

# A Guided Tour of Chapter 10: Reinforcement Learning for Control

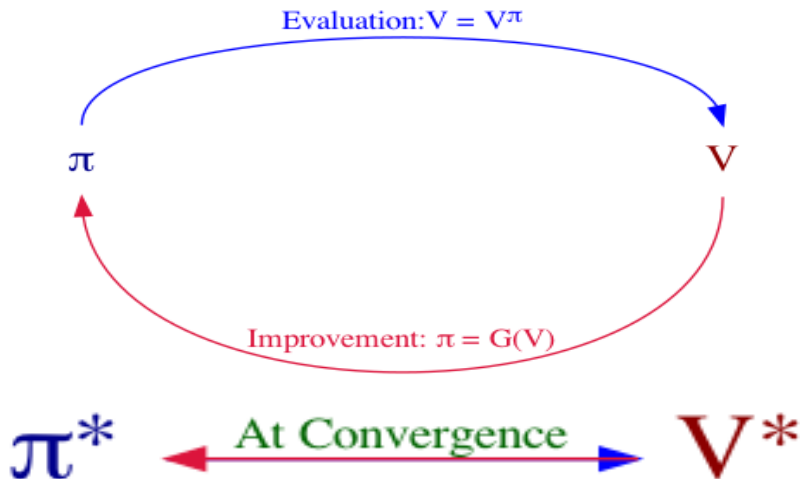
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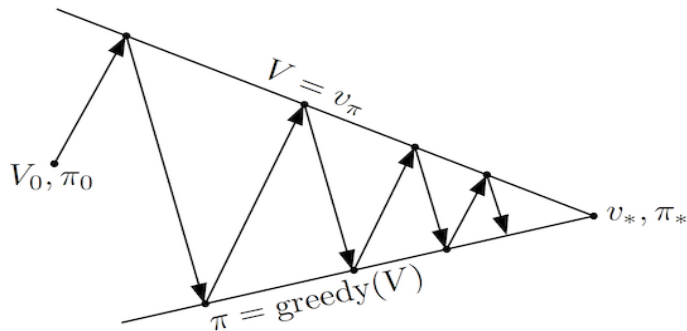
# RL does not have access to a probability model

- DP/ADP assume access to probability model (knowledge of  $\mathcal{P}_R$ )
- Often in real-world, we do not have access to these probabilities
- Which means we'd need to *interact* with the *actual environment*
- Actual Environment serves up individual experiences, not probabilities
- Even if MDP model is available, model updates can be challenging
- Often real-world models end up being too large or too complex
- Sometimes estimating a *sampling model* is much more feasible
- So RL interacts with either *actual* or *simulated* environment
- Either way, we receive *individual experiences* of next state and reward
- We saw how RL Prediction learns from individual experiences
- Now we extend those ideas to RL Control: Learning Optimal VF
- We start with Tabular RL Control

# Let us recall the Policy Iteration algorithm



# The idea of Generalized Policy Iteration (GPI)



- Any Policy Evaluation method, Any Policy Improvement method
- Policy Evaluation estimates  $V^\pi$ , eg: Iterative Policy Evaluation
- Policy Improvement produces  $\pi' \geq \pi$ , eg: Greedy Policy Improvement
- Policy Evaluation and Policy Improvement alternate until convergence

# Natural Idea: GPI with Tabular Monte-Carlo Evaluation

- Let us explore GPI with Tabular Monte-Carlo evaluation
- So we will do Policy Evaluation with Tabular MC evaluation
- And we will do the usual Greedy Policy Improvement
- But Greedy Policy Improvement requires a model of MDP

$$\pi'_D(s) \leftarrow \arg \max_{a \in \mathcal{A}} \{ \mathcal{R}(s, a) + \gamma \sum_{s' \in \mathcal{N}} \mathcal{P}(s, a, s') \cdot V^\pi(s') \}$$

