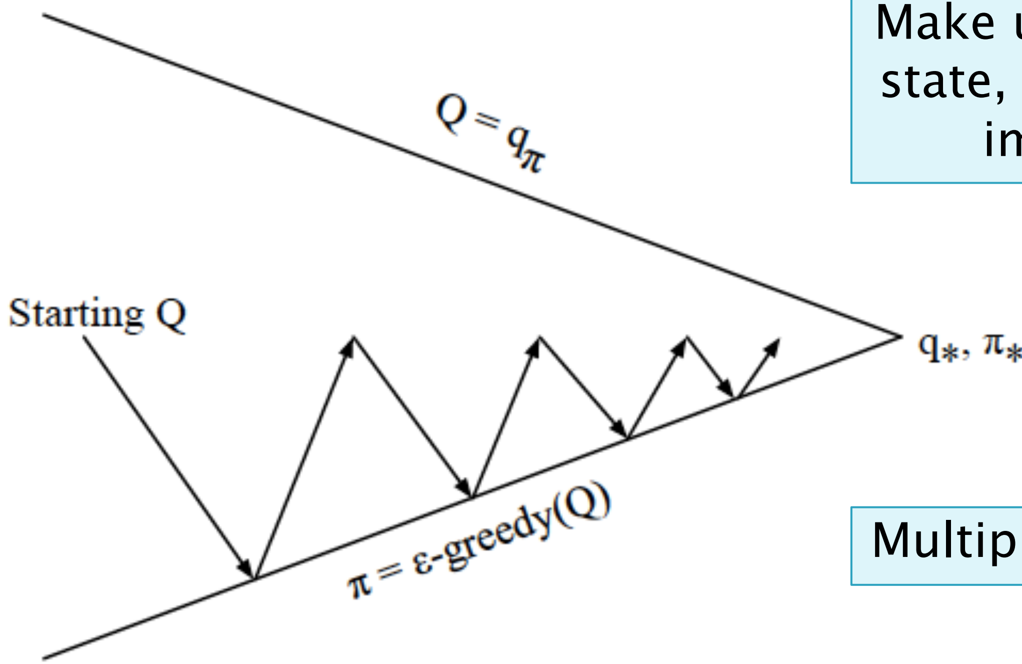
Sample A'

$$Q(S,A) \leftarrow Q(S,A) + \alpha\left(R + \gamma Q(S',A') - Q(S,A)\right)$$

For Value Functions:

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

On-Policy Control with SARSA



Make update to just a single state, and then immediately improve the Policy!

Multiple updates per episode

Every time-step:

Policy evaluation Sarsa, $Q \approx q_\pi$

Policy improvement ϵ-greedy policy improvement

SARSA Algorithm for On-Policy Control

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

Initialize $Q(s, a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Choose A from S using policy derived from Q (e.g., ϵ-greedy)
    Repeat (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

On Policy: Policy being used to generate episode is the same as the policy being learnt

Example: SARSA

$\alpha = 0.8, \gamma = 1$

- **Given the following episode:**

(s1,a0) (r = 3) → (s0,a0) (r = 2) → (s2,a1) (r = -1) → (s0,a0)

assume that the Q values in the starting iteration are given by the following table:

Q(s,a)	a0	a1
s0	2	-1
s1	4	3
s2	0	5

(a) SARSA: $Q(S,A) \leftarrow Q(S,A) + \alpha\,(R + \gamma Q(S',A') - Q(S,A))$

$q(s_1, a_0) = q(s_1, a_0) + 0.8 \times (3 + q(s_0, a_0) - q(s_1, a_0))$

$= 4 + 0.8 \times (3 + 2 - 4) = 4.8$

$q(s_0, a_0) = q(s_0, a_0) + 0.8 \times (2 + q(s_2, a_1) - q(s_0, a_0))$

$= 2 + 0.8 \times (2 + 5 - 2) = 6$

$q(s_2, a_1) = q(s_2, a_1) + 0.8 \times (-1 + q(s_0, a_0) - q(s_2, a_1))$

$= 5 + 0.8 \times (-1 + 6 - 5) = 5$

MC vs TD Control

- Temporal-difference (TD) learning has several advantages over Monte-Carlo (MC)
    - Lower variance
    - Online
    - Incomplete sequences

