

Robust to Dynamics Optimization

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Session on Synergies Between Optimization and Robust Control

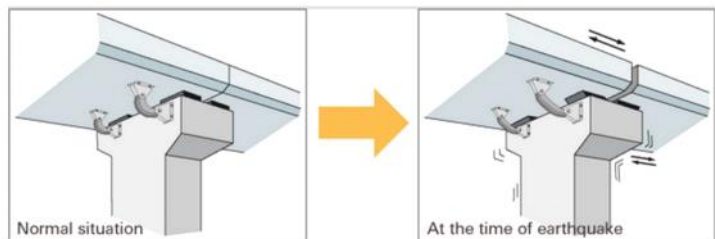
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The setting & motivating applications

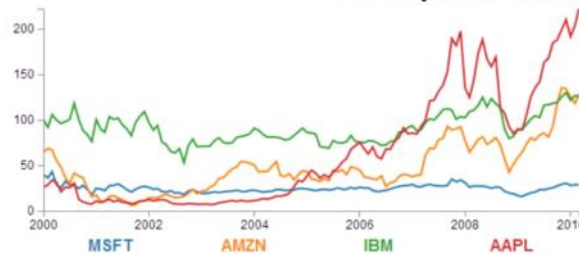
- You solve a constrained optimization problem today
- An external dynamical system may move your optimal point in the future and make it infeasible
- You want your initial decision to be “safe enough” to not let this happen



Drug design



Earthquake-resistant structures



Robust investments

Robust to Dynamics Optimization (RDO)

An RDO is describe by two pieces of input:

1) An optimization problem: $\min_x \{f(x) : x \in \Omega\}$

2) A dynamical system: $x_{k+1} = g(x_k)$ or $\dot{x} = g(x)$

RDO is then the following problem:

(discrete time) $\min_{x_0} \{f(x_0) : x_k \in \Omega, k = 0, 1, 2, \dots\}$

(continuous time) $\min_{x_0} \{f(x_0) : x(t; x_0) \in \Omega, \forall t \geq 0\}$

Various RDO problems to study...

$$\min_{x_0} \{f(x_0) : x_k \in \Omega, \forall k; x_{k+1} = g(x_k)\}$$

This talk:

Optimization Problem	Dynamics
Linear Program	Linear
Integer Program	Nonlinear
Semidefinite Program	Uncertain
Polynomial Program	Time-varying
Robust Linear Program	Discrete/continuous/hybrid of both
⋮	⋮

R-LD-LP

Robust to linear dynamics linear programming (R-LD-LP)

Classical LP:

$$\min_x \{c^T x : Ax \leq b\}$$

Robust LP:

$$\min_x \{c^T x : Ax \leq b, \forall A \in \mathbb{A}, b \in \mathbb{B}\}$$

R-LD-LP:

$$\min_{x_0} \{c^T x_0 : Ax_k \leq b, k = 0, 1, 2, \dots; x_{k+1} = Gx_k\}$$

R-LD-LP

Robust to linear dynamics linear programming (R-LD-LP)

$$\min_{x_0} \{c^T x_0 : Ax_k \leq b, k = 0, 1, 2, \dots; x_{k+1} = Gx_k\}$$

Input data: A, b, c, G

Alternative form:

$$\min_x \{c^T x : Ax \leq b, AGx \leq b, AG^2x \leq b, AG^3x \leq b, \dots\}$$

(An infinite LP)

