

ECE276B-HW3

Zhenyu Wu | PID: A69030822

May 31, 2025

1 Q1

1.1 Q1.1

Below is my hand-written solution:

$$\begin{aligned}
 & t=0 \\
 & Q^\pi(x_0, u_0) = \sin^2(x_0) + u_0^2 + r \cdot Q^\pi\left[(x_0 + u_0), -\frac{x_0 + u_0}{2}\right] \\
 & \quad = \sin^2(x_0) + u_0^2 + r \cdot V^\pi(x_0 + u_0) \\
 & t > 0 \\
 & Q^\pi(x_t, u_t) = x_t^2 + u_t^2 + r \cdot Q^\pi\left(x_t + u_t, -\frac{x_t + u_t}{2}\right) \\
 & \quad = x_t^2 + u_t^2 + r \cdot V^\pi(x_t + u_t) \\
 & V^\pi(x_t) = V\left(x_t, -\frac{x_t}{2}\right) + r V^\pi\left(x_t - \frac{x_t}{2}\right) \\
 & \quad = x_t^2 + \frac{x_t^2}{4} + r V^\pi\left(\frac{x_t}{2}\right) \quad \because t > 0, \sin x \approx x \\
 & \therefore V^\pi(x_t) \text{ is a quadratic form} \\
 & \text{let } V^\pi(x_t) = a \cdot x_t^2 \\
 & \therefore a \cdot x_t^2 = x_t^2 + \frac{x_t^2}{4} + \frac{1}{2} \cdot a \cdot \frac{x_t^2}{4} \\
 & \quad a = 1 + \frac{1}{4} + \frac{1}{2} \cdot a \cdot \frac{1}{4} \\
 & \quad a = \frac{1}{8}a + \frac{5}{4} \\
 & \quad \frac{7}{8}a = \frac{5}{4} \\
 & \quad a = \frac{10}{7} \\
 & \therefore V^\pi(x_t) = \frac{10}{7} x_t^2 \\
 & \therefore \text{For } t=0 \\
 & \quad Q^\pi(x_0, u_0) = \sin^2(x_0) + u_0^2 + \frac{5}{7}(x_0 + u_0)^2 \\
 & \text{For } t > 0 \\
 & \quad Q^\pi(x_t, u_t) = x_t^2 + u_t^2 + \frac{5}{7}(x_t + u_t)^2
 \end{aligned}$$

Figure 1: Q1.1

1.2 Q1.2

Below is my hand-written solution:

2. For $t=0$

$$Q^{\pi}(x_0, u_0) = \sin^2(x_0) + u_0^2 + \frac{5}{7}(x_0 + u_0)^2$$

$$\frac{dQ^{\pi}}{du} = 2u + \frac{10}{7}(x+u)$$

$$0 = 2u + \frac{10}{7}x + \frac{10}{7}u$$

$$24u = -10x$$

$$u = -\frac{5}{12}x$$

For $t>0$

$$Q^{\pi}(x_t, u_t) = x_t^2 + u_t^2 + \frac{5}{7}(x_t + u_t)^2$$

$$\frac{dQ^{\pi}}{du} = 2u + \frac{10}{7}x + \frac{10}{7}u$$

$$u = -\frac{5}{12}x$$

$$\therefore \pi'(x) = -\frac{5}{12}x$$

Figure 2: Q1.2

2 Q2

2.1 Q2.1

Below is my hand-written solution:

