Chapter 5 Duality

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Lagrangian

$$\begin{array}{lll} \text{minimize} & f_0(x) & \\ \text{subject to} & f_i(x) \leq 0, & i = 1, \cdots, m \\ & h_i(x) = 0, & i = 1, \cdots, p \end{array}$$

variable $x \in \mathbb{R}^n$, domain $\mathcal{D}$, optimal value p^*

Lagrangian $L \colon \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ with $\mathbf{dom}\, L = \mathcal{D} \times \mathbb{R}^m \times \mathbb{R}^p$

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x)$$

- weighted sum of objective and constraint functions
- λ_i and ν_i are Lagrange multipliers

Lagrange dual function

Lagrange dual function $\quad g\colon \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$

$$g(\lambda, \nu) = \inf_{x \in \mathcal{D}} L(x, \lambda, \nu)$$

g is concave, can be $-\infty$ for some values of λ and ν

lower bound property $\quad g(\lambda, \nu) \leq p^*$ for any $\lambda \succeq 0$

proof $\quad$ for any feasible $\bar{x}$ and $\lambda \succeq 0$

$$g(\lambda, \nu) = \inf_{x \in \mathcal{D}} L(x, \lambda, \nu) \leq L(\bar{x}, \lambda, \nu) \leq f_0(\bar{x})$$

minimizing over all feasible $\bar{x}$ gives $\quad g(\lambda, \nu) \leq p^*$

Least-norm solution of linear equations

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

- Lagrangian $\quad L(x, \nu) = x^T x + \nu^T (Ax - b)$
- to minimize L over x, set gradient equal to zero

$$\nabla_x L(x, \nu) = 2x + A^T \nu = 0 \quad \Longrightarrow \quad x = -(1/2) A^T \nu$$

- dual function (concave in ν)

$$g(\nu) = L\left((-1/2) A^T \nu, \nu\right) = -(1/4) \nu^T A A^T \nu - b^T \nu$$

- lower bound property $\quad p^* \geq -(1/4) \nu^T A A^T \nu - b^T \nu \quad$ for all ν

Standard form LP

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax = b \\ & x \succeq 0 \end{array}$$

- Lagrangian ($\lambda \succeq 0$, affine in x)

$$L(x, \lambda, \nu) = c^T x + \nu^T (Ax - b) - \lambda^T x = -b^T \nu + (c + A^T \nu - \lambda)^T x$$

- dual function (linear on affine domain hence concave)

$$g(\lambda, \nu) = \inf_x L(x, \lambda, \nu) = \begin{cases} -b^T \nu & A^T \nu - \lambda + c = 0 \\ -\infty & \text{otherwise} \end{cases}$$

- lower bound property $\quad p^* \geq -b^T \nu \quad$ if $A^T \nu + c \succeq 0$

Equality constrained norm minimization

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

- Lagrangian $\quad L(x,\nu) = \|x\| - \nu^T(Ax - b) = \|x\| - \nu^T Ax + b^T\nu$
- dual function

$$g(\nu) = \inf_x L(x,\nu) = \begin{cases} b^T\nu & \|A^T\nu\|_* \le 1 \\ -\infty & \text{otherwise} \end{cases}$$

  where $\|v\|_* = \sup_{\|u\|\le 1} u^T v$ is the dual norm (proof on next page)
- lower bound property $\quad p^* \ge b^T\nu \quad$ if $\|A^T\nu\|_* \le 1$

proof

observe that

$$\inf_x \left(\|x\| - y^T x\right) = \begin{cases} 0 & \|y\|_* \leq 1 \\ -\infty & \text{otherwise} \end{cases}$$

- if $\|y\|_* \leq 1$, then $y^T x \leq \|x\| \|y\|_* \leq \|x\|$ for all x, with equality if $x = 0$
- if $\|y\|_* > 1$, choose $x = tu$ such that $\|u\| \leq 1$ and $y^T u > 1$, then

$$\lim_{t \to \infty} \left(\|x\| - y^T x\right) = t\left(\|u\| - \|y\|_*\right) = -\infty$$

