A minimal introduction to conic programming

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Proper cones

A set $K \subseteq \mathbb{R}^n$ that is

• closed under taking rays $x \in K, \lambda \in \mathbb{R}_{>0} \implies \lambda x \in K$



is called a **cone**.

2/13

Proper cones

A set $K \subseteq \mathbb{R}^n$ that is

- closed under taking rays $x \in K, \lambda \in \mathbb{R}_{>0} \implies \lambda x \in K$
- convex

 $x, y \in K, \lambda \in [0, 1]$ $\implies \lambda x + (1 - \lambda)y \in K$



is called a **convex cone**.

Proper cones

A set $K \subseteq \mathbb{R}^n$ that is

closed under taking rays

 $x \in K, \lambda \in \mathbb{R}_{\geq 0} \implies \lambda x \in K$

- convex
 - $\begin{array}{l} x, y \in K, \lambda \in [0, 1] \\ \Longrightarrow \ \lambda x + (1 \lambda)y \in K \end{array}$
- closed $\partial K \subseteq K$
- solid $int(K) \neq \emptyset$
- pointed $x, -x \in K \implies x = 0$

is called a proper cone.



2/13

Conic inequalities

Proper cones can generalize linear inequalities!

$$\begin{aligned} \alpha \leq \beta & \iff \beta - \alpha \in \mathbb{R}_{\geq \mathbf{0}} \\ & \iff \beta \in \mathbb{R}_{\geq \mathbf{0}} + \{\alpha\} \end{aligned}$$



Conic inequalities

Proper cones can generalize linear inequalities!

$$\begin{split} \alpha \leq \beta & \Longleftrightarrow \ \beta - \alpha \in \mathbb{R}_{\geq \mathbf{0}} \\ & \Longleftrightarrow \ \beta \in \mathbb{R}_{\geq \mathbf{0}} + \{\alpha\} \end{split}$$

$$x \preceq_{\mathcal{K}} y \iff y - x \in \mathcal{K}$$
$$\iff y \in \mathcal{K} + \{x\}$$



x ≤_K y is a convex constraint (has a convex feasible region)

Conic inequalities

Proper cones can generalize linear inequalities!

$$\begin{split} \alpha \leq \beta & \Longleftrightarrow \ \beta - \alpha \in \mathbb{R}_{\geq \mathbf{0}} \\ & \Longleftrightarrow \ \beta \in \mathbb{R}_{\geq \mathbf{0}} + \{\alpha\} \end{split}$$

$$\begin{array}{ll} x \preceq_{\mathcal{K}} y & \Longleftrightarrow \ y - x \in \mathcal{K} \\ & \Longleftrightarrow \ y \in \mathcal{K} + \{x\} \end{array}$$

- \preceq_K is a partial order
- x ≤_K y is a convex constraint (has a convex feasible region)



Conic programs

$$\begin{array}{ll} \underset{X}{\operatorname{minimize}} & c^{T}x\\ \text{subject to} & Ax = b,\\ & Gx \preceq_{K} h \end{array}$$
$$Ax = b \iff \begin{bmatrix} +A\\ -A \end{bmatrix} x \preceq_{\mathbb{R}^{2\dim b}} \begin{pmatrix} +b\\ -b \end{pmatrix}$$

(possibly $K = K_1 \times \cdots \times K_\ell$ is a product cone)

"We can write any convex optimization problem [...] as a conic program[.] The power of conic programming, however, lies in the fact that we only need a few classes of convex cones to express a wide variety of optimization problems."

D. de Laat: "A ten page introduction to conic optimization" (2015)

The nonnegative orthant

$$\binom{x_1}{x_2} \in \mathbb{R}^2_{\geq 0}$$

$$\mathbb{R}_{\geq 0}^{n} = \left\{ \begin{pmatrix} x_{1} \\ \vdots \\ x_{n} \end{pmatrix} \middle| \begin{array}{c} x_{i} \geq 0 \ \forall i \leq n \end{array} \right\}$$

The second order cone

$$\begin{pmatrix} au & x_1 & x_2 \end{pmatrix}^T \in \mathcal{Q}^3$$

$$\mathcal{Q}^n = \left\{ \begin{pmatrix} \tau \\ \mathbf{x} \end{pmatrix} \in \mathbb{R}^n \ \middle| \ \|\mathbf{x}\| \le \tau \right\}$$

Least-norm approximation

$$\begin{array}{l} \min \|Ax - b\| \\ \equiv & \min . \tau \quad \text{s. t. } \|Ax - b\| \leq \tau \\ \equiv & \min . \tau \quad \text{s. t. } \begin{pmatrix} \tau \\ Ax - b \end{pmatrix} \in \mathcal{Q}^{n+1} \\ \equiv & \min . \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} \tau \\ x \end{pmatrix} \quad \text{s. t. } \begin{bmatrix} -1 & 0 \\ 0 & -A \end{bmatrix} \begin{pmatrix} \tau \\ x \end{pmatrix} \preceq_{\mathcal{Q}^{n+1}} \begin{pmatrix} 0 \\ b \end{pmatrix}$$

