Temporal-Difference Learning

DEPARTMENT OF COMPUTER SCIENCE
ST. FRANCIS XAVIER UNIVERSITY

CSCI-531 - Reinforcement Learning

Fall 2025

The Best of Both Worlds

What is Temporal-Difference Learning?

- Combines **Dynamic Programming** and **Monte Carlo** methods

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- Updates at **every time step**

Method Comparison

Method	Model-Free	Bootstraps	Online
Dynamic Programming	No	Yes	Yes
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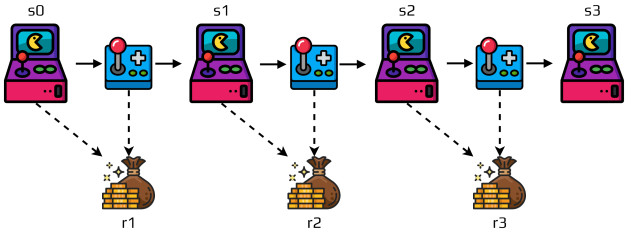
- Faster convergence than Monte Carlo
- More practical for **online learning**

Activity: Monte Carlo Limitation

Recall: Monte Carlo Update



$$V(s_0) = V(s_0) + \alpha\,[G - V(s_0)]$$

Question

What is the main disadvantage of this approach?

Monte Carlo Limitations

Answer: Key Disadvantages

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- Memory grows with episode length

Building the TD Update: What Do We Want?

Recall: Value Function Definition

$$V(s) = \mathbb{E}[G_t | S_t = s] = \mathbb{E}[R_{t+1} + \gamma G_{t+1} | S_t = s] \tag{1}$$

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The Key Insight

The future return G_{t+1} starting from S_{t+1} is just $V(S_{t+1})$!

From Theory to Practice: The Approximation

What We Have (Theory)

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Resolving the Conflict: Learning from Error

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Learning Rule

Move our estimate towards the new evidence:

$$V(s_t)^{\text{new}} = V(s_t)^{\text{old}} + \alpha \times \delta_t \tag{8}$$

The Complete TD Update Rule

Putting It All Together

$$V(s_t) \leftarrow V(s_t) + \alpha \left[r_{t+1} + \gamma V(s_{t+1}) - V(s_t) \right] \tag{9}$$

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- If error is **positive**: our estimate was too low $\rightarrow$ increase it
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- If error is **zero**: our estimate was perfect $\rightarrow$ no change

Why This Works: The Bootstrap Principle

Bootstrap Analogy

"Pulling yourself up by your bootstraps"

- Use current estimates to improve current estimates

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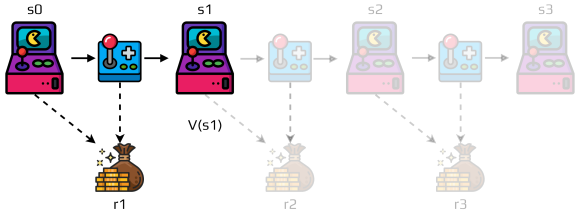
Key Insight

We don't need perfect information - just better information than what we had!

Visual Comparison: MC vs TD



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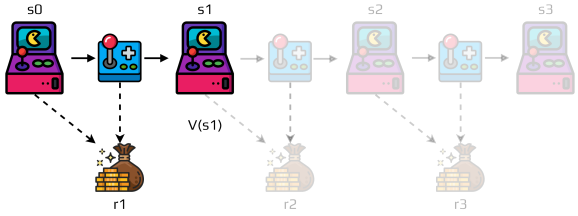

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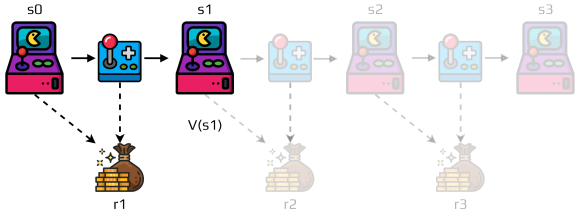

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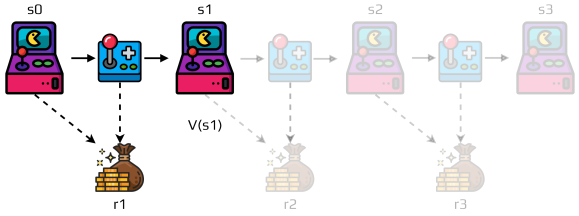

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- **MC**: Uses actual return G_t
- **TD**: Uses estimated return $r_{t+1} + \gamma V(s_{t+1})$
- **TD**: Updates **immediately** after each step

TD(0) for Policy Evaluation

Algorithm TD(0) Algorithm

Inputs: π (policy to evaluate), N (episodes), $\alpha \in [0, 1]$ (step size)
Initialize: $V_\pi(s) \in \mathbb{R}$ arbitrarily, $\forall s \in S$, except $V(\textit{terminal}) = 0$
for $\textit{episode} = 1$ to N **do**
    Initialize s
    while $s \neq \textit{terminal}$ **do**
        $a \leftarrow \pi(s)$
        $r, s' \leftarrow$ Execute a
        $V(s) \leftarrow V(s) + \alpha[r + \gamma V(s') - V(s)]$
        $s \leftarrow s'$
    end while
end for

Why "TD(0)"?

