

10. Special convex optimization problems

- linear programs
- piecewise-linear minimization
- quadratic optimization
- geometric programming
- semidefinite programs
- quasiconvex optimization

Linear program

a *linear program* (LP) is an optimization problem of the form

$$\begin{aligned} &\text{minimize (or maximize)} && \sum_{j=1}^n c_j x_j \\ &\text{subject to} && \sum_{j=1}^n a_{ij} x_j \leq b_i, \quad i = 1, \dots, m \\ &&& \sum_{j=1}^n g_{ij} x_j = h_i, \quad i = 1, \dots, p \end{aligned}$$

- n optimization variables x_1, \dots, x_n
- coefficients $c_j, a_{ij}, g_{ij}, h_i, b_i$ are given
- convex problem with linear objective and linear/affine constraints

LP in compact form

$$\begin{array}{ll}\text{minimize (or maximize)} & c^T x \\ \text{subject to} & Ax \leq b \\ & Gx = h\end{array}$$

- A is an $m \times n$ matrix with entries a_{ij}
- G is an $p \times n$ matrix with entries g_{ij}
- $b = (b_1, \dots, b_m)$
- $h = (h_1, \dots, h_p)$
- $c = (c_1, \dots, c_n)$

Example: diet problem

- create meal with at least 12 units of protein, 9 units of iron, 15 units of thiamine

food	protein	iron	thiamine	cost (cents/g)
A	2 unit/g	1 unit/g	1 unit/g	30
B	1 unit/g	1 unit/g	3 unit/g	40

- how many grams of each food should be used to minimize the cost of the meal?

the problem can formulated as

$$\begin{array}{ll}\text{minimize} & 30x_1 + 40x_2 \\ \text{subject to} & 2x_1 + x_2 \geq 12 \\ & x_1 + x_2 \geq 9 \\ & x_1 + 3x_2 \geq 15 \\ & x_1, x_2 \geq 0\end{array}$$

where x_1 and x_2 are the number of grams of food A and B used in the meal

Example: alloy mixture

- we are given four alloys that have the metal properties listed in the below table

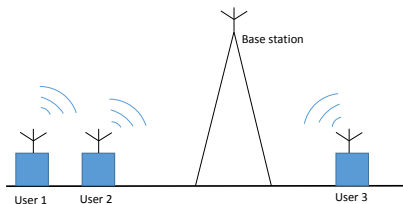
property	alloy 1	alloy 2	alloy 3	alloy 4
% of iron	70	25	40	20
% of nickel	10	15	50	50
% of cobalt	20	60	10	30
cost (\$/kg)	22	18	25	24

- goal is to create new alloy mixture with 40% iron, 35% nickel, 25% cobalt
- what proportions of the alloys should be blended together while minimizing cost?

- let x_i be the proportion of alloy i that is used to produce the new alloy
- the problem can be formulated as

$$\begin{array}{ll}\text{minimize} & 22x_1 + 18x_2 + 25x_3 + 24x_4 \\ \text{subject to} & 0.7x_1 + 0.25x_2 + 0.4x_3 + 0.2x_4 = 0.4 \\ & 0.1x_1 + 0.15x_2 + 0.5x_3 + 0.5x_4 = 0.35 \\ & 0.2x_1 + 0.6x_2 + 0.1x_3 + 0.3x_4 = 0.25 \\ & x_1 + x_2 + x_3 + x_4 = 1 \\ & x_1, x_2, x_3, x_4 \geq 0\end{array}$$

Example: wireless communication



- n “mobile” users
- user i transmits signal to base station with power p_i and attenuation factor of β_i
 - signal power received at the base station from user i is $\beta_i p_i$
- total power received from all other users is considered interference
 - the interference for user i is $\sum_{j \neq i} \beta_j p_j$
- for reliable communication with user i , signal-to-interference ratio must exceed γ_i
- goal is to minimize total power transmitted by all users subject to having reliable communications for all users

Problem formulation

$$\begin{array}{ll}\text{minimize} & \sum_{i=1}^n p_i \\ \text{subject to} & \frac{\beta_i p_i}{\sum_{j \neq i} \beta_j p_j} \geq \gamma_i, \quad i = 1, \dots, n \\ & p_i \geq 0, \quad i = 1, \dots, n\end{array}$$

LP formulation

$$\begin{array}{ll}\text{minimize} & \sum_{i=1}^n p_i \\ \text{subject to} & \beta_i p_i - \gamma_i \sum_{j \neq i} \beta_j p_j \geq 0, \quad i = 1, \dots, n \\ & p_i \geq 0, \quad i = 1, \dots, n\end{array}$$

