

Lec. 17

Ellipsoids (Σ)

$$\Sigma(A, \underline{b}, c) := \left\{ \underline{x} \in \mathbb{R}^n \mid \underbrace{x^T A x + 2x^T b + c}_{\text{convex quadratic}} \leq d \right\}$$

$$A \in \mathbb{S}_{++}^n$$

$$\underline{b} \in \mathbb{R}^n$$

$$c \in \mathbb{R}$$

$$\boxed{\underline{b}^T A^{-1} \underline{b} - c > 0}$$

\Downarrow
 Σ is non-empty

$$\text{Vol}(\Sigma(A, \underline{b}, c)) = \text{const}(n) \cdot \sqrt{\det(\underline{b}^T A^{-1} \underline{b} - c) A^{-1}}$$
$$(\text{Vol}(\cdot))^2 \propto \det(A^{-1})$$

(A, \underline{b}, c) parameterization of Σ

(\underline{a}, Q) parameterization of Ellipsoid Σ

$$\Sigma(\underline{a}, Q) = \{ \underline{x} \in \mathbb{R}^n \mid (\underline{x} - \underline{a})^T Q^{-1} (\underline{x} - \underline{a}) \leq 1 \}$$

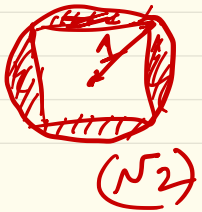
$\underline{a} \in \mathbb{R}^n$ center vector
 $Q \in S_{++}^n$ shape matrix

sq. roots of $\text{eig}(Q) =$ lengths of semi-axes of Σ

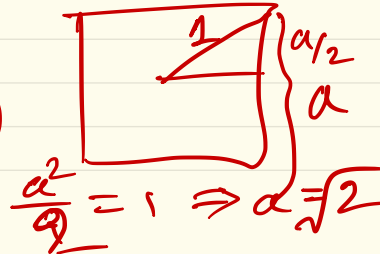
$$\text{Vol}(\Sigma(\underline{a}, Q)) = \frac{\text{Vol}(B_1^n)}{\sqrt{\det(Q^{-1})}} = \frac{\pi^{n/2}}{\Gamma(\frac{n}{2} + 1)} \sqrt{\det(Q)}$$

center position

$$\Leftrightarrow \text{Vol}(\Sigma(\underline{a}, Q)) \propto \sqrt{\det(Q)}$$



shape matrix
 $\frac{\text{Vol}(\text{cube})}{\text{Vol}(B_1^n)}$



$$\text{Success prob.} = \frac{\text{Vol}(\text{Cube})}{\text{Vol}(\mathbb{B}_1^n)} = \frac{(\sqrt{2})^n}{\pi^{n/2}} \Gamma\left(\frac{n}{2}+1\right)$$

Yet another parameterization of Ellipsoid

$$\Sigma(a, M) = \left\{ M\underline{v} + \underline{a} \mid \underline{v} \in \mathbb{R}^n, \|\underline{v}\|_2 \leq 1 \right\}$$

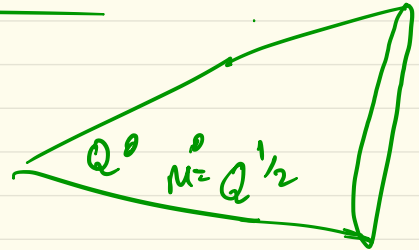
Affine image
of unit ball

rotation
and
scaling

translation

Relation between $(M \ \& \ Q)$:

$$M = Q^{1/2}$$



Relation between $(A, \underline{b}, c) \leftrightarrow (\underline{a}, Q)$

$$\sum_{\geq 0} A = \underbrace{Q^{-1}}_{\sum_{\geq 0}}, \quad \underline{b} \in \mathbb{R}^n, \quad c = \underline{a}^T Q^{-1} \underline{a} - 1$$

$$\Sigma(A, \underline{b}, c) \leftrightarrow \Sigma(\underline{a}, Q) \leftrightarrow \Sigma(\underline{a}, M) \\ \leftrightarrow \Sigma(\underline{a}, P) = \left\{ \underline{x} \in \mathbb{R}^n \mid \|P(\underline{x} - \underline{a})\| \leq 1 \right\}^2$$