Two-way partitioning problem

$$
\begin{array}{ll}
\text{minimize} & x^T W x \\
\text{subject to} & x_i^2 = 1, \qquad i = 1, \cdots, n
\end{array}
$$

- nonconvex problem, feasible set contains 2^n discrete points
- $W \in \mathbb{S}^n$, W_{ij} is cost of assigning i and j to the same set
- interpretation: find the most harmonies way to divide $\{1, \cdots, n\}$ in two sets

- Lagrangian

$$L = x^T W x + \sum_{i=1}^{n} \nu_i (x_i^2 - 1)$$

- dual function

$$g(\nu) = \inf_x \left(x^T (W + \mathbf{diag}(\nu)) x - \mathbf{1}^T \nu \right) = \begin{cases} -\mathbf{1}^T \nu & W + \mathbf{diag}(\nu) \succeq 0 \\ -\infty & \text{otherwise} \end{cases}$$

- lower bound property

$$p^* \geq -\mathbf{1}^T \nu \qquad \text{if } W + \mathbf{diag}(\nu) \succeq 0$$

- example

$$\nu = -\lambda_{\min}(W)\mathbf{1} \quad \text{gives bound} \quad p^* \geq n\lambda_{\min}(W)$$

Lagrange dual & conjugate function

$$\begin{array}{ll} \text{minimize} & f_0(x) \\ \text{subject to} & Ax \preceq b \\ & Cx = d \end{array}$$

dual function

$$\begin{aligned} g(\lambda, \nu) &= \inf_{x \in \mathbf{dom}\, f_0} \left(f_0(x) + \left(A^T \lambda + C^T \nu\right)^T x - b^T \lambda - d^T \nu \right) \\ &= -f_0^* \left(-A^T \lambda - C^T \nu\right) - b^T \lambda - d^T \nu \end{aligned}$$

- recall definition of conjugate $\quad f^*(y) = \sup_{x \in \mathbf{dom}\, f} \left(y^T x - f(x)\right)$
- simplifies derivation of dual if conjugate of f_0 is known

Entropy maximization

$$
\begin{array}{ll}
\text{minimize} & f_0(x) = \sum_{i=1}^{n} x_i \log x_i \\
\text{subject to} & Ax \preceq b \\
& \mathbf{1}^T x = 1
\end{array}
$$

- conjugate of $f_0(x)$

$$f_0^*(y) = \sum_{i=1}^{n} e^{y_i - 1}$$

- dual function

$$g(\lambda, \nu) = -\sum_{i=1}^{n} e^{-a_i^T \lambda - \nu - 1} - b^T \lambda - \nu = -e^{-\nu - 1} \sum_{i=1}^{n} e^{-a_i^T \lambda} - b^T \lambda - \nu$$

Lagrange dual problem

$$\begin{array}{ll} \text{maximize} & g(\lambda, \nu) \\ \text{subject to} & \lambda \succeq 0 \end{array}$$

- finds best lower bound on p^*, obtained from Lagrange dual function
- convex optimization problem, optimal value denoted d^*
- λ and ν are dual feasible if $\lambda \succeq 0$ and $(\lambda, \nu) \in \mathbf{dom}\, g$
- often simplified by making implicit constraint $(\lambda, \nu) \in \mathbf{dom}\, g$ explicit
- original problem is called primal problem

Standard form LP

primal problem

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax = b \\ & x \succeq 0 \end{array}$$

dual problem

$$\begin{array}{ll} \text{maximize} & g(\lambda, \nu) = \begin{cases} -b^T \nu & A^T \nu - \lambda + c = 0 \\ -\infty & \text{otherwise} \end{cases} \\ \text{subject to} & \lambda \succeq 0 \end{array}$$

equivalent form

$$\begin{array}{ll} \text{maximize} & -b^T \nu \\ \text{subject to} & A^T \nu + c \succeq 0 \end{array}$$

