Homework 6

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```
In [1]: import numpy as np
import sympy as sym
import pandas as pd
%matplotlib notebook
from matplotlib import pyplot as plt
from scipy.optimize import minimize
from scipy.integrate import solve_ivp, solve_bvp, trapz
```

Problem 1

Demonstrate numerically that the optimal solution obtained by the Riccati equation form Homework 5 problem 4 is indeed optimal. Evaluate the directional derivative of J at $(x_{sol}(t), u_{sol}(t))$ in 10 different directions. Make a table of the 10 directions and the corresponding value of the directional derivative.

```
In [6]: Q = sym.Matrix([[2,0],[0,0.01]])
         R = sym.Matrix([0.1])
         P1 = sym.Matrix([[1,0],[0,0.01]])
         x0 = sym.Function('x 0')(t)
         x1 = sym.Function('x_1')(t)
         z0 = sym.Function('z_0')(t)
         z1 = sym.Function('z 1')(t)
         x = sym.Matrix([x0, x1])
         z = sym.Matrix([z0, z1])
         x_fin = sym.MatrixSymbol('x(T)', 2, 1).as_explicit()
z_fin = sym.MatrixSymbol('z(T)', 2, 1).as_explicit()
         x_init = sym.Matrix([10,0]) #possibly want this to be zeros
         z_{init} = np.zeros((2,1))
         A = sym.Matrix([[0,1],[-1.6,-0.4]])
         B = sym.Matrix([0,1])
         u0 = sym.Function('u 0')(t)
         v0 = sym.Function('v_0')(t)
         u = sym.Matrix([u0])
         v = sym.Matrix([v0])
         b = u.T * R
         xdot = A * x + B * u
         p = sym.Matrix([sym.Function('p_0')(t), sym.Function('p_1')(t)])
         p_fin = sym.MatrixSymbol('p_{1}', 2, 1).as_explicit()
         pdot = -A.T * p - Q*x
```

```
In [7]: def compute dd for perturb():
            v pert, randos = get rand v()
            pert_init = np.concatenate((z_init, v_pert.subs(t,0)))
            zdot = A * z + B * v pert
            pert = sym.Matrix([z,v])
            zdot_lam = sym.lambdify([t, pert], sym.flatten(sym.Matrix([zdot,
        v pert])))
            ans = solve_ivp(zdot_lam, (0, 10), pert_init.flatten(), t_eval=t_
        vec)
            zed = ans.y[:2,:]
            v_lam = sym.lambdify(t,v_pert)
            ved = np.expand_dims(v_lam(t_vec).flatten(),0)
            J_dd_integrand = np.zeros(zed.shape[1])
            for i in range(zed.shape[1]) :
                J_dd_integrand[i] = np.matmul(np.matmul(x_opt[:,i].T, Q), zed
        [:,i]) \
                                                 + np.matmul(np.matmul(u opt
        [:,i].T, R), ved[:,i])
            J dd term = np.matmul(np.matmul(x opt[:,-1].T, P1), zed[:,-1])
            J_dd_val = trapz(J_dd_integrand, t_vec) + J_dd_term
            return J dd val, randos
```

```
In [8]:
        J dd ave = 0
        num perturbs = 10
        for i in range(num perturbs):
            J dd val, randos = compute dd for perturb()
            print("For A={:.5f}; B={:.5f}; C={:.5f}; D={:.5f};".format(randos
        [0], randos[1], randos[2], randos[3]))
            print("J dd = {:.7f}".format(J dd val))
            print("")
            J_dd_ave += J_dd_val/num_perturbs
        print("This yields an avearge value for the directional derivative of
        J of: \n{:.7f}".format(J_dd_ave))
        For A=0.78787; B=0.40367; C=0.52583; D=0.34221;
        J dd = -0.0068363
        For A=0.78039; B=0.00787; C=0.30829; D=0.82650;
        J dd = -0.0102889
        For A=0.31633; B=0.36641; C=0.56506; D=0.54324;
        J_dd = -0.0067897
        For A=0.60707; B=0.01867; C=0.55751; D=0.57839;
        J dd = -0.0087001
        For A=0.55678; B=0.04196; C=0.45792; D=0.69346;
        J dd = -0.0090747
        For A=0.89390; B=0.43371; C=0.42276; D=0.78645;
        J dd = -0.0107607
        For A=0.20501; B=0.03725; C=0.61571; D=0.30826;
        J dd = -0.0041738
        For A=0.41599; B=0.72144; C=0.07101; D=0.14564;
        J dd = -0.0014059
        For A=0.73852; B=0.61264; C=0.68439; D=0.76566;
        J_dd = -0.0114148
        For A=0.62927; B=0.88871; C=0.83672; D=0.13566;
        J dd = -0.0052745
        This yields an avearge value for the directional derivative of J of:
        -0.0074719
```

Probelm 2

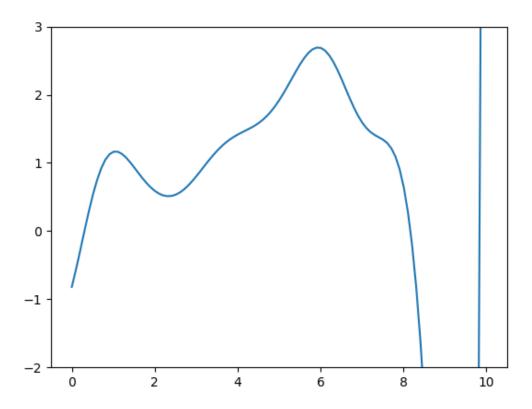
Compute the control u(t) that minimizes the given cost function subject to the given constraint and desired trajectory

