

MATHEMATICS OF DATA SCIENCE

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Today: Duality

November 11: Connection on constraint qualification
 $\Rightarrow$ Only Slater's condition implies
• strong duality!

DUALITY

For every optimization problem, there exists a related problem called the dual that can help you solving the original problem.

① Lagrangian, primal and dual problems

$$(P) \quad \underset{x \in \mathbb{R}^n}{\text{minimize}} \quad f(x) \quad \text{s.t.} \quad \begin{aligned} g_i(x) &\leq 0 & i=1 \dots m \\ h_i(x) &= 0 & i=1 \dots l \end{aligned}$$

$$\begin{aligned} f: \mathbb{R}^n &\rightarrow \mathbb{R} \cup \{+\infty\} \\ g: \mathbb{R}^n &\rightarrow (\mathbb{R} \cup \{+\infty\})^m & h = [h_i]: \mathbb{R}^n &\rightarrow (\mathbb{R} \cup \{+\infty\})^l \end{aligned}$$

Suppose that the problem domain is not empty:

$$X = \text{dom}(f) \cap \bigcap_{i=1}^m \text{dom}(g_i) \cap \bigcap_{i=1}^l \text{dom}(h_i) \neq \emptyset$$

$$F = \left\{ x \in \bigcap_{i=1}^m \text{dom}(g_i) \cap \bigcap_{i=1}^l \text{dom}(h_i) \mid g(x) \leq 0, h(x) = 0 \right\} : \text{feasible set}$$

$$p^* = \inf_{x \in \mathbb{R}^n} \{ f(x) \mid g(x) \leq 0, h(x) = 0 \} \in \bar{\mathbb{R}} = \mathbb{R} \cup \{-\infty, +\infty\}$$

Definition: The Lagrangian function of (P) is

$$\mathcal{L}: \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^l \longrightarrow \bar{\mathbb{R}}$$

$$(x, \lambda, \mu) \longmapsto f(x) + \lambda^T g(x) + \mu^T h(x)$$

$$\rightarrow \text{If } x \in F, \quad \mathcal{L}(x, \lambda, \mu) \leq f(x)$$

($\mathcal{L}$ = lower bound of f for feasible x) $\forall \lambda \geq 0_{\mathbb{R}^m}, \forall \mu \in \mathbb{R}^l$

$\rightarrow$ If $F \neq \emptyset$, (P) is equivalent to

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} \quad p(x)$$

$\downarrow$
Primal problem

(+) Unconstrained

(-) Objective has a complicated form: optimal value to another optimization problem

primal function
 $\downarrow$

$$p(x) = \begin{cases} \sup_{\lambda, \mu} \mathcal{L}(x, \lambda, \mu) & \text{s.t. } \lambda \geq 0 \\ & \text{if } x \in X \\ +\infty & \text{if } x \notin X \end{cases}$$

Dual problem: Flip the roles of x and (λ, μ)

The dual problem associated with (P) is

$$(D) \quad \underset{(\lambda, \mu) \in \mathbb{R}^m \times \mathbb{R}^l}{\text{maximize}} \quad d(\lambda, \mu) \quad \text{s.t.} \quad \lambda \geq 0$$

$\rightarrow$ Dual problem

$$\text{with } \underbrace{d(\lambda, \mu)}_{\text{dual function}} = \begin{cases} \inf_{x \in \mathbb{R}^n} \mathcal{L}(x, \lambda, \mu) & \text{s.t. } x \in X \\ -\infty & \text{if } \lambda \geq 0 \\ & \text{otherwise} \end{cases}$$

Theorem (D) is a convex optimization problem.
(even when (P) is not!)

Proof sketch

• Feasible set for D : $\{(\lambda, \mu) \in \mathbb{R}^m \times \mathbb{R}^l \mid \lambda \geq 0\}$ convex set

• (D) $\Leftrightarrow$ minimize $-d(\lambda, \mu)$ s.t. $\lambda \geq 0$
 (λ, μ)

• $\forall (\lambda, \mu)$ feasible ($\lambda \geq 0$),

$$\begin{aligned} -d(\lambda, \mu) &= -\inf_{x \in X} \mathcal{L}(x, \lambda, \mu) \\ &= \sup_{x \in X} [-\mathcal{L}(x, \lambda, \mu)] \\ &= \sup_{x \in X} [-f(x) - \lambda^T g(x) - \mu^T h(x)] \end{aligned}$$

• $\forall x \in X$, $(\lambda, \mu) \mapsto -f(x) - \lambda^T g(x) - \mu^T h(x)$ is convex
because linear in λ and μ

• The supremum of convex functions is convex (in an extended-value sense), so

$$(\lambda, \mu) \mapsto \sup_{x \in X} [-f(x) - \lambda^T g(x) - \mu^T h(x)]$$

is convex on $\{(\lambda, \mu) \mid \lambda \geq 0\}$

(2) Duality results

Q) what is the link between (P) and (D)?