Inequality form LP

primal problem

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax \preceq b \end{array}$$

dual problem

$$\begin{array}{ll} \text{maximize} & g(\lambda) = \begin{cases} -b^T \lambda & A^T \lambda + c = 0 \\ -\infty & \text{otherwise} \end{cases} \\ \text{subject to} & \lambda \succeq 0 \end{array}$$

equivalent form

$$\begin{array}{ll} \text{maximize} & -b^T \lambda \\ \text{subject to} & A^T \lambda + c = 0 \\ & \lambda \succeq 0 \end{array}$$

Weak duality

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

- always holds (regardless of convexity)
- can be used to find nontrivial lower bounds for difficult problem

example

solving SDP

$$\begin{array}{ll} \text{maximize} & -\mathbf{1}^T \nu \\ \text{subject to} & W + \mathbf{diag}(\nu) \succeq 0 \end{array}$$

gives a lower bound for two-way partitioning problem

Strong duality

$$d^* = p^*$$

- does not hold in general
- usually holds for convex problems

constraint qualifications

- conditions that guarantee strong duality for convex problems
- there exist many types, example below

Slater's constraint qualification

strong duality holds for convex problem

$$
\begin{array}{lll}
\text{minimize} & f_0(x) & \\
\text{subject to} & f_i(x) \leq 0, & i = 1, \cdots, m \\
& Ax = b &
\end{array}
$$

if it is strictly feasible, namely

$$\exists\, x \in \mathbf{int}\, \mathcal{D} \qquad \text{such that} \qquad f_i(x) < 0, \quad i = 1, \cdots, m, \quad Ax = b$$

- also guarantees that the dual optimum is attained if $p^* > -\infty$
- can replace $\mathbf{int}\, \mathcal{D}$ with $\mathbf{relint}\, \mathcal{D}$ (interior relative to affine hull)
- linear inequalities do not need to hold with strict inequality
- strong duality holds for LP unless both primal and dual are infeasible (for LP, dual of dual is primal, Slater's condition and feasibility agree)

Quadratic program

primal problem (assume $P \in \mathbb{S}^n_{++}$)

$$\begin{array}{ll} \text{minimize} & x^T P x \\ \text{subject to} & Ax \preceq b \end{array}$$

dual function

$$g(\lambda) = \inf_x \left(x^T P x + \lambda^T (Ax - b) \right) = -(1/4)\lambda^T A P^{-1} A^T \lambda - b^T \lambda$$

dual problem

$$\begin{array}{ll} \text{maximize} & -(1/4)\lambda^T A P^{-1} A^T \lambda - b^T \lambda \\ \text{subject to} & \lambda \succeq 0 \end{array}$$

- by Slater's condition $p^* = d^*$ holds if primal problem is feasible
- in fact $p^* = d^*$ always holds (dual of dual is primal, dual always satisfies Slater)

A nonconvex problem with strong duality

primal problem (nonconvex if $A \not\succeq 0$)

$$\begin{array}{ll} \text{minimize} & x^T A x + 2b^T x \\ \text{subject to} & x^T x \leq 1 \end{array}$$

dual problem

$$\begin{array}{ll} \text{maximize} & -b^T (A + \lambda I)^\dagger b - \lambda \\ \text{subject to} & A + \lambda I \succeq 0 \\ & b \in \mathcal{R}(A + \lambda I) \end{array}$$

equivalent SDP

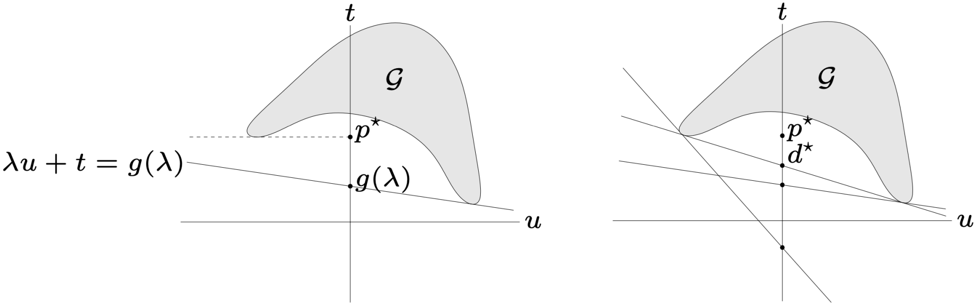
$$\begin{array}{ll} \text{maximize} & -t - \lambda \\ \text{subject to} & \begin{bmatrix} A + \lambda I & b \\ b^T & t \end{bmatrix} \succeq 0 \end{array}$$

strong duality holds although primal problem is nonconvex (not easy to show)

