CME 307 / MS&E 311 / OIT 676: Optimization

Conic optimization

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Outline

Semidefinite programming

Conic optimization

Conic form

Semidefinite program

A **semidefinite program** (SDP) is written as

$$\begin{array}{ll} \text{minimize} & \langle C, X \rangle \\ \text{subject to} & \langle A_i, X \rangle = b_i, \quad i = 1, \ldots, m \\ & X \succeq 0 \\ \text{variable} & X \in \mathbf{S}^n \end{array}$$

where

- $C, A_i \in \mathbf{S}^n$: symmetric matrices
- $\langle A, B \rangle = \mathbf{tr}(A^T B) = \sum_{ij} A_{ij} B_{ij}$: matrix inner product (linear in A and in B)

Semidefinite program: applications

SDPs arise in various fields:

- **Control theory**: stability analysis via Lyapunov functions
- **Combinatorial optimization**: relaxations of NP-hard problems
- **Eigenvalue optimization**: maximizing or minimizing eigenvalues

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Advantages of SDPs:

- convex optimization: globally optimal solutions
- generalizes linear programming (LP)
- efficient algorithms (*e.g.*, interior-point methods, first-order methods)

Example: MaxCut

Given a graph $G = (V, E)$ with edge weights w_{ij}, the **MaxCut** problem seeks to

- partition V into two disjoint sets S and $V \setminus S$
- maximize the total weight of edges crossing the cut

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formulate as an integer quadratic program:

$$\begin{array}{ll} \text{maximize} & \frac{1}{4}\sum_{i,j} w_{ij}(1 - x_i x_j) \\ \text{subject to} & x_i \in \{-1, 1\}, \quad i = 1, \ldots, n \end{array}$$

where

- x_i represents assignment of node i to a partition

interpretation:

- w_{ij} is value of cutting edge (i, j)
- objective is to maximize total cut value

SDP relaxation of MaxCut

Relax integer constraints by allowing x_i to be unit vectors $v_i \in \mathbb{R}^n$:

$$
\begin{array}{ll}
\text{maximize} & \frac{1}{4}\sum_{i,j} w_{ij}(1 - v_i^T v_j) \\
\text{subject to} & \|v_i\| = 1, \quad i = 1, \ldots, n \\
\text{variable} & v_i \in \mathbb{R}^n
\end{array}
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Equivalent SDP formulation, defining $X_{ij} = v_i^T v_j$:

$$\begin{array}{ll} \text{maximize} & \frac{1}{4}\sum_{i,j} w_{ij}(1 - X_{ij}) \\ \text{subject to} & X_{ii} = 1, \quad i = 1, \ldots, n \\ & X \succeq 0 \\ \text{variable} & X \in \mathbf{S}^n \end{array}$$

When is the relaxation tight?

The SDP relaxation is **tight** when $X^\star$ is rank one: $X^\star = x^\star (x^\star)^T$

- $(x^\star (x^\star)^T)_{ii} = 1 \implies x_i^\star \in \{-1, 1\}$, recovering integer solution

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in general:

- SDP provides an upper bound on MaxCut value
- Goemans-Williamson algorithm (1995) uses randomized rounding to obtain integer solution with approximation ratio of 0.878
- this approximation ratio is optimal assuming
  - the Unique Games conjecture and
  - P $\neq$ NP

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For details, see https://math.mit.edu/~goemans/PAPERS/maxcut-jacm.pdf

Outline

Convex cone

Definition (Convex cone)

A convex set $K \subseteq \mathbb{R}^n$ is a **cone** if for all $x \in K$ and $\alpha \geq 0$, we have $\alpha x \in K$.

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examples of convex cones:

- the zero cone $\{0\}$
- the nonnegative orthant $\mathbb{R}^n_+ = \{x \in \mathbb{R}^n \mid x \geq 0\}$
- the second-order cone $\{(x, t) \in \mathbb{R}^n \times \mathbb{R} \mid \|x\| \leq t\}$
- the positive semidefinite cone $\mathbf{S}^n_+ = \{X \in \mathbf{S}^n \mid X \succeq 0\}$
- the exponential cone $\{(x, y, z) \in \mathbb{R}^3 \mid ye^{x/y} \leq z, y > 0\}$
- sums of cones $K_1 + K_2 = \{x_1 + x_2 \mid x_1 \in K_1, x_2 \in K_2\}$

Conic optimization

Definition (Conic optimization)

A **conic optimization problem** is a convex optimization problem of the form

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & b - Ax \in K \\ \text{variable} & x \in \mathbb{R}^n \end{array}$$

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where K is a convex cone.