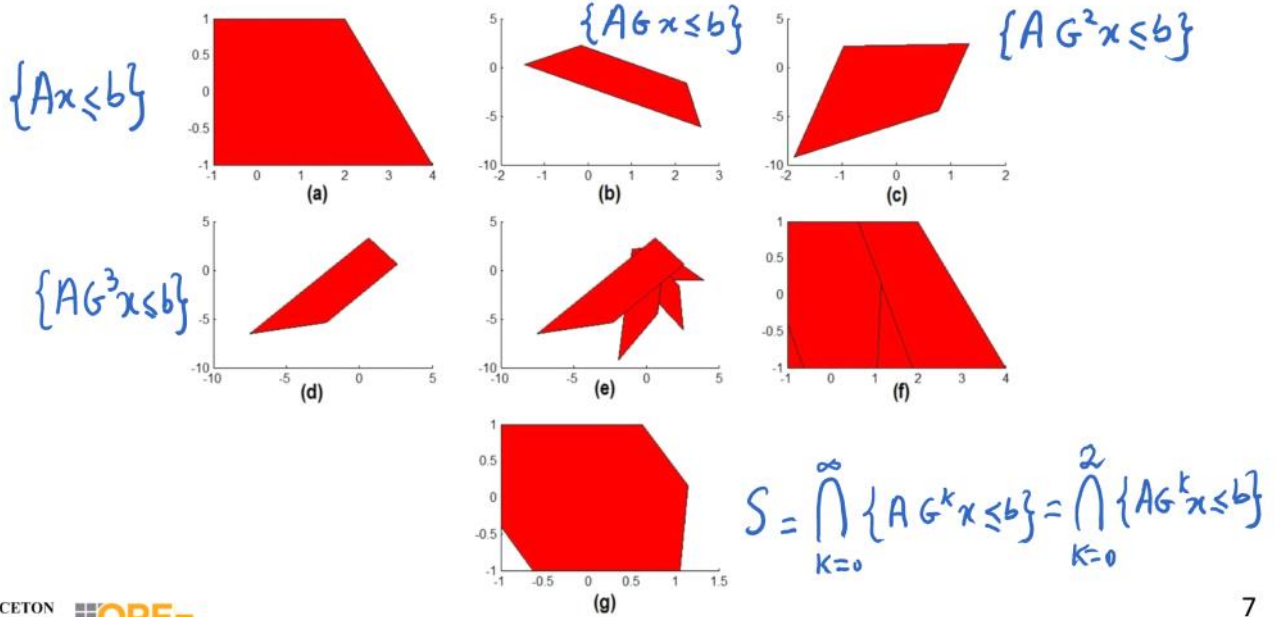
Feasible set of R-LD-LP:

$$\mathcal{S} := \bigcap_{k=0}^{\infty} \{x \mid AG^k x \leq b\}$$

An example...

$$\min_{x_0} \{c^T x_0 : Ax_k \leq b, k = 0, 1, 2, \dots; x_{k+1} = Gx_k\}$$

$$A = \begin{bmatrix} -1 & 0 \\ 0 & -1 \\ 0 & 1 \\ 1 & 1 \end{bmatrix}, b = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 3 \end{bmatrix}, c = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, G = \begin{bmatrix} 0.6 & -0.4 \\ 0.8 & 0.5 \end{bmatrix}$$



Obvious way to get lower bounds

$$\min_{x_0} \{c^T x_0 : Ax_k \leq b, k = 0, 1, 2, \dots; x_{k+1} = Gx_k\}$$

Can get a sequence of lower bounds by solving finite LPs:

$$\min_x \{c^T x : Ax \leq b, AGx \leq b, AG^2x \leq b, \dots, AG^r x \leq b\}$$

Natural questions:

- Is the optimal value of R-LD-LP achieved in a finite number of steps?
- Is the feasible set of R-LD-LP always a polytope?
- When it is, how large are the number of facets?
- How to get **upper bounds**?!
 - (We'll see soon: from **semidefinite programming**)