Convergence of SARSA

Theorem

Sarsa converges to the optimal action-value function, $Q(s, a) \to q_*(s, a)$, under the following conditions:

- *GLIE sequence of policies $\pi_t(a|s)$*
- *Robbins-Monro sequence of step-sizes α_t*

$$\sum_{t=1}^{\infty} \alpha_t = \infty$$

$$\sum_{t=1}^{\infty} \alpha_t^2 < \infty$$

Off Policy Temporal Difference Control: The Q Learning Algorithm

On and Off-Policy Learning

- On-policy learning
  - "Learn on the job"
  - Learn about policy π from experience sampled from π

Policy being used to generate episode is the same as the policy being learnt

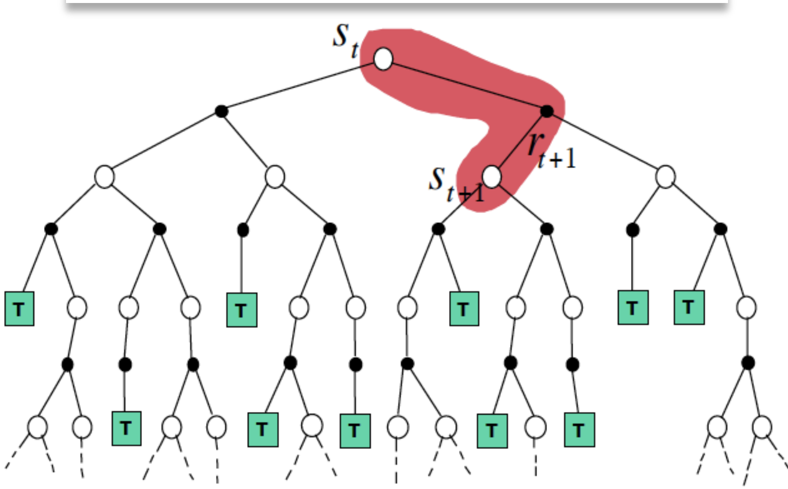
- Off-policy learning
  - "Look over someone's shoulder"
  - Learn about policy π from experience sampled from μ

Policy being used to generate episode is the different than the policy being learnt

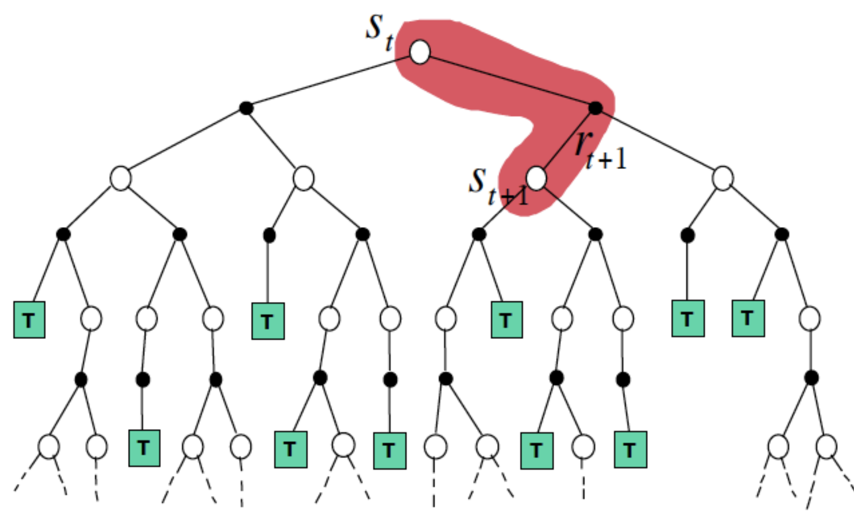
General Off Policy Learning

Behavior Agent chooses actions
Based on its own policy. For example
It can simply choose action with
Equal probability

