

Semidefinite Optimization and Relaxation

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2024-02-12

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Preface

This is the textbook for Harvard ENG-SCI 257: Semidefinite Optimization and Relaxation.

Feedback

I would like to invite you to provide comments to the textbook via the following two ways:

- Inline comments with Hypothesis:
 - Go to Hypothesis and create an account
 - Install the Chrome extension of Hypothesis
 - Provide public comments to textbook contents and I will try to address them
- Blog-style comments with Disqus:
 - At the end of each Chapter, there is a Disqus module where you can leave feedback

I would recommend using Disqus for high-level and general feedback regarding the entire Chapter, but using Hypothesis for feedback and questions about the technical details.

Offerings

Information about the offerings of the class is listed below.

2024 Spring

Time: Mon/Wed 2:15 - 3:30pm

Location: Science and Engineering Complex, 1.413

Instructor: Heng Yang

Teaching Fellow: Safwan Hossain

Syllabus

Notation

We will use the following standard notation throughout this book.

Basics

\mathbb{R}	real numbers
\mathbb{R}_+	nonnegative real
\mathbb{R}_{++}	positive real
\mathbb{Z}	integers
\mathbb{N}	nonnegative integers
\mathbb{N}_+	positive integers
\mathbb{R}^n	n -D column vector
\mathbb{R}_+^n	nonnegative orthant
\mathbb{R}_{++}^n	positive orthant
e_i	standard basic vector
$\Delta_n := \{x \in \mathbb{R}_+^n \mid \sum x_i = 1\}$	standard simplex

Matrices

$\mathbb{R}^{m \times n}$	$m \times n$ real matrices
\mathbb{S}^n	$n \times n$ symmetric matrices
\mathbb{S}_+^n	$n \times n$ positive semidefinite matrices
\mathbb{S}_{++}^n	$n \times n$ positive definite matrices
$\langle A, B \rangle$ or \bullet	inner product in $\mathbb{R}^{m \times n}$
$\text{tr}(A)$	trace of $A \in \mathbb{R}^{n \times n}$
A^\top	matrix transpose
$\det(A)$	matrix determinant
$\text{rank}(A)$	rank of a matrix
$\text{diag}(A)$	diagonal of a matrix
	A as a vector

$\text{Diag}(a)$	turning a vector into a diagonal matrix
$\text{BlkDiag}(A, B, \dots)$	block diagonal matrix with blocks A, B, \dots
$\succeq 0$ and $\preceq 0$	positive / negative semidefinite
$\succ 0$ and $\prec 0$	positive / negative definite
λ_{\max} and λ_{\min}	maximum / minimum eigenvalue
σ_{\max} and σ_{\min}	maximum / minimum singular value
$\text{vec}(A)$	vectorization of $A \in \mathbb{R}^{m \times n}$
$\text{svec}(A)$	symmetric vectorization of $A \in \mathbb{S}^n$
$\ A\ _{\text{F}}$	Frobenius norm
$\text{Range}(A)$	span of the column vectors
$\ker(A)$	right null space

Geometry

$\ a\ _p$	p -norm
$\ a\ $	2-norm
$B(o, r)$	ball with center o and radius r
$\text{aff}(S)$	affine hull of set S
$\text{conv}(S)$	convex hull of set S
$\text{cone}(S)$	conical hull of set S
$\text{int}(S)$	interior of set S
$\text{ri}(S)$	relative interior of set S
∂S	boundary of set S
P°	polar of convex body
P^*	dual of set P
$\text{O}(d)$	orthogonal group of dimension d
$\text{SO}(d)$	special orthogonal group of dimension d
\mathcal{S}^{d-1}	unit sphere in \mathbb{R}^d

Optimization

KKT	Karush–Kuhn–Tucker
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LP	linear program
QP	quadratic program
SOCP	second-order cone program
SDP	semidefinite program

Algebra

$\mathbb{R}[x]$	polynomial ring in x with real coefficients
deg	degree of a monomial / polynomial
$\mathbb{R}[x]_d$	polynomials in x of degree up to d
$[x]_d$	vector of monomials of degree up to d
$\llbracket x \rrbracket_d$	vector of monomials of degree d

Chapter 1

Mathematical Background

1.1 Convexity

A very important notion in modern optimization is that of *convexity*. To a large extent, an optimization problem is “easy” if it is convex, and “difficult” when convexity is lost, i.e., *nonconvex*. We give a basic review of convexity here and refer the reader to (Rockafellar, 1970), (Boyd and Vandenberghe, 2004), and (Bertsekas et al., 2003) for comprehensive treatments.

We will work on a finite-dimensional real vector space, which we will identify with \mathbb{R}^n .

Definition 1.1 (Convex Set). A set S is convex if $x_1, x_2 \in S$ implies $\lambda x_1 + (1 - \lambda)x_2 \in S$ for any $\lambda \in [0, 1]$. In other words, if $x_1, x_2 \in S$, then the line segment connecting x_1 and x_2 lies inside S .

Conversely, a set S is nonconvex if Definition 1.1 does not hold.

Given $x_1, x_2 \in S$, $\lambda x_1 + (1 - \lambda)x_2$ is called a *convex combination* when $\lambda \in [0, 1]$. For convenience, we will use the following notation

$$\begin{aligned} (x_1, x_2) &= \{\lambda x_1 + (1 - \lambda)x_2 \mid \lambda \in (0, 1)\}, \\ [x_1, x_2] &= \{\lambda x_1 + (1 - \lambda)x_2 \mid \lambda \in [0, 1]\}. \end{aligned} \tag{1.1}$$

A **hyperplane** is a common convex set defined as

$$H = \{x \in \mathbb{R}^n \mid \langle c, x \rangle = d\} \tag{1.2}$$

for some $c \in \mathbb{R}^n$ and scalar d . A **halfspace** is a convex set defined as

$$H^+ = \{x \in \mathbb{R}^n \mid \langle c, x \rangle \geq d\}. \tag{1.3}$$

Given two nonempty convex sets C_1 and C_2 , the **distance** between C_1 and C_2 is defined as

$$\text{dist}(C_1, C_2) = \inf\{\|c_1 - c_2\| \mid c_1 \in C_1, c_2 \in C_2\}. \quad (1.4)$$

For a convex set C , the hyperplane H in (1.2) is called a **supporting hyperplane** for C if C is contained in the half space H^+ and the distance between H and C is zero. For example, the hyperplane $x_1 = 0$ is supporting for the hyperboloid $\{(x_1, x_2) \mid x_1 x_2 \geq 1, x_1 \geq 0, x_2 \geq 0\}$ in \mathbb{R}^2 .

An important property of a convex set is that we can *certify* when a point is not in the set. This is usually done via a separation theorem.

Theorem 1.1 (Separation Theorem). *Let S_1, S_2 be two convex sets in \mathbb{R}^n and $S_1 \cap S_2 = \emptyset$, then there exists a hyperplane that separates S_1 and S_2 , i.e., there exists c and d such that*

$$\begin{aligned} \langle c, x \rangle &\geq d, \forall x \in S_1, \\ \langle c, x \rangle &\leq d, \forall x \in S_2. \end{aligned} \quad (1.5)$$

Further, if S_1 is compact (i.e., closed and bounded) and S_2 is closed, then the separation is strict, i.e., the inequalities in (1.5) are strict.

The strict separation theorem is used typically when S_1 is a single point (hence compact).

We will see a generalization of the separation theorem for nonconvex sets later after we introduce the idea of sums of squares.

Exercise 1.1. Provide examples of two disjoint convex sets such that the separation in (1.5) is not strict in one way and both ways.

Exercise 1.2. Provide a constructive proof that the separation hyperplane exists in Theorem 1.1 when (1) both S_1 and S_2 are closed, and (2) at least one of them is bounded.

The intersection of convex sets is always convex (try to prove this).

1.2 Convex Geometry

1.2.1 Basic Facts

Given a set S , its **affine hull** is the set

$$\text{aff}(S) = \left\{ \sum_{i=1}^k \lambda_i u_i \mid \lambda_1 + \cdots + \lambda_k = 1, u_i \in S, k \in \mathbb{N}_+ \right\},$$

where $\sum_{i=1}^k \lambda_i u_i$ is called an *affine combination* of u_1, \dots, u_k when $\sum_i \lambda_i = 1$. The affine hull of a set is the smallest affine subspace that contains S , and the **dimension** of S is the dimension of its affine hull. The affine hull of the empty set is the empty set, of a singleton is the singleton itself. The affine hull of a set of two different points is the line going through them. The affine hull of a set of three points not on one line is the plane going through them. The affine hull of a set of four points not in a plane in \mathbb{R}^3 is the entire space \mathbb{R}^3 .

For a convex set $C \subseteq \mathbb{R}^n$, the **interior** of C is defined as

$$\text{int}(C) := \{u \in C \mid \exists \epsilon > 0, B(u, \epsilon) \subseteq C\},$$

where $B(u, \epsilon)$ denotes a ball centered at u with radius ϵ (using the usual 2-norm). Each point in $\text{int}(C)$ is called an *interior point* of C . If $\text{int}(C) = C$, then C is said to be an **open set**. A convex set with nonempty interior is called a **convex domain**, while a compact (i.e., closed and bounded) convex domain is called a **convex body**.

The **boundary** of C is the subset of points that are in the **closure**¹ of C but are not in the interior of C , and we denote it as ∂C . For example, the closed line segment $C = [0, 1]$ has two points on the boundary: 0 and 1; the open line segment $C = (0, 1)$ has the same two points as its boundary.

It is possible that a convex set has empty interior. For example, a hyperplane has no interior, and neither does a singleton. In such cases, the **relative interior** can be defined as

$$\text{ri}(C) := \{u \in C \mid \exists \epsilon > 0, B(u, \epsilon) \cap \text{aff}(C) \subseteq C\}.$$

For a nonempty convex set, the relative interior always exists. If $\text{ri}(C) = C$, then C is said to be **relatively open**. For example, the relative interior of a singleton is the singleton itself, and hence a singleton is relatively open.

For a convex set C , a point $u \in C$ is called an **extreme point** if

$$u \in (x, y), x \in C, y \in C \Rightarrow u = x = y.$$

For example, consider $C = \{(x, y) \mid x^2 + y^2 \leq 1\}$, then all the points on the boundary $\partial C = \{(x, y) \mid x^2 + y^2 = 1\}$ are extreme points.

A subset $F \subseteq C$ is called a **face** if F itself is convex and

$$u \in (x, y), u \in F, x, y \in C \Rightarrow x, y \in F.$$

Clearly, the empty set \emptyset and the entire set C are faces of C , which are called *trivial faces*. The face F is said to be *proper* if $F \neq C$. The set of any single

¹The closure of a subset C of points, denoted $\text{cl}(C)$, consists of all points in C together with all limit points of C . The closure of C may equivalently be defined as the intersection of all closed sets containing C . Intuitively, the closure can be thought of as all the points that are either in C or “very near” C . For example, the closure of the open line segment $C = (0, 1)$ is the closed line segment $C = [0, 1]$.

extreme point is also a face. A face F of C is called **exposed** if there exists a supporting hyperplane H for C such that

$$F = H \cap C.$$

1.2.2 Cones, Duality, Polarity

Definition 1.2 (Polar). For a nonempty set $T \subseteq \mathbb{R}^n$, its polar is the set

$$T^\circ := \{y \in \mathbb{R}^n \mid \langle x, y \rangle \leq 1, \forall x \in T\}. \quad (1.6)$$

The polar T° is a closed convex set and contains the origin. Note that T is always contained in the polar of T° , i.e., $T \subseteq (T^\circ)^\circ$. Indeed, they are equal under some assumptions.

Theorem 1.2 (Bipolar). *If $T \subseteq \mathbb{R}^n$ is a closed convex set containing the origin, then $(T^\circ)^\circ = T$.*

An important class of convex sets are those that are invariant under positive scalings.² A set $K \subseteq \mathbb{R}^n$ is a **cone** if $tx \in K$ for all $x \in K$ and for all $t > 0$. For example, the positive real line $\{x \in \mathbb{R} \mid x > 0\}$ is a cone. The cone K is **pointed** if $K \cap -K = \{0\}$. It is said to be **solid** if its interior $\text{int}(K) \neq \emptyset$. Any nonzero point of a cone cannot be extreme. If a cone is pointed, the only extreme point is the origin.

The analogue of extreme point for convex cones is the **extreme ray**. For a convex cone K and $0 \neq u \in K$, the line segment

$$u \cdot [0, \infty) := \{tu \mid t \geq 0\}$$

is called an extreme ray of K if

$$u \in (x, y), x, y \in K \quad \Rightarrow \quad u, x, y \text{ are parallel to each other.}$$

If $u \cdot [0, \infty)$ is an extreme ray, then we say u generates the extreme ray.

Definition 1.3 (Proper Cone). A cone K is proper if it is closed, convex, pointed, and solid.

A proper cone K induces a **partial order** on the vector space, via $x \succeq y$ if $x - y \in K$. We also use $x \succ y$ if $x - y$ is in $\text{int}(K)$. Important examples of proper cones are the nonnegative orthant, the second-order cone, the set of symmetric positive semidefinite matrices, and the set of nonnegative polynomials, which we will describe later in the book.

²Some authors define a cone using nonnegative scalings.

Definition 1.4 (Dual). The dual of a nonempty set S is

$$S^* := \{y \in \mathbb{R}^n \mid \langle y, x \rangle \geq 0, \forall x \in S\}.$$

Given any set S , its dual S^* is always a closed convex cone. Duality reverses inclusion, that is,

$$S_1 \subseteq S_2 \Rightarrow S_1^* \supseteq S_2^*.$$

If S is a closed convex cone, then $S^{**} = S$. Otherwise, S^{**} is the closure of the smallest convex cone that contains S .