- However, it works if we were working with Action-Value Function

$$\pi'_D(s) \leftarrow \arg \max_{a \in \mathcal{A}} Q^\pi(s, a)$$

- This means: Policy Evaluation for Action-Value Function  $Q^\pi(s, a)$
- Following a policy  $\pi$ , update Q-value for each  $(S_t, A_t)$  each episode:

$$Count(S_t, A_t) \leftarrow Count(S_t, A_t) + 1$$

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \frac{1}{Count(S_t, A_t)} \cdot (G_t - Q(S_t, A_t))$$

# $\epsilon$ -Greedy Policy Improvement

- A full Policy Evaluation with MC takes too long
- So we typically improve policy after each episode
- This can lead to some actions not being tried enough
- Which can lead to premature (greedy) domination of an action
- Which can lead to other actions getting “locked-out”
- Same as *Explore v/s Exploit* dilemma of Multi-Armed Bandit problem
- Simple solution: Perform an  $\epsilon$ -Greedy Policy Improvement
- All  $|\mathcal{A}|$  actions are tried with non-zero probability (for each state)
- Pick the greedy action with probability  $1 - \epsilon$
- With probability  $\epsilon$ , randomly choose one of the  $|\mathcal{A}|$  actions

$$\text{Stochastic Policy } \pi(s, a) = \begin{cases} \frac{\epsilon}{|\mathcal{A}|} + 1 - \epsilon & \text{if } a = \arg \max_{b \in \mathcal{A}} Q(s, b) \\ \frac{\epsilon}{|\mathcal{A}|} & \text{otherwise} \end{cases}$$

# $\epsilon$ -Greedy improves the policy

## Theorem

*For any  $\epsilon$ -greedy policy  $\pi$ , the  $\epsilon$ -greedy policy  $\pi'$  with respect to  $Q^\pi$  is an improvement, i.e.,  $\mathbf{V}^{\pi'}(s) \geq \mathbf{V}^\pi(s)$  for all  $s \in \mathcal{N}$ .*

- Applying  $\mathbf{B}^{\pi'}$  repeatedly (starting with  $\mathbf{V}^\pi$ ) converges to  $\mathbf{V}^{\pi'}$ :

$$\lim_{i \rightarrow \infty} (\mathbf{B}^{\pi'})^i(\mathbf{V}^\pi) = \mathbf{V}^{\pi'}$$

- So the proof is complete if we prove that:

$$(\mathbf{B}^{\pi'})^{i+1}(\mathbf{V}^\pi) \geq (\mathbf{B}^{\pi'})^i(\mathbf{V}^\pi) \text{ for all } i = 0, 1, 2, \dots$$

- Increasing tower of Value Functions  $[(\mathbf{B}^{\pi'})^i(\mathbf{V}^\pi) | i = 0, 1, 2, \dots]$  with repeated applications of  $\mathbf{B}^{\pi'}$

# Base Case of Proof by Induction

The base case of proof by induction is to show that  $\mathbf{B}^{\pi'}(\mathbf{V}^{\pi}) \geq \mathbf{V}^{\pi}$

$$\begin{aligned}\mathbf{B}^{\pi'}(\mathbf{V}^{\pi})(s) &= (\mathcal{R}^{\pi'} + \gamma \cdot \mathcal{P}^{\pi'} \cdot \mathbf{V}^{\pi})(s) \\ &= \mathcal{R}^{\pi'}(s) + \gamma \cdot \sum_{s' \in \mathcal{S}} \mathcal{P}^{\pi'}(s, s') \cdot \mathbf{V}^{\pi}(s') \\ &= \sum_{a \in \mathcal{A}} \pi'(s, a) \cdot (\mathcal{R}(s, a) + \gamma \cdot \sum_{s' \in \mathcal{S}} \mathcal{P}(s, a, s') \cdot \mathbf{V}^{\pi}(s')) \\ &= \sum_{a \in \mathcal{A}} \pi'(s, a) \cdot Q^{\pi}(s, a) \\ &= \frac{\epsilon}{|\mathcal{A}|} \cdot \sum_{a \in \mathcal{A}} Q^{\pi}(s, a) + (1 - \epsilon) \cdot \max_{a \in \mathcal{A}} Q^{\pi}(s, a) \\ &\geq \frac{\epsilon}{|\mathcal{A}|} \cdot \sum_{a \in \mathcal{A}} Q^{\pi}(s, a) + (1 - \epsilon) \cdot \sum_{a \in \mathcal{A}} \frac{\pi(s, a) - \frac{\epsilon}{|\mathcal{A}|}}{1 - \epsilon} \cdot Q^{\pi}(s, a) \\ &= \sum_{a \in \mathcal{A}} \pi(s, a) \cdot Q^{\pi}(s, a) = \mathbf{V}^{\pi}(s)\end{aligned}$$