Geometric interpretation

interpretation of dual function consider problem with one constraint $f_1(x) \le 0$

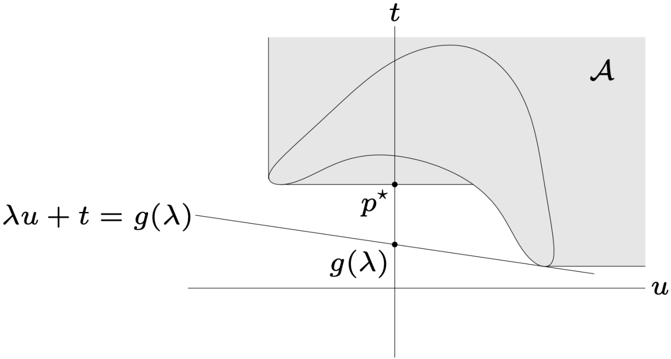
$$g(\lambda) = \inf_{(u,t)\in\mathcal{G}} (t + \lambda u) \quad \text{where} \quad \mathcal{G} = \{(u,t) \mid u = f_1(x), t = f_0(x) \text{ for some } x \in \mathcal{D}\}$$



$\lambda u + t = g(\lambda)$ is (non-vertical) supporting hyperplane to $\mathcal{G}$ meeting t-axis at $t = g(\lambda)$

epigraph variation same interpretation if $\mathcal{G}$ is replaced by

$$\mathcal{A} = \{(u,t) \mid u \geq f_1(x), t \geq f_0(x) \text{ for some } x \in \mathcal{D}\}$$



proof of strong duality (under Slater's condition)

- holds if there is a non-vertical supporting hyperplane H to $\mathcal{A}$ at $(0, p^*)$
- for convex problems, $\mathcal{A}$ is convex, hence H exists
- Slater's condition guarantees the existence of $(\tilde{u}, \tilde{t}) \in \mathcal{A}$ with $\tilde{u} < 0$
- it follows that H cannot be vertical

Complementary slackness

assume x^* is primal optimal, (λ^*, ν^*) is dual optimal

$$
\begin{aligned}
g(\lambda^*, \nu^*) &= \inf_x \left(f_0(x) + \sum_{i=1}^m \lambda_i^* f_i(x) + \sum_{i=1}^p \nu_i^* h_i(x) \right) \\
&\le f_0(x^*) + \sum_{i=1}^m \lambda_i^* f_i(x^*) + \sum_{i=1}^p \nu_i^* h_i(x^*) \le f_0(x^*)
\end{aligned}
$$

assume strong duality holds, then both inequalities hold with equality

- x^* minimizes $L(x, \lambda^*, \nu^*)$
- $\lambda_i^* f_i(x^*) = 0$ for each $i = 1, \cdots, m$, namely, for each pair of inequalities

$$
\lambda_i^* \ge 0 \qquad \text{and} \qquad f_i(x^*) \le 0
$$

at least one of them achieves equality (complementary slackness)

KKT conditions

assume $f_0, f_1, \cdots, f_m$ and $h_1, \cdots, h_p$ are all differentiable (hence with open domains)