For a cone $K \subseteq \mathbb{R}^n$, one can show that

$$K^\circ = \{y \in \mathbb{R}^n \mid \langle x, y \rangle \leq 0, \forall x \in K\}.$$

The set K° is called the **polar cone** of K . The negative of K° is just the **dual cone**

$$K^* = \{y \in \mathbb{R}^n \mid \langle x, y \rangle \geq 0, \forall x \in K\}.$$

Definition 1.5 (Self-dual). A cone K is self-dual if $K^* = K$.

As an easy example, the nonnegative orthant \mathbb{R}_+^n is self-dual.

Example 1.1 (Second-order Cone). The second-order cone, or the Lorentz cone, or the ice cream cone

$$\mathcal{Q}_n := \{(x_0, x_1, \dots, x_n) \in \mathbb{R}^{n+1} \mid \sqrt{x_1^2 + \dots + x_n^2} \leq x_0\}$$

is a proper cone of \mathbb{R}^{n+1} . We will show that it is also self-dual.

Proof. Consider $(y_0, y_1, \dots, y_n) \in \mathcal{Q}_n$, we want to show that

$$x_0 y_0 + x_1 y_1 + \dots + x_n y_n \geq 0, \forall (x_0, x_1, \dots, x_n) \in \mathcal{Q}_n. \quad (1.7)$$

This is easy to verify because

$$x_1 y_1 + \dots + x_n y_n \geq -\sqrt{x_1^2 + \dots + x_n^2} \sqrt{y_1^2 + \dots + y_n^2} \geq -x_0 y_0.$$

Hence we have $\mathcal{Q}_n \subseteq \mathcal{Q}_n^*$.

Conversely, if (1.7) holds, then take

$$x_1 = -y_1, \dots, x_n = -y_n, \quad x_0 = \sqrt{x_1^2 + \dots + x_n^2},$$

we have

$$y_0 \geq \sqrt{y_1^2 + \dots + y_n^2},$$

hence $\mathcal{Q}_n^* \subseteq \mathcal{Q}_n$. ■

Not every proper cone is self-dual.

Exercise 1.3. Consider the following proper cone in \mathbb{R}^2

$$K = \{(x_1, x_2) \mid 2x_1 - x_2 \geq 0, 2x_2 - x_1 \geq 0\}.$$

Show that it is not self-dual.

1.3 Convex Optimization

Definition 1.6 (Convex Function). A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a convex function if

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y), \forall \lambda \in [0, 1], \forall x, y \in \mathbb{R}^n.$$

A function f is convex if and only if its **epigraph** $\{(x, t) \in \mathbb{R}^{n+1} \mid f(x) \leq t\}$ is a convex set.

When a function f is differentiable, then there are several equivalent characterizations of convexity, in terms of the gradient $\nabla f(x)$ or the Hessian $\nabla^2 f(x)$.

Theorem 1.3 (Equivalent Characterizations of Convexity). *Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a twice differentiable function. The following propositions are equivalent.*

i. f is convex, i.e.,

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y), \forall \lambda \in [0, 1], x, y \in \mathbb{R}^n.$$

ii. The first-order convexity condition holds:

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle, \forall x, y \in \mathbb{R}^n,$$

i.e., the hyperplane going through $(x, f(x))$ with slope $\nabla f(x)$ supports the epigraph of f .

iii. The second-order convexity condition holds:

$$\nabla^2 f(x) \succeq 0, \forall x \in \mathbb{R}^n,$$

i.e., the Hessian is positive semidefinite everywhere.

Let's work on a little exercise.

Exercise 1.4. Which one of the following functions $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is not convex?

- a. $\exp(-c^\top x)$, with c constant
- b. $\exp(c^\top x)$, with c constant
- c. $\exp(x^\top x)$
- d. $\exp(-x^\top x)$

1.3.1 Minimax Theorem

Given a function $f : X \times Y \rightarrow \mathbb{R}$, the following inequality always holds

$$\max_{y \in Y} \min_{x \in X} f(x, y) \leq \min_{x \in X} \max_{y \in Y} f(x, y). \quad (1.8)$$

If the maximum or minimum is not attained, then (1.8) holds with \max / \min replaced by \sup and \inf , respectively.

Exercise 1.5. Provide examples of f such that the inequality in (1.8) is strict.

It is of interest to understand when equality holds in (1.8).

Theorem 1.4 (Minimax Theorem). *Let $X \subset \mathbb{R}^n$ and $Y \subset \mathbb{R}^n$ be compact convex sets, and $f : X \times Y \rightarrow \mathbb{R}$ be a continuous function that is convex in its first argument and concave in the second. Then*

$$\max_{y \in Y} \min_{x \in X} f(x, y) = \min_{x \in X} \max_{y \in Y} f(x, y).$$

A special case of this theorem, used in game theory to prove the existence of equilibria for zero-sum games, is when X and Y are standard unit simplices and the function $f(x, y)$ is bilinear. In a research from our group (Tang et al., 2023), we used the minimax theorem to convert a minimax problem into a single-level minimization problem.

1.3.2 Lagrangian Duality

Consider a nonlinear optimization problem

$$\begin{aligned} u^* &= \min_{x \in \mathbb{R}^n} f(x) \\ \text{s.t.} \quad &g_i(x) \leq 0, i = 1, \dots, m, \\ &h_j(x) = 0, j = 1, \dots, p. \end{aligned} \quad (1.9)$$

Define the **Lagrangian** associated with the optimization problem (1.9) as

$$\begin{aligned} L : \mathbb{R}^n \times \mathbb{R}_+^m \times \mathbb{R}^p &\rightarrow \mathbb{R}, \\ (x, \lambda, \mu) &\mapsto f(x) + \sum_{i=1}^m \lambda_i g_i(x) + \sum_{j=1}^p \mu_j h_j(x). \end{aligned} \quad (1.10)$$

The **Lagrangian dual function** is defined as

$$\phi(\lambda, \mu) := \min_{x \in \mathbb{R}^n} L(x, \lambda, \mu). \quad (1.11)$$

Maximizing this function over the dual variables (λ, μ) yields

$$v^* := \max_{\lambda \geq 0, \mu \in \mathbb{R}^p} \phi(\lambda, \mu) \quad (1.12)$$

Applying the minimax Theorem 1.4, we can see that

$$v^* = \max_{(\lambda, \mu)} \min_x L(x, \lambda, \mu) \leq \min_x \max_{(\lambda, \mu)} L(x, \lambda, \mu) = u^*.$$

That is to say solving the dual problem (1.12) always provides a lower bound to the primal problem (1.9).

If the functions f, g_i are convex and h_i are affine, the Lagrangian is convex in x and convex in (λ, μ) . To ensure strong duality (i.e., $u^* = v^*$), compactness or other **constraint qualifications** are needed. An often used condition is the Slater constraint qualification.

Definition 1.7 (Slater Constraint Qualification). There exists a strictly feasible point for (1.9), i.e., a point $z \in \mathbb{R}^n$ such that $h_j(z) = 0, j = 1, \dots, p$ and $g_i(z) < 0, i = 1, \dots, m$.

Under these conditions, we have strong duality.

Theorem 1.5 (Strong Duality). *Consider the optimization (1.9) and assume f, g_i are convex and h_j are affine. If Slater's constraint qualification holds, then the optimal value of the primal problem (1.9) is the same as the optimal value of the dual problem (1.12).*

1.3.3 KKT Optimality Conditions

Consider the nonlinear optimization problem (1.9). A pair of primal and dual variables (x^*, λ^*, μ^*) is said to satisfy the Karush-Kuhn-Tucker (KKT) optimality conditions if

$$\begin{aligned} \text{primal feasibility : } & g_i(x^*) \leq 0, \forall i = 1, \dots, m; h_j(x^*) = 0, \forall j = 1, \dots, p \\ \text{dual feasibility : } & \lambda_i^* \geq 0, \forall i = 1, \dots, m \\ \text{stationarity : } & \nabla_x L(x^*, \lambda^*, \mu^*) = 0 \\ \text{complementarity : } & \lambda_i^* \cdot g_i(x^*) = 0, \forall i = 1, \dots, m. \end{aligned} \tag{1.13}$$

Under certain constraint qualifications, the KKT conditions are necessary for local optimality.

Theorem 1.6 (Necessary Optimality Conditions). *Assume any of the following constraint qualifications hold:*

- *The gradients of the constraints $\{\nabla g_i(x^*)\}_{i=1}^m, \{\nabla h_j(x^*)\}_{j=1}^p$ are linearly independent.*
- *Slater's constraint qualification (cf. Definition 1.7).*

- All constraints $g_i(x)$ and $h_j(x)$ are affine functions.

Then, at every local minimum x^* of (1.9), the KKT conditions (1.13) hold.

On the other hand, for convex optimization problems, the KKT conditions are sufficient for global optimality.

Theorem 1.7 (Sufficient Optimality Conditions). *Assume optimization (1.9) is convex, i.e., f, g_i are convex and h_j are affine. Every point x^* that satisfies the KKT conditions (1.13) is a global minimizer.*

1.4 Linear Optimization

1.4.1 Polyhedra

In \mathbb{R}^n , a **polyhedron** is a set defined by finitely many linear inequalities, i.e.,

$$P = \{x \in \mathbb{R}^n \mid Ax \geq b\}, \quad (1.14)$$

for some matrix $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$. In (1.14), the inequality should be interpreted as $Ax - b \in \mathbb{R}_+^m$, i.e., every entry of Ax is no smaller than the corresponding entry of b .

The convex hull of finitely many points in \mathbb{R}^n is called a **polytope**, where the convex hull of a set S is defined as

$$\text{conv}(S) = \left\{ \sum_{i=1}^k \lambda_i u_i \mid k \in \mathbb{N}_+, \sum_{i=1}^k \lambda_i = 1, \lambda_i \geq 0, i = 1, \dots, k, u_i \in S, \forall i = 1, \dots, k \right\}, \quad (1.15)$$

i.e., all possible convex combinations of points in S . Clearly, a polytope is bounded.

The conic hull of finitely many points in \mathbb{R}^n is called a **polyhedral cone**, where the conic hull of a set S is defined as

$$\text{cone}(S) = \left\{ \sum_{i=1}^k \lambda_i u_i \mid k \in \mathbb{N}_+, \lambda_i \geq 0, i = 1, \dots, k, u_i \in S, \forall i = 1, \dots, k \right\}. \quad (1.16)$$

The only difference between (1.16) and (1.15) is the removal of $\sum_i \lambda_i = 1$. Clearly, the origin belongs to the conic hull of any nonempty set, and the conic hull of any nonempty set is unbounded.

The next theorem characterizes a polyhedron.

Theorem 1.8 (Polyhedron Decomposition). *Every polyhedron P is finitely generated, i.e., it can be written as the Minkowski sum of a polytope and a polyhedral cone:*

$$P = \text{conv}(u_1, \dots, u_r) + \text{cone}(v_1, \dots, v_s),$$

where the Minkowski sum of two sets is defined as $X + Y := \{x + y \mid x \in X, y \in Y\}$.

Further, a bounded polyhedron is a polytope.

An extreme point of a polytope is called a **vertex**. A 1-dimensional face of a polytope is called an **edge**. A $d-1$ -dimensional face of a d -dimensional polytope is called a **facet**.

1.4.2 Linear Program

We will now give a brief review of important results in linear programming (LP). The standard reference for linear programming is (Bertsimas and Tsitsiklis, 1997). In some sense, the theory of semidefinite programming (SDP) has been developed in order to generalize those of LP to the setup where the decision variable becomes a symmetric matrix and the inequality is interpreted as being positive semidefinite.

A standard form linear program (LP) reads

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & \langle c, x \rangle \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned} \tag{1.17}$$

for given $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$, and $c \in \mathbb{R}^n$. Often the tuple (A, b, c) is called the *problem data* because the LP (1.17) is fully defined once the tuple is given (indeed many LP numerical solvers take the tuple (A, b, c) as input). Clearly, the feasible set of the LP (1.17) is a polyhedron. The LP (1.17) is often referred to as the **primal** LP. Associated with (1.17) is the following **dual** LP

$$\begin{aligned} \max_{y \in \mathbb{R}^m} \quad & \langle b, y \rangle \\ \text{s.t.} \quad & c - A^\top y \geq 0 \end{aligned} \tag{1.18}$$

It is worth noting that the dimension of the dual variable y is exactly the number of constraints in the primal LP.

Lagrangian duality. Let us use the idea of Lagrangian duality introduced in Section 1.3.2 to verify that (1.18) is indeed the Lagrangian dual problem of (1.17). The Lagrangian associated with (1.17) is

$$\begin{aligned} L(x, \lambda, \mu) &= \langle c, x \rangle + \langle \mu, Ax - b \rangle + \langle \lambda, -x \rangle, \quad \mu \in \mathbb{R}^m, \lambda \in \mathbb{R}_+^n \\ &= \langle c + A^\top \mu - \lambda, x \rangle - \langle \mu, b \rangle, \quad \mu \in \mathbb{R}^m, \lambda \in \mathbb{R}_+^n. \end{aligned} \tag{1.19}$$

The Lagrangian dual function is therefore

$$\phi(\lambda, \mu) = \min_x L(x, \lambda, \mu) = \begin{cases} -\langle \mu, b \rangle & \text{if } c + A^\top \mu - \lambda = 0 \\ -\infty & \text{Otherwise} \end{cases}, \mu \in \mathbb{R}^m, \lambda \in \mathbb{R}_+^n.$$

The Lagrangian dual problem seeks to maximize the dual function $\phi(\lambda, \mu)$, and hence it must set $c + A^\top \mu - \lambda = 0$ (otherwise it leads to $-\infty$). As a result, the dual problem is

$$\begin{aligned} \max_{\mu \in \mathbb{R}^m} \quad & \langle b, -\mu \rangle \\ \text{s.t.} \quad & c + A^\top \mu = \lambda \geq 0 \end{aligned} \tag{1.20}$$

With a change of variable $y := -\mu$, we observe that problem (1.20) is precisely problem (1.18).

