This handout includes space for every question that requires a written response. Please feel free to use it to handwrite your solutions (legibly, please). If you choose to typeset your solutions, the README.md for this assignment includes instructions to regenerate this handout with your typeset LATEX solutions.

1.a

Initialization (Iteration 0)

- V(-2) = 0 (Terminal State)
- V(-1) = 0
- V(0) = 0
- V(1) = 0
- V(2) = 0 (Terminal State)

Iteration 1

Using the Bellman equation for value iteration, V(s) values are calculated as:

For state -1:

$$V(-1) = \max(0.2 \times (-5+0) + 0.8 \times (20+0), 0.3 \times (-5+0) + 0.7 \times (20+0))$$

$$V(-1) = \max(16, 13.5)$$

$$V(-1) = 16$$

For state 0:

$$V(0) = \max(0.2 \times (-5+0) + 0.8 \times (-5+0), 0.3 \times (-5+0) + 0.7 \times (-5+0))$$

$$V(0) = \max(-5, -5)$$

$$V(0) = -5$$

For state 1:

$$V(1) = \max(0.2 \times (100+0) + 0.8 \times (-5+0), 0.3 \times (100+0) + 0.7 \times (-5+0))$$
$$V(1) = \max(16, 26.5)$$
$$V(1) = 26.5$$

Iteration 2

For state -1:

$$V(-1) = \max(0.2 \times (-5 + -5) + 0.8 \times (20 + 0), 0.3 \times (-5 + -5) + 0.7 \times (20 + 0))$$

$$V(-1) = \max(14, 11)$$

$$V(-1) = 14$$

For state 0:

$$V(0) = \max(0.2 \times (-5 + 26.5) + 0.8 \times (-5 + 16), 0.3 \times (-5 + 26.5) + 0.7 \times (-5 + 16))$$
$$V(0) = \max(13.1, 14.15)$$

$$V(0) = 14.15$$

For state 1:

$$V(1) = \max(0.2 \times (100 + 0) + 0.8 \times (-5 + -5), 0.3 \times (100 + 0) + 0.7 \times (-5 + -5))$$
$$V(1) = \max(12, 23)$$
$$V(1) = 23$$

Summary

After Iteration 0:

- V(-2) = 0
- V(-1) = 0
- V(0) = 0
- V(1) = 0
- V(2) = 0

After Iteration 1:

- V(-2) = 0
- V(-1) = 16
- V(0) = -5
- V(1) = 26.5
- V(2) = 0

After Iteration 2:

- V(-2) = 0
- V(-1) = 14
- V(0) = 14.15
- V(1) = 23
- V(2) = 0

1.b

- \bullet S(-1): the best policy is take A(-1), which will have $V_{\mathrm{opt}}(-1)=14$
- $\bullet~S(0):$ the best policy is take A(1), which will have $V_{\mathrm{opt}}(0)=14.15$
- $\bullet~S(1):$ the best policy is take A(1), which will have $V_{\mathrm{opt}}(0)=23$

2.a

Extend the state space by adding an artificial terminal state S(term)

Redifine the transition actions

- ullet for the artificial state S(term), define its transition probabilities to be $1-\lambda$
- for the original states, update its transition probabilities $T'(s,a,s') = \lambda \times T(s,a,s')$

Redifine the rewards

- ullet for the artificial state S(term), define its rewards 0
- for the original states, keep its rewards as original rewards

4.b

Comparing Q-learning and Value Iteration for smallMDP:

- With state (1, 1, (1, 2)): Differing actions between VI (Take) and QL (Quit)
- With state (5, 1, (2, 1)): Differing actions between VI (Take) and QL (Quit)
- With state (6, 0, (1, 1)): Differing actions between VI (Take) and QL (Quit)

Differing actions between VI and QL: 3

Comparing Q-learning and Value Iteration for largeMDP:

Differing actions between VI and QL: 880

4.d

Comparing Q-learning and Value Iteration for newThresholdMDP: ValueIteration: 5 iterations The expected reward from simulating the original policy on the newThresholdMDP is: 6.868 The expected reward under the new Q-learning policy is: 12.0

5.a

5.b

5.c

5.d