Karush-Kuhn-Tucker conditions

1. primal constraints $\quad f_i(x) \le 0,\ i = 1, \cdots, m; \qquad h_i(x) = 0,\ i = 1, \cdots, p$
2. dual constraints $\quad \lambda \succeq 0$
3. complementary slackness $\quad \lambda_i f_i(x) = 0,\ i = 1, \cdots, m$
4. gradient of Lagrangian with respect to x vanishes

$$\nabla f_0(x) + \sum_{i=1}^{m} \lambda_i \nabla f_i(x) + \sum_{i=1}^{p} \nu_i \nabla h_i(x) = 0$$

necessity if strong duality holds

$$(\tilde{x}, \tilde{\lambda}, \tilde{\nu}) \text{ are optimal} \quad \Longrightarrow \quad (\tilde{x}, \tilde{\lambda}, \tilde{\nu}) \text{ satisfy KKT}$$

sufficiency if primal problem is convex

$$(\tilde{x}, \tilde{\lambda}, \tilde{\nu}) \text{ satisfy KKT} \quad \Longrightarrow \quad (\tilde{x}, \tilde{\lambda}, \tilde{\nu}) \text{ are optimal}$$

proof

- conditions 1 & 2 imply primal and dual feasibility
- condition 3 implies $f_0(\tilde{x}) = L(\tilde{x}, \tilde{\lambda}, \tilde{\nu})$
- condition 4 and convexity imply $g(\tilde{\lambda}, \tilde{\nu}) = L(\tilde{x}, \tilde{\lambda}, \tilde{\nu})$

necessity + sufficiency if Slater's condition holds for convex problem

$$\tilde{x} \text{ is optimal} \quad \Longleftrightarrow \quad (\tilde{x}, \tilde{\lambda}, \tilde{\nu}) \text{ satisfy KKT for some } \tilde{\lambda} \text{ and } \tilde{\nu}$$

Example

assume $\alpha_i > 0$ for $i = 1, \cdots, n$

$$\begin{array}{ll} \text{minimize} & -\sum_{i=1}^{n} \log(x_i + \alpha_i) \\ \text{subject to} & x \succeq 0 \\ & \mathbf{1}^T x = 1 \end{array}$$

x is optimal $\iff$ $x \succeq 0$, $\mathbf{1}^T x = 1$, there exists $\lambda \in \mathbb{R}^n$ and $\nu \in \mathbb{R}$ such that

$$\lambda \succeq 0, \qquad \lambda_i x_i = 0, \qquad \frac{1}{x_i + \alpha_i} + \lambda_i = \nu, \qquad i = 1, \cdots, n$$

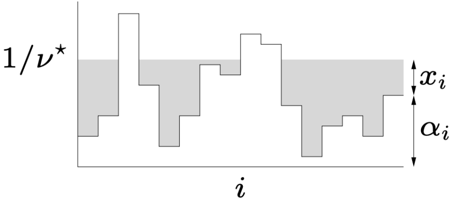
- if $\nu \leq 1/\alpha_i$, then $\lambda_i = 0$ and $x_i = 1/\nu - \alpha_i$
- if $\nu \geq 1/\alpha_i$, then $\lambda_i = \nu - 1/\alpha_i$ and $x_i = 0$

determine ν from

$$\mathbf{1}^T x = \sum_{i=1}^{n} \max\{0, 1/\nu - \alpha_i\} = 1$$

water-filling algorithm

- left-hand side is a piecewise linear increasing function in $1/\nu$
- n patches, level of patch i is at height α_i
- flood area with unit amount of water, resulting level is $1/\nu^*$



Perturbed problem

perturbed primal problem

$$
\begin{array}{lll}
\text{minimize} & f_0(x) & \\
\text{subject to} & f_i(x) \leq u_i, & i = 1, \cdots, m \\
& h_i(x) = v_i, & i = 1, \cdots, p
\end{array}
$$

perturbed dual problem

$$
\begin{array}{ll}
\text{maximize} & g(\lambda, \nu) - u^T \lambda - v^T \nu \\
\text{subject to} & \lambda \succeq 0
\end{array}
$$

- u and v are parameters
- original primal & dual problems are recovered when $u = 0$ and $v = 0$
- $p^*(u, v)$ is optimal value as a function of u and v
- need to understand $p^*(u, v)$ from solution to unperturbed problem