$$\begin{aligned}
 & 2. \quad w_t \sim N(0, \frac{1}{2}) \\
 & \quad l(x, u) = \frac{1}{2}x^2 + \frac{1}{2}u^2 \quad r = \frac{1}{2} \\
 & \quad V^*(x) = ax^2 + bx + c \\
 & \quad x_{t+1} = \sqrt{2}x_t + u_t + 2u_t \\
 & \quad \therefore w \sim N(0, \frac{1}{2}) \\
 & \quad 2w \sim N(0, 2), \text{ let } \varepsilon = 2w \\
 & \quad \therefore x' = \sqrt{2}x + u + \varepsilon, \quad \varepsilon \sim N(0, 2) \\
 & \quad \varepsilon = x' - (\sqrt{2}x + u) \\
 & \quad \therefore P(x' | x, u) = P(\varepsilon = x' - (\sqrt{2}x + u)) \\
 & \quad = \frac{1}{\sqrt{4\pi}} \exp\left(-\frac{(x' - (\sqrt{2}x + u))^2}{4}\right) \\
 & \quad \therefore x' \sim N(\sqrt{2}x + u, 2) \\
 \\
 & \quad V^*(x) = \min_u \left(\frac{1}{2}x^2 + \frac{1}{2}u^2 + r \mathbb{E}(V^*(x')) \right) \\
 & \quad \text{For } \mathbb{E}(V^*(x')) \\
 & \quad \therefore V^*(x) = ax^2 + bx + c \\
 & \quad \therefore \mathbb{E}(V^*(x')) = \mathbb{E}(ax'^2 + bx' + c) \\
 & \quad \therefore x' = \sqrt{2}x + u + 2w, \quad w \sim N(0, \frac{1}{2}) \\
 & \quad \text{For } x', \text{ mean } \mu = \sqrt{2}x + u, \text{ Variance } \sigma^2 = 2 \\
 & \quad \therefore \mathbb{E}(x') = \mu = \sqrt{2}x + u
 \end{aligned}$$

Figure 3: Q2.1

$$\begin{aligned}
E(X') &= \sigma^2 + E(X')^2 = 2 + u^2 \\
&= 2 + (\sqrt{2}x + u)^2 \\
\therefore E(V^*(X')) &= a \cdot [2 + (\sqrt{2}x + u)^2] + b \cdot (\sqrt{2}x + u) + C \\
&= a \cdot (2 + 2x^2 + 2\sqrt{2}xu + u^2) + \sqrt{2}bx + bu + C \\
&= 2a + 2ax^2 + 2\sqrt{2}axu + au^2 + \sqrt{2}bx + bu + C \\
\therefore E(V^*(X')) &= a + ax^2 + \sqrt{2}axu + \frac{1}{2}au^2 + \frac{\sqrt{2}}{2}bx + \frac{1}{2}bu + \frac{1}{2}C \\
\therefore V^*(x) &= \min_u \left[\frac{1}{2}x^2 + \frac{1}{2}u^2 + a + ax^2 + \sqrt{2}axu + \frac{1}{2}au^2 + \frac{\sqrt{2}}{2}bx + \frac{1}{2}bu + \frac{1}{2}C \right] \\
\frac{dV^*}{du} &= u + \sqrt{2}ax + au + \frac{1}{2}b = 0 \\
(1+a)u &= -\sqrt{2}ax - \frac{1}{2}b \\
u &= \frac{-\sqrt{2}ax - \frac{1}{2}b}{1+a} = \frac{-\sqrt{2}a}{1+a}x + \frac{-\frac{1}{2}b}{1+a}
\end{aligned}$$

Figure 4: Q2.1

$$\begin{aligned} \therefore V^*(x) &= \frac{1}{2}x^2 + \frac{1}{2}\left(-\frac{\sqrt{2}ax + \frac{1}{2}b}{1+a}\right)^2 + a + ax^2 + \\ &\quad \sqrt{2}ax \cdot \left(-\frac{\sqrt{2}ax + \frac{1}{2}b}{1+a}\right) + \frac{1}{2}a \cdot \left(-\frac{\sqrt{2}ax + \frac{1}{2}b}{1+a}\right)^2 \\ &\quad + \frac{\sqrt{2}}{2}bx + \frac{1}{2}b\left(\frac{\sqrt{2}ax - \frac{1}{2}b}{1+a}\right) + \frac{1}{2}C \end{aligned}$$