Weak duality. For the pair of primal-dual LPs, it is easy to verify that, for any x that is feasible for the primal (1.17) and y that is feasible for the dual (1.18), we have

$$\langle c, x \rangle - \langle b, y \rangle = \langle c, x \rangle - \langle Ax, y \rangle = \langle c, x \rangle - \langle A^\top y, x \rangle = \langle c - A^\top y, x \rangle \geq 0. \tag{1.21}$$

Therefore, denoting p^* as the optimum of (1.17) and d^* as the optimum of (1.18), we have the weak duality

$$p^* \geq d^*.$$

Note that such weak duality can also be directly obtained since (1.20) is the Lagrangian dual of (1.17).

If $p^* = d^*$, then we say **strong duality** holds. The LP (1.17) is said to be **feasible** if its feasible set is nonempty. It is said to be **unbounded below** if there exists a sequence $\{u_i\}_{i=1}^\infty \subseteq \mathbb{R}_+^n$ such that $\langle c, u_i \rangle \rightarrow -\infty$ and $Au_i = b$. If the primal (1.17) is infeasible (resp. unbounded below), we set $p^* = +\infty$ (resp. $p^* = -\infty$). Similar characteristics are defined for the dual LP (1.18). In particular, if the dual (1.18) is unbounded, then we set $d^* = +\infty$. If the dual is infeasible, then we set $d^* = -\infty$.

Strong duality is well understood in linear programming.

Theorem 1.9 (LP Strong Duality). *For the LP primal-dual pair (1.17) and (1.18), we have*

- If one of (1.17) and (1.18) is feasible, then $p^* = d^*$ (i.e., finite, $+\infty$, or $-\infty$).
- If one of p^* or d^* is finite, then $p^* = d^*$ is finite, and both (1.17) and (1.18) achieve the same optimal value (i.e., they both have optimizers).

- A primal feasible point x^* of (1.17) is a minimizer if and only if there exists a dual feasible point y^* such that $\langle c, x^* \rangle = \langle b, y^* \rangle$.

For example, consider the following primal-dual LP pair

$$\begin{cases} \min_{x \in \mathbb{R}_+^3} & x_1 + x_2 + 2x_3 \\ \text{s.t.} & \begin{bmatrix} -1 & 1 & 1 \\ 1 & 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{cases}, \begin{cases} \max_{y \in \mathbb{R}^2} & y_2 \\ \text{s.t.} & \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix} - \begin{bmatrix} -1 & 1 \\ 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \geq 0 \end{cases}. \quad (1.22)$$

$x^* = [1/2, 1/2, 0]^\top$ is feasible for the primal and attains $p^* = 1$. $y^* = [0, 1]^\top$ is feasible for the dual and attains $d^* = 1$. Therefore, both x^* and y^* are optimizers for the primal and dual, respectively.

Complementary slackness. Strong duality, when combined with (1.21), implies that

$$x_i^*(c - A^\top y^*)_i = 0, \forall i = 1, \dots, n,$$

where $(\cdot)_i$ denotes the i -th entry of a vector. This is known as complementary slackness, which states that whenever a primal optimal solution has a nonzero entry, the corresponding dual inequality must be tight.

An important property of LP is that if the primal problem is feasible and bounded below, then it must have an optimizer that is a **basic feasible point**, i.e., a feasible point has at most m nonzero entries. The simplex method (Bertsimas and Tsitsiklis, 1997) for solving LPs searches for optimizers among the basic feasible points.

We also introduce how to detect infeasibility and unboundedness of LPs.

Theorem 1.10 (LP Infeasibility and Unboundedness). *Infeasibility and Unboundedness of LP can be certified by existence of an improving/decreasing ray for the primal and dual:*

- When the primal (1.17) is feasible, it is unbounded below if and only if it has a decreasing ray, i.e., there exists $u \in \mathbb{R}^n$ such that

$$Au = 0, \quad u \geq 0, \quad \langle c, u \rangle < 0.$$

- When the dual (1.18) is feasible, it is unbounded above if and only if it has an improving ray, i.e., there exists $u \in \mathbb{R}^m$ such that

$$A^\top u \leq 0, \quad \langle b, u \rangle > 0.$$

- The primal problem (1.17) is infeasible if and only if the dual problem (1.18) has an improving ray, i.e., there exists $u \in \mathbb{R}^m$ such that

$$A^\top u \leq 0, \quad \langle b, u \rangle > 0.$$

- The dual problem (1.18) is infeasible if and only if the primal problem (1.17) has a decreasing ray, i.e., there exists $u \in \mathbb{R}^n$ such that

$$Au = 0, \quad u \geq 0, \quad \langle c, u \rangle < 0.$$

It is important to note that both the primal and dual can be infeasible, as in the following example.

$$\left\{ \begin{array}{ll} \min_{x \in \mathbb{R}_+^2} & -x_1 - x_2 \\ \text{s.t.} & \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} x = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \end{array} \right\}, \left\{ \begin{array}{ll} \max_{y \in \mathbb{R}^2} & 2y_1 + 3y_2 \\ \text{s.t.} & \begin{bmatrix} -1 \\ -1 \end{bmatrix} - \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix} y \geq 0 \end{array} \right\}. \quad (1.23)$$

1.4.3 Farkas Lemma

A foundational result in linear programming is the Farkas Lemma.

Theorem 1.11 (Farkas Lemma). *For a given $A \in \mathbb{R}^{m \times n}$ and $c \in \mathbb{R}^n$, if $\langle c, x \rangle \geq 0$ for all x satisfying $Ax \geq 0$, then there exists $\lambda \in \mathbb{R}^m$ such that*

$$c = A^\top \lambda, \quad \lambda \geq 0.$$

As a simple example, take $A = I_n$ as the identity matrix, then Farkas Lemma says if $\langle c, x \rangle \geq 0$ for all $x \geq 0$, then c must be that $c \geq 0$ – this is exactly the fact that the nonnegative orthant \mathbb{R}_+^n is self-dual.

In general, the Farkas Lemma states if the linear function $\langle c, x \rangle$ is nonnegative on the space $\{Ax \geq 0\}$, then there exists $\lambda \in \mathbb{R}^m$ such that

$$\langle c, x \rangle = \langle \lambda, Ax \rangle = \sum_{i=1}^m \lambda_i (a_i^\top x), \quad (1.24)$$

where a_i^\top is the i -th row of A . Note that (1.24) is a polynomial identity. As we will see later in the course, the idea of sums of squares (SOS), to some extent, is to generalize Farkas Lemma to the case where the function is a polynomial and the set is a basic semialgebraic set (i.e., defined by polynomial equalities and inequalities).

A generalization of Farkas Lemma to inhomogeneous affine functions is stated below.

Theorem 1.12 (Inhomogeneous Farkas Lemma). *Suppose the set $P = \{x \in \mathbb{R}^n \mid Ax \geq b\}$ with $A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$ is nonempty. If a linear function $\langle c, x \rangle - d$ is nonnegative on P , then there exists $\lambda \in \mathbb{R}^m$ and $\nu \in \mathbb{R}$ such that*

$$\langle c, x \rangle - d = \nu + \langle \lambda, Ax - b \rangle, \quad \lambda \geq 0, \nu \geq 0.$$

A more general result is called the Theorem of Alternatives, which states that a polyhedral set is empty if and only if another polyhedral set is nonempty.

Theorem 1.13 (Theorem of Alternatives). *Given $A_1 \in \mathbb{R}^{m_1 \times n}$, $A_2 \in \mathbb{R}^{m_2 \times n}$, $b_1 \in \mathbb{R}^{m_1}$, and $b_2 \in \mathbb{R}^{m_2}$, the set*

$$\{x \in \mathbb{R}^n \mid A_1 x > b_1, A_2 x \geq b_2\}$$

is empty if and only if the following set

$$\left\{ (\lambda_1, \lambda_2) \in \mathbb{R}^{m_1} \times \mathbb{R}^{m_2} \mid \begin{array}{l} \lambda_1 \geq 0, \lambda_2 \geq 0, \\ b_1^\top \lambda_1 + b_2^\top \lambda_2 \geq 0, \\ A_1^\top \lambda_1 + A_2^\top \lambda_2 = 0, \\ (e + b_1)^\top \lambda_1 + b_2^\top \lambda_2 = 1 \end{array} \right\}$$

is nonempty, with e being the vector of all ones.

Chapter 2

Semidefinite Optimization

2.1 Positive Semidefinite Matrices

A real matrix $A = (A_{ij}) \in \mathbb{R}^{n \times n}$ is symmetric if $A = A^\top$, i.e., $A_{ij} = A_{ji}$ for all i, j . Let \mathbb{S}^n be the space of all real symmetric matrices.

Any symmetric matrix A defines a **quadratic form** $x^\top Ax$. A matrix A is said to be **positive semidefinite** (PSD) if and only if its associated quadratic form is nonnegative, i.e.,

$$x^\top Ax \geq 0, \quad \forall x \in \mathbb{R}^n.$$

We use \mathbb{S}_+^n to denote the set of $n \times n$ PSD matrices. We also write $A \succeq 0$ to denote positive semidefiniteness when the dimension is clear.

There are several equivalent characterizations of positive semidefiniteness.

Lemma 2.1 (Positive Semidefinite Matrices). *Let $A \in \mathbb{S}^n$ be a symmetric matrix, the following statements are equivalent:*

1. *A is positive semidefinite.*
2. *$x^\top Ax \geq 0, \forall x \in \mathbb{R}^n$.*
3. *All eigenvalues of A are nonnegative.*
4. *All $2^n - 1$ principal minors of A are nonnegative.*
5. *The coefficients of $p_A(\lambda)$ weakly alternate in sign, i.e., $(-1)^{n-k} p_k \geq 0$ for $k = 0, \dots, n-1$, where $p_A(\lambda) = \det(A - \lambda I_n)$ is the characteristics polynomial of A .*
6. *There exists a factorization $A = BB^\top$, where $B \in \mathbb{R}^{n \times r}$ with r the rank of A .*

Among the equivalent characterizations of PSD matrices, (5) is less well-known, but it can be very useful when we want to convert a PSD constraint into multiple scalar constraints. For example, consider the following subset of \mathbb{R}^3 :

$$\left\{ z \in \mathbb{R}^3 \mid X(z) = \begin{bmatrix} 1 & z_1 & z_2 \\ z_1 & z_2 & z_3 \\ z_2 & z_3 & 5z_2 - 4 \end{bmatrix} \succeq 0 \right\}.$$

We can first form the characteristic polynomial of $X(z)$ –whose coefficients will be functions of z – and then invoking (5) to obtain a finite number scalar inequality constraints. We can then pass these scalar constraints to Mathematica and plot the set as in the following figure (Yang et al., 2022).



Figure 2.1: An example spectrahedron.

Similarly, we say a matrix $A \in \mathbb{S}^n$ is **positive definite** (PD) if its associated quadratic form is always positive, i.e.,

$$x^\top A x > 0, \quad \forall x \in \mathbb{R}^n.$$

We use \mathbb{S}_{++}^n to denote the set of $n \times n$ PD matrices, and also write $A \succ 0$ when the dimension is clear.

Below is set of equivalent characterizations of positive definite matrices.

Lemma 2.2 (Positive Definite Matrices). *Let $A \in \mathbb{S}^n$ be a symmetric matrix, the following statements are equivalent:*

1. *A is positive definite.*
2. *$x^\top A x > 0, \forall x \in \mathbb{R}^n$.*
3. *All eigenvalues of A are strictly positive.*

4. All n leading principal minors of A are strictly positive.
5. The coefficients of $p_A(\lambda)$ strictly alternate in sign, i.e., $(-1)^{n-k}p_k > 0$ for $k = 0, \dots, n-1$, where $p_A(\lambda) = \det(A - \lambda \mathbf{I}_n)$ is the characteristics polynomial of A .
6. There exists a factorization $A = BB^\top$ with B square and nonsingular (full-rank).

Schur Complements. A useful technique to check whether a matrix is positive (semi-)definite is to use the Schur Complements. Consider a block-partitioned matrix

$$M = \begin{bmatrix} A & B \\ B^\top & C \end{bmatrix}, \quad (2.1)$$

where A and C are symmetric matrices. If A is invertible, then the Schur complement of A is

$$M/A = C - B^\top A^{-1}B.$$

Similarly, if C is invertible, then the Schur complement of C is

$$M/C = A - BC^{-1}B^\top.$$

We have the following result relating the Schur Complements to positive (semi-)definiteness.