```
In [73]: t = sym.symbols('t')
         Q = sym.Matrix([[10,0],[0,1 + sym.Rational(1,8) * sym.sin(t)]])
         R = sym.Matrix([1])
         P1 = sym.Matrix([[100,0],[0,100]])
         A = sym.Matrix([[0, 1+sym.Rational(1,2) * sym.sin(t)], [-1 - sym.Rati])
         onal(1,2) * sym.cos(t), sym.Rational(1,4) * sym.sin(t)]])
         B = sym.Matrix([0, 1 + sym.Rational(1,2) * sym.sin(t)])
         #lambdify our time varying A and B
         A lam = sym.lambdify([t], A)
         B lam = sym.lambdify([t], B)
In [74]: x0 = \text{sym.Function}('x 0')(t)
         x1 = sym.Function('x 1')(t)
         x = sym.Matrix([x0, x1])
         x_{fin} = sym.MatrixSymbol('x(T)', 2, 1).as_explicit()
         x init = sym.Matrix([1,1])
         u0 = sym.Function('u 0')(t)
         u = sym.Matrix([u0])
         p = sym.Matrix([sym.Function('p_0')(t), sym.Function('p_1')(t)])
         p fin = sym.MatrixSymbol('p {1}', 2, 1).as explicit()
In [75]: x d = sym.Matrix([0.1*t + 1, -0.2*t + 1])
         x d fin = x d.subs(t,10)
In [76]: P_0 = \text{sym.Function}("P_0")(t)
         P 1 = sym.Function("P 1")(t)
         P^2 = sym.Function("P^2")(t)
         P 3 = sym.Function("P 3")(t)
         P = sym.Matrix([[P 0, P 1], [P 2, P 3]])
         Pdot = -P * A - A.T * P + P * B * R.inv() * B.T * P - Q
         P fin = P1
         r0 = sym.Function("r_0")(t)
         r1 = sym.Function("r 1")(t)
         r = sym.Matrix([r0, r1])
         rdot = -A.T * r + Q * x_d + P*B*R.inv()*B.T*r
          r fin = -P1 * x d fin
In [77]: q_Pr = sym.Matrix([P.reshape(4,1), r])
         g Pr dot = sym.Matrix([Pdot.reshape(4,1), rdot])
         q Pr fin = sym.Matrix([P fin.reshape(4,1), r fin])
```

q_Pr_dot_lam = sym.lambdify([t, q_Pr], sym.flatten(q_Pr_dot))

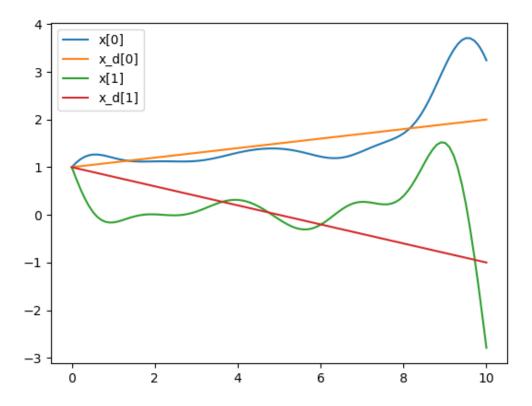
```
#set up boundary condition
In [78]:
          ans_Pr = solve_ivp(q_Pr_dot_lam, [10, 0], np.array(q_Pr_fin).flatten
          (), \max \text{ step} = 0.1)
In [79]: P_t = np.flip(ans_Pr.y[:4,:].reshape(2,2,-1),2)
          r_t = np.flip(ans_Pr.y[4:,:].reshape(2,1,-1),2)
          t_vec = np.flip(ans_Pr.t,-1)
In [80]:
         P_t_{init} = P_t[:,:,0]
          r_t_{init} = r_t[:,:,0]
          # p_init = np.matmul(P_t_init, x_init) + r_t_init
In [81]: q = sym.Matrix([x,p])
          qdot = sym.Matrix([A*x + -B*R.inv()*B.T * p, -Q*x - A.T * p + Q * x d)
          q_init = np.concatenate((np.array(x_init),p_init)).flatten()
          qdot_lam = sym.lambdify([t, q], sym.flatten(qdot))
In [82]: ans x = \text{solve ivp}(\text{qdot lam}, (0,10), \text{q init, t eval=t vec})
In [83]: x_t = ans_x.y[:2, ].reshape(2,1,-1)
In [84]:
         N = ans_x.t.shape[-1]
          u = np.zeros(N)
          R num = np.array(R)[0]
          for i in range(N):
              u[i] = np.matmul(-1/R_num * B_lam(t_vec[i]).T, (np.matmul(P_t
          [:,:,i], x_t[:,:,i]) + r_t[:,:,i])
```