Example: assignment problem

- we want to match N people to N tasks
- each person is assigned to one task (each task assigned to one person)
- cost of assigning person i to task j is c_{ij}
- variable $x_{ij} = 1$ if person i is assigned to task j ; $x_{ij} = 0$ otherwise

Combinatorial formulation

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^N \sum_{j=1}^N c_{ij} x_{ij} \\ \text{subject to} \quad & \sum_{i=1}^N x_{ij} = 1, \quad j = 1, \dots, N \\ & \sum_{j=1}^N x_{ij} = 1, \quad i = 1, \dots, N \\ & x_{ij} \in \{0, 1\}, \quad i, j = 1, \dots, N \end{aligned}$$

$N!$ possible assignments (e.g., $10! = 3628800$)

LP formulation

$$\begin{array}{ll}\text{minimize} & \sum_{i=1}^N \sum_{j=1}^N c_{ij} x_{ij} \\ \text{subject to} & \sum_{i=1}^N x_{ij} = 1, \quad j = 1, \dots, N \\ & \sum_{j=1}^N x_{ij} = 1, \quad i = 1, \dots, N \\ & 0 \leq x_{ij} \leq 1, \quad i, j = 1, \dots, N\end{array}$$

- we have *relaxed* the constraints $x_{ij} \in \{0, 1\}$
- it can be shown that the solution $x_{ij}^* \in \{0, 1\}$
- hence, we can solve this hard combinatorial problem efficiently by solving an LP

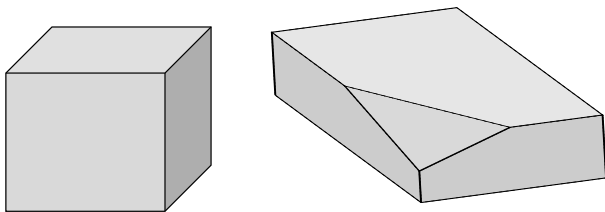
Polyhedron

a *polyhedron* is the intersection of finitely many halfspaces

$$a_1^T x \leq b_1, \dots, a_m^T x \leq b_m$$

in matrix notation, a polyhedron can be defined as

$$\mathcal{P} = \{x \in \mathbb{R}^n \mid Ax \leq b\}$$

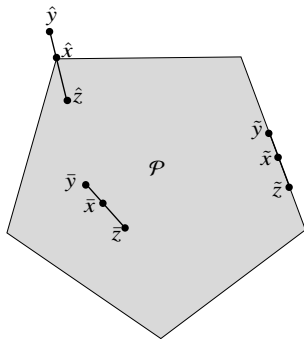


Extreme points

$x \in \mathcal{P}$ is an *extreme point* of \mathcal{P} if it *cannot* be written as convex combination

$$x = \theta y + (1 - \theta)z, \quad \theta \in (0, 1)$$

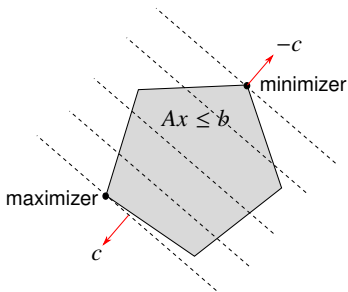
for some $y, z \in \mathcal{P}$



- \hat{x} is an extreme point
- \bar{x} and \tilde{x} are not extreme points

Geometrical interpretation of LP

$$\begin{array}{ll}\text{minimize (or maximize)} & c^T x \\ \text{subject to} & Ax \leq b\end{array}$$



- dashed lines are level sets $c^T x = \alpha$ for different α
- feasible set is a polyhedron
- the optimal solutions occur at an extreme point

Outline

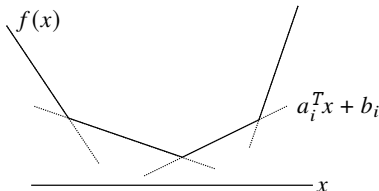
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Piecewise-linear minimization

Piecewise-linear function

$$f(x) = \max_{i=1,\dots,m} (a_i^T x + b_i)$$

- $a_i \in \mathbb{R}^n$ and $b_i \in \mathbb{R}$
- piecewise-linear function is a pointwise maximum of affine functions