Suppose,

$$Q^{-1} = P P^T, \quad P \succ 0 \\ \Rightarrow Q = P^{-2}$$

$$\Rightarrow \sqrt{\det(Q)} = \sqrt{(\det(P^{-1}))^2}$$

$$\Rightarrow \text{vol}(\Sigma(\underline{a}, Q)) \propto \det(P^{-1}) = +(\det(P))^{-1}$$

$$\Rightarrow \log \text{vol}(\Sigma(\underline{a}, Q)) \propto -\log \det(P)$$

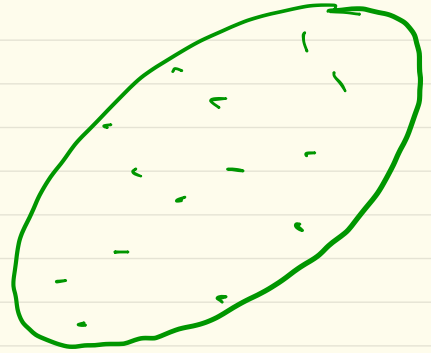
Minimum Vol^m Outer Ellipsoid (MVOE)

also known as

Löwner-John Ellipsoid

Fritz John
(1948)

For any compact set $\mathcal{D} \subset \mathbb{R}^m$,
the MVOE is unique



John's Thm
This inclusion
is tight

$$\Sigma_{LJ} \equiv \Sigma_{MVOE}$$

$$\frac{1}{n} \Sigma_{MVOE} \subseteq \mathcal{D} \subseteq \Sigma_{MVOE}$$

If \mathcal{S} is symmetric ($\Leftrightarrow \underline{x} \in \mathcal{S} \Rightarrow -\underline{x} \in \mathcal{S}$)
 then the factor $\frac{1}{\sqrt{n}}$ can be improved:

$$\frac{1}{\sqrt{n}} \Sigma_{\text{MVOE}} \subseteq \mathcal{S} \subseteq \Sigma_{\text{MVOE}}$$

John's Theorem
 This inclusion
 is
 tight

Max. vol^m Inner Ellipsoid
 (MVIE)

$$\text{MVIE} \subseteq \mathcal{S} \subseteq n \text{ MVIE}$$

for any compact $\mathcal{S} \subset \mathbb{R}^n$

If \mathcal{S} is symmetric, again we have:

$$\text{MVIE} \subseteq \mathcal{S} \subseteq \sqrt{n} \text{ MVIE}$$



} These
 results
 are
 tight

Computing $\Sigma_{\text{MVOE}} \equiv \Sigma_{\text{LJ}}$

For arbitrary \mathcal{S} (say, convex) without loss of generality

$$\min \log \det(P^{-1})$$

$$P > 0$$

s.t.

$$\mathcal{S} \subseteq \Sigma(\underline{a}, P)$$



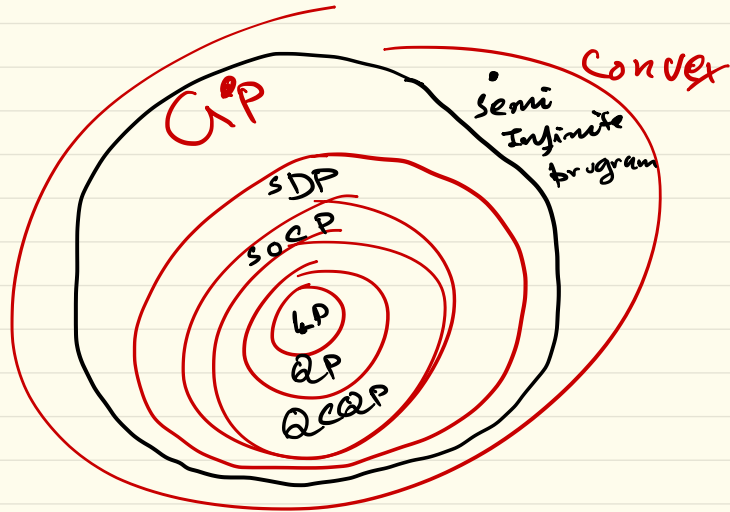
$$\sup_{\underline{x} \in \mathcal{S}} \|P(\underline{x} - \underline{a})\|_2 \leq 1$$

(\because if non-convex set, then take the convex hull)

MVOE problem

Semidefinite programming

$LP \subseteq QP \subseteq QCQP \subseteq SOCP \subseteq SDP \subseteq$ ^{Semi infinite Programs} \subseteq Convex



Example: Suppose S is finite set

$$S \equiv \left\{ \underbrace{a_1}_{\in \mathbb{R}^n}, \dots, \underbrace{a_m}_{\in \mathbb{R}^n} \right\}$$

m points in \mathbb{R}^n

Our MVOE

Problem becomes:

$$\min_{P \succ 0} \log \det(P^{-1})$$

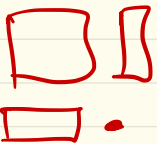
$$\text{s.t. } \boxed{\|P(a_i - \underline{a})\|_2 \leq 1}$$