Feasible set of R-LD-LP

Lemma. The feasible set of R-LD-LP is **closed, convex, and invariant.**

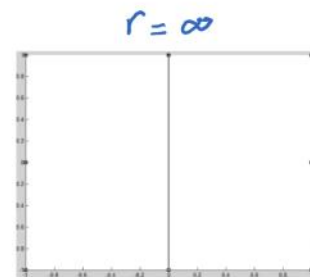
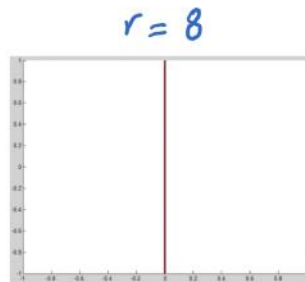
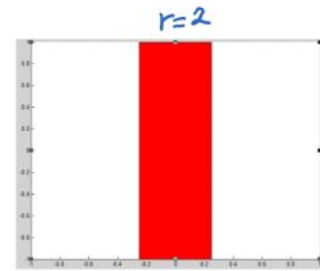
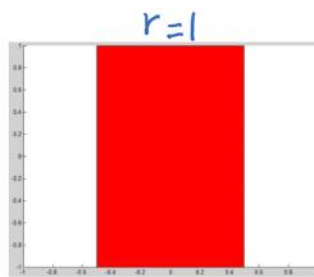
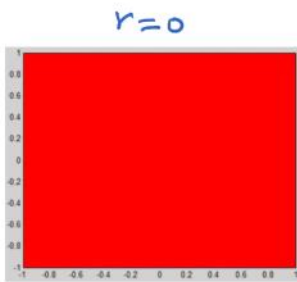
Proof. Easy.
$$\mathcal{S} := \bigcap_{k=0}^{\infty} \{x \mid AG^k x \leq b\}$$

- But it may not be polyhedral.
- Even if it is, it may not be achieved at a finite level.

Feasible set of R-LD-LP

$$G = \begin{pmatrix} 2 & 0 \\ 0 & \frac{1}{2} \end{pmatrix}$$

$$\bigcap_{K=0}^r \{AG^K x \leq b\}$$

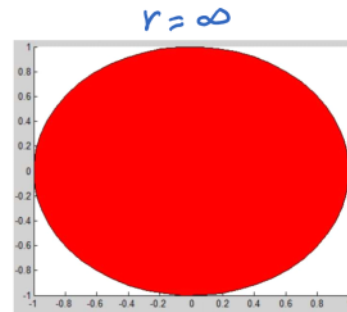
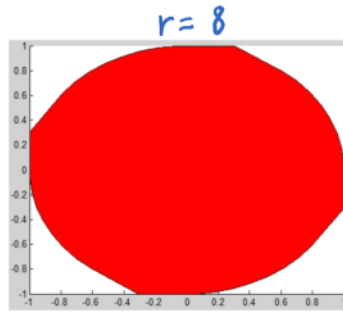
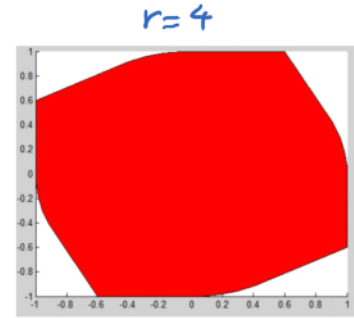
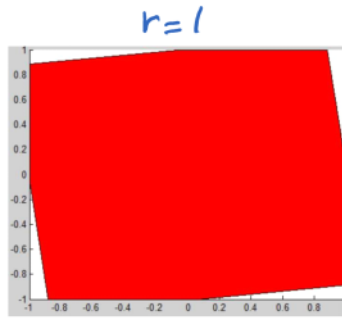
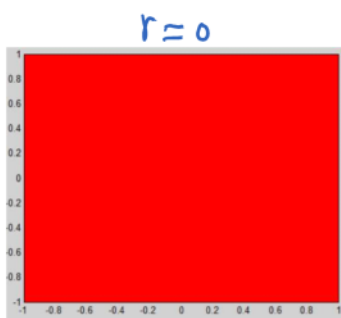


Feasible set of R-LD-LP

$$\bigcap_{k=0}^r \{AG^k x \leq b\}$$

$$G = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix}$$

Rotation by
irrational degree



Detecting termination

Lemma. Let $S_r := \bigcap_{k=0}^r \{x \mid AG^k x \leq b\}$.

Then, $S_r = S_{r+1} \Rightarrow S_r = S_\infty$.

Proof. $x \in S_r \Rightarrow x \in S_{r+1} \Rightarrow Gx \in S_r$, Repeat.