Proposition 2.1 (Schur Complements and PSD). *Consider the block-partitioned matrix M in (2.1),*

- *M is positive definite if and only if both A and M/A are positive definite:*

$$M \succ 0 \Leftrightarrow A \succ 0, M/A = C - B^\top A^{-1}B \succ 0.$$

- *M is positive definite if and only if both C and M/C are positive definite:*

$$M \succ 0 \Leftrightarrow C \succ 0, M/C = A - BC^{-1}B^\top \succ 0.$$

- *If A is positive definite, then M is positive semidefinite if and only if M/A is positive semidefinite:*

$$\text{If } A \succ 0, \text{ then } M \succeq 0 \Leftrightarrow M/A \succeq 0.$$

- *If C is positive definite, then M is positive semidefinite if and only if M/C is positive semidefinite:*

$$\text{If } C \succ 0, \text{ then } M \succeq 0 \Leftrightarrow M/C \succeq 0.$$

2.1.1 Geometric Properties

The set \mathbb{S}_+^n is a proper cone (cf. Definition 1.3). Its interior is \mathbb{S}_{++}^n . Under the inner product

$$\langle A, B \rangle = \text{tr}(AB^\top), \quad A, B \in \mathbb{R}^{n \times n},$$

the PSD cone \mathbb{S}_+^n is self-dual.

Next we want to characterize the face of the PSD cone. We first present the following lemma which will turn out to be useful afterwards.

Lemma 2.3 (Range of PSD Matrices). *Let $A, B \in \mathbb{S}_+^n$, then we have*

$$\text{Range}(A) \subseteq \text{Range}(A + B), \quad (2.2)$$

where $\text{Range}(A)$ denotes the span of the column vectors of A .

Proof. For any symmetric matrix S , we know

$$\text{Range}(S) = \ker(S)^\perp.$$

Therefore, to prove (2.2), it is equivalent to prove

$$\ker(A) \supseteq \ker(A + B).$$

Pick any $u \in \ker(A + B)$, we have

$$(A + B)u = 0 \Rightarrow u^\top(A + B)u = 0 \Rightarrow u^\top Au + u^\top Bu = 0 \Rightarrow u^\top Au = u^\top Bu = 0,$$

where the last derivation is due to $A, B \succeq 0$. Now that we have $u^\top Au = 0$, we claim that $Au = 0$ must hold, i.e., $u \in \ker(A)$. To see this, write

$$u = \sum_{i=1}^n a_i v_i,$$

where $a_i = \langle u, v_i \rangle$ and $v_i, i = 1, \dots, n$ are the eigenvectors of A corresponding to eigenvalues $\lambda_i, i = 1, \dots, n$. Then we have

$$Au = \sum_{i=1}^n a_i Av_i = \sum_{i=1}^n a_i \lambda_i v_i,$$

and

$$u^\top Au = \sum_{i=1}^n \lambda_i a_i^2 = 0.$$

Since $\lambda_i \geq 0, a_i^2 \geq 0$, we have

$$\lambda_i a_i^2 = 0, \forall i = 1, \dots, n.$$

This indicates that if $\lambda_i > 0$, then $a_i = 0$. Therefore, a_i can only be nonzero for $\lambda_i = 0$, which leads to

$$Au = \sum_{i=1}^n a_i \lambda_i v_i = 0.$$

Therefore, $u \in \ker(A)$, proving the result. \square

Lemma 2.3 indicates that if $A \succeq B$, then $\text{Range}(B) \subseteq \text{Range}(A)$. What about the reverse?

Lemma 2.4 (Extend Line Segment). *Let $A, B \in \mathbb{S}_+^n$, if $\text{Range}(B) \subseteq \text{Range}(A)$, then there must exist $C \in \mathbb{S}_+^n$ such that*

$$A \in (B, C),$$

i.e., the line segment from B to A can be extended past A within \mathbb{S}_+^n .

Proof. Since $\text{Range}(B) \subseteq \text{Range}(A)$, we have

$$\ker(A) \subseteq \ker(B).$$

Now consider extending the line segment past A to

$$C_\alpha = A + \alpha(A - B) = (1 + \alpha)A - \alpha B,$$

with some $\alpha > 0$. We want to show that there exists $\alpha > 0$ such that $C_\alpha \succeq 0$.

Pick $u \in \mathbb{R}^n$, then either $u \in \ker(B)$ or $u \notin \ker(B)$. If $u \in \ker(B)$, then

$$u^\top C_\alpha u = (1 + \alpha)u^\top A u - \alpha u^\top B u = (1 + \alpha)u^\top A u \geq 0.$$

If $u \notin \ker(B)$, then due to $\ker(A) \subseteq \ker(B)$, we have $u \notin \ker(A)$ as well. As a result, we have

$$u^\top C_\alpha u = (1 + \alpha)u^\top A u - \alpha u^\top B u = (1 + \alpha)u^\top A u \left(1 - \frac{\alpha}{1 + \alpha} \frac{u^\top B u}{u^\top A u}\right). \quad (2.3)$$

Since

$$\max_{u: u \notin \ker(A)} \frac{u^\top B u}{u^\top A u} \leq \frac{\lambda_{\max}(B)}{\lambda_{\min, > 0}(A)},$$

where $\lambda_{\min, > 0}(A)$ denotes the minimum positive eigenvalue of A , we can always choose α sufficiently small to make (2.3) nonnegative. Therefore, there exists $\alpha > 0$ such that $C_\alpha \succeq 0$. \square

In fact, from Lemma 2.3 we can induce a corollary.

Corollary 2.1 (Range of PSD Matrices). *Let $A, B \in \mathbb{S}_+^n$, then we have*

$$\text{Range}(A + B) = \text{Range}(A) + \text{Range}(B),$$

with “+” the Minkowski sum.

Exercise 2.1. Let $A, B \in \mathbb{S}_+^n$, show that $\langle A, B \rangle = 0$ if and only if $\text{Range}(A) \perp \text{Range}(B)$.

For a subset $T \subseteq \mathbb{S}_+^n$, we use $\text{face}(T, \mathbb{S}_+^n)$ to denote the smallest face of \mathbb{S}_+^n that contains T . We first characterize the smallest face that contains a given PSD matrix, i.e., $\text{face}(A, \mathbb{S}_+^n)$ for $A \succeq 0$. Clearly, if A is PD, then $\text{face}(A, \mathbb{S}_+^n) = \mathbb{S}_+^n$ is the entire cone. If A is PSD but singular with rank $r < n$, then A has the following spectral decomposition

$$Q^\top A Q = \begin{bmatrix} \Lambda & 0 \\ 0 & 0 \end{bmatrix},$$

where $\Lambda \in \mathbb{S}_{++}^r$ is a diagonal matrix with the r nonzero eigenvalues of A , and $Q \in O(n)$ is orthogonal. If

$$A = \lambda B + (1 - \lambda)C, \quad B, C \in \mathbb{S}_+^n, \lambda \in (0, 1),$$

then multiplying both sides by Q^\top and Q we have

$$\begin{bmatrix} \Lambda & 0 \\ 0 & 0 \end{bmatrix} = Q^\top A Q = \lambda Q^\top B Q + (1 - \lambda)Q^\top C Q.$$

Therefore, it must hold that

$$Q^\top B Q = \begin{bmatrix} B_1 & 0 \\ 0 & 0 \end{bmatrix}, \quad Q^\top C Q = \begin{bmatrix} C_1 & 0 \\ 0 & 0 \end{bmatrix}, \quad B_1 \in \mathbb{S}_+^r, C_1 \in \mathbb{S}_+^r,$$

which is equivalent to

$$B = Q \begin{bmatrix} B_1 & 0 \\ 0 & 0 \end{bmatrix} Q^\top, C = Q \begin{bmatrix} C_1 & 0 \\ 0 & 0 \end{bmatrix} Q^\top, \quad B_1 \in \mathbb{S}_+^r, C_1 \in \mathbb{S}_+^r.$$

We conclude that $\text{face}(A, \mathbb{S}_+^n)$ must contain the set

$$G := \left\{ Q \begin{bmatrix} X & 0 \\ 0 & 0 \end{bmatrix} Q^\top \mid X \in \mathbb{S}_+^r \right\}. \quad (2.4)$$

Exercise 2.2. Show that G in (2.4) is a face of \mathbb{S}_+^n , i.e., (i) G is convex; (ii) $u \in (x, y), u \in G, x, y \in \mathbb{S}_+^n \Rightarrow x, y \in G$.

As a result, we have $\text{face}(A, \mathbb{S}_+^n) = G$.

More general faces of the PSD cone \mathbb{S}_+^n can be characterized as follows (Theorem 3.7.1 in (Wolkowicz et al., 2000)).

Theorem 2.1 (Faces of the PSD Cone). *A set $F \subseteq \mathbb{S}_+^n$ is a face if and only if there exists a subspace $L \subseteq \mathbb{R}^n$ such that*

$$F = \{X \in \mathbb{S}_+^n \mid \text{Range}(X) \subseteq L\}.$$

Proof. It is easy to prove the “If” direction using Lemma 2.3.

First we show F is convex. Pick $A, B \in F$. We have $\text{Range}(A) \subseteq L$ and $\text{Range}(B) \subseteq L$. Let v_1, \dots, v_m be a set of basis spanning L . We have that, for any $u \in \mathbb{R}^n$,

$$\begin{aligned} Au \in L &\Rightarrow Au = \sum_{i=1}^m a_i v_i, \\ Bu \in L &\Rightarrow Bu = \sum_{i=1}^m b_i v_i. \end{aligned} \tag{2.5}$$

So for any $\lambda \in [0, 1]$, we have

$$(\lambda A + (1 - \lambda)B)u = \lambda Au + (1 - \lambda)Bu = \sum_{i=1}^m (\lambda a_i + (1 - \lambda)b_i)v_i \in L,$$

implying $\lambda A + (1 - \lambda)B \in F$ for any $\lambda \in [0, 1]$.

Now we show that:

$$X \in (A, B), X \in F, A, B \in \mathbb{S}_+^n \Rightarrow A, B \in F.$$

From $X = \lambda A + (1 - \lambda)B$ for some $\lambda \in (0, 1)$, and invoking Lemma 2.3, we have

$$\begin{aligned} \text{Range}(X) &= \text{Range}(\lambda A + (1 - \lambda)B) \supseteq \text{Range}(\lambda A) = \text{Range}(A) \\ \text{Range}(X) &= \text{Range}(\lambda A + (1 - \lambda)B) \supseteq \text{Range}((1 - \lambda)B) = \text{Range}(B). \end{aligned} \tag{2.6}$$

Since $\text{Range}(X) \subseteq L$ due to $X \in F$, we have

$$\text{Range}(A) \subseteq L, \quad \text{Range}(B) \subseteq L,$$

leading to $A, B \in F$.

The proof for the “**Only If**” direction can be found in Theorem 3.7.1 of (Wolkowicz et al., 2000). \square

2.2 Semidefinite Programming

2.2.1 Spectrahedra

Recall the definition of a polyhedron in (1.14), i.e., a vector x constrained by finitely many linear inequalities. The feasible set of a Linear Program is a polyhedron.

Similarly, we define a **spectrahedron** as a set defined by finitely many **linear matrix inequalities** (LMIs). Spectrahedra are the feasible sets of Semidefinite Programs (SDPs).

A linear matrix inequality has the form

$$A_0 + \sum_{i=1}^m A_i x_i \succeq 0,$$

where $A_i \in \mathbb{S}^n, i = 0, \dots, m$ are given symmetric matrices. Correspondingly, a spectrahedron is defined by finitely many LMIs.

Definition 2.1 (Spectrahedron). A set $S \subseteq \mathbb{R}^m$ is a spectrahedron if it has the form

$$S = \left\{ x \in \mathbb{R}^m \mid A_0 + \sum_{i=1}^m x_i A_i \succeq 0 \right\},$$

for given symmetric matrices $A_0, A_1, \dots, A_m \in \mathbb{S}^n$.

Note that there is no loss of generality in defining a spectrahedron using a single LMI. For example, in the case of a set defined by two LMIs:

$$S = \left\{ x \in \mathbb{R}^m \mid A_0 + \sum_{i=1}^m x_i A_i \succeq 0, B_0 + \sum_{i=1}^m x_i B_i \succeq 0 \right\}, A_i \in \mathbb{S}^n, B_i \in \mathbb{S}^d,$$

we can compress the two LMIs into a single LMI by putting A_i and B_i along the diagonal:

$$S = \left\{ x \in \mathbb{R}^m \mid \begin{bmatrix} A_0 & \\ & B_0 \end{bmatrix} + \sum_{i=1}^m x_i \begin{bmatrix} A_i & \\ & B_i \end{bmatrix} \succeq 0 \right\}.$$

Leveraging (5) of Lemma 2.1, we know that a PSD constraint is equivalent to weakly alternating signs of the characteristic polynomial of the given matrix. Therefore, a spectrahedron is defined by finitely many polynomial inequalities, i.e., a spectrahedron is a (convex) **basic semialgebraic set**, as seen in the following example (Blekherman et al., 2012).

