Introduction

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Welcome to the analysis of the Robust LP Problem!

- 1. All the equations have been coded in LaTeX by me
- 2. The necessary explanations have been provided

```
import numpy as np
import cvxpy as cp
```

▼ (a) Convexity

x = cp.Variable((10,1))

$$f(x) = \sup_{c \in C} \ c^T x = \sup_{c \in C} \ (ext{Affine})$$

This function is a maximum of affine functions = maximum of convex functions = convex

Constraints are polyhedra, so they are convex

```
np.random.seed(10)
(m,n) = (30,10)
A = np.random.rand(m,n)
A = np.asmatrix(A)
b = np.random.rand(m,1)
b = np.asmatrix(b)
c_{nom} = np.ones((n,1)) + np.random.rand(n,1)
c_nom = np.asmatrix(c_nom)
print(c_nom.shape)
print(A.shape)
print(b.shape)
print(type(A))
     (10, 1)
     (30, 10)
     (30, 1)
     <class 'numpy.matrix'>
```

▼ Framing F and g

F needs to be formed according to the constraints defined by

$$c \leq 1.25 \ c_{nom} \ -c \leq -0.75 \ c_{nom} \ ec{1}^T c \leq ec{1}^T c_{nom} \
ightarrow ^T \
ightarrow ^T \ -1 \ c \leq -1 \ c_{nom}$$

In order to make this in matrix form we do the following

```
#Now to generate the values of F and g
I = np.eye(n)
Stacked_identitites = np.block([
        [I],
        [-I]
])
F = np.vstack((np.vstack((Stacked_identitites, np.ones(n))), -1 *np.ones(n)))
print(F)
print(F.shape)
```

```
0.
                                 0.]
    1. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
     0. 0. 0. 0. 1. 0. 0. 0.
     0. 0. 0. 0. 1. 0. 0.
 0.
     0. 0. 0. 0. 0. 1. 0.
        0. 0. 0. 0. 0. 1.
     0.
        0. 0. 0. 0. 0. 0. 0.
     0.
[-1. -0. -0. -0. -0. -0. -0. -0. -0. ]
[-0. -1. -0. -0. -0. -0. -0. -0. -0. -0.]
[-0. -0. -1. -0. -0. -0. -0. -0. -0. -0.]
[-0. -0. -0. -1. -0. -0. -0. -0. -0. -0.]
[-0. -0. -0. -0. -1. -0. -0. -0. -0. -0.]
[-0. -0. -0. -0. -0. -1. -0. -0. -0. -0.]
[-0. -0. -0. -0. -0. -1. -0. -0. -0.]
[-0. -0. -0. -0. -0. -0. -1. -0. -0.]
[-0. -0. -0. -0. -0. -0. -0. -1. -0.]
[-0. -0. -0. -0. -0. -0. -0. -0. -1.]
[ 1. 1. 1. 1. 1. 1. 1. 1.
```

```
[-1. -1. -1. -1. -1. -1. -1. -1. -1.]] (22, 10)
```

```
#to calculate g
#print(c_nom)
stacked_noms = np.vstack( ( (1.25 * c_nom), (-0.75 * c_nom) ) )
# print(stacked_noms.shape)
sum = np.sum(c_nom)
#print(sum)
g_1 = np.vstack((stacked_noms, 1.1*sum))
g = np.vstack((g_1, -0.9*sum))
print(g)
print(g.shape)
```

```
2.00180047]
   1.37159062]
   1.6109186 ]
   2.15099988]
   1.93850758]
   2.29822127]
   1.97541419]
   1.48071467]
   2.01937765]
   2.35869386]
[ -1.20108028]
[ -0.82295437]
[ -0.96655116]
[ -1.29059993]
[ -1.16310455]
[ -1.37893276]
[ -1.18524851]
[ -0.8884288 ]
[ -1.21162659]
[ -1.41521632]
[ 16.90149013]
[-13.82849192]]
(22, 1)
```

lam = cp.Variable(g.shape)

→ (b),(c) Framing a Dual

THe dual of the problem is

$$f(x) = \max g(\lambda)$$

 $\lambda > 0$

Where:-

$$g(\lambda) = \min_{c} \ [c^T x + \lambda^T (Fc - g)]$$

Unbounded unless coefficient of c is zero!

$$F^T \lambda = x$$
$$\therefore g(\lambda) = -\lambda^T g$$

Therefore the solution of the primal

$$egin{aligned} \min_x \ (\max_{\lambda} \ g(\lambda)) &= \min_{x,\lambda} \ (\lambda^T g) \ & \lambda \geq 0 \ & F^T \lambda = x \ & Ax > b \end{aligned}$$

```
objective = cp.Minimize(lam.T @ g)
constraints = [F.T @ lam == x, lam >= 0 , A@x >= b]
prob = cp.Problem(objective, constraints)
result_dual_form = prob.solve()
print(result_dual_form)
x_robust = x.value
```



3.1659610520520705

```
#solving the primal using c_nom
x2 = cp.Variable((10,1))
test_obj = cp.Minimize(c_nom.T @ x2)
test_constraints = [A@x2 >= b]
test_prob = cp.Problem(test_obj,test_constraints)
result_nominal = test_prob.solve()
print("Result of Nominal C = ",result_nominal)
```

Result of Nominal C = 2.1092714620826003

```
print("Result of Robust C = ", (c_nom.T @ x_robust)[0,0])
```

Result of Robust C = 2.5232088648898556

Final Values

$$egin{aligned} c_{nom}^T x_{robust} &= 2.52 \ c_{nom}^T x_{nominal} &= 2.109 \ f(x)_{min} &= 3.165 \end{aligned}$$

×