

Lecture 8 : Examples + Code

goals:

- more example problems
- look at some CVX code

Ex Constrained ∞ -norm minimization

$$\begin{aligned} &\text{minimize } \|x\|_{\infty} \\ &\text{subject to } Ax \leq b \end{aligned}$$



$$\begin{aligned} &\text{minimize } t \\ &\text{subject to } x_i \leq t \quad i=1, \dots, n \\ &\quad \quad \quad -x_i \leq t \\ &\quad \quad \quad Ax \leq b \end{aligned}$$

$$\text{Note: } \|x\|_{\infty} = \max_i |x_i|$$

$$= \max_i \{x_i, -x_i\}$$

$$= \max_i \{x_1, \dots, x_n, -x_1, \dots, -x_n\}$$

$$\begin{aligned} &\text{minimize } t \\ &\text{subject to } -1t \leq x \leq 1t \\ &\quad \quad \quad Ax \leq b \end{aligned}$$

• CVX code

Ex Constrained 1-norm minimization

$$\text{minimize } \|Ax - b\|_1$$

$$\text{subject to } Fx \leq g$$

$$\text{Note: } \|Ax - b\|_1 = \sum_i |(Ax - b)_i|$$

$$= \sum_i \max\{(Ax - b)_i, -(Ax - b)_i\}$$



- epigraph transformation works for each term in a sum separately

$$\text{minimize } t_1 + \dots + t_m$$

$$\text{subject to } (Ax - b)_i \leq t_i$$
$$-(Ax - b)_i \leq t_i$$

$$Fx \leq g$$

$$\text{minimize } \mathbf{1}^T t$$

$$\text{subject to}$$

$$-t \leq Ax - b \leq t$$

$$Fx \leq g$$

- CVX code

Ex Robust LP as an SOCP

- CVX code

- Schur Complements

- an important tool for manipulating matrix inequalities

Consider $X \in S^n$ partitioned as

$$X = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix}$$

If $\det A \neq 0$, then

$$S = C - B^T A^{-1} B$$

is called the Schur complement of X .

We have the following definiteness properties:

① If $A \succ 0$, then $X \succeq 0 \iff S \succeq 0$

② $X \succ 0 \iff A \succ 0$ and $S \succ 0$

• Stability + Stabilization via SDP

Consider the discrete-time linear dynamical system

$$x_{t+1} = A x_t$$

- global asymptotic stability (GAS):

$$\forall x_0 \in \mathbb{R}^n, \quad x_t \rightarrow 0 \text{ as } t \rightarrow \infty$$

- standard linear algebra:

$$x_{t+1} = A x_t \text{ GAS} \iff |\lambda_i(A)| < 1 \quad \forall i$$

$$\iff \rho(A) = \max_i |\lambda_i(A)| < 1$$

\uparrow
spectral radius

- we'll discuss a different characterization related to Lyapunov theory (much more later) and semidefinite programming

- much more useful for going beyond basic stability questions for linear systems

Theorem

$$x_{t+1} = Ax_t \quad \text{GAS}$$



$$\exists P \in S^n \text{ such that } P \succ 0 \text{ and } P \succ A^T P A$$

- Given A , finding such a P is an SDP!
- Proof based on fundamental concept of a Lyapunov function
 - $V(x) = x^T P x$
 - Conditions imply:
 - $V(0) = 0$ and $V(x) > 0 \quad \forall x \neq 0$
 - $V(Ax) < V(x) \quad \forall x \neq 0$
 - This means V decreases monotonically along all system trajectories, leads to GAS
- Note: In this simple case, we don't need SDP since we can also solve the Lyapunov Equation

$$P = Q + A^T P A \quad \text{for } Q \succ 0$$

- Stabilization via state feedback

Consider $x_{t+1} = Ax_t + Bu_t$, $u_t = Kx_t$

$$\Rightarrow x_{t+1} = (A+BK)x_t$$

Does there exist a stabilizing gain matrix $K \in \mathbb{R}^{m \times n}$?

$$\exists K \in \mathbb{R}^{m \times n} : \rho(A+BK) < 1 ?$$

Lyapunov: $A+BK$ GAS \Leftrightarrow

$$\exists P \succ 0 : (A+BK)^T P (A+BK) \prec P$$

$$\text{or } P - (A+BK)^T P (A+BK) \succ 0$$

\Updownarrow Schur complement

$$\begin{bmatrix} P^{-1} & (A+BK)^T \\ A+BK & P \end{bmatrix} \succ 0 \iff \begin{bmatrix} P & P(A+BK)^T \\ (A+BK)P & P \end{bmatrix} \succ 0$$

Mult. L and R by $\begin{bmatrix} P & 0 \\ 0 & I \end{bmatrix}$

Let $L = KP$. Then we have

$$P \succ 0, \begin{bmatrix} P & PA^T + L^T B^T \\ AP + BL & P \end{bmatrix} \succ 0$$

An LMI/SDP on variables L and P !

Solve via convex optimization, recover stabilizing controller

$$K = L P^{-1}$$

• CVX code