Sehnen
complement

$$\begin{bmatrix} I & P(a_i - \underline{a}) \\ (P(a_i - \underline{a}))^T & 1 \end{bmatrix} \succeq 0, \quad i=1, \dots, m$$

$$M_i(P, \underline{a})$$

$i=1, \dots, m$



$$\text{diag}(M_1(P, \underline{a}), \dots, M_m(P, \underline{a})) \succeq 0.$$

Interior-point algorithm (can be done in CVX / CVXPY)

Computing MVIDE

(Max. Vol^m Inner Ellipsoid)

Suppose \mathcal{C} is a convex compact set.

$$\mathcal{E}(\underline{a}, M) := \{ M \underline{v} + \underline{a} \mid \|\underline{v}\|_2 \leq 1 \},$$

$$\text{Vol}(\mathcal{E}) \propto \det(M)$$

$$M \succ 0.$$

$$\max \text{Vol}(\mathcal{E}) \propto \max_{M \succ 0} \det(M) \Leftrightarrow \max_{M \succ 0} \log \det M$$

Therefore, MUIE problem:

$$\max_{M \succ 0} \log \det(M)$$

s.t. $\Sigma(\underline{a}, \underline{v}) \subseteq \mathcal{S}$

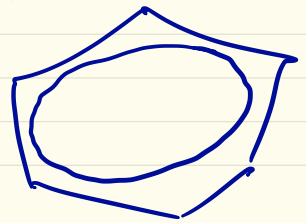
$$\sup_{\|\underline{v}\|_2 \leq 1} \mathbb{1}_{\mathcal{C}}(M\underline{v} + \underline{a}) \leq 0$$

} convex problem

Example: Suppose

$$\mathcal{C} = \left\{ \underline{x} \in \mathbb{R}^n \mid \begin{matrix} \underline{a}_i^T \underline{x} \leq b_i \\ i=1, \dots, m \end{matrix} \right\}$$

} MUIE inside polyhedron



$$\boxed{\begin{array}{l} \max \log \det(M) \\ M \succ 0 \end{array}}$$

$$\Sigma(M, \underline{a}) = \left\{ M \underline{v} + \underline{a} \mid \|\underline{v}\|_2 \leq 1 \right\}$$

$$\text{s.t.} \quad \Sigma \subseteq \mathcal{C}$$



$$\sup_{\underline{x} \in \Sigma} \underline{a}_i^T \underline{x} \leq b_i, \quad i=1, \dots, m$$



$$\sup_{\|\underline{v}\|_2 \leq 1} \underline{a}_i^T (M \underline{v} + \underline{a}) \leq b_i, \quad i=1, \dots, m$$



$$\sup_{\|\underline{v}\|_2 \leq 1} \underline{a}_i^T M \underline{v} + \underline{a}_i^T \underline{a} \leq b_i, \quad i=1, \dots, m$$

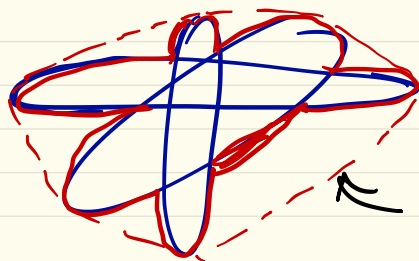
$$\boxed{\|\underline{M} \underline{a}_i\|_2 + \underline{a}_i^T \underline{a} \leq b_i, \quad i=1, \dots, m}$$

$$\text{St.} \left[\begin{array}{cc} (b_i - a_i^T \underline{a}) \mathbb{I} & M a_i \\ a_i^T M & (b_i - a_i^T \underline{a}) \end{array} \right] \succeq 0$$

$i=1, \dots, m$

can be done in cvx/cvxpy.

union of Ellipsoids ($\Sigma M \cup a_i$ can be computed)



↖ convex hull of the union

Computing $\sum_{i=1}^m \epsilon_i$ for $\bigcup_{i=1}^m \epsilon_i$; makes use of the so-called "S-procedure".

Main idea: When is one quadratic inequality a consequence of another (or a set of other) quadratic inequalities?

S-procedure for two quadratic forms:

Suppose $F_0, F_1 \in \mathcal{S}^n$.

When is it true that $\forall \underline{z} \in \mathbb{R}^n$, the inequality

$$\underline{z}^T F_1 \underline{z} \geq 0 \Rightarrow \underline{z}^T F_0 \underline{z} \geq 0?$$

In words,

when does non-negativity of one quadratic form imply non-negativity of other?