# Induction Step of Proof by Induction

Induction step is proved by monotonicity of  $\mathbf{B}^\pi$  operator (for any  $\pi$ ):

Monotonicity Property of  $\mathbf{B}^\pi : \mathbf{X} \geq \mathbf{Y} \Rightarrow \mathbf{B}^\pi(\mathbf{X}) \geq \mathbf{B}^\pi(\mathbf{Y})$

So  $(\mathbf{B}^{\pi'})^{i+1}(\mathbf{V}^\pi) \geq (\mathbf{B}^{\pi'})^i(\mathbf{V}^\pi) \Rightarrow (\mathbf{B}^{\pi'})^{i+2}(\mathbf{V}^\pi) \geq (\mathbf{B}^{\pi'})^{i+1}(\mathbf{V}^\pi)$



## Definition

*Greedy in the Limit with Infinite Exploration (GLIE):*

- All state-action pairs are explored infinitely many times

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

- The policy converges to a greedy policy

$$\lim_{k \rightarrow \infty} \pi_k(s, a) = \mathbb{I}_{a=\arg \max_{b \in \mathcal{A}} Q(s, b)}$$

$\epsilon$ -greedy can be made GLIE if  $\epsilon$  is reduced as:  $\epsilon_k = \frac{1}{k}$

# GLIE Tabular Monte-Carlo Control

- Sample  $k$ -th episode using  $\pi$ :  $\{S_0, A_0, R_1, S_1, A_1, \dots, R_T, S_T\} \sim \pi$
- For each state  $S_t$  and action  $A_t$  in episode, updates at *episode-end*:

$$\text{Count}(S_t, A_t) \leftarrow \text{Count}(S_t, A_t) + 1$$

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \frac{1}{\text{Count}(S_t, A_t)} \cdot (G_t - Q(S_t, A_t))$$

- Improve policy at end of episode based on updated  $Q$ -Value function:

$$\epsilon \leftarrow \frac{1}{k}$$

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

## Theorem

*GLIE Tabular Monte-Carlo Control converges to the Optimal Action-Value function:  $Q(s, a) \rightarrow Q^*(s, a)$ .*

# MC versus TD Control

- TD learning has several advantages over MC learning:
  - Lower variance
  - Online
  - Can work with incomplete traces or continuing traces
  - Generic interface of `Iterable` of atomic experiences allows for serving up atomic experiences in any order (eg: atomic experience replays)
- So use TD instead of MC in our Control loop
  - Apply TD to  $Q(S, A)$  (instead of  $V(S)$ )
  - Use  $\epsilon$ -greedy Policy Improvement
  - Update  $Q(S, A)$  after each *atomic experience*
  - $\epsilon$ -greedy policy **automatically updated** after each atomic experience

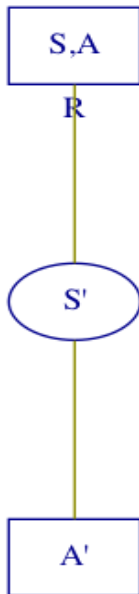
# Tabular SARSA Algorithm

- Tabular SARSA is our first TD Control algorithm
- Like Tabular MC Control, Policy Improvement is  $\epsilon$ -greedy
- But here Policy Evaluation is with a TD target, as below:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \cdot (R_{t+1} + \gamma \cdot Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t))$$