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



Behavior Agent



Target Agent

Follows Behavior Agent
AND In Parallel
Computes Best Possible Action

Model Free Off Policy Temporal-Difference Algorithm – Q Learning

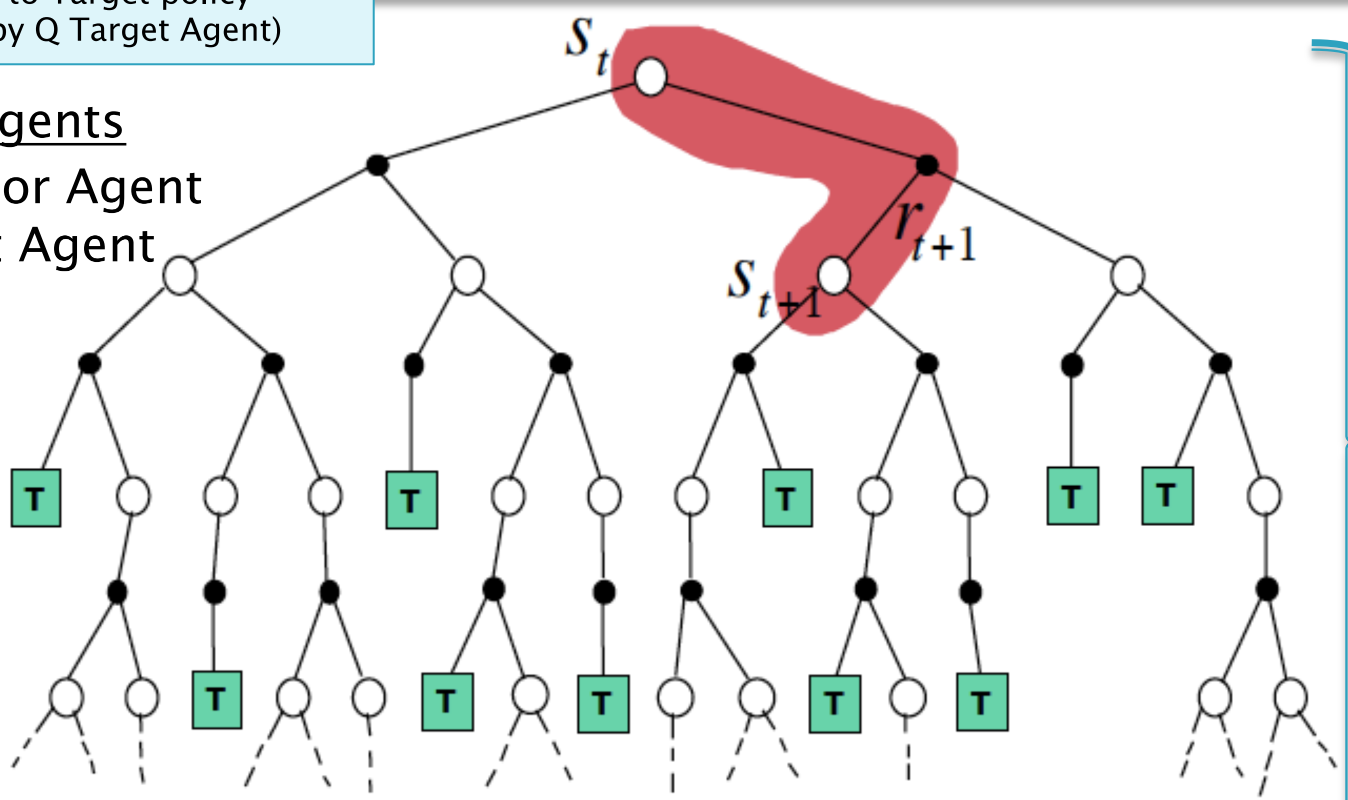
$$Q(S, A) \leftarrow Q(S, A) + \alpha\left(R + \gamma \max_{a'} Q(S', a') - Q(S, A)\right)$$