Theorem (Weak duality)

$$\bullet \forall (x, \lambda, \mu) \in \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p, \quad d(\lambda, \mu) \leq p(x)$$

$$\bullet \forall x \in X, \quad \forall (\lambda, \mu) \in \{(\lambda, \mu) \mid \lambda \geq 0\},$$

$$d(\lambda, \mu) \leq f(x)$$

$$\bullet \sup_{(\lambda, \mu)} \{d(\lambda, \mu) \mid \lambda \geq 0\} \leq \inf_{x \in \mathbb{R}^n} \{f(x) \mid g(x) \leq 0, h(x) = 0\}$$

d^*
↓
Optimal value
for the dual
problem

p^*
↓
Optimal value for
the primal / the original
problem

→ Weak duality: $d^* \leq p^*$: the optimal value of the dual approximates p^*

→ In general, $d^* < p^*$: we say there is a duality gap between (P) and (D)

→ $d^* < p^* \Rightarrow$ the two problems are not equivalent, and in particular you cannot solve (P) by solving (D)

Strong duality: Strong duality holds for (P) and (D) when $p^* = d^*$

→ Under strong duality, we can write

$$d^* = \sup_{(\lambda, \mu)} \inf_x \mathcal{L}(x, \lambda, \mu) = \inf_x \sup_{(\lambda, \mu)} \mathcal{L}(x, \lambda, \mu) = p^*$$

"Min-max Theorem"

→ Under strong duality, if x^* solution of (P) and (λ^*, μ^*) solution of (D), we have

$$\forall (x, \lambda, \mu), \quad \mathcal{L}(x^*, \lambda, \mu) \leq \mathcal{L}(x^*, \lambda^*, \mu^*) \leq \mathcal{L}(x, \lambda^*, \mu^*)$$

$\begin{matrix} \uparrow \\ p^* \\ \uparrow \\ d^* \end{matrix}$

(x^*, λ^*, μ^*) is a saddle point of the Lagrangian
(minimum w.r.t. x , maximum w.r.t. (λ, μ))

Key question: when does strong duality hold?

- An example for which strong duality does not hold

(P) minimize $f(x)$ s.t. $x_1 \leq 0$
 $x \in \mathbb{R}^2$

$$f(x) = \begin{cases} e^{-\sqrt{x_1 x_2}} & \text{if } x \geq 0 \\ +\infty & \text{otherwise} \end{cases}$$

$$X = \{x \geq 0\}$$

$$\forall (x, \lambda), \quad \mathcal{L}(x, \lambda) = f(x) + \lambda x_1$$

Optimal value of (P)

$$\begin{aligned} \inf_{x \in X} \sup_{\lambda \geq 0} \mathcal{L}(x, \lambda) &= \inf_{x \in X} \sup_{\lambda \geq 0} [f(x) + \lambda x_1] \\ &= \inf_{x \in X} \left[f(x) + \sup_{\lambda \geq 0} \lambda x_1 \right] \end{aligned}$$

$\rightarrow x_1 \geq 0$
 $\forall x \in X$

$\uparrow$ independent of λ

$$\forall x_1 \geq 0$$

$$\sup_{\lambda \geq 0} \lambda x_1 = \begin{cases} +\infty \\ 0 \end{cases}$$

$$\begin{cases} \text{if } x_1 > 0 \\ \text{if } x_1 = 0 \end{cases}$$

it suffices to take the infimum over $x \in X$ such that $x_1 = 0$

$$\text{Thus } \inf_{x \in X} \sup_{\lambda \geq 0} \mathcal{L}(x, \lambda) = \inf_{x \in X} f(x)$$

$$x_1 = 0$$

$$= \inf_{\substack{x \in X \\ x_1 = 0}} (1)$$

$$e^{-\sqrt{0 \times x_2}} = 1$$

$$= 1$$

Primal value
optimal value of (P) : 1

Dual value

$$\sup_{\lambda \geq 0} \inf_{x \in X} \mathcal{L}(x, \lambda) = \sup_{\lambda \geq 0} \left[\inf_{x \in X} [f(x) + \lambda x_1] \right]$$

$$= \sup_{\lambda \geq 0} \left[\inf_{x \in X} (e^{-\sqrt{x_1 x_2}} + \lambda x_1) \right] = 0$$