Piecewise-linear minimization

$$\text{minimize } f(x) = \max_{i=1,\dots,m} (a_i^T x + b_i)$$

Equivalent LP formulation

$$\begin{array}{ll}\text{minimize} & t \\ \text{subject to} & a_i^T x + b_i \leq t, \quad i = 1, \dots, m\end{array}$$

- with additional variable $t \in \mathbb{R}$
- for fixed x , the optimal t is $t = f(x)$

Matrix form

$$\begin{array}{ll}\text{minimize} & \tilde{c}^T \tilde{x} \\ \text{subject to} & \tilde{A} \tilde{x} \leq \tilde{b}\end{array}$$

where

$$\tilde{x} = \begin{bmatrix} x \\ t \end{bmatrix}, \quad \tilde{c} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad \tilde{A} = \begin{bmatrix} a_1^T & -1 \\ \vdots & \vdots \\ a_m^T & -1 \end{bmatrix}, \quad \tilde{b} = \begin{bmatrix} -b_1 \\ \vdots \\ -b_m \end{bmatrix}$$

ℓ_1 -Norm approximation

$$\text{minimize} \quad \|Ax - b\|_1$$

- $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$
- for a vector $y \in \mathbb{R}^m$, we have

$$\|y\|_1 = \sum_{i=1}^m |y_i| = \sum_{i=1}^m \max\{y_i, -y_i\}$$

Equivalent LP formulation

$$\begin{array}{ll}\text{minimize} & \sum_{i=1}^m u_i \\ \text{subject to} & -u \leq Ax - b \leq u\end{array}$$

with variables $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$

Robust curve fitting

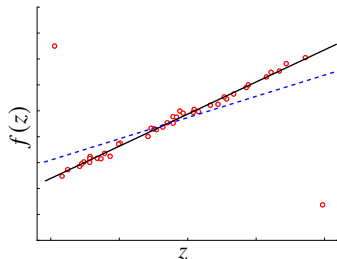
fit data points (z_i, y_i) to the straight line $x_1 + x_2 z \approx y$ using ℓ_1 -norm:

$$\text{minimize } \|Ax - b\|_1$$

where

$$A = \begin{bmatrix} 1 & z_1 \\ \vdots & \vdots \\ 1 & z_m \end{bmatrix}, \quad b = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

- red circles represent the data
- blue dotted line from minimizing $\|Ax - b\|^2$
- black line from minimizing $\|Ax - b\|_1$
- ℓ_1 -norm more robust to outliers



Interview scheduling

- a company needs to schedule job interviews for n candidates $(1, 2, \dots, n)$
- candidate i is scheduled to be the i th interview
- the starting time of candidate i must be in the interval $[\alpha_i, \beta_i]$, where $\alpha_i < \beta_i$
- goal is to find n starting times of interviews so that the minimal starting time difference between consecutive interviews is maximal

- let t_i denote the starting time of interview i
- the objective function is the minimal difference between consecutive starting times:

$$f(t) = \min\{t_2 - t_1, t_3 - t_2, \dots, t_n - t_{n-1}\},$$

Problem formulation

$$\begin{array}{ll} \text{maximize} & \min\{t_2 - t_1, t_3 - t_2, \dots, t_n - t_{n-1}\} \\ \text{subject to} & \alpha_i \leq t_i \leq \beta_i, \quad i = 1, 2, \dots, n, \end{array}$$

with variable $t \in \mathbb{R}^n$

Equivalent LP

$$\begin{array}{ll} \text{maximize} & s \\ \text{subject to} & t_{i+1} - t_i \geq s, \quad i = 1, 2, \dots, n-1 \\ & \alpha_i \leq t_i \leq \beta_i, \quad i = 1, 2, \dots, n, \end{array}$$

with variables $t \in \mathbb{R}^n$ and $s \in \mathbb{R}$

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Quadratic optimization

Quadratic program (quadratic optimization problem)

$$\begin{array}{ll}\text{minimize} & (1/2)x^T Q x + r^T x \\ \text{subject to} & A x \leq b \\ & G x = h\end{array}$$

- $Q \in \mathbb{S}_+^n$, so objective is convex quadratic
- $r \in \mathbb{R}^n$, $A \in \mathbb{R}^{m \times n}$, $G \in \mathbb{R}^{p \times n}$, $h \in \mathbb{R}^p$, and $b \in \mathbb{R}^m$
- minimize a convex quadratic function over a polyhedron