The Q value updates made at each step according to Target policy (by Q Target Agent)

Two Agents

Behavior Agent

Target Agent



All of the Actions chosen according to Behavior Policy $\pi 1$ (by Behavior Agent

Off Policy Control with Q Learning

$$Q(S,A) \leftarrow Q(S,A) + \alpha(R + \gamma Q(S', argmax_{a'} Q(S',a')) - Q(S,A))$$

Behavior Policy

Target Policy

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

Next Action chosen according to a randomized Behavior Policy
This ensures Exploration of the State Space

But: Q-Value Update made according to the 'Optimal' Target Policy

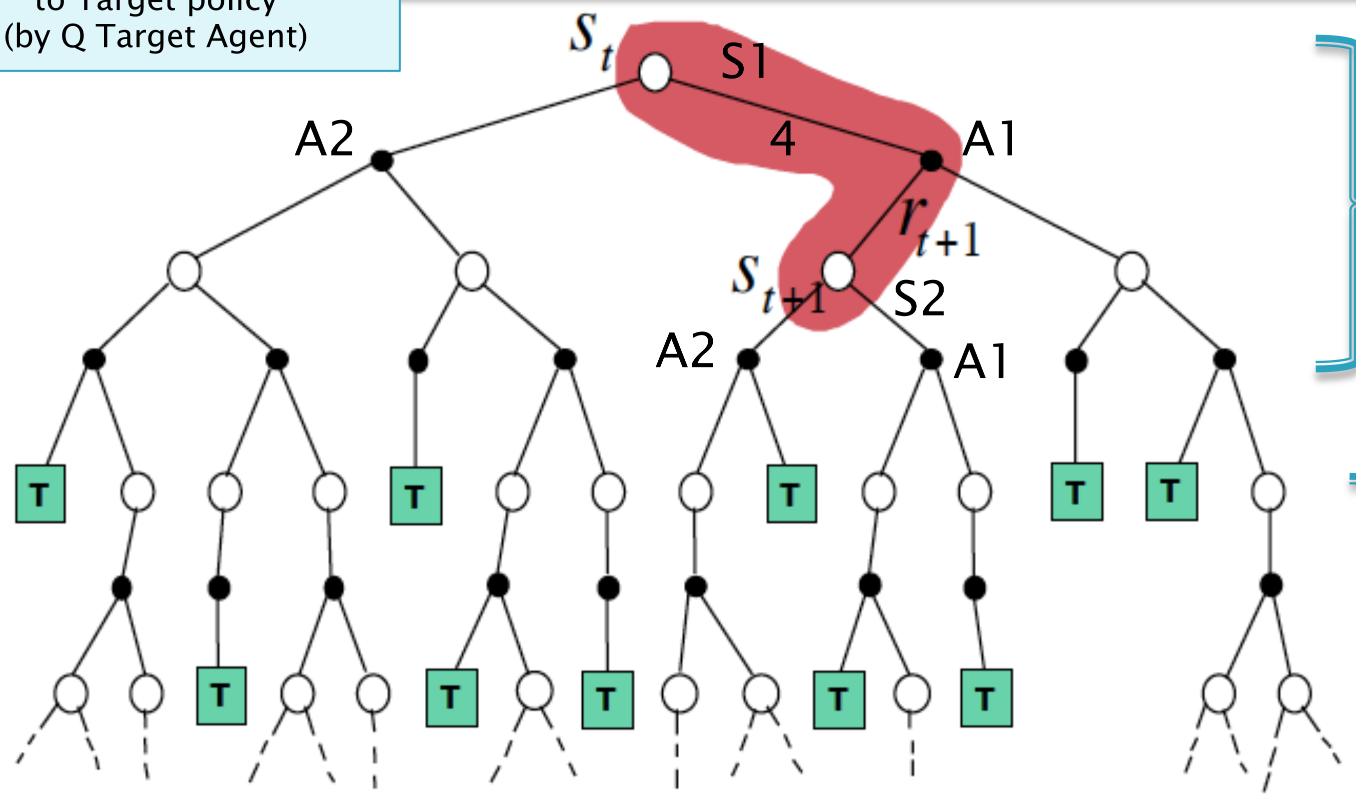
$$Q(S,A) \leftarrow Q(S,A) + \alpha\left(R + \gamma Q(S',A') - Q(S,A)\right)$$