Recall: Second order cone (SOC)

$$\mathcal{Q}^n = \left\{ \begin{pmatrix} \tau \\ \mathsf{x} \end{pmatrix} \in \mathbb{R}^n \ \middle| \ \|\mathsf{x}\| \leq \tau \right\}$$

The rotated second order cone

$$\begin{pmatrix} \alpha & \beta & x_1 \end{pmatrix}^T \in \mathcal{Q}_r^3$$

$$\mathcal{Q}_r^n = \left\{ \begin{pmatrix} \alpha \\ \beta \\ x \end{pmatrix} \in \mathbb{R}^n \ \middle| \begin{array}{l} \|x\|^2 \leq 2\alpha\beta, \\ \alpha, \beta \geq 0 \end{array} \right\}$$



Convex quadratic programming

$$\min_{x} x^{T} Qx + q^{T} x + r \quad \text{where } Q \in \mathbb{S}_{+}^{n}$$

$$\equiv \min_{x} \tau + q^{T} x + r \quad \text{s.t. } x^{T} R^{T} Rx \leq \tau \quad \text{where } Q = R^{T} R$$

$$\equiv \min_{x} \tau + q^{T} x + r \quad \text{s.t. } ||Rx||^{2} \leq \tau$$

$$\equiv \min_{x} \tau + q^{T} x + r \quad \text{s.t. } \begin{pmatrix} \frac{1}{2} \\ \tau \\ Rx \end{pmatrix} \in \mathcal{Q}_{r}^{n+2}$$

Recall: Rotated second order cone

$$\mathcal{Q}_r^n = \left\{ \begin{pmatrix} \alpha \\ \beta \\ x \end{pmatrix} \in \mathbb{R}^n \ \middle| \ \|x\|^2 \le 2\alpha\beta \land \alpha, \beta \ge 0 \right\}$$

Symmetric positive semidefinite matrices

$$S_{+}^{n} = \left\{ A \in \mathbb{S}^{n} \middle| x^{T} A x \ge 0 \ \forall x \in \mathbb{R}^{n} \right\}$$
(non-negative quadratic form)
$$= \left\{ A \in \mathbb{S}^{n} \middle| \lambda_{\min}(A) \ge 0 \right\}$$
(non-negative eigenvalues)
$$= \left\{ A \in \mathbb{S}^{n} \middle| \det(A_{J,J}) \ge 0 \ \forall J \right\}$$
(non-negative principal minors)

$$\begin{bmatrix} \alpha & \gamma \\ \gamma & \beta \end{bmatrix} \in \mathbb{S}^2_+$$

Hermitian positive semidefinite matrices

$$\mathbb{H}^{n}_{+} = \left\{ \mathbf{A} \in \mathbb{H}^{n} \middle| x^{\dagger} \mathbf{A} x \ge 0 \; \forall x \in \mathbb{C}^{n} \right\}$$

(non-negative quadratic form)

$$= \left\{ \mathbf{A} \in \mathbb{H}^n \middle| \lambda_{\min}(\mathbf{A}) \ge \mathbf{0} \right\}$$

(non-negative eigenvalues)

$$= \left\{ \boldsymbol{A} \in \mathbb{H}^n \middle| \det(\boldsymbol{A}_{J,J}) \geq 0 \; \forall J \right\}$$

(non-negative principal minors)

$$\begin{bmatrix} \alpha & \gamma + \delta i \\ \gamma - \delta i & \beta \end{bmatrix} \in \mathbb{H}^2_+$$

(insert 4D sketch above)

Eigenvalue bounds

$$\lambda_{\max}(X) \leq \tau \quad \text{for } X \in \mathbb{S}^{n}$$

$$\iff \sup_{\|v\|=1} v^{T} X v \leq \tau \quad (X = Q^{T} D Q)$$

$$\iff \sup_{v \in \mathbb{R}^{n} \setminus \{0\}} \frac{v^{T} X v}{v^{T} v} \leq \tau$$

$$\iff v^{T} (\tau I_{n} - X) v \geq 0 \quad \forall v \in \mathbb{R}^{n}$$

$$\iff \tau I_{n} - X \in \mathbb{S}^{n}_{+}$$

$$\iff X \leq \tau I_{n} \quad (\text{"linear matrix inequality"})$$

Similarly,
$$\lambda_{\min}(X) \geq \tau \iff X \succeq \tau I_n$$
.

Recall: Positive semidefinite cone

$$\mathbb{S}^{n}_{+} = \left\{ \mathbf{A} \in \mathbb{S}^{n} \mid x^{T} \mathbf{A} x \geq \mathbf{0} \; \forall x \in \mathbb{R}^{n} \right\}$$

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Modeling languages

Conic programs

- extend linear programs
- express many convex objectives and constraints using few cones
- efficient numeric solution (using interior point methods)

Issues

- conic reformulation requires mathematical insights
- conic form can be cumbersome to write down
- resulting programs are hard to understand and update

Solution: optimization modeling languages, e.g.

- ▶ CVX, YALMIP in Matlab
- ► Convex.jl, JuMP in Julia
- CVXPY, PICOS, Pyomo in Python