The "0" in TD(0)

The target uses the estimate **0 steps** into the future:

$$r_{t+1} + \gamma V(s_{t+1}) \tag{10}$$

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Key Insight

Higher n: More like Monte Carlo (less bias, more variance)
Lower n: More like DP (more bias, less variance)

Activity: TD vs Monte Carlo Differences

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What major differences can you see between TD(0) and Monte Carlo?

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Key Differences

1. **Update frequency**: Every step vs. end of episode
2. **Target**: Estimate vs. actual return
3. **Memory**: Constant vs. growing with episode length
4. **Convergence**: May converge faster

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TD Error Definition

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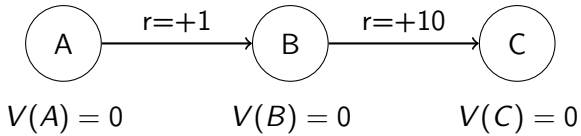
Why TD Target is an Estimate

1. Expected value $V(s')$ is **sampled**
2. Uses current **estimate** $V(s')$, not true value

TD Learning with Numbers: A Simple Example

Setup: 3-State Chain

- States: A $\rightarrow$ B $\rightarrow$ C (terminal)



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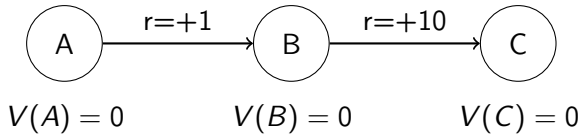

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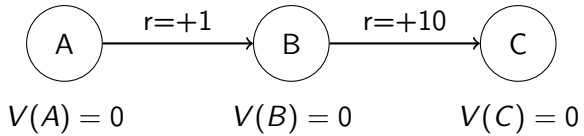

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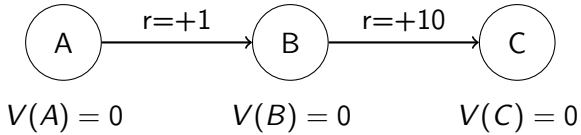
- $\gamma = 0.9$, $\alpha = 0.5$
- Initial estimates: $V(A) = 0$, $V(B) = 0$, $V(C) = 0$



Step-by-Step TD Updates

Episode: $A \rightarrow B \rightarrow C$

Let's trace through one episode and see how values update:

Step-by-Step TD Updates

Episode: A $\rightarrow$ B $\rightarrow$ C

Let's trace through one episode and see how values update:

Step 1: A $\rightarrow$ B (receive reward = +1)

TD Update for A:

$$\begin{aligned} V(A) &= V(A) + \alpha[r + \gamma V(B) - V(A)] \\ &= 0 + 0.5[1 + 0.9 \times 0 - 0] \\ &= 0 + 0.5 \times 1 = 0.5 \end{aligned}$$

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Step-by-Step TD Updates

Episode: A $\rightarrow$ B $\rightarrow$ C

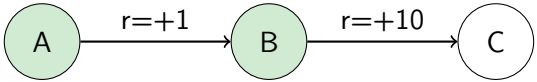
Let's trace through one episode and see how values update:

Step 2: B $\rightarrow$ C (receive reward = +10)

TD Update for B:

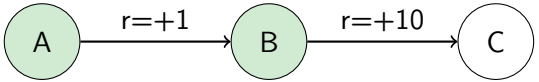
$$\begin{aligned} V(B) &= V(B) + \alpha[r + \gamma V(C) - V(B)] \\ &= 0 + 0.5[10 + 0.9 \times 0 - 0] \\ &= 0 + 0.5 \times 10 = 5.0 \end{aligned}$$

After First Episode



$V(A) = 0.5$ $V(B) = 5.0$ $V(C) = 0$

After First Episode

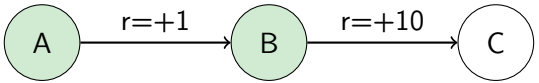


Second Episode: A $\rightarrow$ B $\rightarrow$ C

Now A uses updated V(B):

$$
\begin{aligned}
V(A) &\leftarrow 0.5 + 0.5[1 + 0.9 \times 5.0 - 0.5] \\
&\leftarrow 0.5 + 0.5[1 + 4.5 - 0.5] \\
&\leftarrow 0.5 + 0.5 \times 5.0 = 3.0
\end{aligned}
$$

After First Episode



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Key Insight

TD uses updated estimates - V(A) learned from V(B)'s improvement!

Compare with Monte Carlo

Monte Carlo

- Waits for complete episode

TD Learning

Compare with Monte Carlo

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- A gets return: $1 + 0.9 \times 10 = 10$

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- Updates at each step
- A uses estimate: $1 + 0.9 \times 0 = 1$

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Why This Matters

- TD starts learning **immediately**

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- Values **propagate** through the chain
- More robust to **incomplete episodes**

Practical Example: Driving to Friend's House

Scenario

- Predict travel time to friend's house

State	Elapsed Time	Predicted Total	Actual Total
Leaving office	0	30 min	43 min
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Practical Example: Driving to Friend's House

Scenario

- Predict travel time to friend's house
- Consider: time of day, weather, traffic, etc.
- Learn from experience over multiple trips

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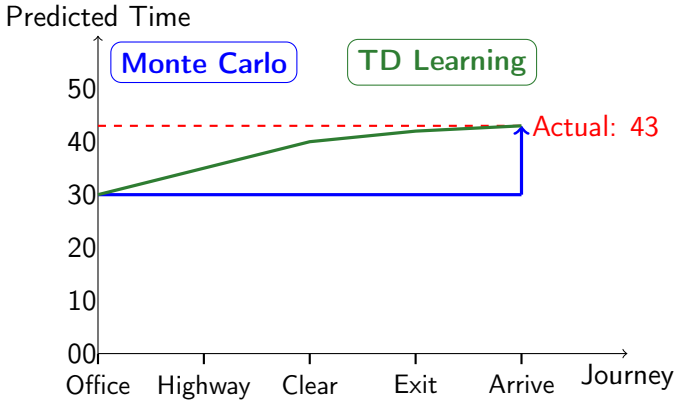
MC vs TD Learning Comparison



Observations

- **TD**: Updates prediction continuously during the trip

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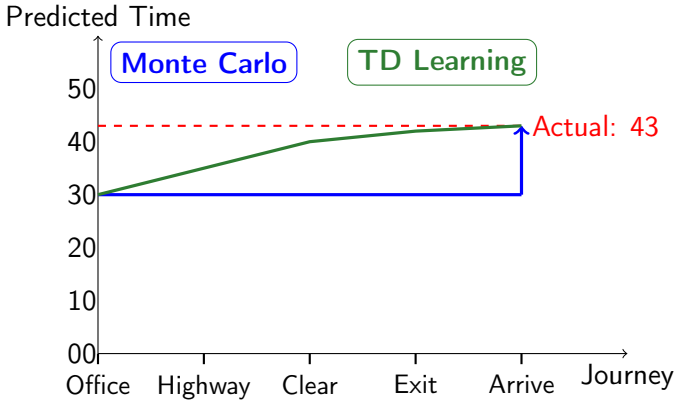

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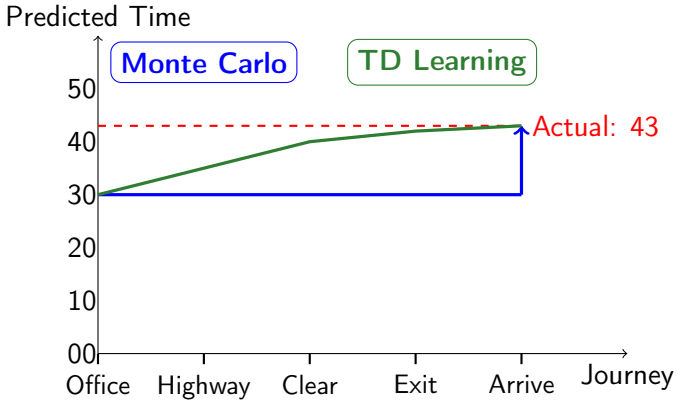

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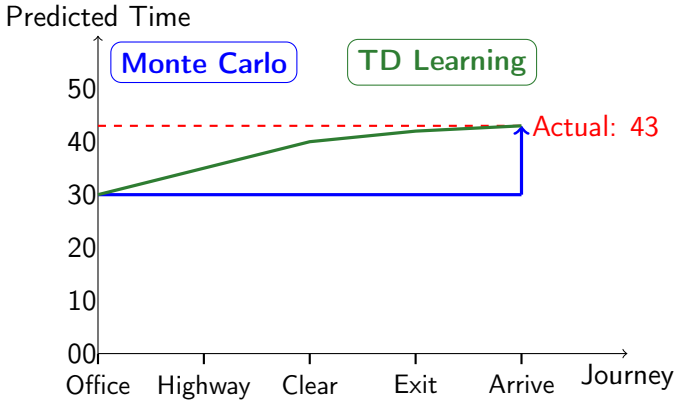

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- When episodes are very long or infinite

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When to Use TD

- When episodes are very long or infinite
- When you need **real-time** learning
- When computational resources are limited

Moving to Control: Action-Value Functions

Why Action-Value Functions?

- Need to estimate $q_\pi(s, a)$ for all states and actions

Moving to Control: Action-Value Functions

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Answer

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Activity

Why do we need state-action pairs instead of just states?

Answer

- Need to know **value of each action** in each state
- Essential for **policy improvement**
- Cannot improve policy with only state values

SARSA Update Rule

From State Values to Action Values

Replace $V(s)$ with $Q(s, a)$ in the TD update:

Uses every element: $(s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1})$

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$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t) \right] \tag{12}$$

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Uses every element: $(s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1})$

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- Reward r_{t+1}

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SARSA Algorithm

Algorithm SARSA

Inputs: N (episodes), $\alpha \in [0, 1]$ (step size)
Initialize: $Q(s, a) \in \mathbb{R}$ arbitrarily, $\forall s \in S, a \in A$, except $Q(\textit{terminal}, \cdot) = 0$
for $\textit{episode} = 1$ to N **do**
    Initialize s
    $a \leftarrow$ action from $Q(s, \cdot)$ using ϵ-greedy
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SARSA Key Properties

On-Policy Learning

- Learns about the **same policy** it follows

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Important Note

No explicit policy is stored! The policy is **implicit** in the Q-values.

Q-Learning: A Classic Algorithm

Historical Note

- Introduced in **1989** by Chris Watkins

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Key Difference from SARSA

- Uses $\max_{a'} Q(s_{t+1}, a')$ instead of $Q(s_{t+1}, a_{t+1})$

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Key Difference from SARSA

- Uses $\max_{a'} Q(s_{t+1}, a')$ instead of $Q(s_{t+1}, a_{t+1})$
- Approximates q^* (optimal action-value function)

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Algorithm Q-Learning

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Activity: Spot the Differences

Question

What is the difference between SARSA and Q-Learning algorithms?

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Key Differences

1. **Policy Type**:
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   - Q-Learning: $\max_{a'} Q(s_{t+1}, a')$ (best possible action)
3. **Next Action Selection**:
   - SARSA: Needs a_{t+1} before update
   - Q-Learning: No need for actual next action

On-Policy vs Off-Policy Behavior

SARSA (On-Policy)

- **Conservative**

Q-Learning (Off-Policy)

On-Policy vs Off-Policy Behavior

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- Considers exploration in learning
- Safer in dangerous environments

Q-Learning (Off-Policy)

- **Optimistic**
- Learns the value of the **optimal policy**
- Ignores exploration in learning
- Faster convergence to optimal

On-Policy vs Off-Policy Behavior

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Practical Implications

- **SARSA**: Better for **risky** environments (cliff walking)

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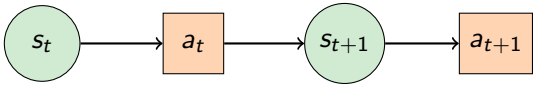
- **Q-Learning**: Better for finding **optimal** policies

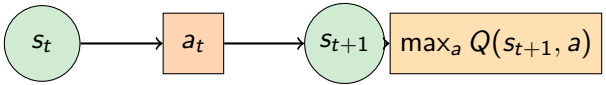
Visual Comparison: Update Mechanisms

SARSA



Uses actual a_{t+1}

Q-Learning



Uses best possible action

Why TD Learning Matters

Core Advantages

- **Model-free**: No environment model required

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- Suitable for **real-time** applications
- Foundation for **modern deep RL**

Method Comparison Summary

Method	Model-Free	Online	Policy Type	Convergence
Monte Carlo	Yes	No	On/Off	Guaranteed
TD(0)	**Yes**	**Yes**	**On**	**Guaranteed**
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When to Use Each

- **SARSA**: Safe exploration, learns about followed policy
- **Q-Learning**: Optimal policies, faster convergence
- Both: Foundation for function approximation methods

Key Takeaways

Fundamental Concepts

- **TD Error**: Measures prediction accuracy

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Questions?

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Thank you for your attention!

Next: Function Approximation Methods