Q Learning: Behavior Policy also Evolves

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

The Q value updates made at each step according to Target policy (by Q Target Agent)

Use ϵ Greedy to Choose Behavior Policy



Actions chosen according to Behavior Policy $\pi 1$ (by Behavior Agent)

Actions chosen according to improved Behavior Policy $\pi 2$ (by Behavior Agent)

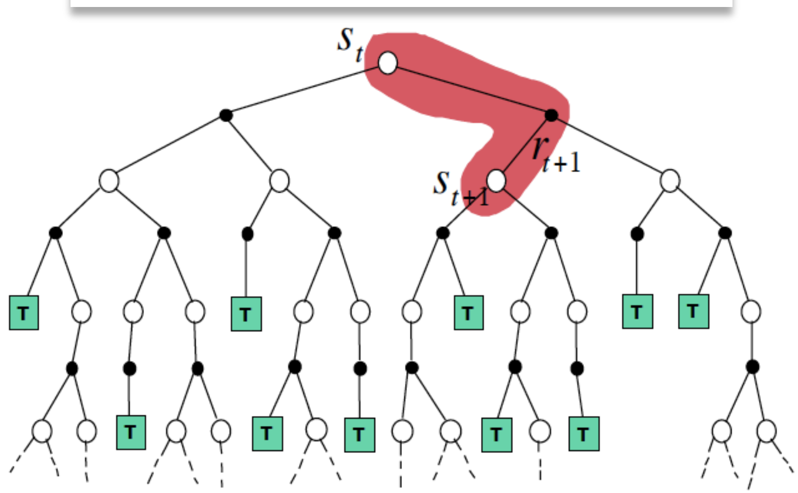
Behavior Agent uses the same Q value to choose actio

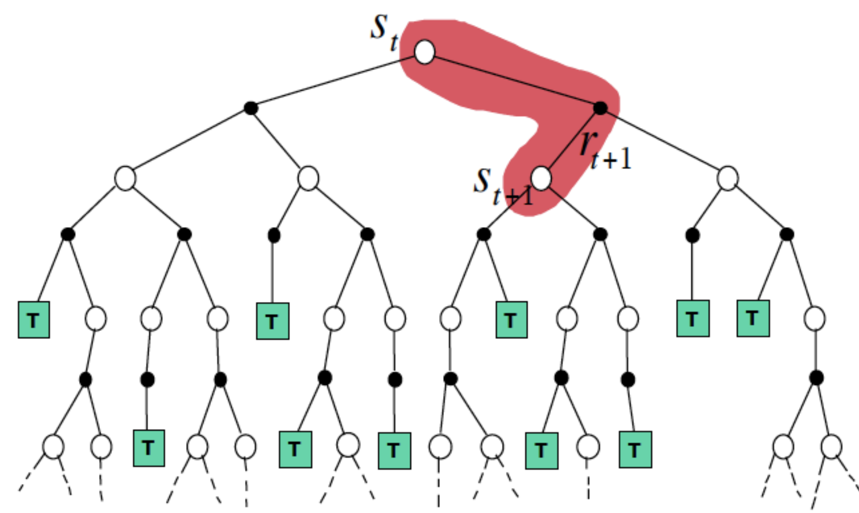
Q Learning

A special case of
Off Policy Learning

Behavior Agent chooses actions using
The Q values that the Target Agent
computes

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





Behavior Agent

Controls All Actions Actually Taken
Using epsilon-greedy algo

Target Agent

Follows Behavior Agent
AND In Parallel
Computes Best Possible Action

Off Policy Control with Q Learning

- We now allow both behaviour and target policies to improve
- The target policy π is greedy w.r.t. $Q(s, a)$