$$\begin{matrix} \uparrow \\ x_1 \geq 0 \\ x_2 \geq 0 \end{matrix}$$

$$\geq 0$$

subset of X

$$0 \leq \inf_{x \in X} (e^{-\sqrt{x_1 x_2}} + \lambda x_1) \leq \inf_{x \in X} \left\{ e^{-\sqrt{x_1 x_2}} + \lambda x_1 \mid \begin{matrix} x_2 = \frac{1}{x_1^2} \\ x_1 > 0 \end{matrix} \right\}$$

$$\begin{aligned} \forall x_1 \in X_2, \\ \inf_{x \in X_2} f(x) &\leq \inf_{x \in X_1} f(x) \end{aligned}$$

$$= \inf_{x \in X} \left\{ \underbrace{e^{-\frac{1}{\sqrt{x_1}}}}_{\rightarrow 0 \text{ as } x_1 \rightarrow 0} + \lambda x_1 \mid x_2 = \frac{1}{x_1^2}, x_1 > 0 \right\}$$

$$= 0$$

Dual value $0 < 1$ (Primal value)

- Dual variables provide useful information under constraint qualifications

⚠ Some formulations may satisfy constraint qualifications while others do not

Two examples of CQ:

- If $f: \mathbb{R}^n \rightarrow \mathbb{R}$ (real-valued function) and all constraints are linear, we say that linear CQ holds

Ex) The example without strong duality can be reformulated as

$$\text{minimize}_{x \in \mathbb{R}^2} e^{-\sqrt{x_1 x_2}} \quad \text{s.t.} \quad \begin{aligned} x_1 &\leq 0 \\ x_2 &\geq 0 \end{aligned}$$

Both satisfy linear CQ but not strong duality

$$(\Rightarrow) \text{minimize}_{x \in \mathbb{R}^2} 1 \quad \text{s.t.} \quad \begin{aligned} x_1 &= 0 \\ x_2 &\geq 0 \end{aligned}$$

→ linear CQ will hold for linear programs, quadratic programs.

- A more involved CQ: Slater's CQ (implies strong duality for convex problems!)

$$\text{minimize}_{x \in \mathbb{R}^n} f(x) \quad \text{s.t.} \quad \begin{aligned} g_i(x) &\leq 0 \\ a_i^T x - b_i &= 0 \end{aligned} \quad \begin{aligned} f, g_i \\ &\text{convex} \\ &X \text{ domain} \end{aligned}$$

$u(x)$
 $\{x\} \exists \varepsilon > 0$

relative interior

$\{B_\varepsilon(x) \cap \text{aff}(X) \subseteq X\}$ If $\exists x \in \text{ri}(X)$ such that

strictly feasible point

$$g_i(x) < 0 \\ a_i^T x - b_i = 0$$

, then Slater CQ holds

open ball

Illustration: Duality for linear programs

$$(P) \underset{x \in \mathbb{R}^n}{\text{minimize}} \quad c^T x \quad \text{s.t.} \quad \begin{aligned} Ax &= b & (Ax-b=0) \\ x &\geq 0 & (-x \leq 0) \end{aligned}$$

$$c \in \mathbb{R}^n, \quad A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m$$

$$\mathcal{L}(x, \lambda, \mu) = f(x) + \mu^T (Ax - b) - \lambda^T x$$

$$\inf_x \mathcal{L}(x, \lambda, \mu) = \begin{cases} -b^T \mu & \text{if } \lambda \geq 0 \text{ and } A^T \mu - \lambda + c = 0 \\ -\infty & \text{otherwise} \end{cases}$$

The dual can be formulated as:

$$(D) \underset{(\lambda, \mu)}{\text{maximize}} \quad -b^T \mu \quad \text{s.t.} \quad \begin{aligned} A^T \mu - \lambda + c &= 0 \\ \lambda &\geq 0 \end{aligned}$$

$$\underset{(\lambda, \mu)}{\text{minimize}} \quad b^T \mu \quad \text{s.t.} \quad \begin{aligned} A^T \mu - \lambda + c &= 0 \\ \lambda &\geq 0 \end{aligned}$$

$\Rightarrow$ Another linear program

Key result for (LP)

Exactly one of the three cases occurs

- (1) (P) and (D) are both infeasible
- (2) (P) is infeasible and (D) is unbounded
or (D) is infeasible and (P) is unbounded

(3) (P) and (D) are both feasible, and there exist (x^*, λ^*, μ^*) such that x^* solution of (P), (λ^*, μ^*) solution of (D) and

$$-b^T \mu^* = c^T x^*$$