Global sensitivity

assume for the unperturbed problem that

- strong duality holds (e.g. convex + Slater)
- λ^* and ν^* are dual optimal

then weak duality for the perturbed problem implies

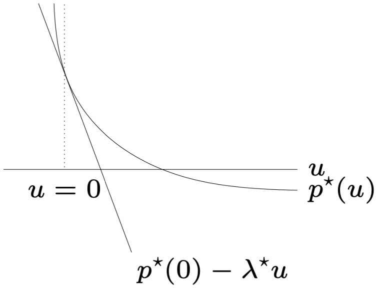
$$\begin{aligned} p^*(u,v) &\geq g(\lambda^*,\nu^*) - u^T\lambda^* - v^T\nu^* \\ &= p^*(0,0) - u^T\lambda^* - v^T\nu^* \end{aligned}$$

- λ_i^* large $\implies$ p^* increases greatly if $u_i < 0$ (tighten constraint)
- λ_i^* small $\implies$ p^* does not decrease much if $u_i > 0$ (loosen constraint)
- $\nu_i^* > 0$ large $\implies$ p^* increases greatly if $v_i < 0$
- $\nu_i^* < 0$ large $\implies$ p^* increases greatly if $v_i > 0$
- $\nu_i^* > 0$ small $\implies$ p^* does not decrease much if $v_i > 0$
- $\nu_i^* < 0$ small $\implies$ p^* does not decrease much if $v_i < 0$

Local sensitivity

assume in addition that $p^*(u, v)$ is differentiable at $(0, 0)$ then

$$\lambda_i^* = -\frac{\partial p^*}{\partial u_i}(0,0), \qquad \nu_i^* = -\frac{\partial p^*}{\partial v_i}(0,0)$$



(above picture exhibits $p^*(u)$ for a problem with one inequality constraint)

Duality and problem reformulations

principle

- equivalent formulations of a problem can lead to very different duals
- reformulation can be useful when dual is difficult to derive or uninteresting

common reformulations

- introduce new variables and equality constraints
- make explicit constraints implicit or vice-versa
- apply an increasing function to objective or constraint functions

Introducing new variables and equality constraints

unconstrained problem

primal problem

$$\text{minimize} \quad f_0(Ax+b)$$

dual problem

$$g = \inf_x f_0(Ax+b) = p^*$$

- no dual variable, hence dual function is constant
- strong duality holds, but dual is useless

reformulated primal problem

$$\begin{array}{ll} \text{minimize} & f_0(y) \\ \text{subject to} & Ax + b - y = 0 \end{array}$$

dual of reformulated problem

$$\begin{array}{ll} \text{maximize} & b^T\nu - f_0^*(\nu) \\ \text{subject to} & A^T\nu = 0 \end{array}$$

it follows from

$$g(\nu) = \inf_{x,y} \left(f_0(y) - \nu^T y + \nu^T Ax + b^T\nu \right) = \begin{cases} -f_0^*(\nu) + b^T\nu & A^T\nu = 0 \\ -\infty & \text{otherwise} \end{cases}$$

norm approximation problem

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

reformulated problem

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

dual of the reformulated problem

$$\begin{array}{ll} \text{maximize} & b^T \nu \\ \text{subject to} & A^T \nu = 0 \\ & \|\nu\|_* \leq 1 \end{array}$$

Implicit constraints

LP with box constraints

primal problem

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax = b \\ & -\mathbf{1} \preceq x \preceq \mathbf{1} \end{array}$$

dual problem

$$\begin{array}{ll} \text{maximize} & -b^T\nu - \mathbf{1}^T\lambda_1 - \mathbf{1}^T\lambda_2 \\ \text{subject to} & c + A^T\nu + \lambda_1 - \lambda_2 = 0 \\ & \lambda_1 \succeq 0, \qquad \lambda_2 \succeq 0 \end{array}$$

reformulated primal problem

$$\begin{array}{ll} \text{minimize} & f_0(x) = \begin{cases} c^T x & -1 \preceq x \preceq 1 \\ \infty & \text{otherwise} \end{cases} \\ \text{subject to} & Ax = b \end{array}$$