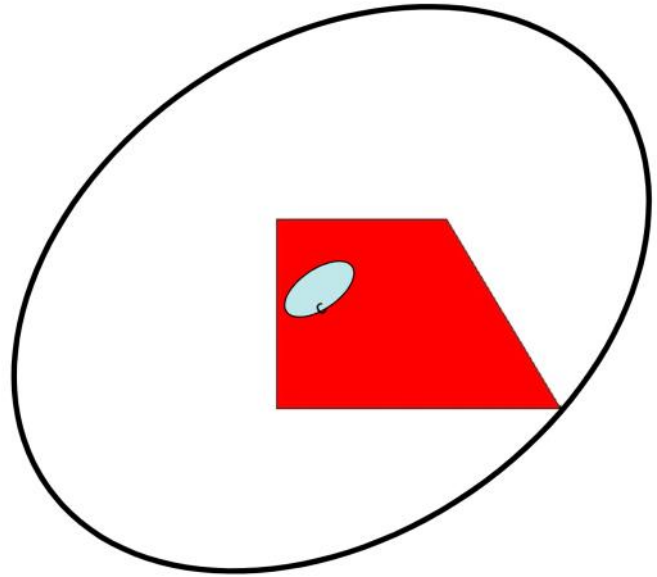
Note. The condition $S_r = S_{r+1}$ can be efficiently checked.

Solving R-LD-LP exactly via LP

Theorem. If $\rho(G) < 1$, then convergence is finite. Moreover, the number of steps needed is polynomial in the size of the input (A, b, c, G) .

(Recall: $\rho(A) = \lim_{k \rightarrow \infty} \|A^k\|^{1/k}$)

Proof idea.



Upper bound on the number of iterations

- Find an invariant ellipsoid defined by a positive definite matrix P
- Find a shrinkage factor $\gamma \in (0, 1)$; i.e., a scalar satisfying $G^T P G \preceq \gamma P$
- Find a scalar $\alpha_2 > 0$ such that

$$\{Ax \leq b\} \subseteq \{x^T P x \leq \alpha_2\}$$

- Find a scalar $\alpha_1 > 0$ such that

$$\{x^T P x \leq \alpha_1\} \subseteq \{Ax \leq b\}$$

- Let

$$r = \left\lceil \frac{\log \frac{\alpha_1}{\alpha_2}}{\log \gamma} \right\rceil$$

Finding an invariant ellipsoid

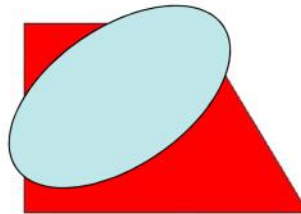
- Computation of P .

To find an invariant ellipsoid for G , we solve the linear system

$$G^T P G - P = -I,$$

where I is the $n \times n$ identity matrix. This is called the Lyapunov equation.

The matrix P will automatically turn out to be positive definite.



Finding the shrinkage factor

- Computation of γ .

$$\gamma = 1 - \frac{1}{\max_i \{P_{ii} + \sum_{j \neq i} |P_{i,j}|\}}.$$

Proof idea.

$$\begin{aligned} x^T G^T P G x &= x^T P x - x^T x \\ &\leq x^T P x (1 - \eta) \end{aligned}$$

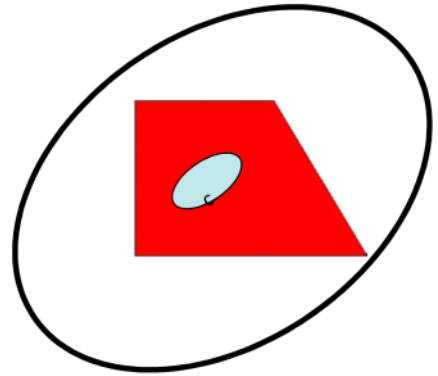
where η is any number such that

$$\eta x^T P x \leq x^T x$$

Shrinkage is at least $1 - \frac{1}{\lambda_{\max}(P)}$

$$\lambda_{\max}(P) \leq \max_i \{P_{ii} + \sum_{j \neq i} |P_{i,j}|\}.$$

(Bound from Greshgorin's circle theorem)