$$\pi(S_{t+1}) = \underset{a'}{\operatorname{argmax}}\ Q(S_{t+1}, a')$$

- The behaviour policy μ is e.g. ϵ-greedy w.r.t. $Q(s, a)$
- The Q-learning target then simplifies:

$$\begin{aligned}
&R_{t+1} + \gamma Q(S_{t+1}, A') \\
=&R_{t+1} + \gamma Q(S_{t+1}, \underset{a'}{\operatorname{argmax}}\ Q(S_{t+1}, a')) \\
=&R_{t+1} + \max_{a'} \gamma Q(S_{t+1}, a')
\end{aligned}$$

Q Learning Algorithm for Off Policy Control

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

Initialize $Q(s, a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Repeat (for each step of episode):
        Choose A from S using policy derived from Q (e.g., ϵ-greedy)
        Take action A, observe R, S'
        $Q(S, A) \leftarrow Q(S, A) + \alpha\left[R + \gamma \max_a Q(S', a) - Q(S, A)\right]$
        $S \leftarrow S'$
    until S is terminal

Behavior Policy

Target Policy

Example: Q Learning

$\alpha = 0.8, \gamma = 1$

Given the following episode:

(s1,a0) (r = 3) → (s0,a0) (r = 2) → (s2,a1) (r = -1) → (s0,a0)

assume that the Q values in the starting iteration are given by the following table:

Q(s,a)	a0	a1
s0	2	-1
s1	4	3
s2	0	5

(b) Q~Learning: $Q(S,A) \leftarrow Q(S,A) + \alpha(R + \gamma \max_{a'} Q(S',a') - Q(S,A))$

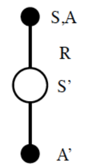
$q(S_1, a_0) = 4 + 0.8 \times (3 + \max(2,-1) - 4) = 4.8$

$q(S_0, a_0) = 2 + 0.8 \times (2 + \max(0,5) - 2) = 6$

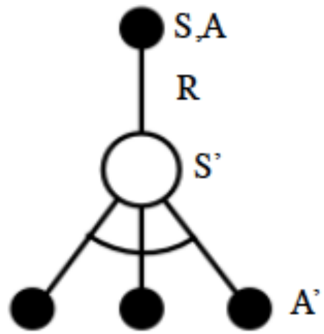
$q(S_2, a_1) = 5 + 0.8 \times (-1 + \max(6,-1) - 5) = 5$

Q Learning Control Algorithm

SARSA



$Q(S,A) \leftarrow Q(S,A) + \alpha \left(R + \gamma Q(S',A') - Q(S,A)\right)$



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

Theorem

Q-learning control converges to the optimal action-value function, $Q(s,a) \rightarrow q_*(s,a)$

Other Uses of Off Policy Learning

- Learn about *optimal* policy while following *exploratory* policy
- Learn from observing humans or other agents
- Learn about *multiple* policies while following *one* policy
- Re-use experience generated from old policies $\pi_1, \pi_2, ..., \pi_{t-1}$

Critical Idea used in
Deep Reinforcement Learning

Q Learning in Batch Mode

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

(S1,A1,R1,S1')

(S2,A2,R2,S2')

(S3,A3,R3,S3')

(S4,A4,R4,S4')