Quadratically constrained quadratic problem (QCQP)

$$\begin{array}{ll}\text{minimize} & (1/2)x^T Q_0 x + r_0^T x + s_0 \\ \text{subject to} & (1/2)x^T Q_i x + r_i^T x + s_i \leq 0, \quad i = 1, \dots, p \\ & A x = b\end{array}$$

- $Q_i \in \mathbb{S}_+^n$ ($i = 0, 1, \dots, m$) are positive semidefinite
- feasible set is intersection of n ellipsoids and an affine set

Examples

Least squares

$$\text{minimize} \quad \|Ax - b\|^2 = x^T A^T A x - 2b^T A x + b^T b$$

Constrained least squares

$$\begin{aligned} &\text{minimize} && \|Ax - b\|^2 \\ &\text{subject to} && Gx = h \\ &&& l_i \leq x_i \leq u_i, \quad i = 1, \dots, n \end{aligned}$$

this problem has no simple analytical solution

Example: power distribution (aggregator model)

- in electricity markets, an aggregator
 - buys wholesale p units of power (Megawatt) from power distribution utilities
 - and resells this power to a group of n business or industrial customers
- the i th customer, $i = 1, \dots, n$, would ideally wants p_i Megawatts
- the customer i does not want to receive more or less power than needed
- the customer dissatisfaction can be modeled as

$$f_i(x_i) = c_i(x_i - p_i)^2, \quad i = 1, \dots, n$$

x_i is power given to customer i ; c_i is a given customer parameter

- the aggregator problem is finding the power allocations $x_i, i = 1, \dots, n$, such that
 - the average customer dissatisfaction is minimized,
 - the whole power p is sold,
 - and that the dissatisfaction level is no greater than a contract level, say d
- the aggregator problem is

$$\begin{aligned}
 &\text{minimize} && \frac{1}{n} \sum_{i=1}^n c_i (x_i - p_i)^2 \\
 &\text{subject to} && \sum_{i=1}^n x_i = p, \\
 &&& c_i (x_i - p_i)^2 \leq d, \quad i = 1, \dots, n \\
 &&& x_i \geq 0, \quad i = 1, \dots, n
 \end{aligned}$$

this is a QCQP

Example: portfolio optimization

we want to invest on n stocks to achieve a good return while minimizing risks of losses

- let $x_i \geq 0$ be the proportion of investment on stock i
- let r_i be the return for stock i ; we assume that the expected returns are known,

$$\mu_j = \mathbb{E}(r_j), \quad j = 1, 2, \dots, n,$$

and that the covariances of all the pairs of variables are also known,

$$\sigma_{ij}^2 = \mathbb{E}[(r_i - \mu_i)(r_j - \mu_j)], \quad i, j = 1, 2, \dots, n$$

(typically, the mean and variance are estimated from historical data)

- a high variance indicates high risk; a low variance indicates low risk
- positive covariance $\sigma_{ij}^2 > 0$ means stocks i and j prices move in the same direction
- a negative $\sigma_{ij}^2 < 0$ means they one change in opposite direction

- the overall return is the random variable

$$R = \sum_{j=1}^n x_j r_j = r^T x$$

whose expectation and variance are given by

$$\mathbb{E}(R) = \mu^T x, \quad \text{Var}(R) = x^T \Sigma x$$

- $\mu = (\mu_1, \mu_2, \dots, \mu_n)$
- Σ is the covariance matrix whose elements are $\Sigma_{ij} = \sigma_{ij}$
- the covariance matrix is always positive semidefinite

Portfolio problem QP formulation:

$$\begin{array}{ll}\text{minimize} & x^T \Sigma x \\ \text{subject to} & \mu^T x \geq \alpha \\ & \mathbf{1}^T x = 1 \\ & x \geq 0\end{array}$$

where α is the minimal return value

Portfolio problem QCQP formulation:

$$\begin{array}{ll}\text{maximize} & \mu^T x \\ \text{subject to} & x^T \Sigma x \leq \beta \\ & \mathbf{1}^T x = 1 \\ & x \geq 0\end{array}$$

where β is the upper bound on the risk

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Monomials and posynomials

Monomial function

$$f(x) = cx_1^{a_1}x_2^{a_2}\dots x_n^{a_n}, \quad \text{dom } f = \mathbb{R}_{++}^n$$