Finding the outer ellipsoid

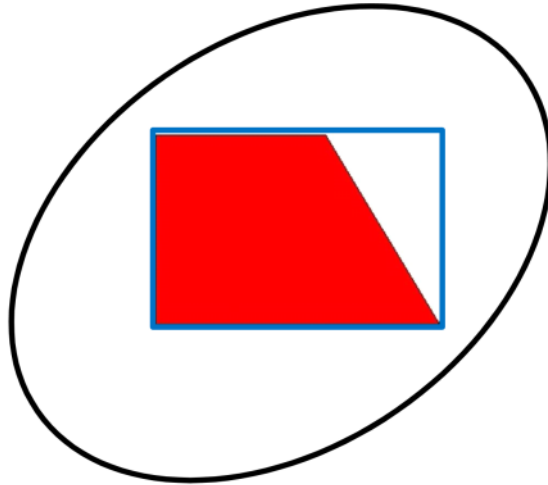
- **Computation of α_2 .** By solving, e.g., n LPs, we can place our polytope $\{Ax \leq b\}$ in a box; i.e., compute $2n$ scalars l_i, u_i such that

$$\{Ax \leq b\} \subseteq \{l_i \leq x_i \leq u_i\}.$$

We then bound $x^T P x = \sum_{i,j} P_{i,j} x_i x_j$ term by term to get α_2 :

$$\alpha_2 = \sum_{i,j} \max\{P_{i,j} u_i u_j, P_{i,j} l_i l_j, P_{i,j} u_i l_j, P_{i,j} l_i u_j\}.$$

This ensures that $\{l_i \leq x_i \leq u_i\} \subseteq \{x^T P x \leq \alpha_2\}$. Hence, $\{Ax \leq b\} \subseteq \{x^T P x \leq \alpha_2\}$.



Finding the inner ellipsoid

- **Computation of α_1 .** For $i = 1, \dots, m$, we compute a scalar η_i by solving the convex program

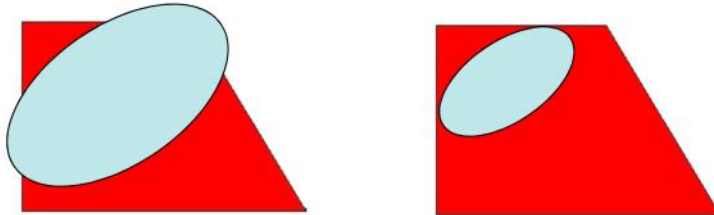
$$\eta_i := \min_x \{a_i^T x : x^T P x \leq 1\},$$

where a_i is the i -th row of the constraint matrix A . This problem has a closed form solution:

$$\eta_i = -\sqrt{a_i^T P^{-1} a_i}.$$

Note that P^{-1} exists since $P \succ 0$. We then let

$$\alpha_1 = \min_i \left\{ \frac{b_i^2}{\eta_i^2} \right\}.$$



Upper bounds on R-LD-LP via SDP

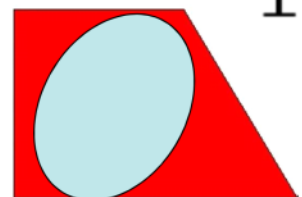
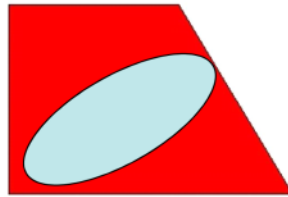
- Goal: Find the best invariant ellipsoid inside the original polytope and optimize over that.

$$\min_{x, P} c^T x$$

$$P \succ 0$$

$$G^T P G \preceq P$$

$$x^T P x \leq 1$$



$$[\forall z, z^T P z \leq 1 \Rightarrow Az \leq b] \xleftrightarrow{\text{S-Lemma}} b - a^T z \geq \delta_i (1 - z^T P z) \quad \delta_i \geq 0$$

Non-convex formulation

Upper bounds on R-LD-LP via SDP

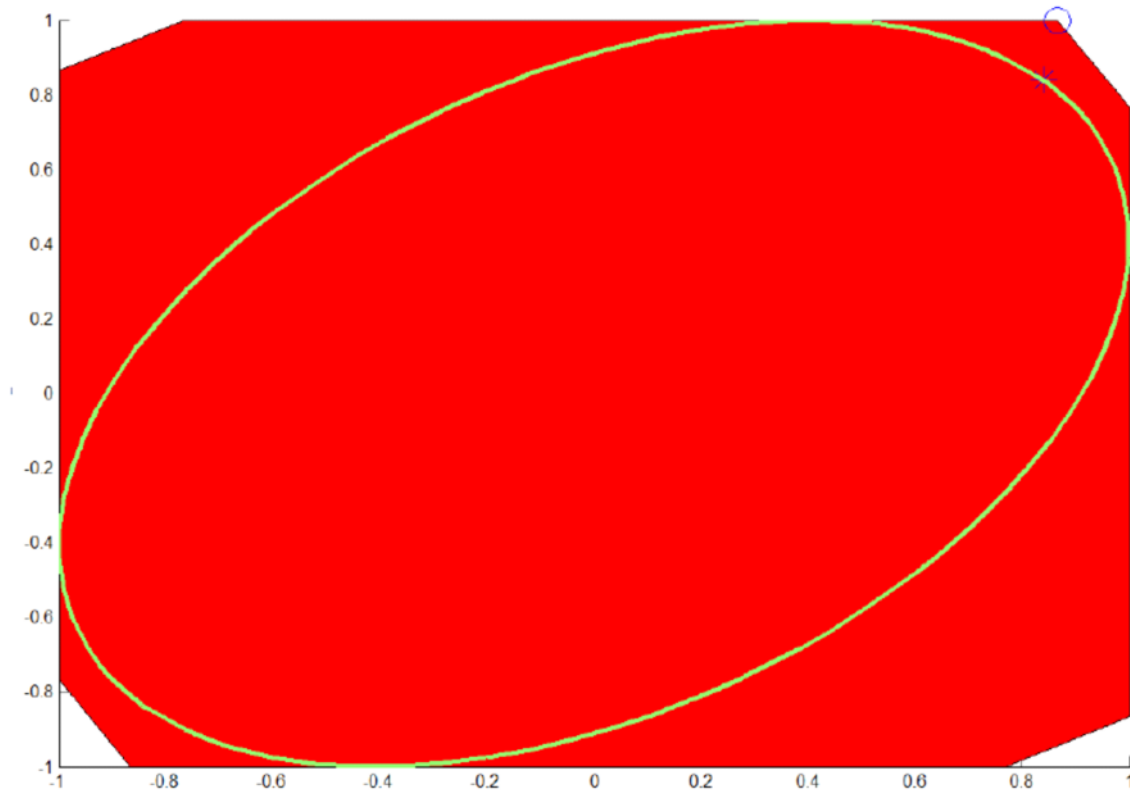
- If we parameterize in terms of P^{-1} instead, then it becomes convex!

$$\begin{array}{l}
 \min_{x, P} \quad c^T x \\
 P y_0 \\
 G^T P G \preceq P \\
 x^T P x \leq 1
 \end{array}
 \quad \left\{ \begin{array}{l} \xleftarrow{\text{Dynamics}} \\ \xrightarrow{\text{Duality}} \end{array} \right.
 \quad \left\{ \begin{array}{l}
 \min_{x, Q} \quad c^T x \\
 Q y_0 \\
 G Q G^T \preceq Q \\
 \left[\begin{array}{c|c} Q & x \\ \hline x^T & 1 \end{array} \right] \preceq y_0 \\
 a_i^T Q a_i \leq 1
 \end{array} \right.$$

$$[\forall z, z^T P z \leq 1 \Rightarrow A z \leq b]$$

$$\text{ellipsoid} \subseteq \text{polytope} \quad \xleftrightarrow{\text{Polar duality}} \quad (\text{polytope})^* \subseteq (\text{ellipsoid})^*$$

Upper bounds on R-LD-LP via SDP

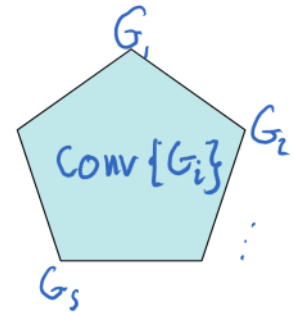


LP + Uncertain & time-varying linear systems

R-ULD-LP

Robust to uncertain linear dynamics linear programming (R-ULD-LP)

$$x_{k+1} \in \text{conv}\{G_1, \dots, G_S\} x_k$$



Models **uncertainty** and **variations with time** in the dynamics

$$\min_x \{c^T x : AGx \leq b, \forall G \in \mathbb{G}^*\} \quad (\text{An infinite LP})$$

\mathbb{G}^* : set of all finite products of G_1, \dots, G_S

Feasible set of R-ULD-LP

It's still convex, closed, and invariant (but typically much more nasty).

Theorem. If the *joint spectral radius* of G_1, \dots, G_S is less than one, then the feasible set is a polytope.

Joint spectral radius (JSR):

$$\rho(G_1, \dots, G_S) = \lim_{k \rightarrow \infty} \max_{\sigma \in \{1, \dots, S\}^k} \|G_{\sigma_1} \cdots G_{\sigma_k}\|^{1/k}$$

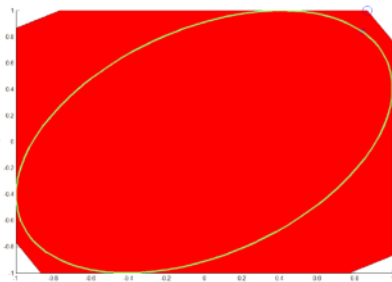
- Unlike the spectral radius, computation of the JSR is difficult (Testing if $\text{JSR} \leq 1$ is undecidable already for two 47×47 matrices [Blondel, Tsitsiklis], [Blondel, Canterini])

Lower and upper bounds for R-ULD-LP

- To get **lower bounds**, truncate the sequence and solve an LP.
For example,

$$\min_x \{c^T x : Ax \leq b, AG_1 x \leq b, AG_1 G_2 x \leq b, \dots, AG_1 G_2 G_1 x \leq b\}$$

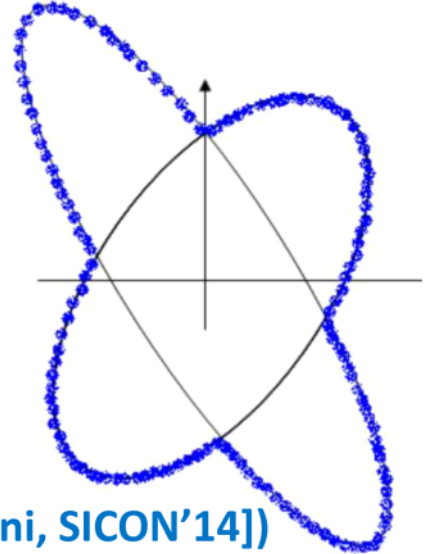
- What about **upper bounds**?



$$\begin{aligned} & \min_{x, Q} c^T x \\ & Q \succ 0 \\ & G Q G^T \preceq Q \\ & \left[\begin{array}{c|c} Q & x \\ \hline x^T & 1 \end{array} \right] \succ 0 \\ & a_i^T Q a_i \leq 1 \end{aligned}$$

Invariant ellipsoid may not exist even when JSR < 1

Idea: search instead for union of ellipsoids



Theorem ([AAA, Jungers, Parrilo, Roozbehani, SICON'14])

If $JSR < 1$,

then there exists an invariant set which is a union of k ellipsoids.

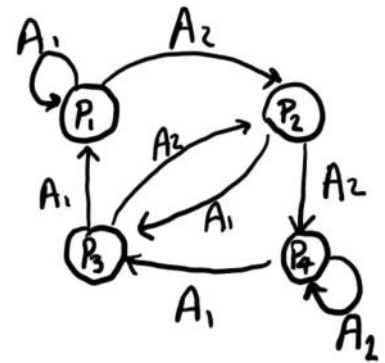
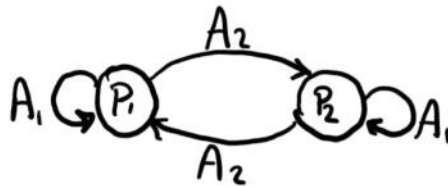
Moreover,

- We give you a bound on k .
- We tell you how to find the k ellipsoids by SDP.

The SDPs have a recipe!

$$\textcircled{P_i} \xrightarrow{A_\ell} \textcircled{P_j} \iff A_\ell^T P_j A_\ell \preceq P_i$$

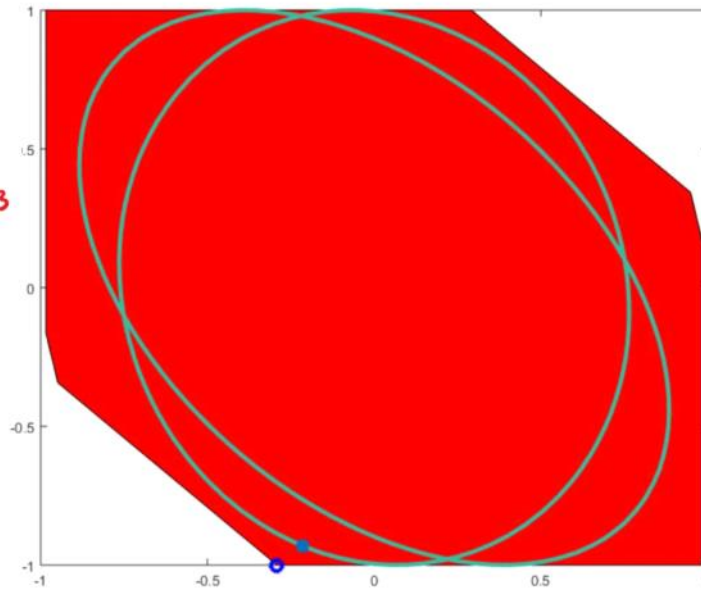
De Bruijn graphs



A numerical example

$$\{Ax \leq b\} = \square_{(-1,-1)}^{(1,1)}, \quad c = \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \quad G_1 = 0.254 \begin{bmatrix} -1 & -1 \\ -4 & 0 \end{bmatrix}, \quad G_2 = 0.254 \begin{bmatrix} 3 & 3 \\ -2 & 1 \end{bmatrix}$$

Red (LP)
 $\{x \mid AG_0 x \leq b\}$
 \downarrow
 Products of length 0,1,2,3
 (15 total)



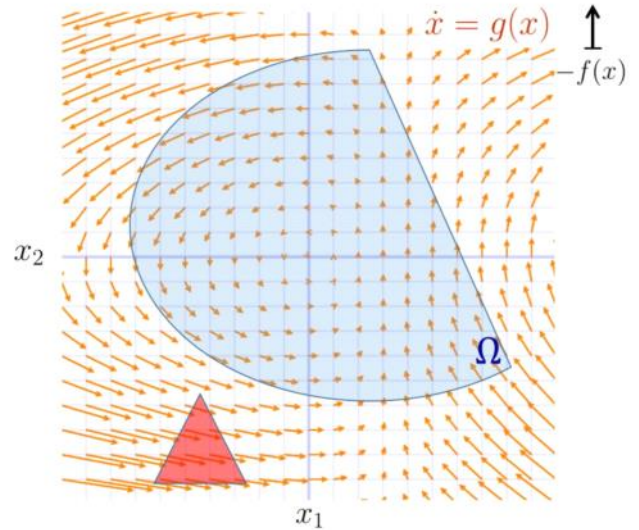
Green (SDP)
 $A_1 \rightarrow (P_1) \xrightarrow{A_2} (P_2) \rightarrow A_1$
 A_2
 Union of ellipses invariant

$$-2.292 \leq C^T x^* \leq -2.076$$

The broader perspective

Optimization problems with dynamical systems (DS) constraints

$$\begin{aligned} &\text{minimize} && f(x) \\ &\text{subject to} && x \in \Omega \cap \Omega_{DS}. \end{aligned}$$



Optimization Problem “ f, Ω ”	Type of Dynamical System “ g ”	DS Constraint “ Ω_{DS} ”
Linear program*	Linear*	Invariance*
Convex quadratic program*	Linear and uncertain/stochastic	Inclusion in region of attraction
Semidefinite program	Linear and time-varying*	Collision avoidance
Robust linear program	Nonlinear (polynomial)	Reachability
Polynomial program	Nonlinear and time-varying	Orbital stability
Integer program	Discrete/continuous/hybrid of both	Stochastic stability
⋮	⋮	⋮