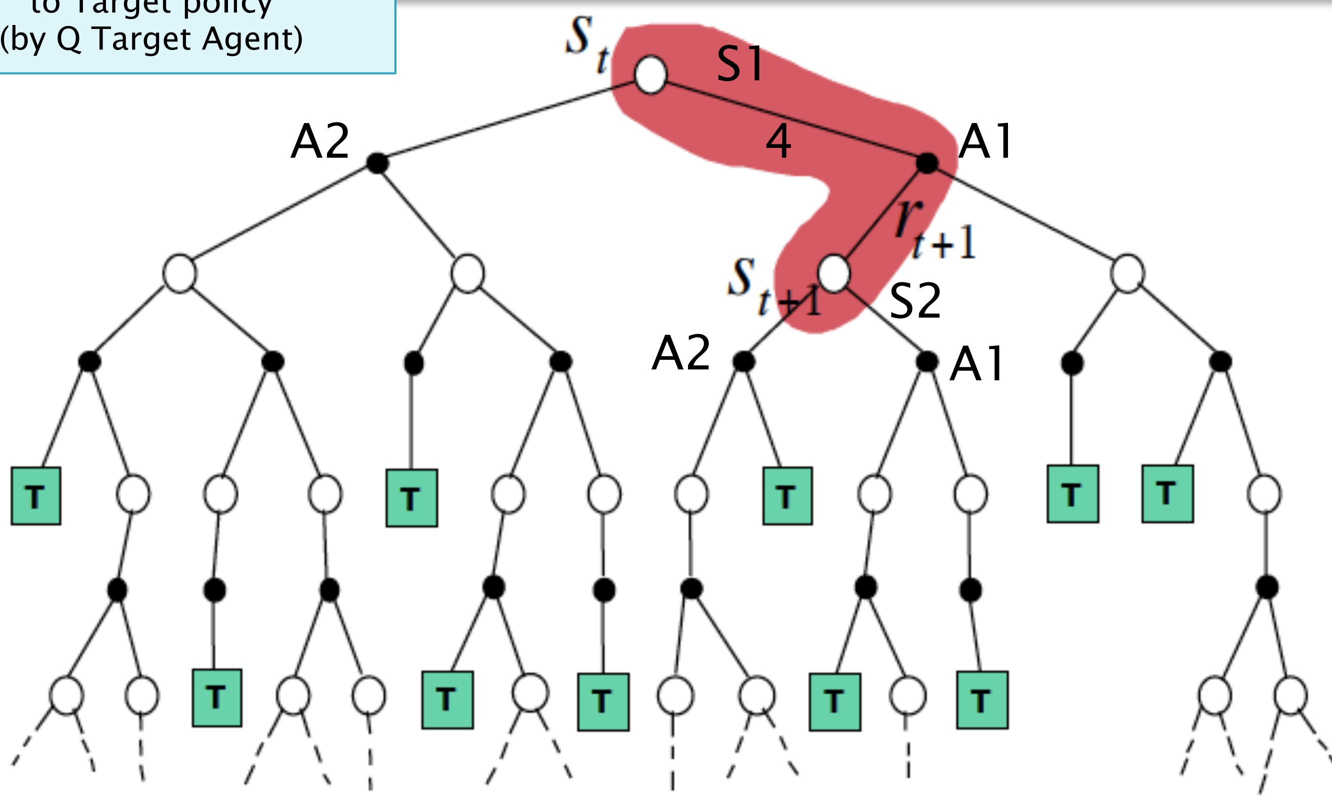
A Collection of
1-Step Transitions

Q Learning: Behavior Policy also Evolves

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

The Q value updates made at each step according to Target policy (by Q Target Agent)