dual function

$$\begin{aligned} g(\nu) &= \inf_{-1 \preceq x \preceq 1} \left(c^T x + \nu^T (Ax - b)\right) \\ &= -b^T \nu - \|A^T \nu + c\|_1 \end{aligned}$$

dual of the reformulated problem

$$\text{maximize} \qquad -b^T \nu - \|A^T \nu + c\|_1$$

Problems with generalized inequalities

primal problem (proper cone $K_i \subseteq \mathbb{R}^{k_i}$ for $i = 1, \cdots, m$)

$$\begin{array}{lll} \text{minimize} & f_0(x) & \\ \text{subject to} & f_i(x) \preceq_{K_i} 0, & i = 1, \cdots, m \\ & h_i(x) = 0, & i = 1, \cdots, p \end{array}$$

- Lagrange multiplier for $f_i(x) \preceq_{K_i} 0$ is vector $\lambda_i \in \mathbb{R}^{k_i}$, for $h_i(x) = 0$ scalar $\nu_i \in \mathbb{R}$
- Lagrangian $\quad L\colon \mathbb{R}^n \times \mathbb{R}^{k_1} \times \cdots \times \mathbb{R}^{k_m} \times \mathbb{R}^p \longrightarrow \mathbb{R}$

$$L(x, \lambda_1, \cdots, \lambda_m, \nu) = f_0(x) + \sum_{i=1}^{m} \lambda_i^T f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x)$$

- dual function $\quad g\colon \mathbb{R}^{k_1} \times \cdots \times \mathbb{R}^{k_m} \times \mathbb{R}^p \longrightarrow \mathbb{R}$

$$g(\lambda_1, \cdots, \lambda_m, \nu) = \inf_{x \in \mathcal{D}} L(x, \lambda_1, \cdots, \lambda_m, \nu)$$

lower bound property if $\lambda_i \succeq_{K_i^*} 0$, then $g(\lambda_1, \cdots, \lambda_m, \nu) \leq p^*$

proof

$$\begin{aligned} f_0(\tilde{x}) &\geq f_0(\tilde{x}) + \sum_{i=1}^{m} \lambda_i^T f_i(\tilde{x}) + \sum_{i=1}^{p} \nu_i h_i(\tilde{x}) \\ &\geq \inf_{x \in \mathcal{D}} L(x, \lambda_1, \cdots, \lambda_m, \nu) \\ &= g(\lambda_1, \cdots, \lambda_m, \nu) \end{aligned}$$

holds for all feasible $\tilde{x}$, then minimize over all such $\tilde{x}$ to conclude

dual problem

$$\begin{array}{ll} \text{maximize} & g(\lambda_1, \cdots, \lambda_m, \nu) \\ \text{subject to} & \lambda_i \succeq_{K_i^*} 0, \qquad i = 1, \cdots, m \end{array}$$

weak duality (always holds)

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

strong duality (holds for convex problem with constraint qualification)

$$p^* = d^*$$

Slater's condition: primal problem is strictly feasible

Semidefinite program

primal SDP (assume $F_i, G \in \mathbb{S}^k$)

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & x_1 F_1 + \cdots + x_n F_n \preceq G \end{array}$$

Lagrange multiplier

$$Z \in \mathbb{S}^k$$

Lagrangian

$$L(x, Z) = c^T x + \mathbf{tr}\left(Z(x_1 F_1 + \cdots + x_n F_n - G)\right)$$

dual function

$$g(Z) = \inf_x L(x, Z) = \begin{cases} -\,\mathbf{tr}(GZ) & \mathbf{tr}(F_i Z) + c_i = 0 \text{ for all } i = 1, \cdots, n \\ -\infty & \text{otherwise} \end{cases}$$

dual SDP

$$\begin{array}{ll} \text{maximize} & -\,\mathbf{tr}(GZ) \\ \text{subject to} & Z \succeq 0 \\ & \mathbf{tr}(F_i Z) + c_i = 0, \qquad i = 1, \cdots, n \end{array}$$

strong duality

$p^* = d^*$ holds if primal SDP is strictly feasible ($\exists\ x$ such that $x_1 F_1 + \cdots + x_n F_n \prec G$)