Then I use sympy to simplify the equation
After getting coefficients of x^2 , x and c ,
we have following equations:

$$a = \frac{3a}{2a+2} + \frac{1}{2a+2}$$

$$b = \frac{\sqrt{2}b}{2a+2} \quad c = \frac{a^2}{a+1} + \frac{ac}{2a+2} + \frac{a}{a+1} + \frac{b^2}{8a+8} + \frac{c}{2a+2}$$

Lastly I use sympy to solve once
again, have following answers

$$\begin{array}{ll} a=1 & a=-\frac{1}{2} \\ b=0 & b=0 \\ c=2 & c=-1 \end{array}$$

\therefore we should have positive expected cost
 $\therefore a=1$, $b=0$, $c=2$
 $V^*(x) = x^2 + 2$

Figure 5: Q2.1

2.2 Q2.2

Below is my hand-written solution:

$$\begin{aligned} 2. Q^*(x, u) &= l(x, u) + r \mathbb{E}[\min_{u'} Q^*(x', u')] \\ \therefore V^*(x') &= \min_{u'} Q^*(x', u') \\ \therefore Q^*(x, u) &= l(x, u) + r \mathbb{E}[V^*(x')] \\ \therefore Q^*(x, u) &= \frac{1}{2}x^2 + \frac{1}{2}u^2 + a + ax^2 + \sqrt{2}axu + \frac{1}{2}au^2 \\ &\quad + \frac{\sqrt{2}}{2}bx + \frac{1}{2}bu + \frac{1}{2}C \\ \therefore a=1, b=0, c=2 \\ \therefore Q^*(x, u) &= \frac{1}{2}x^2 + \frac{1}{2}u^2 + 1 + x^2 + \sqrt{2}xu + \frac{1}{2}u^2 \\ &\quad + 1 \\ &= \frac{3}{2}x^2 + \sqrt{2}xu + u^2 + 2 \end{aligned}$$

Figure 6: Q2.2

3 Q3

3.1 Q3.1

In the given Discounted problem, we have state space $\mathcal{X} = \{1, 2\}$, control space $\mathcal{U} = \{a, b\}$. From the given transition matrix P^a and P^b , we define the transition model as follow:

$$p_f(j|i, a) = P_{i,j}^a$$

$$p_f(j|i, b) = P_{i,j}^b$$

where i, j entries in P^a specifies the transition probability from state i to j under action a ; i, j entries in P^b specifies the transition probability from state i to j under action b .

Firstly, we need to add virtual terminal state to the state space, $\mathcal{X} = \mathcal{X} \cup \{\tau\}$ and $\mathcal{T} = \{\tau\}$. Therefore, the state space is $\mathcal{X} = \{1, 2, \tau\}$. We will use the same control space. Then, for the motion model, we will use $1 - \gamma$ as the probability of terminate. Therefore, we have

$$p_f(j|i, a) = \gamma p_f(j|i, a) = \gamma P_{i,j}^a, \quad p_f(j|i, b) = \gamma p_f(j|i, b) = \gamma P_{i,j}^b, \quad \text{for } j \neq \tau$$

$$p_f(j|i, a) = p_f(j|i, b) = 1 - \gamma, \quad \text{for } j = \tau$$

$$p_f(j|\tau, a) = p_f(j|\tau, b) = 0, \quad \text{for } j \neq \tau$$

$$p_f(\tau|\tau, a) = p_f(\tau|\tau, b) = 1$$

Put together, we have following transition matrices (we consider $\tau = 3$):

$$\mathbf{P}^a := \begin{bmatrix} 0.1 & 0.7 & 0.2 \\ 0.5 & 0.3 & 0.2 \\ 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{P}^b := \begin{bmatrix} 0.3 & 0.5 & 0.2 \\ 0.5 & 0.3 & 0.2 \\ 0 & 0 & 1 \end{bmatrix}$$

For the stage cost, we have

$$\ell(x, u) := \begin{cases} 16x & \text{if } u = a \text{ and } x \neq \tau \\ 5x & \text{if } u = b \text{ and } x \neq \tau. \\ 0 & \text{if } x = \tau \end{cases}$$