$c > 0$ and each $a_i \in \mathbb{R}$ can be any number

Posynomial function: sum of monomials

$$f(x) = \sum_{k=1}^K c_k x_1^{a_{1k}} x_2^{a_{2k}} \dots x_n^{a_{nk}}, \quad \text{dom } f = \mathbb{R}_{++}^n$$

each $c_k > 0$

Example

- wireless cellular network with n paired transmitters and receivers
- p_1, \dots, p_n are the transmit powers for these pairs
- each transmitter i is intended to communicate with its corresponding receiver i
- each receiver i receives signal: $G_{ii}p_i + \sum_{j \neq i} G_{ij}p_j$, $i = 1, \dots, n$,
 - G_{ij} are the known path gains from transmitter j to receiver i
- signal to interference plus noise ratio (SINR) for each receiver is:

$$\gamma_i(p) = \frac{G_{ii}p_i}{\sigma_i + \sum_{j \neq i} G_{ij}p_j}, \quad i = 1, \dots, n,$$

- σ_i is the receiver's noise power
- while the SINR functions aren't posynomials, their inverses are:

$$\gamma_i^{-1}(p) = \frac{\sigma_i}{G_{ii}}p_i^{-1} + \sum_{j \neq i} \frac{G_{ij}}{G_{ii}}p_jp_i^{-1}, \quad i = 1, \dots, n$$

Geometric program (GP)

$$\begin{array}{ll}\text{minimize} & f(x) \\ \text{subject to} & g_i(x) \leq 1, \quad i = 1, \dots, m \\ & h_i(x) = 1, \quad i = 1, \dots, p\end{array}$$

- f, g_1, \dots, g_m are posynomials
- h_1, \dots, h_p are monomials
- the domain is $\mathcal{D} = \mathbb{R}_{++}^n$ (implicit constraint $x > 0$)

Example

- consider the optimization problem:

$$\begin{array}{ll}\text{maximize} & x/y \\ \text{subject to} & 2 \leq x \leq 3 \\ & x^2 + 3y/z \leq \sqrt{y} \\ & x/y = z^2\end{array}$$

where $x, y, z \in \mathbb{R}_{++}$

- the problem can be recast into the standard GP form:

$$\begin{array}{ll}\text{minimize} & x^{-1}y \\ \text{subject to} & 2x^{-1} \leq 1 \\ & (1/3)x \leq 1 \\ & x^2y^{-1/2} + 3y^{1/2}z^{-1} \leq 1 \\ & xy^{-1}z^{-2} = 1\end{array}$$

Change of variable

- geometric programs are generally not convex optimization problems
- but, they can be recast into convex forms through suitable transformations

Change of variable: $y_i = \log x_i$ ($x_i = e^{y_i}$); take logarithm of cost, constraints

- monomial $f(x) = cx_1^{a_1}x_2^{a_2}\cdots x_n^{a_n}$ can be transformed to

$$f(y) = e^{a^T y + \log c} \iff \log f(y) = a^T y + b, \quad (b = \log c)$$

- posynomials $f(x) = \sum_{k=1}^K c_k x_1^{a_{1k}} x_2^{a_{2k}} \cdots x_n^{a_{nk}}$ can be transformed to

$$f(y) = \sum_{k=1}^K e^{a_k^T y + \log c_k} \iff \log f(y) = \log\left(\sum_{k=1}^K e^{a_k^T y + b_k}\right), \quad (b_k = \log c_k)$$

with $a_k = (a_{1k}, \dots, a_{nk})$

Geometric program in convex form

applying the logarithm to the objective/constraint functions results in

$$\begin{array}{ll}\text{minimize} & \tilde{f}(y) = \log\left(\sum_{k=1}^{K_0} \exp(a_{0k}^T y + b_{0k})\right) \\ \text{subject to} & \tilde{g}_i(y) = \log\left(\sum_{k=1}^{K_i} \exp(a_{ik}^T y + b_{ik})\right) \leq 0, \quad i = 1, \dots, m \\ & \tilde{h}_i(y) = h_i^T y + d_i = 0, \quad i = 1, \dots, p\end{array}$$

- $a_{ik} \in \mathbb{R}^n, i = 1, \dots, m$ contain exponents of posynomial inequality constraints
- $h_i \in \mathbb{R}^n, i = 1, \dots, p$, contain exponents of monomial equality constraints
- convex problem since \tilde{f}, \tilde{g}_i are convex, and \tilde{h}_i are affine
- called *geometric program in convex form*
- the original form is called *geometric program in posynomial form*

Example

- consider a cylindrical liquid storage tank with height, h , and diameter, d
- unlike the main body of the tank, its base is made from a distinct material
- assume the height of base remains unchanged irrespective of tank's height
- $V_{\text{tank}} = \pi(d/2)^2 h$ is the volume of the tank
- V_{supp} is the volume supplied within a designated time frame
- total costs associated with manufacturing/operating the tank over a set duration (e.g., a year) is divided into
 - filling cost
 - construction cost
- goal is to minimize cost subject to some constraints