- Note that  $Q(S, A)$  is updated after each atomic experience
- $\epsilon$ -greedy policy automatically updated after each atomic experience
- Action  $A_t$  is chosen from State  $S_t$  based on  $\epsilon$ -greedy policy
- Action  $A_{t+1}$  is chosen from State  $S_{t+1}$  based on  $\epsilon$ -greedy policy
- Unlike MC Control, trace experience is incrementally generated
- Note: Instead of  $\epsilon$ -greedy, we could employ a more sophisticated exploratory policy derived from  $Q$ -value function ( $\epsilon$ -greedy is just our default simple exploratory policy derived from  $Q$ -value function)

# SARSA Visualization



# Convergence of Tabular SARSA

## Theorem

*Tabular SARSA converges to the Optimal Action-Value function,  $Q(s, a) \rightarrow Q^*(s, a)$ , under the following conditions:*

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

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

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

# Tabular $n$ -step SARSA

- Tabular SARSA bootstraps the  $Q$ -Value Function with update:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t))$$

- So it's natural to extend this to bootstrapping with 2 steps ahead:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma R_{t+2} + \gamma^2 Q(S_{t+2}, A_{t+2}) - Q(S_t, A_t))$$

- Generalize to bootstrapping with  $n \geq 1$  time steps ahead:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(G_{t,n} - Q(S_t, A_t))$$

- $G_{t,n}$  (call it  $n$ -step bootstrapped return) is defined as:

$$\begin{aligned} G_{t,n} &= \sum_{i=t+1}^{t+n} \gamma^{i-t-1} \cdot R_i + \gamma^n \cdot Q(S_{t+n}, A_{t+n}) \\ &= R_{t+1} + \gamma \cdot R_{t+2} + \dots + \gamma^{n-1} \cdot R_{t+n} + \gamma^n \cdot Q(S_{t+n}, A_{t+n}) \end{aligned}$$



# Tabular $\lambda$ -Return SARSA

- Instead of  $G_{t,n}$ , a valid target is a weighted-average target:

$$\sum_{n=1}^N u_n \cdot G_{t,n} + u \cdot G_t \text{ where } u + \sum_{n=1}^N u_n = 1$$

- Any of the  $u_n$  or  $u$  can be 0, as long as they all sum up to 1
- The  $\lambda$ -Return target is a special case of weights  $u_n$  and  $u$

$$u_n = (1 - \lambda) \cdot \lambda^{n-1} \text{ for all } n = 1, \dots, T - t - 1$$

$$u_n = 0 \text{ for all } n \geq T - t \text{ and } u = \lambda^{T-t-1}$$

- We denote the  $\lambda$ -Return target as  $G_t^{(\lambda)}$ , defined as:

$$G_t^{(\lambda)} = (1 - \lambda) \cdot \sum_{n=1}^{T-t-1} \lambda^{n-1} \cdot G_{t,n} + \lambda^{T-t-1} \cdot G_t$$

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \cdot (G_t^{(\lambda)} - Q(S_t, A_t))$$

# Tabular SARSA( $\lambda$ )

- $\lambda$  can be tuned from SARSA ( $\lambda = 0$ ) to MC Control ( $\lambda = 1$ )
- Note that for  $\lambda > 0$ ,  $\lambda$ -Return SARSA is an Offline Algorithm
- SARSA( $\lambda$ ) is online “version” of  $\lambda$ -Return SARSA
- Similar to TD( $\lambda$ ) for Prediction, SARSA( $\lambda$ ) uses Eligibility Traces
- Eligibility Trace for a given trace experience at time  $t$  is a function

$$E_t : \mathcal{N} \times \mathcal{A} \rightarrow \mathbb{R}_{\geq 0}$$

$$E_0(s, a) = 0, \text{ for all } s \in \mathcal{N}, a \in \mathcal{A}$$

$$E_t(s, a) = \gamma \cdot \lambda \cdot E_{t-1}(s, a) + \mathbb{I}_{S_t=s, A_t=a}, \text{ for all } s \in \mathcal{N}, a \in \mathcal{A}, \text{ for all } t$$

