Algorithms for control

reading: Sutton & Barto, Chap 10

Policy Iteration from data

- We have seen how to learn V^π from data (TD)
- If we can learn Q^π, then we can do control (policy optimization) by running policy iteration
- How to learn Q^π? similar idea
- Bellman eq for Q^π: $Q^\pi(s,a) = R(s,a) + \gamma \mathbb{E}_{s' \sim P(s,a)}[Q^\pi(s', \pi(s'))]$
- Given $(s_t, a_t, r_t, s_{t+1}, a_{t+1})$ where all actions are taken according to π, update rule for learning Q^π: "SARSA"

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t))$$

  - Do you need a_{t+1}? check out: expected Sarsa.

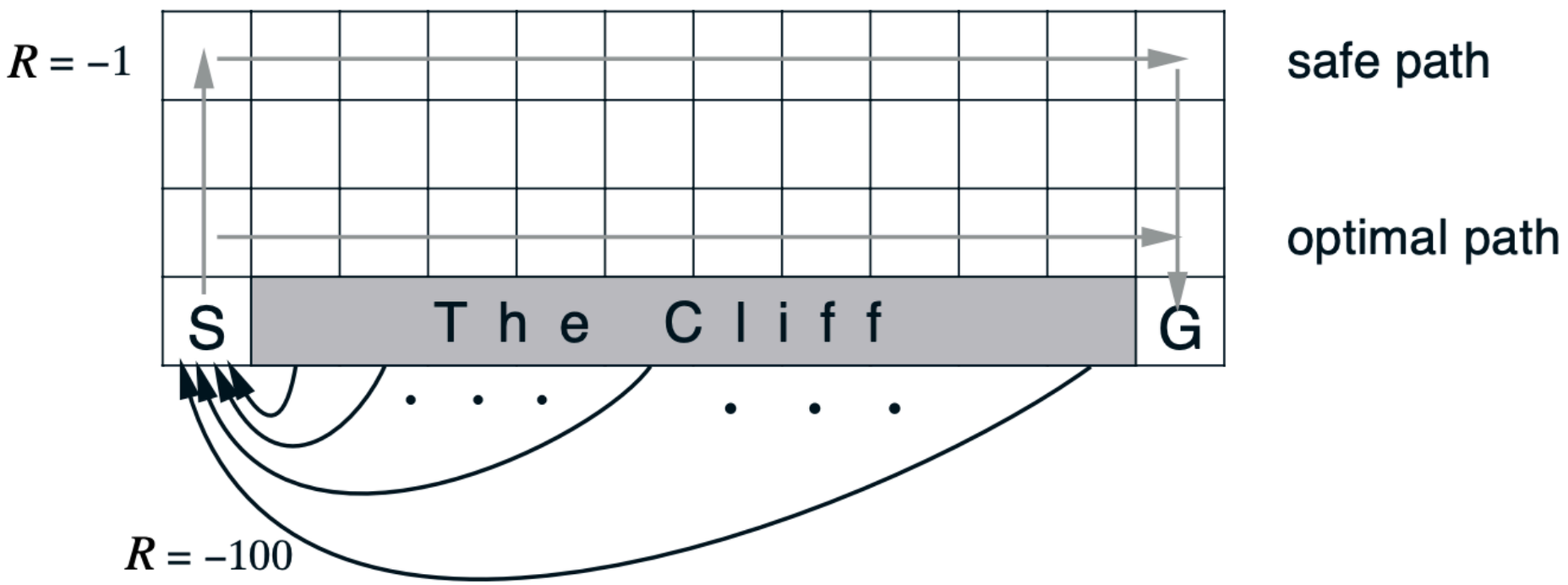
- In TD (for learning V^π), we require that each state is visited sufficiently often
- Similarly, here we require that each state-action pair is visited sufficiently often
- π must be stochastic! (so we cannot run PI exactly)

SARSA with epsilon-greedy policy

- $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t))$
- Take epsilon-greedy policy w.r.t the current Q-estimate
  - At each time step t, with probability ε, choose a_t from the action space uniformly at random. otherwise, $a_t = \mathbf{argmax}_a\, Q(s_t, a)$
- Greedy part: “no-wait” version of policy improvement. Take greedy action w.r.t. Q every time step!
  - the policy being evaluated is constantly changing
  - “ε-greedy policy” is not a fixed policy
- ε part: make sure to explore all actions
- Precisely speaking, this is SARSA(0)
  - Can be extended to SARSA(λ) just as TD

Does SARSA converge to optimal policy?

