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Lecture 9 Convex quadratic programming

quadratic function

$$\begin{split} f(x) &= x^T P x + 2 q^T x + r \\ &= \begin{bmatrix} x \\ 1 \end{bmatrix}^T \begin{bmatrix} P & q \\ q^T & r \end{bmatrix} \begin{bmatrix} x \\ 1 \end{bmatrix} \end{split}$$

Quadratic functions and forms

convex if and only if $P \succeq 0$

- quadratic form $f(x) = x^T P x$ convex if and only if $P \succeq 0$
- Euclidean norm f(x) = ||Ax + b||(f^2 is a convex quadratic function ...)

quadratic optimization problems

- (quadratically constrained) quadratic programming

- second-order cone programming
- examples and applications

Convex quadratic programming

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Minimizing a quadratic function

$$\text{minimize } f(x) = x^T P x + 2q^T x + r$$

nonconvex case $(P \not\succeq 0)$: unbounded below

proof: take x=tv, $t\to\infty$, where $Pv=\lambda v$, $\lambda<0$

convex case $(P \succeq 0)$: x is optimal if and only if

$$\nabla f(x) = 2Px + 2q = 0$$

two cases:

- $q \in \mathsf{Range}(P)$: $f^* > -\infty$
- $-q \notin \mathbf{Range}(P)$: unbounded below

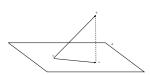
important special case, $P\succ 0$: unique optimal point $x_{\rm opt}=-P^{-1}q;\ f^{\star}=r-q^TP^{-1}q$

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Least-squares problems

minimize Euclidean norm

$$egin{aligned} (A = [a_1 \cdots a_n] & \mathsf{full} \; \mathsf{rank, \; skinny}) \ & \mathsf{minimize} \; \|Ax - b\| \end{aligned}$$

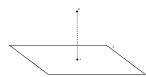


solution: $x_{|s} = (A^T A)^{-1} A^T b$

minimum norm solution

(A full rank, fat)

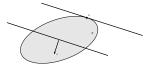
$$\begin{array}{ll} \text{minimize} & \|x\| \\ \text{subject to} & Ax = b \end{array}$$



solution: $x_{mn} = A^T (AA^T)^{-1}b$

Minimizing a linear function with quadratic constraint

minimize $c^T x$ subject to $x^T A x \le 1$ $(A = A^T \succ 0)$



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$$x_{\mathsf{opt}} = -A^{-1}c/\sqrt{c^T A^{-1}c}$$

proof. Change of variables $y = A^{1/2}x$, $\tilde{c} = A^{-1/2}c$

optimal solution: $y_{\mathrm{opt}} = -\tilde{c}/\|\tilde{c}\|$

Quadratic program (QP)

minimize $x^T P x + 2q^T x + r$ subject to $Ax \leq b$, Fx = g

quadratic objective, linear inequalities & equalities

convex optimization problem if $P \succeq 0$

very hard problem if $P \not\succeq 0$

Convex quadratic programming

QCQP and SOCP

quadratically constrained quadratic programming (QCQP):

minimize $x^TP_0x+2q_0^Tx+r_0$ subject to $x^TP_ix+2q_i^Tx+r_i\leq 0,\quad i=1,\ldots,L$

- convex if $P_i \succeq 0$, $i = 0, \ldots, L$
- nonconvex QCQP very difficult

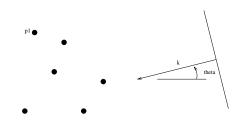
second-order cone programming (SOCP):

minimize
$$c^Tx$$
 subject to $\|A_ix+b_i\| \leq e_i^Tx+d_i, \quad i=1,\ldots,L$

includes QCQP (QP, LP)

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Phased-array antenna beamforming



- omnidirectional antenna elements at positions $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
- unit plane wave incident from angle θ induces in ith element a signal $e^{j(x_i\cos\theta+y_i\sin\theta-\omega t)}$

$$(j = \sqrt{-1}, \text{ frequency } \omega, \text{ wavelength } 2\pi)$$

- demodulate to get output $e^{j(x_i\cos\theta+y_i\sin\theta)}\in\mathbf{C}$
- linearly combine with complex weights w_i :

$$y(\theta) = \sum_{i=1}^{n} w_i e^{j(x_i \cos \theta + y_i \sin \theta)}$$

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- $y(\theta)$ is (complex) antenna array gain pattern
- $|y(\theta)|$ gives sensitivity of array as function of incident angle θ
- depends on design variables $\operatorname{Re} w$, $\operatorname{Im} w$ (called antenna array weights or shading coefficients)

 $\ensuremath{\operatorname{design}}$ problem: choose w to achieve desired gain pattern

Sidelobe level minimization

make $|y(\theta)|$ small for $|\theta - \theta_{\rm tar}| > \alpha$

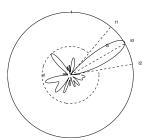
(θ_{tar} : target direction; 2α : beamwidth)

via least-squares (discretize angles)

minimize
$$\Sigma_i |y(\theta_i)|^2$$
 subject to $y(\theta_{\mathsf{tar}}) = 1$

(sum over angles outside beam)

least-squares problem with two (real) linear equality constraints



Convex quadratic programming

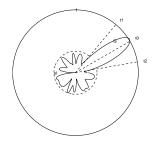
minimize sidelobe level (discretize angles)

 $\begin{array}{ll} \text{minimize} & \max_i |y(\theta_i)| \\ \text{subject to} & y(\theta_{\mathsf{tar}}) = 1 \end{array}$

(max over angles outside beam)

can be cast as SOCP

$$\begin{array}{ll} \text{minimize} & t \\ \text{subject to} & |y(\theta_i)| \leq t \\ & y(\theta_{\text{tar}}) = 1 \end{array}$$



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Extensions

convex (& quasiconvex) extensions:

- $y(\theta_0) = 0$ (null in direction θ_0)
- w is real (amplitude only shading)
- $|w_i| \le 1$ (attenuation only shading)
- minimize $\sigma^2 \sum_{i=1}^n |w_i|^2$ (thermal noise power in y)
- minimize beamwidth given a maximum sidelobe level

nonconvex extension:

- maximize number of zero weights

Optimal receiver location

N transmitter frequencies $1,\ldots,N$ transmitters @ $a_i,\,b_i$ use frequency i ($a_i,\,b_i\in\mathbf{R}^2$) transmitters @ $a_1,\,a_2,\,\ldots,\,a_N$ are wanted transmitters @ $b_1,\,b_2,\,\ldots,\,b_N$ are interfering

o3 o2 x2 P

(signal) receiver power from a_i : $||x - a_i||^{-\alpha}$

(interfering) receiver power from b_i : $\|x-b_i\|^{-\alpha}$ ($\alpha \approx 2.1$)

worst signal to interference ratio as a function of receiver position \boldsymbol{x} :

$$S/I = \min_{i} \frac{\|x - a_i\|^{-\alpha}}{\|x - b_i\|^{-\alpha}}$$

what is the optimal receiver location?