Filling costs

$$C_{\text{fill}}(d, h) = \alpha_1 \frac{V_{\text{supp}}}{V_{\text{tank}}} = c_1 h^{-1} d^{-2}$$

- α_1 is a positive constant (in dollars), and $c_1 = \frac{4\alpha_1 V_{\text{supp}}}{\pi}$
- tied to supplying a certain volume, V_{supp} , of a liquid within the time-frame
- $V_{\text{supp}}/V_{\text{tank}}$ determines the frequency of tank refilling; hence its cost
- as the volume of the tank diminishes relative to the supply volume, filling costs rise

Construction costs

$$C_{\text{constr}}(d, h) = c_2 d^2 + c_3 dh$$

- $c_2 = \alpha_2 \frac{\pi}{4}$ and $c_3 = \alpha_3 \pi$ (α_2, α_3 are +ve dollar-per-square-meter constants)
- include the expenses of constructing the tank's and its base
- the base's cost is proportional to its area, $\frac{\pi d^2}{4}$
- the tank's cost correlates with its surface area, πdh

Total cost

$$\begin{aligned}C_{\text{total}}(d, h) &= C_{\text{fill}}(d, h) + C_{\text{constr}}(d, h) \\&= c_1 h^{-1} d^{-2} + c_2 d^2 + c_3 dh\end{aligned}$$

this posynomial objective function is subject to constraints such as upper and lower limits on the diameter and height, represented as:

$$0 < d \leq d_{\max}, \quad 0 < h \leq h_{\max}$$

GP formulation

$$\begin{array}{ll}\text{minimize} & c_1 h^{-1} d^{-2} + c_2 d^2 + c_3 dh \\ \text{subject to} & d_{\max}^{-1} d \leq 1 \\ & h_{\max}^{-1} h \leq 1\end{array}$$

with variables $d, h > 0$

Example: Frobenius norm diagonal scaling

we seek diagonal matrix $D = \text{diag}(d)$, $d > 0$, with

$$\text{minimize} \quad \|DMD^{-1}\|_F^2$$

- express as

$$\|DMD^{-1}\|_F^2 = \sum_{i,j=1}^n (DMD^{-1})_{ij}^2 = \sum_{i,j=1}^n M_{ij}^2 d_i^2 / d_j^2$$

- a posynomial in d (with exponents 0, 2, and -2)
- in convex form, with $y_i = \log d_i$,

$$\log \|DMD^{-1}\|_F^2 = \log \left(\sum_{i,j=1}^n \exp(2(y_i - y_j + \log |M_{ij}|)) \right)$$

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Semidefinite program

a *linear matrix inequality* (LMI) constrains a vector of variables $x \in \mathbb{R}^n$ as

$$F(x) = F_0 + \sum_{i=1}^m x_i F_i \preceq 0$$

with symmetric coefficient matrices F_0, \dots, F_n of size $m \times m$

Semidefinite program (SDP)

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & F(x) = F_0 + \sum_{i=1}^n x_i F_i \preceq 0 \end{array}$$

- $x \in \mathbb{R}^n$ is the optimization variable and $c \in \mathbb{R}^n$
- each F_i is a known $m \times m$ symmetric matrices
- if F_0, F_1, \dots, F_m are diagonal matrices the SDP becomes a linear program

General form SDP

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & F^{(i)}(x) = x_1 F_1^{(i)} + \cdots + x_n F_n^{(i)} + F_0^{(i)} \preceq 0, \quad i = 1, \dots, K \\ & Gx \leq h \\ & Ax = b\end{array}$$

can be equivalently represented as an SDP

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & \text{diag}(Gx - h, F^{(1)}(x), \dots, F^{(K)}(x)) \preceq 0 \\ & Ax = b\end{array}$$

Example: maximum eigenvalue minimization

$$\text{minimize } \lambda_{\max}(A(x))$$

- for symmetric argument, $\lambda_{\max}(A) = \sup_{\|x\|=1} x^T A x$ is convex
- this problem can be equivalently reformulated as:

$$\begin{array}{ll}\text{minimize} & t \\ \text{subject to} & A(x) - tI \preceq 0\end{array}$$

with variables are $x \in \mathbb{R}^n$ and $t \in \mathbb{R}$

- this is a specific instance of an SDP in the augmented (vector) variable:

$$\hat{x} = \begin{bmatrix} t \\ x \end{bmatrix}, \quad \hat{c} = (1, 0, \dots, 0), \quad \hat{F}(\hat{x}) = A(x) - tI$$