- Tabular SARSA( $\lambda$ ) performs following update at each time step  $t$  in each trace experience (for each  $s \in \mathcal{N}, a \in \mathcal{A}$ ):

$$Q(s, a) \leftarrow Q(s, a) + \alpha \cdot (R_{t+1} + \gamma \cdot Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)) \cdot E_t(s, a)$$

- Estimate VF for *target policy*  $\pi$  while following *behavior policy*  $\mu$

$$\{S_0, A_0, R_1, S_1, A_1, \dots, R_T, S_T\} \sim \mu$$

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

# Importance Sampling for Off-Policy Learning

- Importance Sampling refers to methods to estimate properties of a distribution  $P$ , given access to samples from a different distribution  $Q$
- We can calculate  $\mathbb{E}_{X \sim P}[f(X)]$  given samples from  $Q$  as follows:

$$\begin{aligned}\mathbb{E}_{X \sim P}[f(X)] &= \sum P(X) \cdot f(X) \\ &= \sum Q(X) \cdot \frac{P(X)}{Q(X)} \cdot f(X) \\ &= \mathbb{E}_{X \sim Q}\left[\frac{P(X)}{Q(X)} \cdot f(X)\right]\end{aligned}$$

# Importance Sampling for Off-Policy Monte-Carlo

- Use returns generated from  $\mu$  to estimate Value Function for  $\pi$
- Weight return  $G_t$  according to similarity between policies
- Multiply importance sampling corrections along whole episode

$$G_t^{\pi/\mu} = \frac{\pi(S_t, A_t)}{\mu(S_t, A_t)} \cdot \frac{\pi(S_{t+1}, A_{t+1})}{\mu(S_{t+1}, A_{t+1})} \cdots \frac{\pi(S_T, A_T)}{\mu(S_T, A_T)} \cdot G_t$$

- Update value towards *corrected* return

$$V(S_t) \leftarrow V(S_t) + \alpha \cdot (G_t^{\pi/\mu} - V(S_t))$$

- Likewise for Q-Value Function for MC Control
- Note: We cannot use this method if  $\mu$  is zero when  $\pi$  is non-zero
- Importance sampling can dramatically increase variance

# Importance Sampling for Off-Policy Temporal-Difference

- Use TD targets generated from  $\mu$  to evaluate Value Function for  $\pi$
- Weight TD target  $R + \gamma \cdot V(S')$  with importance sampling
- Here we only need a single importance sampling correction

$$V(S_t) \leftarrow V(S_t) + \alpha \cdot \left( \frac{\pi(S_t, A_t)}{\mu(S_t, A_t)} \cdot (R_{t+1} + \gamma \cdot V(S_{t+1})) - V(S_t) \right)$$

- Likewise for Q-Value Function for TD Control
- This has much lower variance than MC importance sampling
- Policies only need to be similar over a single step

# Tabular Q-Learning

- We now consider off-policy learning of action-values  $Q(s, a)$
- **No** importance sampling is required
- The next action is chosen using behavior policy  $A_{t+1} \sim \mu(S_t, \cdot)$
- But we consider an alternative successor action  $A' \sim \pi(S_t, \cdot)$
- Update  $Q(S_t, A_t)$  towards value of alternative action

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \cdot (R_{t+1} + \gamma \cdot Q(S_{t+1}, A') - Q(S_t, A_t))$$

# Off-Policy Control with Tabular Q-Learning

- We now allow both experience and target policies to **improve**
- The target (deterministic) policy  $\pi_D$  is **greedy** w.r.t Q-Value Function

$$\pi_D(S_{t+1}) = \arg \max_{a' \in \mathcal{A}} Q(S_{t+1}, a')$$

- The behavior policy  $\mu$  is also improving, eg:  $\epsilon$ -greedy w.r.t.  $Q$
- The Q-learning target then simplifies to:

$$\begin{aligned} & R_{t+1} + \gamma \cdot Q(S_{t+1}, A') \\ &= R_{t+1} + \gamma \cdot Q(S_{t+1}, \arg \max_{a' \in \mathcal{A}} Q(S_{t+1}, a')) \\ &= R_{t+1} + \gamma \cdot \max_{a' \in \mathcal{A}} Q(S_{t+1}, a') \end{aligned}$$