Sufficient condition: $\exists \underline{z} \geq 0$ s.t. $F_0 \geq \underline{z} F_1$

Then $\underline{z}^T F_1 \underline{z} \geq 0 \Rightarrow \underline{z}^T F_0 \underline{z} \geq 0$

Proof (Easy): $F_0 \geq \underline{z} F_1 \Rightarrow \underline{z}^T F_0 \underline{z} \geq \underbrace{\underline{z}^T F_1 \underline{z}}_{\geq 0} \geq 0$

≥ 0 . (Proved)

Fact: The converse holds (i.e., the condition is also necessary),

provided $\exists \underline{u} \in \mathbb{R}^n$ s.t.
 $\underline{u}^T F_1 \underline{u} > 0$

Proof: (Not easy)

S-procedure for two quadratic forms with strict inequalities

When does $z^T F_1 z \geq 0, z \neq 0 \Rightarrow z^T F_0 z > 0$?

Answer: Again,

(if) $\exists \tau \geq 0$ s.t. $F_0 > \tau F_1$

(then) the implication holds.

Fact: Again, converse holds provided $\exists u \in \mathbb{R}^n$ s.t.
 $u^T F_1 u > 0$.

slightly general version in Text, Appendix B.2 for quadratic forms $x^T A_i x + 2b_i^T x + c_i$, etc.
 $i=1, 2$

Also see Example B.1 here (p. 655 in text)

Back to computing $\Sigma_{\text{MVOE}} \supseteq \bigcup_{i=1}^m \Sigma_i$.

Suppose

$$\Sigma_i = \{ \underline{x} \in \mathbb{R}^n \mid \underline{x}^T A_i \underline{x} + 2 \underline{b}_i^T \underline{x} + c_i \leq 0 \},$$

where $A_i \in \mathbb{S}_{++}^n \forall i=1, \dots, m$.

For Σ_{MVOE} , we do the (\underline{a}, P) parameterization.

$$\text{Recall: } \Sigma_{\text{MVOE}}(\underline{a}, P) \equiv \{ \underline{x} \in \mathbb{R}^n \mid \|P(\underline{x} - \underline{a})\|_2 \leq 1 \}$$

$$\Leftrightarrow \Sigma_{\text{MVOE}}(\underline{r}, P) = \{ \underline{x} \in \mathbb{R}^n \mid \|P\underline{x} + \underline{r}\|_2 \leq 1 \}$$

where $\underline{r} := -P\underline{a} \in \mathbb{R}^m$

So we have $\Sigma_i \equiv \Sigma(A_i, \underline{b}_i, c_i)$, $i=1, \dots, m$

and $\Sigma_{\text{MVOE}} \equiv \Sigma(\underline{r}, P)$

By "S-procedure",

$$\Sigma_i \subseteq \Sigma_{\text{MVOE}} \iff \exists \tau \geq 0 \text{ s.t.}$$

(if and only if)

$$\begin{bmatrix} (P^2 - \tau A_i) & (P\underline{r} - \tau \underline{b}_i) \\ (P\underline{r} - \tau \underline{b}_i)^T & \underline{r}^T \underline{r} - 1 - \tau c_i \end{bmatrix} \preceq 0.$$

Since $\text{vol}(\Sigma_{\text{MVOE}}) \propto \det(P^{-1})$, therefore,

minimize $\log \det(P^{-1})$

s.t. $\tau_1 \geq 0, \dots, \tau_m \geq 0$

$$\begin{bmatrix} (P^2 - \tau_i A_i) & (P\underline{r} - \tau_i \underline{b}_i) \\ (P\underline{r} - \tau_i \underline{b}_i)^T & \underline{r}^T \underline{r} - 1 - \tau_i c_i \end{bmatrix} \preceq 0, \quad i=1, \dots, m$$

Introducing new variables $\underline{\tilde{r}} := P\underline{r}$, $\tilde{P} := P^2$,

minimize $\log \det(A^{-1})$

s.t. $\tau_1 \geq 0, \dots, \tau_m \geq 0$

m
LMIs

$(\tilde{P}, \underline{\tilde{r}}, \tau_1, \dots, \tau_m)$

$$\begin{bmatrix} (\tilde{P} - \tau_i A_i) & (\underline{\tilde{r}} - \tau_i b_i) & 0 \\ (\underline{\tilde{r}} - \tau_i b_i) & (-1 - \tau_i c_i) & \tau_i^T \\ 0 & \underline{\tilde{r}} & -P \end{bmatrix} \preceq 0, \quad i=1, \dots, m$$

which is a convex problem in variables:

$\tilde{P}, \underline{\tilde{r}}, \tau_1, \dots, \tau_m$

Affine invariance of Σ_{LJ} (both Σ_{MVQE} and Σ_{MVIE})

Given compact $\mathcal{S} \subset \mathbb{R}^n$.

Consider $T \in \mathbb{R}^{n \times n}$ nonsingular. Then

$$\Sigma_{LJ}(T\mathcal{S}) = T \Sigma_{LJ}(\mathcal{S})$$