Example: spectral matrix norm minimization

$$\text{minimize} \quad \|A(x)\|_2$$

- $A(x) = A_0 + x_1 A_1 + \cdots + x_n A_n \in \mathbb{R}^{p \times m}$
- this problem is equivalent to the following SDP:

$$\begin{array}{ll} \text{minimize} & t \\ \text{subject to} & \begin{bmatrix} tI_m & A^T(x) \\ A(x) & tI_p \end{bmatrix} \succeq 0 \end{array}$$

with decision variables $x \in \mathbb{R}^n$ and $t \in \mathbb{R}$ ($t \geq 0$)

- to show this, recall that the spectral norm is

$$\|A(x)\|_2 = \sqrt{\lambda_{\max}(A^T(x)A(x))}$$

- it follows that

$$\|A(x)\|_2 \leq t \iff A^T(x)A(x) \preceq t^2 I, \quad t \geq 0$$

- using the Schur complement rule, this matrix inequality is same as

$$\begin{bmatrix} t^2 I_m & A^T(x) \\ A(x) & I_p \end{bmatrix} \succeq 0 \iff \begin{bmatrix} t I_m & A^T(x) \\ A(x) & t I_p \end{bmatrix} \succeq 0$$

right inequality obtained by congruence transformation with

$$\text{diag}(1/\sqrt{t}I_m, \sqrt{t}I_p)$$

for $t > 0$

Example: Frobenius norm minimization

$$\text{minimize} \quad \|A(x)\|_F^2$$

- equivalent to SDP:

$$\begin{array}{ll} \text{minimize} & \text{tr}(Y) \\ \text{subject to} & \begin{bmatrix} Y & A(x) \\ A^T(x) & I_m \end{bmatrix} \succeq 0 \end{array}$$

with variables $x \in \mathbb{R}^n$ and $Y \in \mathbb{S}^p$

- the equivalence of this formulation can be established by noting

$$\|A(x)\|_F^2 = \text{tr}(A(x)A^T(x))$$

and

$$A(x)A^T(x) \preceq Y \iff \begin{bmatrix} Y & A(x) \\ A^T(x) & I_m \end{bmatrix} \succeq 0$$

Outline

- linear programs
- piecewise-linear minimization
- quadratic optimization
- geometric programming
- semidefinite programs
- **quasiconvex optimization**

Quasiconvex function

$f : \mathbb{R}^n \rightarrow \mathbb{R}$ is *quasiconvex* if its domain and all of its sublevel sets

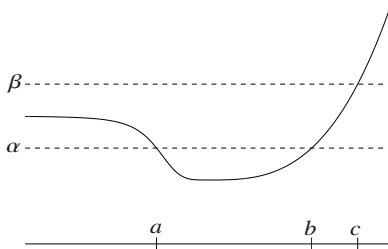
$$\mathcal{S}_\gamma = \{x \in \text{dom } f \mid f(x) \leq \gamma\}$$

are convex for every real number γ

- every convex function naturally possesses convex level sets
- there exist nonconvex functions that have convex level sets
- a function is *quasiconcave* if its negative $(-f)$ is quasiconvex
- a function that's both quasiconvex and quasiconcave is called *quasilinear*
 - both their domain and each level set $\{x \mid f(x) = \gamma\}$ are convex

Graphical illustration

quasiconvex function that is non-convex



- $S_\alpha = [a, b]$ is convex
- $S_\beta = (\infty, c]$ is convex

Examples

- $f(x) = \sqrt{|x|}$ is nonconvex, but it is quasiconvex
 - when $\gamma < 0$, then $\mathcal{S}_\gamma = \emptyset$
 - for $\gamma \geq 0$, the sublevel set is given by:

$$\mathcal{S}_\gamma = \{x \mid \sqrt{|x|} \leq \gamma\} = \{x \mid |x| \leq \gamma^2\} = [-\gamma^2, \gamma^2]$$

- $\log x$ over \mathbb{R}_{++} is both quasiconvex and quasiconcave, making it quasilinear
- $\text{ceil}(x) = \inf\{z \in \mathbb{Z} \mid z \geq x\}$ is quasilinear
- the nonconvex $f(x_1, x_2) = x_1 x_2$ is quasiconcave on \mathbb{R}_+^2 but not on \mathbb{R}^2