Example 2.1 (Elliptic Curve). Consider the spectrahedron in \mathbb{R}^2 defined by

$$\left\{ (x, y) \in \mathbb{R}^2 \mid A(x, y) = \begin{bmatrix} x+1 & 0 & y \\ 0 & 2 & -x-1 \\ y & -x-1 & 2 \end{bmatrix} \succeq 0 \right\}.$$

To obtain scalar inequalities defining the set, let

$$p_A(\lambda) = \det(\lambda I - A(x, y)) = \lambda^3 + p_2 \lambda^2 + p_1 \lambda + p_0$$

be the characteristic polynomial of $A(x, y)$. $A(x, y) \succeq 0$ is then equivalent to the coefficients weakly alternating in sign:

$$\begin{aligned} p_2 &= -(x+5) \leq 0, \\ p_1 &= -x^2 + 2x - y^2 + 7 \geq 0, \\ p_0 &= -(3+x-x^3-3x^2-2y^2) \leq 0. \end{aligned} \tag{2.7}$$

We can use the following Matlab script to plot the set shown in Fig. 2.2. (The code is also available at [here](#).) As we can see, the spectrahedron is convex, but it is not a polyhedron.

```
x = -2:0.01:2;
y = -2:0.01:2;
[X,Y] = meshgrid(x,y);

ineq = (-X - 5 <= 0) & ...
        (-X.^2 + 2*X - Y.^2 + 7 >= 0) & ...
        (3 + X - X.^3 - 3*X.^2 - 2*Y.^2 >= 0);

h = pcolor(X,Y,double(ineq)) ;
h.EdgeColor = 'none' ;
```

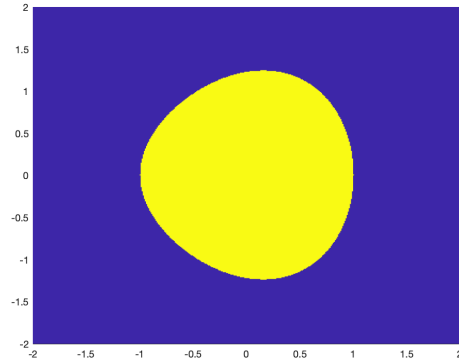


Figure 2.2: Elliptic Curve.

We can use the same technique to visualize the ellipptope, a spectrahedron that we will see again later when we study the MAXCUT problem.

Example 2.2 (Elliptope). Consider the 3D ellipptope defined by

$$\left\{ (x, y, z) \in \mathbb{R}^3 \left| A(x, y, z) = \begin{bmatrix} 1 & x & y \\ x & 1 & z \\ y & z & 1 \end{bmatrix} \succeq 0 \right. \right\}.$$

The characteristic polynomial of $A(x, y, z)$ is

$$p_A(\lambda) = \lambda^3 - 3\lambda^2 + (-x^2 - y^2 - z^2 + 3)\lambda + x^2 - 2xyz + y^2 + z^2 - 1.$$

The coefficients need to weakly alternative in sign, we have the inequalities

$$\begin{aligned} -x^2 - y^2 - z^2 + 3 &\geq 0 \\ x^2 - 2xyz + y^2 + z^2 - 1 &\leq 0 \end{aligned} \tag{2.8}$$

Using the Matlab script here, we generate the following plot.



Figure 2.3: Elliptope.

Another example is provided in Fig. 2.1.

2.2.2 Formulation and Duality

Semidefinite programs (SDPs) are linear optimization problems over spectrahedra. A standard SDP in **primal** form is written as

$$\begin{aligned} p^* = \min_{X \in \mathbb{S}^n} \quad & \langle C, X \rangle \\ \text{s.t.} \quad & \mathcal{A}(X) = b, \\ & X \succeq 0 \end{aligned} \tag{2.9}$$

where $C \in \mathbb{S}^n$, $b \in \mathbb{R}^m$, and the linear map $\mathcal{A} : \mathbb{S}^n \rightarrow \mathbb{R}^m$ is defined as

$$\mathcal{A}(X) := \begin{bmatrix} \langle A_1, X \rangle \\ \vdots \\ \langle A_i, X \rangle \\ \vdots \\ \langle A_m, X \rangle \end{bmatrix}.$$

Recall that $\langle C, X \rangle = \text{tr}(CX)$. The feasible set of (2.9) is the intersection of the PSD cone (\mathbb{S}_+^n) and the affine subspace defined by $\mathcal{A}(X) = b$.

Closely related to the primal SDP (2.9) is the **dual** problem

$$\boxed{\begin{array}{ll} d^* = \max_{y \in \mathbb{R}^m} & \langle b, y \rangle \\ \text{s.t.} & C - \mathcal{A}^*(y) \succeq 0 \end{array}} \quad (2.10)$$

where $\mathcal{A}^* : \mathbb{R}^m \rightarrow \mathbb{S}^n$ is the **adjoint** map defined as

$$\mathcal{A}^*(y) := \sum_{i=1}^m y_i A_i.$$

Observe how the primal-dual SDP pair (2.9)-(2.10) parallels the primal-dual LP pair (1.17)-(1.18).

Weak duality. We have a similar weak duality between the primal and dual. Pick any X that is feasible for the primal (2.9) and y that is feasible for the dual (2.10), we have

$$\boxed{\langle C, X \rangle - \langle b, y \rangle = \langle C, X \rangle - \langle \mathcal{A}(X), y \rangle = \langle C - \mathcal{A}^*(y), X \rangle \geq 0,}$$

where the last inequality holds because both $C - \mathcal{A}^*(y)$ and X are positive semidefinite. As a result, we have the weak duality

$$d^* \leq p^*.$$

Similar to the LP case, we will denote $p^* = +\infty$ if the primal is infeasible, $p^* = -\infty$ if the primal is unbounded below. We will denote $d^* = +\infty$ if the dual is unbounded above, and $d^* = -\infty$ if the dual is infeasible. We say the primal (or the dual) is **solvable** if it admits optimizers. We denote $p^* - d^*$ as the **duality gap**.

Recall Theorem 1.9 states that in LP, if at least one of the primal and dual is feasible, then strong duality holds (i.e., $p^* = d^* = \{\pm\infty, \text{finite}\}$). Unfortunately, this does not carry over to SDPs. Let us provide several examples.

Example 2.3 (Failure of SDP Strong Duality). The first example, from (Ramana, 1997), shows that even if both primal and dual are feasible, there could exist a nonzero duality gap. Consider the following SDP pair for some $\alpha \geq 0$

$$\left\{ \begin{array}{ll} \min_{X \in \mathbb{S}^3} & \alpha X_{11} \\ \text{s.t.} & X_{22} = 0 \\ & X_{11} + 2X_{23} = 1 \\ & \begin{bmatrix} X_{11} & X_{12} & X_{13} \\ * & X_{22} & X_{23} \\ * & * & X_{33} \end{bmatrix} \succeq 0 \end{array} \right\}, \left\{ \begin{array}{ll} \max_{y \in \mathbb{R}^2} & y_2 \\ \text{s.t.} & \begin{bmatrix} \alpha & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \succeq \begin{bmatrix} y_2 & 0 & 0 \\ 0 & y_1 & y_2 \\ 0 & y_2 & 0 \end{bmatrix} \end{array} \right\}$$

To examine the primal feasible set, let us pick the bottom-right 2×2 submatrix of X . The determinant of this submatrix needs to be nonnegative (due to (4) of Lemma 2.1):

$$X_{22}X_{33} - X_{23}^2 \geq 0.$$

Because $X_{22} = 0$, we have $X_{23} = 0$ and hence $X_{11} = 1$. Therefore, $p^* = \alpha$ is attained.

To examine the dual feasible set, pick the bottom-right 2×2 submatrix of

$$\begin{bmatrix} \alpha - y_2 & 0 & 0 \\ 0 & -y_1 & -y_2 \\ 0 & -y_2 & 0 \end{bmatrix} \succeq 0,$$

we have $y_2 = 0$. As a result, $d^* = 0$, and strong duality fails.

The second example, from (Todd, 2001), shows that the duality gap can even be infinite. Consider the primal-dual SDP

$$\left\{ \begin{array}{ll} \min_{X \in \mathbb{S}^2} & 0 \\ \text{s.t.} & X_{11} = 0 \\ & X_{12} = 1 \\ & \begin{bmatrix} X_{11} & X_{12} \\ * & X_{22} \end{bmatrix} \succeq 0 \end{array} \right\}, \left\{ \begin{array}{ll} \max_{y \in \mathbb{R}^2} & 2y_2 \\ \text{s.t.} & \begin{bmatrix} -y_1 & -y_2 \\ -y_2 & 0 \end{bmatrix} \succeq 0 \end{array} \right\}$$

Clearly, the primal is infeasible because

$$\begin{bmatrix} 0 & 1 \\ 1 & X_{22} \end{bmatrix}$$

can never be PSD. So $p^* = +\infty$. The dual problem, however, is feasible. From the PSD constraint we have $y_2 = 0$ and $d^* = 0$. Therefore, the duality gap is infinite.

The third example, from (Todd, 2001), shows that even when the duality gap is zero, the primal or dual problem may not admit optimizers. Consider the primal-dual SDP

$$\left\{ \begin{array}{ll} \min_{X \in \mathbb{S}^2} & 2X_{12} \\ \text{s.t.} & -X_{11} = -1 \\ & -X_{22} = 0 \\ & \begin{bmatrix} X_{11} & X_{12} \\ * & X_{22} \end{bmatrix} \succeq 0 \end{array} \right\}, \left\{ \begin{array}{ll} \max_{y \in \mathbb{R}^2} & -y_1 \\ \text{s.t.} & \begin{bmatrix} y_1 & 1 \\ 1 & y_2 \end{bmatrix} \succeq 0 \end{array} \right\}$$

To examine the primal feasible set, we have

$$\begin{bmatrix} 1 & X_{12} \\ X_{12} & 0 \end{bmatrix} \succeq 0$$

implies $X_{12} = 0$. Hence the primal feasible set only has one point and $p^* = 0$. The dual feasible set reads

$$y_1 y_2 \geq 1, \quad y_1 \geq 0, \quad y_2 \geq 0,$$

and we want to minimize y_1 . Clearly, $d^* = 0$ but it is not attainable. Therefore, strong duality holds but the dual problem is not solvable.

A Matlab script that passes these three examples to SDP solvers can be found [here](#).

The examples above are somewhat “pathological” and they show that SDPs in general can be more complicated than LPs. It turns out, with the addition of **Slater’s condition**, i.e., **strict feasibility** of the primal and dual, we can recover nice results parallel to those of LP.

Theorem 2.2 (SDP Strong Duality). *Assume both the primal SDP (2.9) and the dual SDP (2.10) are strictly feasible, i.e., there exists $X \succ 0$ such that $\mathcal{A}(X) = b$ for the primal and there exists $y \in \mathbb{R}^m$ such that $C - \mathcal{A}^*(y) \succ 0$ for the dual, then strong duality holds, i.e., both problems are solvable and admit optimizers, and $p^* = d^*$ equals to some finite number.*

Further, a pair of primal-dual feasible points (X, y) is optimal if and only if

$$\langle C, X \rangle = \langle b, y \rangle \Leftrightarrow \langle C - \mathcal{A}^*(y), X \rangle = 0 \Leftrightarrow (C - \mathcal{A}^*(y))X = 0.$$

One can relax the requirement of both primal and dual being strictly feasible to only one of them being strictly feasible, and similar results would hold. Precisely, if the primal is bounded below and strictly feasible, then $p^* = d^*$ and the dual is solvable. If the dual is bounded above and strictly feasible, then $p^* = d^*$ and the primal is solvable (Nie, 2023).

Example 2.4 (SDP Strong Duality). Consider the following primal-dual SDP pair

$$\left\{ \begin{array}{l} \min_{X \in \mathbb{S}^2} \quad 2X_{11} + 2X_{12} \\ \text{s.t.} \quad X_{11} + X_{22} = 1 \\ \begin{bmatrix} X_{11} & X_{12} \\ * & X_{22} \end{bmatrix} \succeq 0 \end{array} \right\}, \left\{ \begin{array}{l} \max_{y \in \mathbb{R}} \quad y \\ \text{s.t.} \quad \begin{bmatrix} 2-y & 1 \\ 1 & -y \end{bmatrix} \succeq 0 \end{array} \right.$$

Choose

$$X = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \succ 0$$

we see the primal is strictly feasible. Choose $y = -1$, we have

$$\begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix} \succ 0$$

and the dual is strictly feasible. Therefore, strong duality holds.

In this case, pick the pair of primal-dual feasible points

$$X^* = \begin{bmatrix} \frac{2-\sqrt{2}}{4} & -\frac{1}{2\sqrt{2}} \\ -\frac{1}{2\sqrt{2}} & \frac{2+\sqrt{2}}{4} \end{bmatrix}, \quad y^* = 1 - \sqrt{2},$$

we have

$$\langle C, X^* \rangle = 1 - \sqrt{2} = \langle b, y^* \rangle,$$

and both X^* and y^* are optimal.

2.2.3 Geometric Properties

2.3 Software for Conic Optimization

Linear optimization over the nonnegative orthant (\mathbb{R}_+^n), the second-order cone (\mathcal{Q}_n), and the positive semidefinite cone (\mathbb{S}_+^n) forms the foundation of modern convex optimization, commonly referred to as conic optimization. These three types of cones are self-dual, and there exist efficient algorithms to solve the convex optimization problems. Popular solvers include SDPT3, SeDuMi, MOSEK, and SDPNAL+.

In this section, we introduce how we should “talk to” the numerical solvers for conic optimization, i.e., how should we pass a mathematically written conic optimization to a numerical solver. Note that in many cases, this “transcription” can be done by programming packages such as CVX, CVXPY, YALMIP etc., but I think it is important to understand the standard interface of numerical solvers because (i) it reinforces our understanding of the mathematical basics, (ii) it gets us closer to designing custom numerical solvers for specific problems, (iii) if you are a heavy convex optimization user you will realize that many of the programming packages are not “efficient” in transcribing the original optimization problem (but they are indeed very general). I have had cases where solving the conic optimization takes a few minutes but transcribing the problem to the solver takes half an hour.

