Today

- Reminder: P3 lab Friday, 2-4pm, 275 Soda
- Reinforcement learning
  - Temporal-difference learning
  - Q-learning
  - Function approximation

Recap: Passive Learning

- Learning about an unknown MDP
- Simplified task
  - You don’t know the transitions \(T(s,a,s')\)
  - You don’t know the rewards \(R(s)\)
  - You DO know the policy \(\pi(s)\)
- Goal: learn the state values (and maybe the model)
- Last time: try to learn \(T\), \(R\) and then solve as a known MDP

Model-Free Learning

- Big idea: why bother learning \(T\)?
  - Update each time we experience a transition
  - Frequent outcomes will contribute more updates (over time)
- Temporal difference learning (TD)
  - Policy still fixed
  - Move values toward value of whatever successor occurs

\[
U^\pi(s) = R(s) + \gamma \sum_{s'} U^\pi(s') T(s, \pi(s), s')
\]

\[
U^\pi(s) \leftarrow U^\pi(s) + \alpha \left( R(s) + \gamma U^\pi(s') - U^\pi(s) \right)
\]

\[
U^\pi(s) \leftarrow (1 - \alpha) U^\pi(s) + \alpha \left( R(s) + \gamma U^\pi(s') \right)
\]

Example: Passive TD

\[
U^\pi(s) \leftarrow U^\pi(s) + \alpha \left( R(s) + \gamma U^\pi(s') - U^\pi(s) \right)
\]

(Greedy) Active Learning

- In general, want to learn the optimal policy
- Idea:
  - Learn an initial model of the environment:
    - Solve for the optimal policy for this model (value or policy iteration)
  - Refine model through experience and repeat
Example: Greedy Active Learning

- Imagine we find the lower path to the good exit first
- Some states will never be visited following this policy from (1,1)
- We’ll keep re-using this policy because following it never collects the regions of the model we need to learn the optimal policy

What Went Wrong?

- Problem with following optimal policy for current model:
  - Never learn about better regions of the space
- Fundamental tradeoff: exploration vs. exploitation
  - Exploration: must take actions with suboptimal estimates to discover new rewards and increase eventual utility
  - Exploitation: once the true optimal policy is learned, exploration reduces utility
  - Systems must explore in the beginning and exploit in the limit

Q-Functions

- Alternate way to learn:
  - Utilities for state-action pairs rather than states
  - AKA Q-functions

\[
Q(a, s) = R(s) + \gamma \sum_{a'} T(s, a, a') \max_{s'} Q(a', s');
\]

\[
\pi(s) = \max_{a} Q(a, s);
\]

\[
U(3, 2) = 0.660 \quad \pi(3, 2) = \text{up}
\]

\[
Q(\text{up}, (3, 2)) = 0.660\]

\[
Q(\text{right}, (3, 2)) = -0.535\]

Learning Q-Functions: MDPs

- Just like Bellman updates for state values:
  - For fixed policy \( \pi \)
    \[
    Q_{t+1}(a, s) \leftarrow R(s) + \gamma \sum_{a'} T(s, a, a') \max_{s'} Q_{t}(a', s');
    \]
  - For optimal policy
    \[
    Q_{t+1}(a, s) \leftarrow R(s) + \gamma \sum_{a'} T(s, a, a') \max_{s'} Q_{t}(a', s');
    \]
- Main advantage of Q functions over values U is that you don’t need a model for learning or action selection!

Q-Learning

- Model free, TD learning with Q-functions:

\[
Q_{t+1}(a, s) \leftarrow R(s) + \gamma \sum_{a'} T(s, a, a') \max_{s'} Q_{t}(a', s');
\]

\[
Q_{t+1}(a, s) \leftarrow Q_{t}(a, s) + \alpha \left( R(s) + \gamma \max_{a'} Q_{t}(a', s') - Q_{t}(a, s) \right)
\]

\[
Q_{t+1}(a, s) \leftarrow (1 - \alpha)Q_{t}(a, s) + \alpha \left( R(s) + \gamma \max_{a'} Q_{t}(a', s') \right)
\]

Example

- [DEMOS]
Exploration / Exploitation

- Several schemes for forcing exploration
  - Simplest: random actions
    - Every time step, flip a coin
    - With probability $\epsilon$, act randomly
  - With probability $1-\epsilon$, act according to current policy
  - Problems with random actions?
    - Will take a non-optimal long route to reduce risk which stems from exploration actions!
    - Solution: lower $\epsilon$ over time

Exploration Functions

- When to explore
  - Random actions: explore a fixed amount
  - Better idea: explore areas whose badness is not (yet) established

- Exploration function
  - Takes a value estimate and a count, and returns an optimistic utility, e.g. $f(u, n) = u + k/n$

\[
\begin{align*}
Q_{t+1}(a, s) &\leftarrow (1 - \alpha)Q_t(a, s) + \alpha \left( R(s) + \gamma \max_{a'} Q_t(s', a') \right) \\
Q_{t+1}(a, s) &\leftarrow (1 - \alpha)Q_t(a, s) + \alpha \left( R(s) + \gamma \max_{a'} f(Q_t(s', a'), N(s', a')) \right)
\end{align*}
\]

Function Approximation

- Problem: too slow to learn each state’s utility one by one
- Solution: what we learn about one state should generalize to similar states
  - Very much like supervised learning
  - If states are treated entirely independently, we can only learn on very small state spaces

Discretization

- Can put states into buckets of various sizes
  - E.g. can have all angles between 0 and 5 degrees share the same Q estimate
  - Buckets too fine $\Rightarrow$ takes a long time to learn
  - Buckets too coarse $\Rightarrow$ learn suboptimal, often jerky control

- Real systems that use discretization usually require clever bucketing schemes
  - Adaptive sizes
  - Tile coding
  - [DEMO]

Linear Value Functions

- Another option: values are linear functions of features of states (or action-state pairs)

\[
E_g(s) = \sum_k \theta_k f_k(s)
\]

- Good if you can describe states well using a few features (e.g. for game playing board evaluations)
- Now we only have to learn a few weights rather than a value for each state

\[
E_g(s) = 0.3 + 0.05x + 0.15
\]

TD Updates for Linear Values

- Can use TD learning with linear values
  - (Actually it’s just like the perceptron!)
  - Old Q-learning update:

\[
\begin{align*}
Q(a, s) &\leftarrow Q(a, s) + \alpha \left( R(s) + \gamma \max_{a'} Q(a', s') - Q(a, s) \right) \\
\theta_k &\leftarrow \theta_k + \alpha \left( R(s) + \gamma \max_{a'} Q_k(a', s') - Q_k(a, s) \right) f_k(a, s)
\end{align*}
\]