- generalizes linear programming ($K = \mathbb{R}^m_+$)
- structured representation of constraints: no oracles needed!
- can be solved efficiently for many cones

Conic duality

compared to linear programming, conic optimization over cone K replaces

$$b - Ax \geq 0 \quad \text{with} \quad b - Ax \in K$$

define **slack vector** $s = b - Ax \in K$
for weak duality, dual y must satisfy

$$\langle y, s \rangle \geq 0 \quad \forall s \in K$$

Dual cones

this inequality defines the **dual cone** K^*:

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examples of cones and their duals:

- K acute, K^* obtuse
- $K = \mathbb{R}^m_+$,
- $K = \{x \in \mathbb{R}^{n+1} \mid \|x_{1:n}\| \leq x_{n+1}\}$,
- $K = \{X \in \mathbf{S}^n \mid X \succeq 0\}$,

inner product $\langle X, Y\rangle = \mathbf{tr}(X^T Y) = \sum_{ij} X_{ij} Y_{ij}$ for $X, Y \in \mathbf{S}^n$

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primal problem with solution $x^\star \in \mathbb{R}^n$, optimal value $p^\star$, variable $x \in \mathbb{R}^n$:

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again we have weak duality $p^\star \geq d^\star$ and (under constraint qual) strong duality

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Conic form: LP example

we can represent many functions as the solution to a conic-form problem using an epigraph transformation, by **lifting** the problem to a higher dimension:

$$\|x\|_1 \quad =$$

Conic form: LP example

we can represent many functions as the solution to a conic-form problem using an epigraph transformation, by **lifting** the problem to a higher dimension:

$$
\begin{aligned}
\|x\|_1 \quad &= \quad \begin{array}{ll} \text{min} & \mathbf{1}^T s \\ \text{subject to} & -s \leq x \leq s \end{array} \\
&= \quad \begin{array}{ll} \text{min} & \mathbf{1}^T s \\ \text{subject to} & s - x \in \mathbb{R}^n_+ \\ & s + x \in \mathbb{R}^n_+ \end{array}
\end{aligned}
$$

we say that $\|x\|_1$ is **LP-representable** since this conic representation is a linear program.

Conic form: SOC example

many functions involving quadratics can be represented using the second-order cone: for example, for $x \in \mathbb{R}^n$,

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Conic form: SOC example

many functions involving quadratics can be represented using the second-order cone: for example, for $x \in \mathbb{R}^n$,

$$\|x\|^2 \quad = \quad \begin{array}{ll} \text{minimize} & t \\ \text{subject to} & \|(2x, t-1)\|_2 \le t+1 \iff (2x, t-1, t+1) \in \mathrm{SOC} \end{array}$$

since

$$\begin{array}{rcl} \|(2x, t-1)\|_2 & \le & t+1 \\ 0 & \le & (t+1)^2 - \|(2x, t-1)\|_2^2 = (t+1)^2 - 4\|x\|^2 - (t-1)^2 \\ & = & 4t - 4\|x\|^2 \\ \|x\|^2 & \le & t \end{array}$$

we say that $\|x\|^2$ is **SOC-representable** since this conic representation is a second-order cone program.

Conic form: SDP example

many functions of the eigenvalues of a matrix can be represented as a semidefinite program: for example, for $X \in \mathbf{S}_+^n$,

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$$\lambda_{\max}(X) = \begin{array}{ll} \text{minimize} & t \\ \text{subject to} & tI - X \succeq 0 \end{array}$$

we say that $\lambda_{\max}(X)$ is **SDP-representable** since this conic representation is a semidefinite program.

- particularly useful in controls, where we may have the constraint $X = \sum_{i=1}^m x_i A_i$, where A_i are known matrices

Conic form constraints

which of the following is a convex constraint?

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epigraph transformation works iff constraint is convex!

use epigraph transformation to represent $\|x\|_1$ through affine constraints:

$$\{(x,t) \mid \|x\|_1 \leq t\} = \{(x,t) \mid t \geq \mathbf{1}^T s,\ -s \leq x \leq s\}$$

Example: transforming a problem to conic form

consider the square-root Lasso problem: minimize regularized loss with $\lambda > 0$ fixed:

$$\text{minimize} \quad \|Ax - b\|_2 + \lambda \|x\|_1$$

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$$\text{minimize} \quad \|Ax - b\|_2 + \lambda \|x\|_1$$

Q: Transform this problem to conic form.

$$\begin{array}{lll} \text{minimize} & t + 1^T s & \\ \text{subject to} & -s \leq x \leq s & \text{LP constraints} \\ & r = Ax - b & \text{zero-cone constraints} \\ & \|r\|_2 \leq t & \text{SOC constraint} \end{array}$$

Solving conic programs

modeling conic programs:

- CVX, cvxpy, Convex.jl reformulate problems as conic programs
- (gurobipy, pyomo, JuMP do the same for (MI)LPs)

solvers specialize in solving conic programs with different cones:

- solvers compatible with cvxpy
- Mosek and COpt: excellent commercial conic solvers
- Clarabel: open-source conic solver, with Julia and Rust implementations