- The epsilon part can prevent convergence!
- The cliff example (pg 132 of Sutton & Barto)
  - Deterministic navigation, high penalty when falling off the cliff
  - Optimal policy: walk near the cliff
  - Unless epsilon is super small, SARSA will avoid the cliff
- Will need to reduce ε over time—but small ε does not sufficiently explore, and Q-value estimates converge slower



SARSA with epsilon-greedy policy

- ε-greedy can be replaced by softmax: chooses action a with probability $\frac{e^{Q(s_t,a)/T}}{\sum_{a'} e^{Q(s_t,a')/T}}$, here T is temperature and needs to decrease over time (playing a role similar to ε in ε-greedy)
- Can use other stochastic policy that assigns most probability to the greedy action and explore all other actions at the same time
- Exercise: derive SARSA with function approximation

Q-learning

- We've seen how to derive a control algorithm (SARSA) based on the idea of policy iteration (or Bellman eq. for policy eval)
- How about value iteration (Bellman optimality eq.)?
- $Q^\star(s,a) = R(s,a) + \gamma \mathbb{E}_{s' \sim P(s,a)}[\max_{a'} Q^\star(s',a')]$
- Update rule:

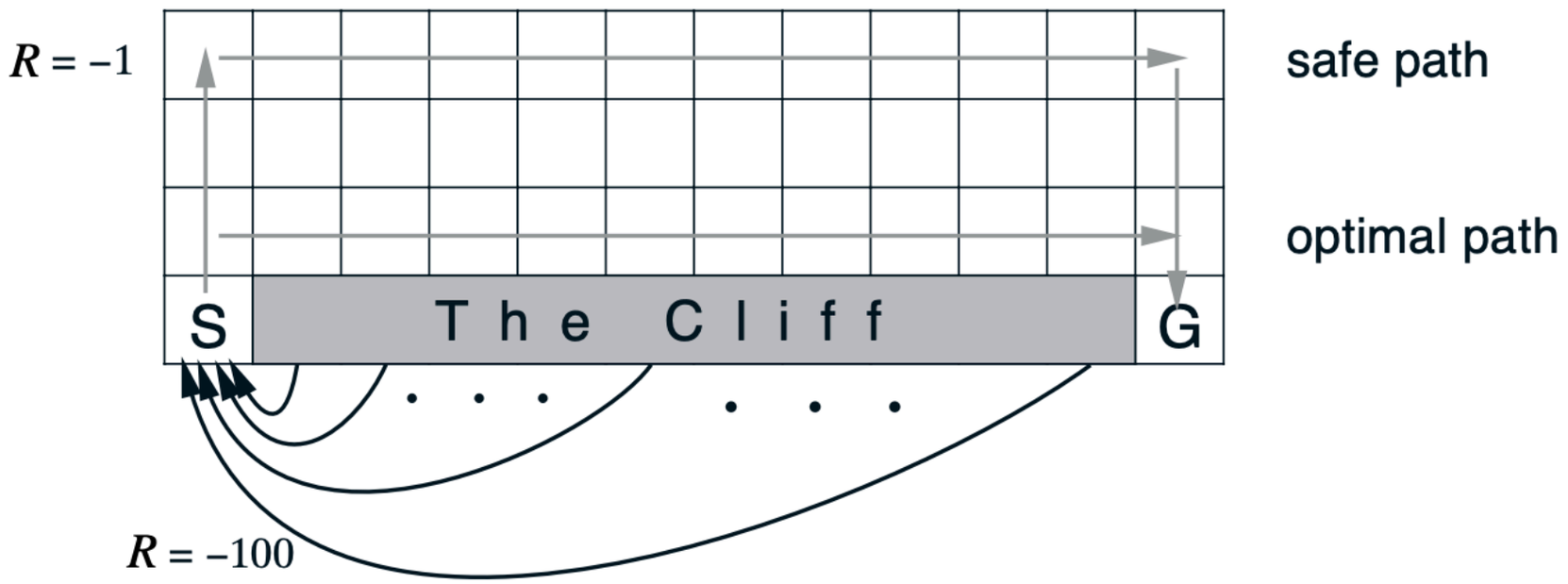
$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha(r_t + \gamma \max_{a'} Q(s_{t+1},a') - Q(s_t,a_t))$$

- Algorithms for control always have a "max" somewhere
  - the max in Q-learning is explicit in the update rule
  - Exercise: where is the "max" in SARSA?