Lastly, for the terminal cost, we have $q(x_\tau) = 0$. The problem terminates at $T := \inf\{t \geq 0 | x_t = 3\}$. Our objective is

$$\begin{aligned} V^*(\mathbf{x}) = \min_{\pi} V^{\pi}(\mathbf{x}) &:= \mathbb{E} \left[q(x_\tau) + \sum_{t=0}^{T-1} \ell(x_t, \pi(x_t)) \mid x_0 = \mathbf{x} \right] \\ \text{s.t. } & x_{t+1} \sim p_f(\cdot \mid x_t, \pi(x_t)), \\ & x_t \in \mathcal{X}, \quad \pi(x_t) \in \mathcal{U} \end{aligned}$$

3.2 Q3.2

Below is my hand-written solution:

For $X=1$

① For $u=a$

$$P(1|1,a)V(1) + P(2|1,a)V(2) + P(3|1,a)V(3)$$

$$= 0.1 \times 20 + 0.7 \times 10 = 9$$

$$L(1,a) + r \cdot 9 = 16 + 0.8 \times 9 = 23.2$$

② For $u=b$

$$P(1|1,b)V(1) + P(2|1,b)V(2) + P(3|1,b)V(3)$$

$$= 0.3 \times 20 + 0.5 \times 10 = 11$$

$$L(1,b) + r \cdot 11 = 5 + 0.8 \times 11 = 13.8$$

$$\therefore V_1(X=1) = 13.8$$

For $X=2$

① For $u=a$

$$P(1|2,a)V(1) + P(2|2,a)V(2) + P(3|2,a)V(3)$$

$$= 0.5 \times 20 + 0.3 \times 10 = 13$$

$$L(2,a) + r \cdot 13 = 32 + 0.8 \times 13 = 42.4$$

② For $u=b$

$$P(1|2,b)V(1) + P(2|2,b)V(2) + P(3|2,b)V(3)$$

$$= 0.5 \times 20 + 0.3 \times 10 = 13$$

$$L(2,b) + r \cdot 13 = 10 + 0.8 \times 13 = 20.4$$

$$\therefore V_1(X=2) = 20.4$$

Figure 7: Q3.2

3.3 Q3.3

Let ℓ^a denotes the stage cost if $u = a$ and ℓ^b denotes the stage cost if $u = b$, and we have

$$\ell^a = [16 \times 1, 16 \times 2]^T = [16, 32]^T$$

$$\ell^b = [5 \times 1, 5 \times 2]^T = [5, 10]^T$$

since $x \in \{1, 2\}$. Then, based on the lecture slides, we can formulate the given discounted problem as LP problem as follow:

$$\begin{aligned} \max_V & w^T V \\ \text{s.t.} & (I - \gamma P^u)V \leq \ell^u, \forall u \in \mathcal{U} \end{aligned}$$

where P^u is the 2×2 transition matrix, $V \in \mathbb{R}^2$ is the value vector, $w \in \mathbb{R}^2$ is the weight vector and $w_i > 0 \quad \forall i = \{1, 2\}$.

In the implementation, I initialize w as random vector where each entry is uniformly sampled from $(0, 1]$. The result I have is $V^* = [35.4166667439.58333341]$, and $V^*(1) = 35.41666674$, $V^*(2) = 39.58333341$

4 Q4

Below is my hand-written process:

TD(0):

$$V^\pi(x) \leftarrow V^\pi(x) + \alpha [l(x, u) + V^\pi(x') - V^\pi(x)]$$

① 1st episode

$$1 \xrightarrow{3} 1 : V^\pi(1) = 0.5 + 0.2 [-3 + 0.5 - 0.5] = -0.1$$

$$1 \xrightarrow{2} 2 : V^\pi(1) = -0.1 + 0.2 [-2 + 0.5 + 0.1] = -0.38$$

$$2 \xrightarrow{4} 1 : V^\pi(2) = 0.5 + 0.2 [4 - 0.38 - 0.5] = 1.124$$

$$1 \xrightarrow{3} 2 : V^\pi(1) = -0.38 + 0.2 [-3 + 1.124 + 0.38] = -0.6792$$

$$2 \xrightarrow{3} 3 : V^\pi(2) = 1.124 + 0.2 [3 + 0.5 - 1.124] = 1.5992$$

② 2nd episode

$$2 \xrightarrow{4} 1 : V^\pi(2) = 1.5992 + 0.2 [4 - 0.6792 - 1.5992] = 1.94352$$

$$1 \xrightarrow{2} 2 : V^\pi(1) = -0.6792 + 0.2 [-2 + 1.94352 + 0.6792] = -0.354656$$

$$2 \xrightarrow{3} 3 : V^\pi(2) = 1.94352 + 0.2 [3 + 0.5 - 1.94352] = 2.254816$$

Figure 8: Q4

$$= 2.254816$$

$$\therefore V^\pi(1) = -0.354656$$

$$V^\pi(2) = 2.254816$$

$$V^\pi(3) = 0.5$$

Figure 9: Q4

The result I have is $V(1) = -0.354656$, $V(2) = 2.254816$, $V(3) = 0.5$

References


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In [1]: import sympy as sp
import numpy as np

x, u, a, b, c = sp.symbols('x u a b c')

gamma = sp.Rational(1, 2)
sqrt2 = sp.sqrt(2)

# stage cost
stage_cost = sp.Rational(1, 2) * x**2 + sp.Rational(1, 2) * u**2

# expected value of V*
E_x_next_squared = 2*x**2 + 2*sqrt2*x*u + u**2 + 2
E_x_next = sqrt2*x + u
E_V_next = a*E_x_next_squared + b*E_x_next + c

# Bellman equation RHS (before minimization)
bellman_rhs = stage_cost + gamma * E_V_next

# find optimal u by taking derivative and setting to zero
du_bellman = sp.diff(bellman_rhs, u)
u_star = sp.solve(du_bellman, u)[0]

# substitute back into bellman equation
bellman_rhs_optimal = bellman_rhs.subs(u, u_star)
bellman_rhs_optimal_simplified = sp.simplify(bellman_rhs_optimal)
bellman_expanded = sp.expand(bellman_rhs_optimal_simplified)
bellman_collected = sp.collect(bellman_expanded, x)
coeff_x2 = bellman_collected.coeff(x, 2)
coeff_x1 = bellman_collected.coeff(x, 1)
coeff_x0 = bellman_collected.coeff(x, 0)

# set up equations by matching coefficients
eq1 = sp.Eq(a, coeff_x2)
eq2 = sp.Eq(b, coeff_x1)
eq3 = sp.Eq(c, coeff_x0)

# solve the system of equations
# first solve for a from eq1
a_solutions = sp.solve(eq1, a)

# choose positive solution for a
a_val = 1 # From (2a + 1)(a - 1) = 0, we choose a = 1

# substitute a = 1 into eq2 to find b
eq2_with_a = eq2.subs(a, a_val)
b_val = sp.solve(eq2_with_a, b)[0]

# substitute a = 1 and b = 0 into eq3 to find c

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```
eq3_with_a_b = eq3.subs([(a, a_val), (b, b_val)])
c_val = sp.solve(eq3_with_a_b, c)[0]

print("FINAL SOLUTION:")
print(f"a = {a_val}")
print(f"b = {b_val}")
print(f"c = {c_val}")
print(f"V*(x) = {a_val}x^2 + {b_val}x + {c_val}")
```

FINAL SOLUTION:

a = 1

b = 0

c = 2

$V^*(x) = 1x^2 + 0x + 2$

```
In [6]: import numpy as np

# Transition probability matrices
PA = np.array([[0.1, 0.7, 0.2],
               [0.5, 0.3, 0.2],
               [0.0, 0.0, 1.0]])