We will use the SeDuMi format as an example. Consider the following general linear convex optimization problem

$$\begin{aligned} \max_{y \in \mathbb{R}^m} \quad & b^\top y \\ \text{s.t.} \quad & Fy = g \\ & f \geq Gy \\ & h_i^\top y + \tau_i \geq \|H_i y + p_i\|_2, i = 1, \dots, r \\ & B_{j,0} + \sum_{k=1}^m y_k B_{j,k} \succeq 0, j = 1, \dots, s, \end{aligned} \tag{2.11}$$

for given matrices and vectors

$$F \in \mathbb{R}^{\ell_1 \times m}, G \in \mathbb{R}^{\ell_2 \times m}, H_i \in \mathbb{R}^{l_i \times m}, B_{j,k} \in \mathbb{S}^{n_j}, h_i \in \mathbb{R}^m, p_i \in \mathbb{R}^{l_i}, \tau_i \in \mathbb{R}, g \in \mathbb{R}^{\ell_1}, f \in \mathbb{R}^{\ell_2}.$$

Define the linear function

$$\phi(y) := \left(Fy, Gy, \begin{bmatrix} -h_1^\top y \\ -H_1 y \end{bmatrix}, \dots, \begin{bmatrix} -h_r^\top y \\ -H_r y \end{bmatrix}, -\sum_{k=1}^m y_k B_{1,k}, \dots, -\sum_{k=1}^m y_k B_{s,k} \right),$$

which is a linear map from \mathbb{R}^m to the vector space of Cartesian products

$$V := \mathbb{R}^{\ell_1} \times \mathbb{R}^{\ell_2} \times \mathbb{R}^{l_1+1} \times \dots \times \mathbb{R}^{l_r+1} \times \mathbb{S}^{n_1} \times \dots \times \mathbb{S}^{n_s}.$$

A vector $X \in V$ can be written as a tuple

$$X = (x_1, x_2, x_1, \dots, x_r, X_1, \dots, X_s).$$

Given another vector $Y \in V$

$$Y = (y_1, y_2, y_1, \dots, y_r, Y_1, \dots, Y_s),$$

the inner product between X and Y is defined as

$$\langle X, Y \rangle = \langle x_1, y_2 \rangle + \langle x_2, y_2 \rangle + \sum_{i=1}^r \langle x_i, y_i \rangle + \sum_{j=1}^s \langle X_j, Y_j \rangle.$$

Let \mathcal{K} be the Cartesian product of the free cone, the nonnegative orthant, the second-order cone, and the PSD cone

$$\mathcal{K} := \mathbb{R}^{\ell_1} \times \mathbb{R}_+^{\ell_2} \times \mathcal{Q}_{l_1} \times \dots \times \mathcal{Q}_{l_r} \times \mathbb{S}_+^{n_1} \times \dots \times \mathbb{S}_+^{n_s}.$$

Its dual cone is

$$\mathcal{K}^* = \{0\}^{\ell_1} \times \mathbb{R}_+^{\ell_2} \times \mathcal{Q}_{l_1} \times \dots \times \mathcal{Q}_{l_r} \times \mathbb{S}_+^{n_1} \times \dots \times \mathbb{S}_+^{n_s}.$$

Note that all the cones there are self-dual except the free cone whose dual is the zero point. Then denote

$$C := \left(g, f, \begin{bmatrix} \tau_1 \\ p_1 \end{bmatrix}, \dots, \begin{bmatrix} \tau_r \\ p_r \end{bmatrix}, B_{1,0}, \dots, B_{s,0} \right) \in V,$$

we have that the original optimization (2.11) is simply the following dual conic problem

$$\max_{y \in \mathbb{R}^m} \{ b^\top y \mid C - \phi(y) \in \mathcal{K}^* \}. \quad (2.12)$$

The linear map $\phi(y)$ can be written as

$$\phi(y) = y_1 A_1 + \dots + y_m A_m$$

for vectors A_1, \dots, A_m in the space V . Therefore, the primal problem to (2.12) is

$$\min_{X \in V} \{ \langle C, X \rangle \mid \langle A_i, X \rangle = b_i, i = 1, \dots, m, X \in \mathcal{K} \}. \quad (2.13)$$

Let us practice an example from (Nie, 2023).

Example 2.5 (SeDuMi Example). Consider the following optimization problem as an instance of (2.11):

$$\begin{aligned}
& \max_{y \in \mathbb{R}^3} && y_3 - y_1 \\
& \text{s.t.} && y_1 + y_2 + y_3 = 3 \\
& && -1 \geq -y_1 - y_2 \\
& && -1 \geq -y_2 - y_3 \\
& && y_1 + y_3 \geq \sqrt{(y_1 - 1)^2 + y_2^2 + (y_3 - 1)^2} \\
& && \begin{bmatrix} 1 & y_1 & y_2 \\ y_1 & 2 & y_3 \\ y_2 & y_3 & 3 \end{bmatrix} \succeq 0
\end{aligned} \tag{2.14}$$

Clearly we have $b = (-1, 0, 1)$. The linear map $\phi(y)$ is

$$\phi(y) = \left(y_1 + y_2 + y_3, \begin{bmatrix} -y_1 - y_2 \\ -y_2 - y_3 \end{bmatrix}, \begin{bmatrix} -y_1 - y_3 \\ -y_1 \\ -y_2 \\ -y_3 \end{bmatrix}, \begin{bmatrix} 0 & -y_1 & -y_2 \\ -y_1 & 0 & -y_3 \\ -y_2 & -y_3 & 0 \end{bmatrix} \right).$$

The vector space $V = \mathbb{R} \times \mathbb{R}^2 \times \mathbb{R}^4 \times \mathbb{S}^3$, and the cone \mathcal{K} is

$$\mathcal{K} = \mathbb{R} \times \mathbb{R}_+^2 \times \mathcal{Q}_3 \times \mathbb{S}_+^3.$$

The vectors A_1, A_2, A_3 are

$$\begin{aligned}
A_1 &= \left(1, \begin{bmatrix} -1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 & -1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \right) \\
A_2 &= \left(1, \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ -1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix} \right) \\
A_3 &= \left(1, \begin{bmatrix} 0 \\ -1 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix} \right).
\end{aligned} \tag{2.15}$$

The vector C is

$$C = \left(3, \begin{bmatrix} -1 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \right).$$

To input this problem to SeDuMi, we only need to provide the data (A, b, C) together with the description of the cones \mathcal{K} .


```

% describe dimensions of the cones
K.f = 1; % free cone
K.l = 2; % nonnegative orthant
K.q = 4; % second order cone
K.s = 3; % psd cone

% provide A,b,c
c = [3,-1,-1,0,-1,0,-1,1,0,0,0,2,0,0,0,3];
b = [-1,0,1];
A = [
    1,-1,0,-1,-1,0,0,0,-1,0,-1,0,0,0,0,0;
    1,-1,-1,0,0,-1,0,0,0,-1,0,0,0,-1,0,0;
    1,0,-1,-1,0,0,-1,0,0,0,0,0,-1,0,-1,0
];

% solve using sedumi
[xopt,yopt,info] = sedumi(A,b,c,K);

```

Note that in providing A , we vectorize each A_i and place it along the i -th row of the matrix A . The above Matlab script gives us the optimal solution

$$y^* = (0, 1, 2).$$

To run the code, make sure you download SeDuMi and add that to your Matlab path.

2.4 Interior Point Algorithm

2.5 Applications

2.5.1 Lyapunov Stability

One of the earliest and most important applications of semidefinite optimization is in the context of dynamical systems and control theory. The main reason is that it is possible to characterize the dynamical properties of a system (e.g., stability, contraction) in terms of algebraic statements such as the feasibility of specific forms of inequalities. We provide a simple example in the case of Lyapunov stability for linear dynamical systems. For a comprehensive overview, see (Boyd et al., 1994).

Consider a discrete-time linear dynamical system

$$x_{k+1} = Ax_k, \quad k = 0, \dots \quad (2.16)$$

where $x \in \mathbb{R}^n$ is called the state of the system, and k indexes the time. An important property that one wants to understand about the system (2.16) is whether it is **stable**, i.e., given an initial state x_0 , does x_k tend to zero as k tends to infinity.

It is well-known that x_k tends to zero for all initial conditions x_0 if and only if $|\lambda_i(A)| < 1, \forall i = 1, \dots, n$, i.e., all the eigenvalues of the transition matrix A lies inside the unit circle.

Equivalently, one can also **certify** the stability of the system if a **Lyapunov function**

$$V(x_k) = x_k^\top P x_k \quad (2.17)$$

is given that satisfies the following matrix inequalities.

Lemma 2.5 (Lyapunov Stability). *Given $A \in \mathbb{R}^{n \times n}$, the following statements are equivalent:*

1. *All eigenvalues of A lie strictly inside the unit circle, i.e., $|\lambda_i(A)| < 1, i = 1, \dots, n$*
2. *There exists a matrix $P \in \mathbb{S}^n$ such that*

$$P \succ 0, \quad A^\top P A - P \prec 0.$$

Proof. $2 \Rightarrow 1$: Let $\lambda \in \mathbb{C}$ and $v \neq 0 \in \mathbb{C}^n$ be a pair of eigenvalue and eigenvector of A such that $Av = \lambda v$. Since $A^\top P A - P \prec 0$, we have

$$v^*(A^\top P A - P)v < 0 \Rightarrow (\lambda v)^* P (\lambda v) - v^* P v < 0 \Rightarrow (|\lambda|^2 - 1)(v^* P v) < 0.$$

Since $P \succ 0$, we have $v^* P v > 0$. Hence, $|\lambda|^2 - 1 < 0$ and $|\lambda| < 1$.

$1 \Rightarrow 2$: Construct

$$P := \sum_{k=0}^{\infty} (A^k)^\top A^k.$$

The sum converges by the condition that $|\lambda_i(A)| < 1, \forall i$ and $P \succ 0$. Then we have

$$A^\top P A - P = \sum_{k=1}^{\infty} (A^k)^\top A^k - \sum_{k=0}^{\infty} (A^k)^\top A^k = -I \prec 0,$$

proving the result. □

Intuitively, the Lyapunov function (2.17) defines a positive definite energy function. The fact that $P \succ 0$ implies $V(0) = 0$ and $V(x) > 0$ for any x that is nonzero. The condition $A^\top P A - P \prec 0$ guarantees that the system's energy strictly decreases along any possible system trajectory. To see this, write

$$V(x_{k+1}) - V(x_k) = V(Ax_k) - V(x_k) = x_k^\top (A^\top P A - P) x_k < 0, \forall x_k \neq 0.$$

Therefore, the existence of a Lyapunov function guarantees any system trajectory will converge to the origin.

The nice property of constructing such a Lyapunov function is that it goes beyond linear systems and can be similarly generalized to nonlinear systems, where one can compute a stability certificate from semidefinite optimization. See for example this lecture notes.

Control Design. Consider now the case where A is not stable, but we can use a linear **feedback controller** to stabilize the system, i.e.,

$$u_k = Kx_k, \quad x_{k+1} = Ax_k + Bu_k = (A + BK)x_k,$$

where the matrix $K \in \mathbb{R}^{m \times n}$ is the feedback law we wish to design. We wish to design K using convex optimization, in particular semidefinite optimization.

Involving Lemma~2.5, we see that designing K to stabilize $A + BK$ is equivalent to finding

$$P \succ 0, \quad (A + BK)^\top P(A + BK) - P \prec 0. \quad (2.18)$$

Using the Schur complement technique in Proposition 2.1, we know (2.18) is equivalent to

$$\begin{bmatrix} P & (A + BK)^\top P \\ P(A + BK) & P \end{bmatrix} \succ 0.$$

This matrix inequality is, however, not jointly convex in the unknowns (P, A) . To address this issue, we can pre-multiply and post-multiply the equation by $\text{BlkDiag}(P^{-1}, P^{-1})$, which leads to

$$\begin{aligned} \begin{bmatrix} P^{-1} & \\ & P^{-1} \end{bmatrix} \begin{bmatrix} P & (A + BK)^\top P \\ P(A + BK) & P \end{bmatrix} \begin{bmatrix} P^{-1} & \\ & P^{-1} \end{bmatrix} \succ 0 &\Leftrightarrow \\ \begin{bmatrix} P^{-1} & P^{-1}(A + BK)^\top \\ (A + BK)P^{-1} & P^{-1} \end{bmatrix} \succ 0. & \quad (2.19) \end{aligned}$$

Now with a change of variable $Q := P^{-1}$, $Y = KP^{-1}$, we have

$$\begin{bmatrix} Q & QA^\top + Y^\top B^\top \\ AQ + BY & Q \end{bmatrix} \succ 0,$$

which is indeed a linear matrix inequality in the unknowns (Q, Y) . Solving the LMI, we can recover

$$P = Q^{-1}, K = YQ^{-1}.$$

2.5.2 Linear Quadratic Regulator

Another (somewhat surprising) application of semidefinite optimization is that it can be used to convexify the direct optimization of the linear quadratic regulator problem (one of the cornerstones in modern optimal control). In fact, such a

convex formulation is the key to prove why **policy optimization** works in reinforcement learning, as least in the linear quadratic case (Hu et al., 2023) (Mohammadi et al., 2021).