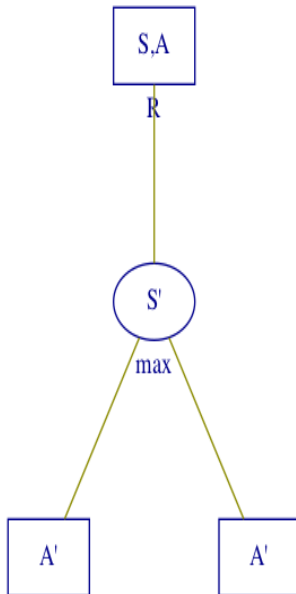
- Thus the update to Q-Value Function after each atomic experience is:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \cdot (R_{t+1} + \gamma \cdot \max_{a' \in \mathcal{A}} Q(S_{t+1}, a') - Q(S_t, A_t))$$

- Convergence proofs require infinite exploration of all (state, action) pairs & appropriate stochastic approximation conditions for step sizes.



# Q-Learning Control Visualization



# RL Control with Function Approximation

- Natural extension of Tabular Control to function approximations
- Instead of parameterized approximation  $V(s; \mathbf{w})$ , we have  $Q(s, a; \mathbf{w})$
- GPI's Policy Evaluation is Approximate Q-Value Policy Evaluation
- Loss Function for  $Q(s, a; \mathbf{w})$  estimate relative to appropriate return
- For MC Control, the loss function for  $(S_t, A_t)$  in an episode is:

$$\mathcal{L}_{(S_t, A_t, G_t)}(\mathbf{w}) = \frac{1}{2} \cdot (Q(S_t, A_t; \mathbf{w}) - G_t)^2$$

- Therefore, the gradient of the loss function for this  $(S_t, A_t)$  is:

$$\nabla_{\mathbf{w}} \mathcal{L}_{(S_t, A_t, G_t)}(\mathbf{w}) = (Q(S_t, A_t; \mathbf{w}) - G_t) \cdot \nabla_{\mathbf{w}} Q(S_t, A_t; \mathbf{w})$$

- Therefore, parameters update for this  $(S_t, A_t)$  at episode-end is:

$$\Delta \mathbf{w} = \alpha \cdot (G_t - Q(S_t, A_t; \mathbf{w})) \cdot \nabla_{\mathbf{w}} Q(S_t, A_t; \mathbf{w})$$

- $\epsilon$ -greedy policy improvement is automatic from updated  $Q$  estimate

# Bootstrapped Control with Function Approximation

- For SARSA, parameters update after each atomic experience:

$$\Delta \mathbf{w} = \alpha \cdot (R_{t+1} + \gamma \cdot Q(S_{t+1}, A_{t+1}; \mathbf{w}) - Q(S_t, A_t; \mathbf{w})) \cdot \nabla_{\mathbf{w}} Q(S_t, A_t; \mathbf{w})$$

- For Q-Learning, parameters update after each atomic experience:

$$\Delta \mathbf{w} = \alpha \cdot (R_{t+1} + \gamma \cdot \max_{a' \in \mathcal{A}} Q(S_{t+1}, a'; \mathbf{w}) - Q(S_t, A_t; \mathbf{w})) \cdot \nabla_{\mathbf{w}} Q(S_t, A_t; \mathbf{w})$$

- For offline  $\lambda$ -Return Control, parameters update at episode-end:

$$\Delta \mathbf{w} = \alpha \cdot (G_t^{(\lambda)} - Q(S_t, A_t; \mathbf{w})) \cdot \nabla_{\mathbf{w}} Q(S_t, A_t; \mathbf{w})$$

- For online SARSA( $\lambda$ ), update after each atomic experience:

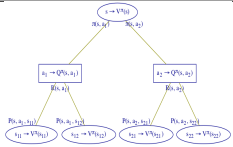
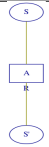
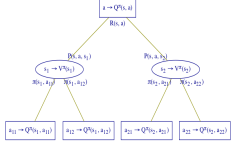

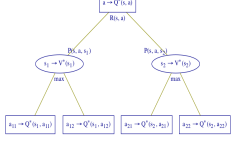

$$\delta_t = R_{t+1} + \gamma \cdot Q(S_{t+1}, A_{t+1}; \mathbf{w}) - Q(S_t, A_t; \mathbf{w})$$

$$\mathbf{E}_t = \gamma \lambda \cdot \mathbf{E}_{t-1} + \nabla_{\mathbf{w}} Q(S_t, A_t; \mathbf{w})$$

$$\Delta \mathbf{w} = \alpha \cdot \delta_t \cdot \mathbf{E}_t$$

- $\epsilon$ -greedy policy improvement is automatic from updated  $Q$  estimate

# Relationship between DP and TD

	Full Backup (DP)	Sample Backup (TD)
Bellman Expectation Equation for $V^\pi(s)$	 <p>Iterative Policy Evaluation</p>	 <p>TD Learning</p>
Bellman Expectation Equation for $Q^\pi(s, a)$	 <p>Q-Policy Iteration</p>	 <p>SARSA</p>
Bellman Optimality Equation for $Q^*(s, a)$	 <p>Q-Value Iteration</p>	 <p>Q-Learning</p>

# Relationship between DP and TD

Full Backup (DP)	Sample Backup (TD)
Iterative Policy Evaluation: $V(S)$ update $\mathbb{E}[R + \gamma V(S') S]$	TD Learning: $V(S)$ update sample $R + \gamma V(S')$
Q-Policy Iteration: $Q(S, A)$ update $\mathbb{E}[R + \gamma Q(S', A') S, A]$	SARSA: $Q(S, A)$ update sample $R + \gamma Q(S', A')$
Q-Value Iteration: $Q(S, A)$ update $\mathbb{E}[R + \gamma \max_{a'} Q(S', a') S, A]$	Q-Learning: $Q(S, A)$ update sample $R + \gamma \max_{a'} Q(S', a')$

# Convergence of Prediction Algorithms

On/Off Policy	Algorithm	Tabular	Linear	Non-Linear
On-Policy	MC	✓	✓	✓
	TD(0)	✓	✓	✗
	TD( $\lambda$ )	✓	✓	✗
Off-Policy	MC	✓	✓	✓
	TD(0)	✓	✗	✗
	TD( $\lambda$ )	✓	✗	✗

# Gradient Temporal-Difference Learning

- TD does not follow the gradient of *any* objective function
- This is why TD can diverge:
  - when running off-policy, or
  - when using non-linear function approximation
- **Gradient TD** follows true gradient of projected Bellman Error

On/Off Policy	Algorithm	Tabular	Linear	Non-Linear
On-Policy	MC	✓	✓	✓
	TD	✓	✓	✗
	<b>Gradient TD</b>	✓	✓	✓
Off-Policy	MC	✓	✓	✓
	TD	✓	✗	✗
	<b>Gradient TD</b>	✓	✓	✓

# Convergence of Control Algorithms

Algorithm	Tabular	Linear	Non-Linear
MC Control	✓	( ✓ )	✗
SARSA	✓	( ✓ )	✗
Q-Learning	✓	✗	✗
<b>Gradient Q-Learning</b>	✓	✓	✗

( ✓ ) means it chatters around near-optimal Value Function



# Key Takeaways from this Chapter

- RL Control is based on the idea of Generalized Policy Iteration (GPI)
  - Policy Evaluation with  $Q$ -Value Function (instead of  $V$ )
  - Improved Policy needs to be exploratory, eg:  $\epsilon$ -greedy
- On-Policy versus Off-Policy
- Deadly Triad  $:=$  [Bootstrapping, Function Approximation, Off-Policy]