- the function

$$f(x) = \frac{a^T x + b}{c^T x + d}, \quad \text{dom } f = \{x \in \mathbb{R}^n \mid c^T x + d > 0\}, c \neq 0$$

is quasiconvex since

$$\mathcal{S}_\gamma = \{x \mid f(x) \leq \gamma\} = \{x \in \mathbb{R}^n \mid (a - \gamma c)^T x + (b - \gamma d) \leq 0\}$$

is a convex set

- given points $a, b \in \mathbb{R}^n$, the function

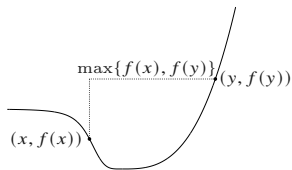
$$f(x) = \frac{\|x - a\|}{\|x - b\|}, \quad \text{dom } f = \{x \mid \|x - a\|_2 \leq \|x - b\|_2\}$$

is quasiconvex since its sublevel set represents the halfspace where the distance to a is less than or equal to the distance to b

Properties of quasiconvex function

- f is quasiconvex iff $\text{dom } f$ is convex and for any $x, y \in \text{dom } f$ with $0 \leq \theta \leq 1$,

$$f(\theta x + (1 - \theta)y) \leq \max\{f(x), f(y)\}$$



- a differentiable f with convex domain is quasiconvex if and only if

$$f(y) \leq f(x) \implies \nabla f(x)^T(y - x) \leq 0$$

- a sum of quasiconvex functions is not necessarily quasiconvex

Examples

- the cardinality $x \in \mathbb{R}^n$, denoted $\text{card}(x)$, is the no. of its nonzero entries
 $\text{card}(x)$ is quasiconcave on \mathbb{R}_+^n (but not on \mathbb{R}^n) since

$$\text{card}(x + y) \geq \min\{\text{card}(x), \text{card}(y)\}$$

valid for non-negative vectors x, y

- the rank is quasiconcave on positive semidefinite matrices since

$$\text{rank}(X + Y) \geq \min\{\text{rank } X, \text{rank } Y\}$$

holds for positive semidefinite matrices X, Y

Quasiconvex optimization

a quasiconvex optimization problem in standard form is represented as

$$\begin{array}{ll} \text{minimize} & f(x) \\ \text{subject to} & g_i(x) \leq 0, \quad i = 1, \dots, m \\ & Ax = b \end{array} \quad (10.1)$$

- the objective f is quasiconvex
- g_i are convex
- can have locally optimal points that are not (globally) optimal

Convex representation of sublevel sets of f

if f is quasiconvex, there exists a family of functions $\phi_t(x)$ such that:

- $\phi_t(x)$ is convex in x for fixed t
- t -sublevel set of f is 0-sublevel set of $\phi_t(x)$:

$$f(x) \leq t \iff \phi_t(x) \leq 0$$

where for every x , we have $\phi_s(x) \leq \phi_t(x)$ for any $s \geq t$

Example

$$f(x) = \frac{p(x)}{q(x)}$$

with p convex, q concave, and $p(x) \geq 0$, $q(x) > 0$ on $\text{dom } f$

can take $\phi_t(x) = p(x) - tq(x)$:

- for $t \geq 0$, ϕ_t convex in x
- $p(x)/q(x) \leq t$ if and only if $\phi_t(x) \leq 0$

Quasiconvex optimization via convex feasibility problems

$$\begin{array}{ll}\text{find} & x \\ \text{subject to} & \phi_t(x) \leq 0 \\ & f_i(x) \leq 0, \quad i = 1, \dots, m \\ & Ax = b\end{array}$$

- if feasible then $p^\star \leq t$; p^\star is optimal solution of original quasiconvex problem
- if infeasible, then $p^\star \geq t$

Bisection for quasiconvex problems

given: $l \leq p^\star, u \geq p^\star$ and a tolerance $\epsilon > 0$

repeat

1. $t := \frac{l+u}{2}$
2. solve the convex feasibility problem
3. if feasible, set $u := t$; else, set $l := t$

until $u - l \leq \epsilon$

References and further readings

- S. Boyd and L. Vandenberghe. *Convex Optimization*. Cambridge University Press, 2004. (chapters 2.2.1, 2.2.4, 4.3)
- G. C. Calafiore and L. El Ghaoui. *Optimization Models*. Cambridge University Press, 2014. (chapter 9).