Consider a continuous-time linear dynamical system

$$\dot{x} = Ax + Bu, \quad x \in \mathbb{R}^n, u \in \mathbb{R}^m, A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times m}, \quad (2.20)$$

where x denotes the state and u denotes the control. Consider the following optimal control problem

$$\begin{aligned} \min_{u(t)} \quad & \mathbb{E} \left\{ \int_{t=0}^{\infty} x(t)^\top Q x(t) + u(t)^\top R u(t) dt \right\} \\ \text{s.t.} \quad & \dot{x} = Ax + Bu, \quad x(0) \sim \mathcal{N}(0, \Omega) \end{aligned} \quad (2.21)$$

where $Q, R \succ 0$ are known cost matrices, and $x(0)$ is supposed to satisfy the zero-mean Gaussian distribution with covariance $\Omega \succ 0$. In the case where A, B, Q, R are perfectly known to the control designer, and (A, B) is controllable (to be defined soon), problem (2.21) can be solved exactly and optimally, with the optimal controller being a linear feedback controller of the form

$$u(t) = -Kx(t),$$

where

$$K = R^{-1}B^\top S,$$

with S the unique positive definite solution to the continuous-time **algebraic Riccati equation** (ARE)

$$SA + A^\top S - SBR^{-1}B^\top S + Q = 0.$$

Policy Optimization. The control and reinforcement learning community are interested in whether it is possible to directly find the optimal feedback policy K , i.e., directly solving

$$\begin{aligned} \min_{K \in \mathcal{S}} \quad & \mathbb{E} \left\{ \int_{t=0}^{\infty} x(t)^\top Q x(t) + u(t)^\top R u(t) dt \right\} \\ \text{s.t.} \quad & \dot{x} = Ax + Bu, \quad u = -Kx, \quad x(0) \sim \mathcal{N}(0, \Omega). \end{aligned} \quad (2.22)$$

Note that problem (2.22) is different from the original problem (2.21) in the sense that we assume the knowledge that the optimal controller is linear and directly optimize K . The feasible set \mathcal{S} contains the set of **stabilizing controllers**, i.e.,

$$\mathcal{S} = \{K \in \mathbb{R}^{m \times n} \mid A - BK \text{ is Hurwitz}\}, \quad (2.23)$$

where a matrix A is Hurwitz means $\text{Re}(\lambda_i(A)) < 0$ for all $i = 1, \dots, n$, i.e., all the eigenvalues of A have strictly negative real parts. When $A - BK$ is Hurwitz, the closed-loop system is stable and the integral in (2.22) will not blow up (so it is sufficient to consider the class of stabilizing controllers).

We will first observe that the direct optimization (2.22) is nonconvex, because the feasible set \mathcal{S} is nonconvex. The following example is adapted from (Fazel et al., 2018).

Example 2.6 (Nonconvex Set of Stabilizing Controllers). Consider the dynamical system (2.20) with

$$A = 0_{3 \times 3}, \quad B = I_3.$$

It is easy to show that both

$$K_1 = \begin{bmatrix} 1 & 0 & -10 \\ -1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad K_2 = \begin{bmatrix} 1 & -10 & 0 \\ 0 & 1 & 0 \\ -1 & 0 & 1 \end{bmatrix}$$

are stabilizing controllers, as

$$\lambda(A - BK_1) = (-1, -1, -1), \quad \lambda(A - BK_2) = (-1, -1, -1).$$

However, pick

$$K = \frac{K_1 + K_2}{2} = \begin{bmatrix} 1 & -5 & -5 \\ -0.5 & 1 & 0 \\ -0.5 & 0 & 1 \end{bmatrix},$$

we have

$$\lambda(A - BK) = (-3.2361, 1.2361, -1)$$

and K does not stabilize the closed-loop system.

Convex Parameterization with Semidefinite Optimization. We will now show that it is possible to reparameterize problem (2.22) as a semidefinite optimization so it becomes convex. To do so, we note

$$x^\top Qx + u^\top Ru = x^\top Qx + x^\top K^\top RKx = x^\top (Q + K^\top RK)x = \text{tr}((Q + K^\top RK)xx^\top),$$

and therefore the objective of (2.22) can be written as

$$\mathbb{E} \left\{ \int_0^\infty \text{tr}((Q + K^\top RK)xx^\top) dt \right\} = \text{tr} \left((Q + K^\top RK) \mathbb{E} \left\{ \int_0^\infty xx^\top dt \right\} \right). \quad (2.24)$$

For any given initial condition, the solution of the closed-loop dynamics is given by the matrix exponential

$$x(t) = e^{(A-BK)t}x(0).$$

For the distribution of initial conditions, we have

$$\mathbb{E} \{x(t)x(t)^\top\} = e^{(A-BK)t} \mathbb{E} \{x(0)x(0)^\top\} e^{(A-BK)^\top t} = e^{(A-BK)t} \Omega e^{(A-BK)^\top t}.$$

The integral of this function, call it X , represents the expected energy of the closed-loop response

$$X = \mathbb{E} \left\{ \int_0^\infty xx^\top dt \right\}.$$

For every $K \in \mathcal{S}$ that is stabilizing, X can be computed as the solution to the Lyapunov equation

$$(A - BK)X + X(A - BK)^\top + \Omega = 0. \quad (2.25)$$

As a result, the objective of (2.22) is simplified as

$$\text{tr}((Q + K^\top RK)X),$$

with X solves (2.25). We arrive at an optimization problem

$$\begin{aligned} \min_{X, K} \quad & \text{tr}(QX) + \text{tr}(K^\top RKX) \\ \text{s.t.} \quad & (A - BK)X + X(A - BK)^\top + \Omega = 0, \\ & X \succ 0 \end{aligned} \quad (2.26)$$

which is still nonconvex. We do a change of variable $Y = KX$, so $K = YX^{-1}$ and obtain

$$\begin{aligned} \min_{X, Y} \quad & \text{tr}(QX) + \text{tr}(X^{-1}Y^\top RY) \\ \text{s.t.} \quad & AX - BY + XA^\top - Y^\top B^\top + \Omega = 0, \\ & X \succ 0 \end{aligned} \quad (2.27)$$

The second term in the objective is still nonconvex, but we can use the Schur complement technique again, and arrive at the final optimization

$$\begin{aligned} \min_{X, Y, Z} \quad & \text{tr}(QX) + \text{tr}(Z) \\ \text{s.t.} \quad & AX - BY + XA^\top - Y^\top B^\top + \Omega = 0 \\ & X \succ 0 \\ & \begin{bmatrix} Z & R^{1/2}Y \\ Y^\top R^{1/2} & X \end{bmatrix} \succeq 0 \end{aligned} \quad (2.28)$$

Note that the last two matrix inequalities of (2.28) implies, by Schur complement

$$Z - R^{1/2}YX^{-1}Y^\top R^{1/2} \succeq 0 \Rightarrow \text{tr}(Z - R^{1/2}YX^{-1}Y^\top R^{1/2}) \geq 0.$$

Since the optimization is trying to minimize $\text{tr}(Z)$, it will push the equality to hold

$$Z - R^{1/2}YX^{-1}Y^\top R^{1/2} = 0,$$

and thus

$$\text{tr}(Z) = \text{tr}(R^{1/2}YX^{-1}Y^\top R^{1/2}) = \text{tr}(X^{-1}Y^\top RY).$$

Example 2.7 (Convex LQR). For the same linear system as in Example 2.6, let $Q = R = I_3$.

If we solve the optimal feedback controller K by solving the ARE, we get the optimal controller is $K^* = I_3$.

If we implement the SDP in (2.28), we also get $K^* = I_3$, confirming the correctness of the convex parameterization. The implementation is shown below and can be found here.

```
%% Show the feasible set is nonconvex
A = zeros(3,3);
B = eye(3);
K1 = [1, 0, -10; -1, 1, 0; 0, 0, 1];
K2 = [1, -10, 0; 0, 1, 0; -1, 0, 1];
K = (K1 + K2)/2;

%% get the groundtruth LQR controller
Q = eye(3); R = eye(3);
K_lqr = lqr(A,B,Q,R,zeros(3,3));
Omega = eye(3);

%% solve SDP
addpath(genpath('..YALMIP'))
addpath(genpath('..../mosek'))

X = sdpvar(3,3);
Y = sdpvar(3,3,'full');
Z = sdpvar(3,3);
M = [Z, R*Y; Y'*R, X];
F = [
    A*X - B*Y + X*A' - Y'*B' + Omega == 0;
    M >= 0
];
obj = trace(Q*X) + trace(Z);
optimize(F,obj);
K_sdp = value(Y)*inv(value(X));
```

2.5.3 Domain Adaptation

(Mansour et al., 2009)

Chapter 3

Shor's Semidefinite Relaxation

In this Chapter, we introduce one of the most important and well-known applications of semidefinite optimization, namely its use in the formulation of **convex relaxations** of nonconvex optimization problems.

We will focus on the so-called Shor's semidefinite relaxation (Shor, 1987), which is particularly designed for quadratically constrained quadratic programs (QCQPs). Shor's semidefinite relaxation is relatively easy to formulate and understand, and as we will see later, is essentially the first-order relaxation in the moment-SOS hierarchy.

3.1 Semidefinite Relaxation of QCQPs

Consider a quadratically constrained quadratic program (QCQP):

$$\begin{aligned} f^* &= \min_{x \in \mathbb{R}^n} x^\top C x \\ \text{s.t. } & x^\top A_i x = b_i, i = 1, \dots, m \end{aligned} \tag{3.1}$$

where $C, A_1, \dots, A_m \in \mathbb{S}^n$ are given symmetric matrices and $b = [b_1, \dots, b_m] \in \mathbb{R}^m$ is a given vector. We assume the problem (3.1) is feasible, solvable, and bounded from below, i.e., $-\infty < f^* < +\infty$ and is attained. Many practical problems in optimization, engineering, and applied sciences can be formulated as (3.1). For example, problem (3.1) includes binary quadratic optimization (BQP) problems by letting

$$A_i = e_i e_i^\top, i = 1, \dots, n$$

with $e_i \in \mathbb{R}^n$ the standard Euclidean basis vector, in which case the i -th constraint becomes

$$x_i^2 = 1 \Leftrightarrow x_i \in \{+1, -1\}, i = 1, \dots, n.$$

We will discuss a particular type of BQP known as the MAXCUT problem in more details later. From this simple example, since QCQP includes BQP, we know in general the problem (3.1) is nonconvex and it is NP-hard to compute f^* and find a global optimizer.

3.1.1 Lagrangian Dual Problem

Since the original QCQP is hard to solve in general, we turn to computing a **lower bound** of (3.1). The most natural way to find a lower bound, according to Section 1.3.2, is to derive its Lagrangian dual problem. Towards this goal, we associate a Lagrangian multiplier $-y_i$ with each equality constraint and obtain the Lagrangian

$$L(x, y) = x^\top C x - \sum_{i=1}^m y_i (x^\top A_i x - b_i), \quad x \in \mathbb{R}^n, y \in \mathbb{R}^m.$$

The Lagrangian dual, by definition, is

$$\phi(y) = \min_x L(x, y) = \sum_{i=1}^m y_i b_i + \min_{x \in \mathbb{R}^n} x^\top \underbrace{\left(C - \sum_{i=1}^m y_i A_i \right)}_Z x.$$

Clearly, if Z is positive semidefinite, then $\min_x x^\top Z x = 0$ (by choosing $x = 0$); otherwise, $\min_x x^\top Z x = -\infty$. Therefore, the dual function is

$$\phi(y) = \begin{cases} \sum_{i=1}^m y_i b_i & \text{if } C - \sum_{i=1}^m y_i A_i \succeq 0 \\ -\infty & \text{otherwise} \end{cases}.$$

The Lagrangian dual problem seeks to maximize y , and hence it will make sure Z is PSD

$$\begin{aligned} d^* &= \max_{y \in \mathbb{R}^m} b^\top y \\ \text{s.t. } & C - \mathcal{A}^*(y) \succeq 0. \end{aligned} \tag{3.2}$$

By Lagrangian duality, we have

$$d^* \leq f^*.$$

Note that problem (3.2) is a convex SDP and can be solved by off-the-shelf solvers.

Another nice property of the dual problem is that it naturally leads to a **certifier**.

Proposition 3.1 (Dual Optimality Certifier). *Let x_* be a feasible solution to the QCQP (3.1), if there exists $y_* \in \mathbb{R}^m$ such that*

$$C - \mathcal{A}^*(y_*) \succeq 0, \quad [C - \mathcal{A}^*(y_*)]x_* = 0, \quad (3.3)$$

then x_ is a global minimizer of (3.1), and y_* is a global minimizer of (3.2).*

Proof. We have zero duality gap

$$\begin{aligned} x_*^\top C x_* - b^\top y_* &= \langle C, x_* x_*^\top \rangle - \langle b, y_* \rangle = \langle C, x_* x_*^\top \rangle - \langle \mathcal{A}(x_* x_*^\top), y_* \rangle \\ &= \langle C - \mathcal{A}^*(y_*), x_* x_*^\top \rangle = x_*^\top [C - \mathcal{A}^*(y_*)] x_* = 0. \end{aligned} \quad (3.4)$$

and (x_*, y_*) is primal-dual feasible. Therefore, (x_*, y_*) is primal-dual optimal. \square

The reason why Proposition 3.1 can be quite useful is that it gives a very efficient algorithm to certify global optimality of a candidate (potentially locally) optimal solution x_* . In particular, in several practical applications in computer vision and robotics, the second equation in (3.3) is a linear system of n equations in m variables with $m \leq n$, and hence it has a unique solution. Therefore, one can first solve the linear system and obtain a candidate y_* , and then simply check the PSD condition $C - \mathcal{A}^*(y_*) \succeq 0$. This leads to optimality certifiers that can run in real time (Garcia-Salguero et al., 2021) (Holmes and Barfoot, 2023).