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha(r_t + \gamma Q(s_{t+1},a_{t+1}) - Q(s_t,a_t))$$

Q-learning

- Q-learning does not specify how a_t should be taken
  - Q-learning is *off-policy*: how we take actions have nothing to do with our current Q-estimate (or its greedy policy)
  - Learning rule is completely disentangled from the exploration rule (how to take actions during data collection). Explore however you want using a “behavior policy”
    - e.g., uniformly random action, or ε-greedy (here you do not need to reduce ε)
  - Exercise: think about how Q-learning behaves in the cliff example



Connection between Q-learning and SARSA

- Expected sarsa: $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma Q(s_{t+1}, \pi) - Q(s_t, a_t))$
  - recall that when π is stochastic, $Q(s, \pi) := \mathbb{E}_{a \sim \pi(\cdot|s)}[Q(s, a)]$
- Expected sarsa can be run off-policy!
  - Sarsa needs to be on-policy because we use a_{t+1} from data; this action needs to be consistent with π according to Bellman equation
  - If we replace it with the expectation (i.e., "imagined" action that is not actually taken in the environment), it removes any restriction on the behavior policy
  - (Insight due to Rich Sutton): Q-learning is a special case of expected Sarsa! Which policy are we evaluating?

Exercise: Multi-step Q-learning?

- Does the target $r_t + \gamma r_{t+1} + \gamma^2 \max_{a'} Q(s_{t+2}, a')$ work? If not, why?
  - Consider the expected target conditioned on s_t, a_t . Express it using standard Bellman update operators
  - Give away: the expected target is $(\mathcal{T}^{\pi}(\mathcal{T}Q))(s_t, a_t)$, where π is behavior policy

Q-learning with experience replay

- So far most algorithms we see are “one-pass”
  - i.e., use each data point once and discard them
  - # updates = # data points
- Concern 1: We need many updates for optimization to converge. Can we separate optimization from data collection?
- Concern 2: Need to reuse data if sample size is limited
  - Q-learning as an example: suppose we are given a bag of (s, a, r, s') tuples and we cannot collect further data, what to do?
  - Sample (with replacement) a tuple randomly from the bag, and apply the Q-learning update rule.
    - # updates >> # data points
  - Converges with appropriate learning rate
    - Guess what it converges to?
    - Model-based RL!

Q-learning with function approximation

- As before, we first derive the batch version
- Approximate Q^* using a (parameterized) function class $\mathcal{F}$
- Want to approximate Bellman update operator using data (a bag of (s, a, r, s') tuples)
- Fitted Q-Iteration (FQI):
  $f_{k+1} \leftarrow \arg\min_{f_\theta \in \mathcal{F}} \sum_{(s,a,r,s')} (f_\theta(s,a) - r - \gamma \max_{a'} f_k(s',a'))^2$

- Q-learning with function approximation
- $\theta \leftarrow \theta - \alpha \cdot (f_\theta(s,a) - r - \gamma \max_{a'} f_\theta(s',a')) \nabla f_\theta(s,a)$
- Exercise: this is Q-learning when using tabular function class
- Similar to TD, we only take gradient on $f_\theta(s,a)$ and ignore $f_\theta(s',a')$, because the latter is treated as a constant (it plays the role of f_k)

Quick Recap of the TD Part

How to go from a Bellman update operator to a learning rule?

1. Write down the Bellman up op for the thing you want to learn
   - e.g., $Q_{k+1} \leftarrow \mathcal{T}^{\pi} Q_k$ if we want to learn Q^{π}
2. Write down the detailed equation for a single s (or (s,a))
   - $Q_{k+1}(s,a) \leftarrow R(s,a) + \gamma \mathbb{E}_{s' \sim P(s,a)}[Q_k(s', \pi(s'))]$
3. Replace the expectations with their sampled version to form the target (assuming data is (s, a, r, s', a'))
   - target: $r + \gamma Q(s', \pi(s'))$ (expected Sarsa)
   - alternative target: $r + \gamma Q(s', a')$ if on-policy ($a' \sim \pi(s')$)
4. Online tabular ver: Plug into the template
   - $Q(s,a) \leftarrow Q(s,a) + \alpha(\text{target} - Q(s,a))$
5. Batch function approximation ver: run least sq regression on
   - $\{(s,a) \mapsto \text{target}\}$

Quick Recap of the TD Part

Another example: TD(0)

1. Write down the Bellman up op for the thing you want to learn
   - $V_{k+1} \leftarrow \mathcal{T}^{\pi} V_k$
2. Write down the detailed equation for a single s (or (s,a))
   - $V_{k+1}(s) \leftarrow R(s, \pi(s)) + \gamma \mathbb{E}_{s' \sim P(s,\pi(s))}[V_k(s')]$
3. Replace the expectations with their sampled version to form the target (assuming data is (s, a, r, s'))
   - target: $r + \gamma V(s')$
   - Be careful! This is only a sampled version of above if on-policy ($a \sim \pi(s)$)
   - Difference between learning V and Q: learning V^{π} has to be on-policy (for now), but learning Q^{π} can be easily off-policy (expected sarsa)