```
In [85]: plt.figure()
  plt.plot(t_vec, u)
  plt.ylim([-2,3])
  plt.show()
```



Out[86]: (2, 1, 110)

```
In [89]: plt.figure()
   plt.plot(t_vec, x_t[0,0,:])
   plt.plot(t_vec, x_d_traj[0,0,:])
   plt.plot(t_vec, x_t[1,0,:])
   plt.plot(t_vec, x_d_traj[1,0,:])
   plt.legend(["x[0]", "x_d[0]", "x[1]", "x_d[1]"])
   plt.show()
```



Note:

I spent >10 hours trying to get the terminal conditions to line up. I have tried my above implementation as well as a seperate implementation in which i also simultaneously integrate P and r backwards and the integrate P, r, and x forward together I am not sure what I am missing. I tried a sympy version and a pure numpy version, would love a comment if you could see where I went wrong.

Problem 3

Linearize dynamics of the presented diff drive system to obtain matrix A of costate variable p, use algebra to get u out of TPBVP.

```
In [19]: Q = \text{sym.Matrix}([[1000,0,0],[0,50,0],[0,0,1]])
         R = sym.Matrix([[50, 0], [0, 0.1]])
         P1 = sym.Matrix([[10000, 0, 0], [0, 10000, 0], [0, 0, 10]])
         t = sym.symbols('t')
         u0 = sym.Function('u 0')(t)
         u1 = sym.Function('u 1')(t)
         u = sym.Matrix([u0, u1])
         x = sym.Function('x')(t)
         y = sym.Function('y')(t)
         theta = sym.Function('theta')(t)
         q = sym.Matrix([x, y, theta])
         xdot = sym.cos(theta) * u0
         ydot = sym.sin(theta) * u0
         thetadot = u1
         qdot = sym.Matrix([xdot, ydot, thetadot])
         q init = np.array([0,0,np.pi/4])
In [20]: tspan = np.linspace(0,1,100)
         x d = 4 / (2 * sym.pi) * t
         y d = 0
         theta d = sym.pi/2
         q d = sym.Matrix([x d, y d, theta d])
         y d traj = np.zeros(tspan.shape[0])
         x d traj = sym.lambdify([t], 2 * t / sym.pi)(tspan)
         q d fin = np.array(sym.Matrix([x d traj[-1], 0, np.pi/2])).flatten()
         q d fin
Out[20]: array([0.636619772367581, 0, 1.57079632679490], dtype=object)
In [21]:
         #linearize dynamic to obtain A matrix
         p = sym.Matrix([sym.Function('p 0')(t), sym.Function('p 1')(t), sym.F
         unction('p 2')(t)])
         p_fin = sym.MatrixSymbol('p_{1}', 3, 1).as_explicit()
         # p1 = P1.T * x(T)
         p1 = np.matmul(P1.T, q_d_fin).flatten()
         p1.shape
Out[21]: (3,)
In [22]: A = qdot.jacobian(q)
         B = qdot.jacobian(u)
```

```
xdot = A *q + -B * R.inv() * B.T * p
          pdot = -Q * q + -A.T*p + Q * q d
In [24]: |u| sub = -R.inv() * B.T * p
In [25]:
          xdot pdot = sym.Matrix([xdot, pdot])
          xdot pdot = xdot pdot.subs({u[0]:u sub[0], u[1]:u sub[1]})
          xp = sym.Matrix([q,p])
          xdot pdot lam = sym.lambdify([t, xp], xdot pdot)
          def my dot(t, xp):
              return np.squeeze(xdot pdot lam(t, xp).reshape(6,-1,1))
In [26]: x_fin
Out[26]: [x(T)_{0,0}]
          \lfloor x(T)_{1,0} \rfloor
In [27]:
         def bc(x_a, x_b):
              #a = t 0, #b = T
              #check x against known inital
              x_{err} = x_a[:3] - np.squeeze(q_init)
              #check p against known final
              x_fin = x_b[:3]
               x fin = q d fin
              p fin = x b[3:] #current guess
               p1 = P1.T * x(T)
              p1 = np.matmul(np.array(P1.T), x fin - q d fin) #actual
              p err = p fin - p1
              return np.concatenate((x_err, p_err))
In [28]:
         ya = np.concatenate((np.array([[*q_init, *p1]]),np.zeros((6, 99)).T))
          . T
          \# ya = np.zeros((6,100))
          ans = solve_bvp(fun=my_dot,bc=bc, x=tspan, y=ya)
```

```
In [29]: x_found = ans.y[0,:]
    y_found = ans.y[1,:]

    plt.figure()
    plt.plot(x_found, y_found)
    plt.scatter([q_init[0], q_d_fin[0]], [q_init[1], q_d_fin[1]])
    plt.show()
```