Use ϵ Greedy to Choose Behavior Policy

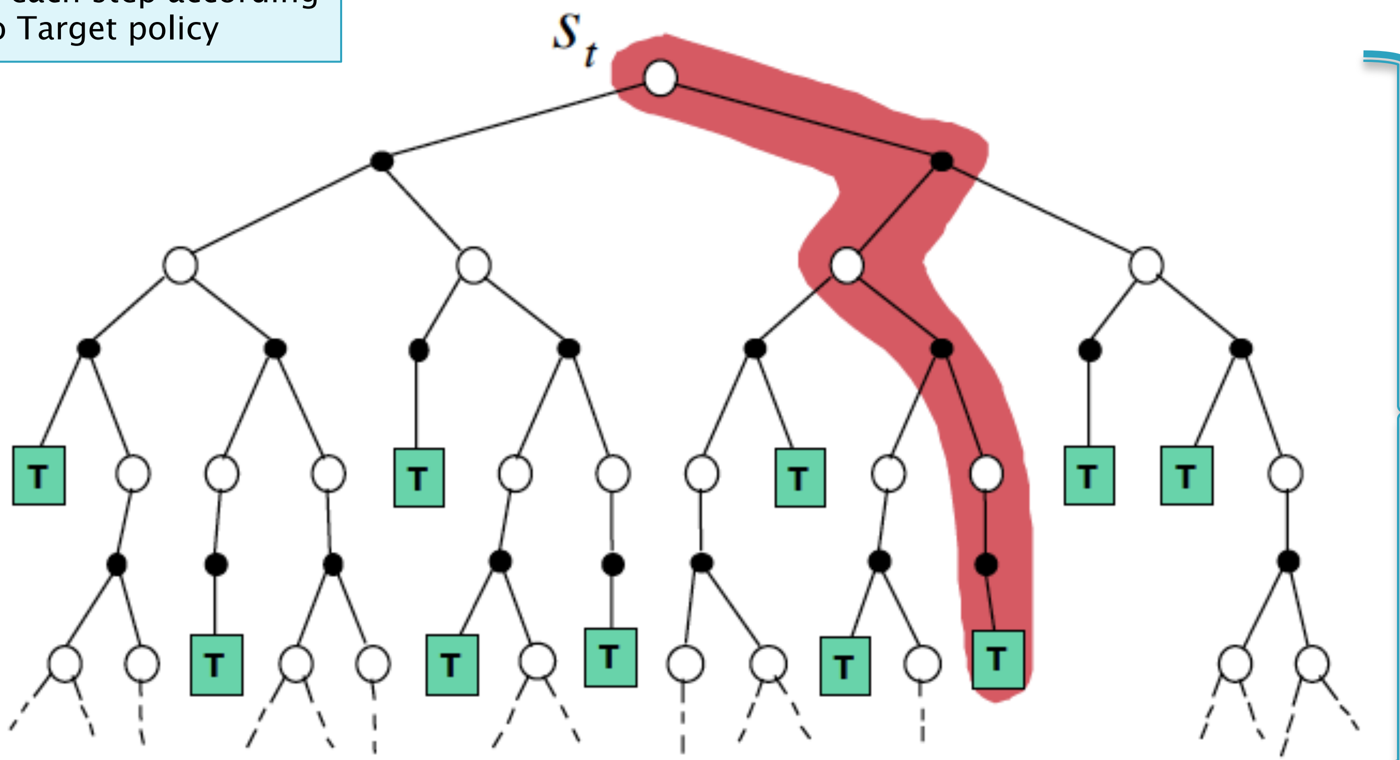


Allows reuse of a single transition multiple times

Q Learning in Batch Mode

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

The Q value updates made at each step according to Target policy



All of the Actions in the episode are fixed

Allows reuse of a single episode multiple times

Summary

Summary

- On Policy Monte Carlo Control: This involves a Policy Evaluation step follows by a Policy Improvement Step. Policy Evaluation is done based on the data from a complete episode of the MDP. This is followed by Policy Improvement using the new Q values, and the new policy is used to generate the next episode.

- On Policy Temporal Difference Control (SARSA): This also involves Policy Evaluation followed by Policy Improvement. However the Policy Evaluation is based on the data from a single step of the MDP. This is immediately followed by Policy Improvement, and the improved policy is used to generate the next step of the MDP.

- Off Policy Temporal Difference Control (Q Learning): In this case the Agent taking the Actions (using the Behavior Policy) is different from the Agent computing the optimal Q function (using the Target Policy). Behavior Policy uses some randomness to traverse the MDP, and Target Policy uses the data generated from this traversal to compute the optimal Q function.

Further Reading

Sutton and Barto:

- Chapter 5: Sections 5.3 – 5.4
- Chapter 6: Sections 6.4 – 6.5