PB = np.array([[0.3, 0.5, 0.2],
               [0.5, 0.3, 0.2],
               [0.0, 0.0, 1.0]])

# State and control spaces
STATE = np.array([1, 2, 3])
CONTROL = ['a', 'b']
TERMINAL_STATE = 3
TERMINAL_COST = 0

def get_stage_cost(state, control):
    """Get the stage cost for a given state and control"""
    if state == TERMINAL_STATE:
        return 0
    else:
        if control == 'a':
            return 16 * state
        else:
            return 5 * state

def get_transition_prob(state, control, next_state):
    """Get transition probability P(next_state | state, control)"""
    state_index = state - 1 # Convert to 0-based index
    next_state_index = next_state - 1
    if control == 'a':
        return PA[state_index, next_state_index]
    else:
        return PB[state_index, next_state_index]

def get_updated_value(state, value_func, gamma=0.8):
    """Compute the updated value for a single state using Bellman operator"""
    if state == TERMINAL_STATE:
        return TERMINAL_COST

    min_value = np.inf
    for control in CONTROL:
        # Compute expected value for this control
```

```

        expected_value = get_stage_cost(state, control)
        for next_state in STATE:
            prob = get_transition_prob(state, control, next_state)
            expected_value += gamma * prob * value_func[next_state - 1]

        # Keep track of minimum value across all controls
        if expected_value < min_value:
            min_value = expected_value

    return min_value

def value_iteration(initial_value, gamma=0.8, max_iter=1):
    """Perform value iteration for specified number of iterations"""
    value = initial_value.copy()

    for iteration in range(max_iter):
        new_value = value.copy()

        # Update values for all non-terminal states
        for state in STATE:
            if state != TERMINAL_STATE:
                new_value[state - 1] = get_updated_value(state, value, gamma)

        # Update value function
        value = new_value

        print(f"After iteration {iteration + 1}:")
        print(f"V(1) = {value[0]:.2f}")
        print(f"V(2) = {value[1]:.2f}")
        print(f"V(3) = {value[2]:.2f}")
        print()

    return value

# Initial value function
V0 = np.array([20.0, 10.0, 0.0])

print("Initial value function:")
print(f"V0(1) = {V0[0]}")
print(f"V0(2) = {V0[1]}")
print(f"V0(3) = {V0[2]}")
print()

# Perform one iteration of value iteration
V1 = value_iteration(V0, gamma=0.8, max_iter=1)

print("Final result after one iteration:")
print(f"V1 = [{V1[0]:.1f}, {V1[1]:.1f}, {V1[2]:.1f}]")

```

Initial value function:

$V_0(1) = 20.0$

$V_0(2) = 10.0$

$V_0(3) = 0.0$

After iteration 1:

$V(1) = 13.80$

$V(2) = 20.40$

$V(3) = 0.00$

Final result after one iteration:

$V_1 = [13.8, 20.4, 0.0]$

```
In [ ]: import numpy as np
import cvxpy as cp

# params
n_control = 2
n_state = 2

# weights positive
w = np.random.rand(2)

# Problem parameters
gamma = 0.8

# Transition probability matrices
P_a = np.array([[1/8, 7/8],
                [5/8, 3/8]])

P_b = np.array([[3/8, 5/8],
                [5/8, 3/8]])
identity = np.eye(n_state)

# stage cost
cost_a = np.array([16., 32.])
cost_b = np.array([5., 10.])

# decision variables
value = cp.Variable(n_state)

# LP objective
objective = cp.Maximize(w.T @ value)

# LP constraints
constraints = []
# control a
constraints.append((identity - gamma * P_a) @ value <= cost_a)
# control b
constraints.append((identity - gamma * P_b) @ value <= cost_b)

# solve
problem = cp.Problem(objective, constraints)
problem.solve()
print(f"Optimal value: {value.value}")
```

Optimal value: [35.41666674 39.58333341]

In []: