

Semidefinite Programming

Computational Intelligence, Lecture 10

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SEMIDEFINITE PROGRAMMING (SDP)

General form of a semidefinite program is:

$$\begin{aligned} & \underset{\mathbf{x}}{\text{minimize}} && \mathbf{c}^\top \mathbf{x}, \\ & \text{subject to} && \begin{cases} \mathbf{G} + \sum \mathbf{F}_i x_i \preceq 0, \\ \mathbf{A}\mathbf{x} = \mathbf{b}. \end{cases} \end{aligned} \tag{1}$$

where $\mathbf{F}_i \succeq 0$ and $\mathbf{G} \succeq 0$ (meaning they are positive semidefinite).

Constraint $\mathbf{G} + \sum \mathbf{F}_i x_i \preceq 0$ is called *linear matrix inequality* or *LMI*.

SDP can have several LMIs. Assume you have:

$$\begin{cases} \mathbf{G} + \sum \mathbf{F}_i x_i \preceq 0 \\ \mathbf{D} + \sum \mathbf{H}_i x_i \preceq 0 \end{cases} \quad (2)$$

This is equivalent to:

$$\begin{bmatrix} \mathbf{G} & \mathbf{0} \\ \mathbf{0} & \mathbf{D} \end{bmatrix} + \sum \begin{bmatrix} \mathbf{F}_i & \mathbf{0} \\ \mathbf{0} & \mathbf{H}_i \end{bmatrix} x_i \preceq 0 \quad (3)$$

Sometimes it is easier to directly think of semidefinite matrices as of decision variables. This leads to programs with such formulation:

$$\begin{array}{ll} \underset{\mathbf{X}}{\text{minimize}} & \text{tr}(\mathbf{E}^\top \mathbf{X}), \\ \text{subject to} & \begin{cases} \text{tr}(\mathbf{A}_i^\top \mathbf{X}) = \mathbf{b}_i, \\ \mathbf{C}\mathbf{X} \preceq \mathbf{D}. \end{cases} \end{array} \quad (4)$$

where cost and constraints should adhere to the SDP limitations.

TRACE OF A MATRIX PRODUCT

Consider a matrices $\mathbf{E} = [\mathbf{e}_1 \quad \dots \quad \mathbf{e}_n]$ and $\mathbf{X} = [\mathbf{x}_1 \quad \dots \quad \mathbf{x}_n]$.
Their product can be written as:

$$\mathbf{E}^\top \mathbf{X} = \begin{bmatrix} \mathbf{e}_1^\top \mathbf{x}_1 & \mathbf{e}_1^\top \mathbf{x}_2 & \dots \\ \mathbf{e}_2^\top \mathbf{x}_1 & \mathbf{e}_2^\top \mathbf{x}_2 & \dots \\ \dots & \dots & \dots \end{bmatrix} \quad (5)$$

Thus, the trace of this product is given as:

$$\text{tr}(\mathbf{E}\mathbf{X}) = \mathbf{e}_1^\top \mathbf{x}_1 + \dots + \mathbf{e}_n^\top \mathbf{x}_n \quad (6)$$

We can see that this is equivalent to an element-wise dot product.

In a cost function, matrix \mathbf{E} plays the role of weights, similar to \mathbf{f} in the linear cost $\mathbf{f}^\top \mathbf{x}$. Quadratic cost can be expressed as $\mathbf{X}^\top \mathbf{X}$.

CONTINUOUS LYAPUNOV EQ. AS SDP/LMI (1)

In control theory, Lyapunov equation is a condition of whether or not a continuous LTI system $\dot{\mathbf{x}} = \mathbf{A}\mathbf{x}$ is stable:

$$\begin{cases} \mathbf{A}^\top \mathbf{P} + \mathbf{P} \mathbf{A} \preceq -\mathbf{Q} \\ \mathbf{P} \succeq 0 \end{cases} \quad (7)$$

where $\mathbf{Q} \succeq 0$ is a constant and decision variable is \mathbf{P} . This can be represented as an SDP:

$$\begin{aligned} & \underset{\mathbf{P}}{\text{minimize}} && 0, \\ & \text{subject to} && \begin{cases} \mathbf{P} \succeq 0, \\ \mathbf{A}^\top \mathbf{P} + \mathbf{P} \mathbf{A} + \mathbf{Q} \preceq 0. \end{cases} \end{aligned} \quad (8)$$

CONTINUOUS LYAPUNOV EQ. AS SDP/LMI (2)

```
0 n = 7; A = randn(n, n) - 3*rand*eye(n);  
  Q = eye(n);  
2  
  cvx_begin sdp  
4      variable P(n, n) symmetric  
      minimize 0  
6      subject to  
          P >= 0;  
          A'*P + P*A + Q <= 0;  
8  cvx_end  
10  
  if strcmp(cvx_status, 'Solved')  
12      [eig(A), eig(A*P + P*A' + Q), eig(P)]  
  else  
14      eig(A)  
  end
```


In control theory, Discrete Lyapunov equation is a condition of whether or not a discrete LTI system $\mathbf{x}_{i+1} = \mathbf{A}\mathbf{x}_i$ is stabilizable:

$$\begin{cases} \mathbf{A}^\top \mathbf{P} \mathbf{A} - \mathbf{P} + \mathbf{Q} \preceq 0 \\ \mathbf{P} \succeq 0 \end{cases} \quad (9)$$

where $\mathbf{Q} \succeq 0$ is a constant and decision variable is \mathbf{P} . This can be represented as an SDP:

$$\begin{aligned} & \underset{\mathbf{P}}{\text{minimize}} && 0, \\ & \text{subject to} && \begin{cases} \mathbf{P} \succeq 0, \\ \mathbf{A}^\top \mathbf{P} \mathbf{A} - \mathbf{P} + \mathbf{Q} \preceq 0. \end{cases} \end{aligned} \quad (10)$$

DISCRETE LYAPUNOV EQ. AS SDP/LMI (2)

```
0 n = 7; A = 0.35*randn(n, n);  
  Q = eye(n);  
2  
  cvx_begin sdp  
4      variable P(n, n) symmetric  
      minimize 0  
6      subject to  
          P >= 0;  
          A'*P*A - P + Q <= 0;  
8      cvx_end  
10  
  if strcmp(cvx_status, 'Solved')  
12      [abs(eig(A)), eig(A'*P*A - P), eig(P)]  
  else  
14      abs(eig(A))  
  end
```

Schur compliment. Given \mathbf{M}

$$\mathbf{M} = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^\top & \mathbf{C} \end{bmatrix} \quad (11)$$

with full-rank \mathbf{A} , we can make the following statement:

$$\blacksquare \mathbf{M} \succ 0 \text{ iff } \mathbf{A} \succ 0 \text{ and } \mathbf{C} - \mathbf{B}^\top \mathbf{A}^{-1} \mathbf{B} \succ 0$$

If \mathbf{C} is full-rank, we can make the following statement:

$$\blacksquare \mathbf{M} \succ 0 \text{ iff } \mathbf{C} \succ 0 \text{ and } \mathbf{A} - \mathbf{B} \mathbf{C}^{-1} \mathbf{B}^\top \succ 0$$

Let us prove that SOCP is a sub-set of SDP. SOC constraint is:

$$\|\mathbf{Ax} + \mathbf{b}\| \leq \mathbf{c}^\top \mathbf{x} + d \quad (12)$$

where $\mathbf{c}^\top \mathbf{x} + d \geq 0$, and we can rewrite the SOC as:

$(\mathbf{Ax} + \mathbf{b})^\top (\mathbf{Ax} + \mathbf{b}) = (\mathbf{c}^\top \mathbf{x} + d)^2$, and assuming $\mathbf{c}^\top \mathbf{x} + d > 0$

we can write it as:

$$\frac{(\mathbf{Ax} + \mathbf{b})^\top (\mathbf{Ax} + \mathbf{b})}{\mathbf{c}^\top \mathbf{x} + d} \leq \mathbf{c}^\top \mathbf{x} + d \quad (13)$$

which is equivalent to:

$$-\frac{(\mathbf{Ax} + \mathbf{b})^\top (\mathbf{Ax} + \mathbf{b})}{-(\mathbf{c}^\top \mathbf{x} + d)} \leq \mathbf{c}^\top \mathbf{x} + d \quad (14)$$

Note that $-\frac{(\mathbf{Ax}+\mathbf{b})^\top(\mathbf{Ax}+\mathbf{b})}{-(\mathbf{c}^\top\mathbf{x}+d)} \leq \mathbf{c}^\top\mathbf{x} + d$ is equivalent to:

$$-\frac{(\mathbf{Ax} + \mathbf{b})^\top (\mathbf{Ax} + \mathbf{b})}{(\mathbf{c}^\top \mathbf{x} + d)} + (\mathbf{c}^\top \mathbf{x} + d) \geq 0 \quad (15)$$

Using Schur we can re-write it as:

$$\begin{bmatrix} (\mathbf{c}^\top \mathbf{x} + d) & (\mathbf{Ax} + \mathbf{b}) \\ (\mathbf{Ax} + \mathbf{b})^\top & (\mathbf{c}^\top \mathbf{x} + d) \end{bmatrix} \succeq 0 \quad (16)$$

which is an LMI constraint.

Consider the following constraint, where $\mathbf{X} \succeq 0$:

$$\|\mathbf{X}\mathbf{v} + \mathbf{b}\| \leq \mathbf{c}^\top \mathbf{x} + d \quad (17)$$

Can we re-write it as an LMI? Using the same process as before we get:

$$\begin{bmatrix} (\mathbf{c}^\top \mathbf{x} + d) & (\mathbf{X}\mathbf{v} + \mathbf{b}) \\ (\mathbf{X}\mathbf{v} + \mathbf{b})^\top & (\mathbf{c}^\top \mathbf{x} + d) \end{bmatrix} \succeq 0 \quad (18)$$

So, (17) is an admissible constraint in an SDP.

Consider the problem: minimize the largest eigenvalue of A .
The solution is:

$$\begin{aligned} & \underset{\mathbf{A}, t}{\text{minimize}} && t, \\ & \text{subject to} && \mathbf{A} \preceq t\mathbf{I} \end{aligned} \tag{19}$$

Proof. If λ is an eigenvalue of \mathbf{A} , then $\mathbf{A}\mathbf{v} = \lambda\mathbf{v}$, hence $(\mathbf{A} - t\mathbf{I})\mathbf{v} = (\lambda - t)\mathbf{v}$, meaning $\lambda - t$ is eigenvalue of $(\mathbf{A} - t\mathbf{I})$. Thus, if $(\mathbf{A} - t\mathbf{I})$ is negative semi-definite, then $\lambda - t \leq 0$ and $\lambda \leq t$. □

HOW TO DESCRIBE AN ELLIPSOID

Unit sphere transformation

Let us first remember how we describe a unit sphere:

$$\mathcal{S} = \{\mathbf{x} : \|\mathbf{x}\| \leq 1\} \quad (20)$$

An ellipsoid can be seen as a linear transformation of a unit sphere:

$$\mathcal{E} = \{\mathbf{Ax} + \mathbf{b} : \|\mathbf{x}\| \leq 1\} \quad (21)$$

HOW TO DESCRIBE AN ELLIPSOID

A dual description

Let us introduce a change of variables $\mathbf{z} = \mathbf{A}\mathbf{x} + \mathbf{b}$. Assuming \mathbf{A} is invertible, we get:

$$\mathbf{x} = \mathbf{A}^{-1}(\mathbf{z} - \mathbf{b}) \quad (22)$$

So, we can describe the exact same ellipsoid using an alternative formula:

$$\mathcal{E} = \{\mathbf{z} : \|\mathbf{B}\mathbf{z} + \mathbf{c}\| \leq 1\} \quad (23)$$

where $\mathbf{B} = \mathbf{A}^{-1}$ and $\mathbf{c} = -\mathbf{A}^{-1}\mathbf{b}$.

For an ellipsoid of the form

$$\mathcal{E} = \{\mathbf{A}\mathbf{x} + \mathbf{b} : \|\mathbf{x}\| \leq 1\} \quad (24)$$

the "bigger" the \mathbf{A} , the bigger the ellipsoid. This concept can be made concrete by talking about the determinant of \mathbf{A} .

Thus, maximizing the volume of this ellipsoid is the same as maximizing $\det(\mathbf{A})$. Or, it is the same as *minimizing* the $\det(\mathbf{A}^{-1})$, since $\det(\mathbf{A}^{-1}) = 1/\det(\mathbf{A})$.

Finally, note that $\log \det(\mathbf{A})$ is a concave function and $\log \det(\mathbf{A}^{-1})$ is a convex function.

For an ellipsoid of the form

$$\mathcal{E} = \{\mathbf{z} : \|\mathbf{B}\mathbf{z} + \mathbf{c}\| \leq 1\} \quad (25)$$

the "bigger" the \mathbf{B} , the *smaller* the ellipsoid. We can make it obvious by thinking that increasing \mathbf{B} leaves less room for valid \mathbf{z} , and it is the volume of valid \mathbf{z} that makes the volume of the ellipsoid in this case.

This concept can be made concrete by talking about the determinant of \mathbf{B} . Thus, maximizing the volume of this ellipsoid is the same as *minimizing* $\det(\mathbf{B})$. Or, it is the same as *maximizing* the $\det(\mathbf{B}^{-1})$.

Consider the problem: given V-polytope, defined by its vertices \mathbf{v}_i , find minimum-volume ellipsoid \mathcal{E} containing the polytope.

We will start with defining the ellipsoid as

$\mathcal{E} = \{\mathbf{z} : \|\mathbf{B}\mathbf{z} + \mathbf{c}\| \leq 1\}$. The ellipsoid is smaller when $\|\mathbf{B}\|$ is bigger, and thus we can write the minimization as minimizing $\det(\mathbf{B}^{-1})$.

$$\begin{aligned} & \underset{\mathbf{B}, \mathbf{c}}{\text{minimize}} && \log(\det(\mathbf{B}^{-1})), \\ & \text{subject to} && \begin{cases} \mathbf{B} \succeq 0, \\ \|\mathbf{B}\mathbf{v}_i + \mathbf{c}\| \leq 1. \end{cases} \end{aligned} \tag{26}$$

The solution gives us Löwner-John ellipsoid.

MAX VOLUME INSCRIBED ELLIPSOID (1)

Consider the problem: given H-polytope, defined by its half-spaces $\mathbf{a}_i^\top \mathbf{x} \leq b_i$, find maximum-volume ellipsoid \mathcal{E} contained in the polytope. We will start with defining the ellipsoid as $\mathcal{E} = \{\mathbf{C}\mathbf{x} + \mathbf{d} : \|\mathbf{x}\| \leq 1\}$. The ellipsoid is larger when $\|\mathbf{C}\|$ is bigger, and thus we can write the minimization as minimizing $\det(\mathbf{C}^{-1})$.

Let us write down the constraint requiring that \mathcal{E} lies in the polytope. We know that $\mathbf{a}_i^\top (\mathbf{C}\mathbf{x} + \mathbf{d}) \leq b_i$ holds for all $\|\mathbf{x}\| \leq 1$. The worst-case scenario is when \mathbf{x} aligned with $\mathbf{a}_i^\top \mathbf{C}$ and has length 1:

$$\mathbf{x} = \frac{\mathbf{a}_i^\top \mathbf{C}}{\|\mathbf{a}_i^\top \mathbf{C}\|} \quad (27)$$

Thus the constraint becomes

$$\|\mathbf{a}_i^\top \mathbf{C}\| + \mathbf{a}_i^\top \mathbf{d} \leq b_i \quad (28)$$

Here is the resulting problem:

$$\begin{array}{ll} \underset{\mathbf{C}, \mathbf{d}}{\text{minimize}} & \log(\det(\mathbf{C}^{-1})), \\ \text{subject to} & \begin{cases} \mathbf{C} \succeq 0, \\ \|\mathbf{a}_i^\top \mathbf{C}\| + \mathbf{a}_i^\top \mathbf{d} \leq b_i. \end{cases} \end{array} \quad (29)$$

The solution gives us inscribed (inner) Löwner-John ellipsoid.

Implement both examples from page 2 of the LMI CVX documents.

Lecture slides are available via Github, links are on Moodle:

github.com/SergeiSa/Computational-Intelligence-2025



Let us prove that $\mathbf{M} \succ 0$ iff $\mathbf{A} \succ 0$ and $\mathbf{C} - \mathbf{B}^\top \mathbf{A}^{-1} \mathbf{B} \succ 0$.

First we prove that $\mathbf{A} \succ 0$ and $\mathbf{C} - \mathbf{B}^\top \mathbf{A}^{-1} \mathbf{B} \succ 0$ implies $\mathbf{M} \succ 0$. We need to prove that the following quadratic form is positive definite:

$$f = \begin{bmatrix} \mathbf{x}^\top & \mathbf{y}^\top \end{bmatrix} \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B}^\top & \mathbf{C} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \quad (30)$$

$$= \mathbf{x}^\top \mathbf{A} \mathbf{x} + \mathbf{x}^\top \mathbf{B} \mathbf{y} + \mathbf{y}^\top \mathbf{B}^\top \mathbf{x} + \mathbf{y}^\top \mathbf{C} \mathbf{y} \quad (31)$$

Since $\mathbf{C} - \mathbf{B}^\top \mathbf{A}^{-1} \mathbf{B} \succ 0$, the following quadratic form is positive-definite:

$$\mathbf{y}^\top (\mathbf{C} - \mathbf{B}^\top \mathbf{A}^{-1} \mathbf{B}) \mathbf{y} > 0 \quad (32)$$

We define a change of variables $\mathbf{x} = -\frac{1}{2}\mathbf{A}^{-1}\mathbf{B}\mathbf{y}$, giving us two equations:

$$\mathbf{y}^\top \mathbf{C} \mathbf{y} + 2\mathbf{x}^\top \mathbf{B} \mathbf{y} > 0 \quad (33)$$

$$\mathbf{y}^\top \mathbf{C} \mathbf{y} + 2\mathbf{y}^\top \mathbf{B}^\top \mathbf{x} > 0 \quad (34)$$

Their sum gives us:

$$2\mathbf{y}^\top \mathbf{C} \mathbf{y} + 2\mathbf{x}^\top \mathbf{B} \mathbf{y} + 2\mathbf{y}^\top \mathbf{B}^\top \mathbf{x} > 0 \quad (35)$$

$$\mathbf{y}^\top \mathbf{C} \mathbf{y} + \mathbf{x}^\top \mathbf{B} \mathbf{y} + \mathbf{y}^\top \mathbf{B}^\top \mathbf{x} > 0 \quad (36)$$

Since $\mathbf{A} \succ 0$ we conclude that:

$$\mathbf{x}^\top \mathbf{A} \mathbf{x} + \mathbf{y}^\top \mathbf{C} \mathbf{y} + \mathbf{x}^\top \mathbf{B} \mathbf{y} + \mathbf{y}^\top \mathbf{B}^\top \mathbf{x} > 0 \quad (37)$$

This finishes first part of the proof.