3.1.2 Dual of the Dual (Bidual)

The dual problem (3.2) should appear familiar to us at this moment – it is simply a standard-form dual SDP (2.10). Therefore, we can write down the SDP dual of the QCQP dual (3.2)

$$\begin{aligned} p^* &= \min_{X \in \mathbb{S}^n} \quad \langle C, X \rangle \\ \text{s.t.} \quad &\mathcal{A}(X) = b \\ &X \succeq 0 \end{aligned} \quad (3.5)$$

Under the assumption of SDP strong duality (e.g., both (3.5) and (3.2) are strictly feasible), we have

$$p^* = d^* \leq f^*.$$

The weak duality $d^* \leq f^*$ can be interpreted using standard Lagrangian duality. How about the weak duality $p^* \leq f^*$? It turns out the dual of the dual (bidual) also has a nice interpretation.

We first observe that the original QCQP (3.1) is equivalent to a rank-constrained matrix optimization problem.

Proposition 3.2 (Rank-Constrained Matrix Optimization). *The QCQP (3.1) is equivalent to the following rank-constrained matrix optimization*

$$\begin{aligned} f_m^* &= \min_{X \in \mathbb{S}^n} \langle C, X \rangle \\ \text{s.t. } & \mathcal{A}(X) = b \\ & X \succeq 0 \\ & \text{rank}(X) = 1 \end{aligned} \tag{3.6}$$

in the sense that

1. $f^* = f_m^*$
2. For every optimal solution x_* of the QCQP (3.1), $X_* = x_* x_*^\top$ is globally optimal for the matrix optimization (3.6)
3. Every optimal solution X_* of the matrix optimization can be factorized as $X_* = x_* x_*^\top$ so that x_* is optimal for the QCQP (3.1).

Proof. We will show that the feasible set of the QCQP (3.1) is the same as the feasible set of (3.6).

Let x be feasible for the QCQP (3.1), we have $X = xx^\top$ must be feasible for (3.6) because $X \succeq 0$ by construction, $\text{rank}(X) = \text{rank}(xx^\top) = \text{rank}(x) = 1$, and

$$x^\top A_i x = b_i \Rightarrow \text{tr}(x^\top A_i x) = b_i \Rightarrow \text{tr}(A_i x x^\top) = b_i \Rightarrow \langle A_i, X \rangle = b_i, \forall i.$$

Conversely, let X be feasible for the matrix optimization (3.6). Since $X \succeq 0$ and $\text{rank}(X) = 1$, $X = xx^\top$ must hold for some $x \in \mathbb{R}^n$. In the meanwhile,

$$\langle A_i, X \rangle = b_i \Rightarrow \langle A_i, xx^\top \rangle = b_i \Rightarrow x^\top A_i x = b_i, \forall i.$$

Therefore, x is feasible for the QCQP (3.1).

Finally, it is easy to observe that

$$\langle C, X \rangle = \langle C, xx^\top \rangle = x^\top C x,$$

and the objective is also the same. □

Since the QCQP is equivalent to the matrix optimization (3.6), one should expect the matrix optimization to be NP-hard in general as well. In fact, this is true due to the nonconvex rank constraint $\text{rank}(X) = 1$. Comparing the nonconvex SDP (3.6) and the convex SDP (3.5), we see the only difference is that we have dropped the nonconvex rank constraint in (3.5) to make it convex, hence the SDP (3.5) is a convex relaxation of the QCQP (3.1) and $p^* \leq f^*$.

This convex relaxation perspective also provides a way to certify global optimality, by checking the rank of the optimal solution after solving the convex SDP (3.5).

Proposition 3.3 (Exactness of SDP Relaxation). *Let X_* be an optimal solution to the SDP (3.5), if $\text{rank}(X_*) = 1$, then X_* can be factorized as $X_* = x_* x_*^\top$ with x_* a globally optimal solution to the QCQP (3.1). If so, we say the relaxation (3.5) is exact, or tight.*

It is worth noting that, even when the relaxation is exact, i.e., $p^* = f^*$, it may not be trivial to numerically certify the exactness, due to several reasons

- If the SDP (3.5) is solved using interior point methods such as MOSEK, then it is well known that they converge to the *maximum-rank solution* (Wolkowicz et al., 2000). This is saying that even if the SDP (3.5) has rank-one solutions, the solvers may not find them. Consider the case where x_1 and x_2 are both optimal solutions to the QCQP (3.1) and the relaxation is exact, it is easy to check that

$$X = \lambda_1 x_1 x_1^\top + \lambda_2 x_2 x_2^\top, \quad \lambda_1, \lambda_2 \geq 0, \lambda_1 + \lambda_2 = 1$$

is globally optimal for the SDP. When $x_1 x_1^\top$ and $x_2 x_2^\top$ are linearly independent, X can have rank equal to two. In this case, interior point methods will not converge to either $x_1 x_1^\top$ or $x_2 x_2^\top$, but will instead find X with some unknown coefficients of λ_1 and λ_2 .

- Even if the original QCQP has a unique optimal solution and the relaxation is exact, the SDP solver will converge to a solution that is approximately rank-one (i.e., the second largest singular value / eigenvalue will still be nonzero) and it may be difficult to draw a conclusion about exactness. Therefore, in practice one can compute a **relative suboptimality gap** by rounding a feasible point to the QCQP from the SDP (it may or may not be easy to round a feasible point), denoted as \hat{x} , then compute

$$\hat{f} = \hat{x}^\top C \hat{x},$$

which serves as an upper bound

$$p^* \leq f^* \leq \hat{f}.$$

The relative suboptimality gap can be computed as

$$\eta = \frac{|\hat{f} - p^*|}{1 + |\hat{f}| + |p^*|}.$$

Clearly, $\eta \approx 0$ certifies exactness of the SDP relaxation.

3.1.3 MAXCUT

We will now study binary quadratic optimization problems, in particular the MAXCUT problem. The original QCQP reads

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & x^\top C x \\ \text{s.t.} \quad & x_i^2 = 1, i = 1, \dots, n. \end{aligned} \tag{3.7}$$

For the MAXCUT problem, a standard formulation is

$$\max_{x_i^2=1} \frac{1}{4} \sum_{i,j} w_{ij} (1 - x_i x_j). \quad (3.8)$$

It is clear that if x_i, x_j have the same sign, then $1 - x_i x_j = 0$, otherwise, $1 - x_i x_j = 2$. Removing the constant terms in (3.8), it is equivalent to the following BQP

$$\min_{x_i^2=1} \sum_{i,j} w_{ij} x_i x_j. \quad (3.9)$$

Random Rounding. In general, solving the SDP relaxation of the MAXCUT problem will not produce a certifiably optimal solution. It is therefore interesting to ask if solving the SDP relaxation can produce provably good approximations.

Let X be the optimal solution of the SDP relaxation, and $X = V^\top V$ be a rank- r factorization with $V \in \mathbb{R}^{r \times n}$

$$V = [v_1, \dots, v_n]$$

and each vector $v_i \in \mathbb{R}^r$. We have $X_{ij} = v_i^\top v_j$. Since $X_{ii} = 1$, the vectors v_i 's lie on the unit sphere. Goemans and Williamson (Goemans and Williamson, 1995) proposed to obtain a feasible point to the original BQP by first choosing a random unit direction $p \in \mathbb{R}^r$ and then assign

$$x_i = \text{sgn}(p^\top v_i), i = 1, \dots, n.$$

The expected value of this solution can be written as

$$\mathbb{E}_p \{x^\top C x\} = \sum_{i,j} C_{ij} \mathbb{E}_p \{x_i x_j\} = \sum_{i,j} C_{ij} \mathbb{E}_p \{\text{sgn}(p^\top v_i) \text{sgn}(p^\top v_j)\}.$$

This expectation can be computed using geometric intuition. Consider the plane spanned by v_i and v_j and let θ_{ij} be the angle between them. Then, it is easy to see that the desired expectation is equal to the probability that both points are on the same side of the hyperplane, minus the probability that they are on different sides. These probabilities are $1 - \theta_{ij}/\pi$ and θ_{ij}/π , respectively. Therefore, the expected value of the rounded solution is

$$\sum_{i,j} C_{ij} \left(1 - \frac{2\theta_{ij}}{\pi}\right) = \sum_{i,j} C_{ij} \left(1 - \frac{2}{\pi} \arccos(v_i^\top v_j)\right) = \frac{2}{\pi} \sum_{i,j} C_{ij} \arcsin X_{ij},$$

where we have used

$$\arccos t + \arcsin t = \frac{\pi}{2}.$$

MAXCUT Bound. For the MAXCUT problem, there are constant terms involved in the original cost function, which leads to the expected cut of the rounded solution to be

$$c_{\text{expected}} = \frac{1}{4} \sum_{i,j} w_{ij} \left(1 - \frac{2}{\pi} \arcsin X_{ij}\right) = \frac{1}{4} \frac{2}{\pi} \sum_{i,j} w_{ij} \arccos X_{ij}.$$

On the other hand, the optimal value of the SDP relaxation produces an upper bound on the true MAXCUT

$$c_{\text{ub}} = \frac{1}{4} \sum_{i,j} w_{ij} (1 - X_{ij}).$$

We have

$$c_{\text{expected}} \leq c_{\text{MAXCUT}} \leq c_{\text{ub}}.$$

We want to find the maximum possible α such that

$$\alpha c_{\text{ub}} \leq c_{\text{expected}} \leq c_{\text{MAXCUT}} \leq c_{\text{ub}},$$

so that α acts to be the best approximation ratio. To find such α , we need to find the maximum α such that

$$\alpha(1-t) \leq \frac{2}{\pi} \arccos(t), \forall t \in [-1, 1].$$

The best possible α is 0.878, see Fig. 3.1.

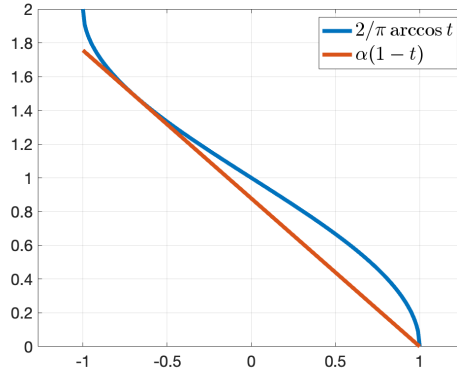


Figure 3.1: Best approximation ratio.

Bibliography

- Bertsekas, D., Nedic, A., and Ozdaglar, A. (2003). *Convex analysis and optimization*, volume 1. Athena Scientific. 11
- Bertsimas, D. and Tsitsiklis, J. N. (1997). *Introduction to linear optimization*, volume 6. Athena scientific Belmont, MA. 20, 22
- Blekherman, G., Parrilo, P. A., and Thomas, R. R. (2012). *Semidefinite optimization and convex algebraic geometry*. SIAM. 32
- Boyd, S., El Ghaoui, L., Feron, E., and Balakrishnan, V. (1994). *Linear matrix inequalities in system and control theory*. SIAM. 41
- Boyd, S. P. and Vandenberghe, L. (2004). *Convex optimization*. Cambridge university press. 11
- Fazel, M., Ge, R., Kakade, S., and Mesbahi, M. (2018). Global convergence of policy gradient methods for the linear quadratic regulator. In *International conference on machine learning*, pages 1467–1476. PMLR. 45
- Garcia-Salguero, M., Briales, J., and Gonzalez-Jimenez, J. (2021). Certifiable relative pose estimation. *Image and Vision Computing*, 109:104142. 51
- Goemans, M. X. and Williamson, D. P. (1995). Improved approximation algorithms for maximum cut and satisfiability problems using semidefinite programming. *Journal of the ACM (JACM)*, 42(6):1115–1145. 54
- Holmes, C. and Barfoot, T. D. (2023). An efficient global optimality certificate for landmark-based slam. *IEEE Robotics and Automation Letters*, 8(3):1539–1546. 51
- Hu, B., Zhang, K., Li, N., Mesbahi, M., Fazel, M., and Başar, T. (2023). Toward a theoretical foundation of policy optimization for learning control policies. *Annual Review of Control, Robotics, and Autonomous Systems*, 6:123–158. 44
- Mansour, Y., Mohri, M., and Rostamizadeh, A. (2009). Domain adaptation: Learning bounds and algorithms. *arXiv preprint arXiv:0902.3430*. 47

- Mohammadi, H., Zare, A., Soltanolkotabi, M., and Jovanović, M. R. (2021). Convergence and sample complexity of gradient methods for the model-free linear-quadratic regulator problem. *IEEE Transactions on Automatic Control*, 67(5):2435–2450. 44
- Nie, J. (2023). *Moment and Polynomial Optimization*. SIAM. 37, 39
- Ramana, M. V. (1997). An exact duality theory for semidefinite programming and its complexity implications. *Mathematical Programming*, 77:129–162. 35
- Rockafellar, R. T. (1970). *Convex Analysis*. Princeton university press. 11
- Shor, N. Z. (1987). Quadratic optimization problems. *Soviet Journal of Computer and Systems Sciences*, 25:1–11. 49
- Tang, Y., Lasserre, J.-B., and Yang, H. (2023). Uncertainty quantification of set-membership estimation in control and perception: Revisiting the minimum enclosing ellipsoid. *arXiv preprint arXiv:2311.15962*. 17
- Todd, M. J. (2001). Semidefinite optimization. *Acta Numerica*, 10:515–560. 36
- Wolkowicz, H., Saigal, R., and Vandenberghe, L. (2000). *Handbook of semidefinite programming: theory, algorithms, and applications*, volume 27. Springer. 30, 31, 53
- Yang, H., Liang, L., Carlone, L., and Toh, K.-C. (2022). An inexact projected gradient method with rounding and lifting by nonlinear programming for solving rank-one semidefinite relaxation of polynomial optimization. *Mathematical Programming*, pages 1–64. 26