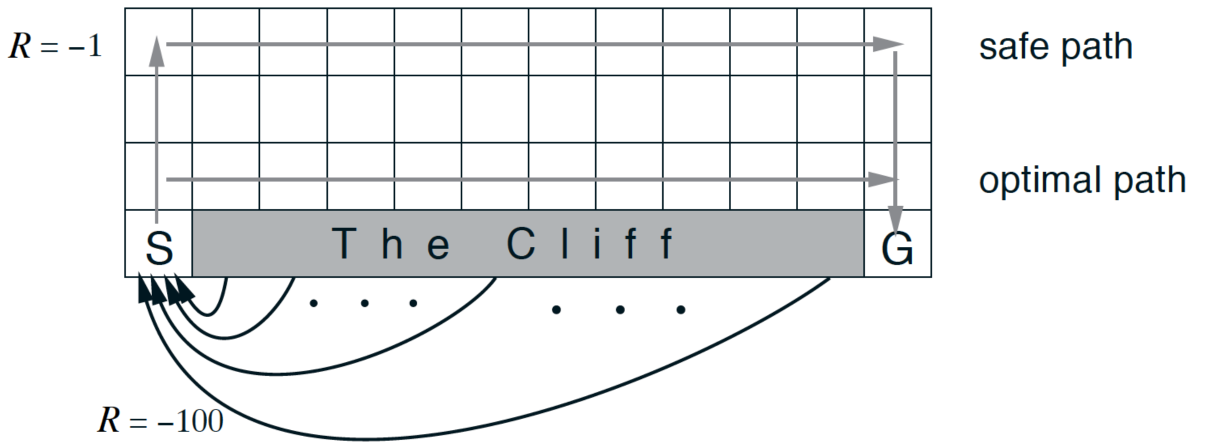
1.9 Temporal Difference Methods Summary



The cliff-walking task (Sutton and Barto, 2017)

Temporal-Difference Methods

- Whereas Monte Carlo (MC) prediction methods must wait until the end of an episode to update the value function estimate, temporal-difference (TD) methods update the value function after every time step.

TD Control

- **Sarsa(0)** (or **Sarsa**) is an on-policy TD control method. It is guaranteed to converge to the optimal action-value function q_*, as long as the step-size parameter α is sufficiently small and ϵ is chosen to satisfy the **Greedy in the Limit with Infinite Exploration (GLIE)** conditions.

Algorithm 13: Sarsa

Input: policy π, positive integer *num_episodes*, small positive fraction α, GLIE $\{\epsilon_i\}$
Output: value function Q ($\approx q_\pi$ if *num_episodes* is large enough)
Initialize Q arbitrarily (e.g., $Q(s,a) = 0$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$, and $Q(\textit{terminal-state}, \cdot) = 0$)
for $i \leftarrow 1$ ***to*** *num_episodes* **do**
    $\epsilon \leftarrow \epsilon_i$
    Observe S_0
    Choose action A_0 using policy derived from Q (e.g., ϵ-greedy)
    $t \leftarrow 0$
    repeat
        Take action A_t and observe R_{t+1}, S_{t+1}
        Choose action A_{t+1} using policy derived from Q (e.g., ϵ-greedy)
        $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t))$
        $t \leftarrow t + 1$
    until S_t *is terminal*;
end
return Q

- **Sarsamax** (or **Q-Learning**) is an off-policy TD control method. It is guaranteed to converge to the optimal action value function q_*, under the same conditions that guarantee convergence of the Sarsa control algorithm.

Algorithm 14: Sarsamax (Q-Learning)

Input: policy π, positive integer *num_episodes*, small positive fraction α, GLIE $\{\epsilon_i\}$
Output: value function Q ($\approx q_\pi$ if *num_episodes* is large enough)
Initialize Q arbitrarily (e.g., $Q(s,a) = 0$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$, and $Q(\textit{terminal-state}, \cdot) = 0$)
for $i \leftarrow 1$ ***to*** *num_episodes* **do**
    $\epsilon \leftarrow \epsilon_i$
    Observe S_0
    $t \leftarrow 0$
    repeat
        Choose action A_t using policy derived from Q (e.g., ϵ-greedy)
        Take action A_t and observe R_{t+1}, S_{t+1}
        $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t))$
        $t \leftarrow t + 1$
    until S_t *is terminal*;
end
return Q

- **Expected Sarsa** is an on-policy TD control method. It is guaranteed to converge to the optimal action value function q_*, under the same conditions that guarantee convergence of Sarsa and Sarsamax.

Algorithm 15: Expected Sarsa

Input: policy π, positive integer *num_episodes*, small positive fraction α, GLIE $\{\epsilon_i\}$
Output: value function Q ($\approx q_\pi$ if *num_episodes* is large enough)
Initialize Q arbitrarily (e.g., $Q(s,a) = 0$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$, and $Q(\textit{terminal-state}, \cdot) = 0$)
for $i \leftarrow 1$ ***to*** *num_episodes* **do**
    $\epsilon \leftarrow \epsilon_i$
    Observe S_0
    $t \leftarrow 0$
    repeat
        Choose action A_t using policy derived from Q (e.g., ϵ-greedy)
        Take action A_t and observe R_{t+1}, S_{t+1}
        $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \gamma \sum_a \pi(a|S_{t+1}) Q(S_{t+1}, a) - Q(S_t, A_t))$
        $t \leftarrow t + 1$
    until S_t *is terminal*;
end
return Q

Analyzing Performance

- On-policy TD control methods (like Expected Sarsa and Sarsa) have better online performance than off-policy TD control methods (like Q-learning).
- Expected Sarsa generally achieves better performance than Sarsa.