

# Duality

## Lecture 12-3 - CMSE 382

Prof. Elizabeth Munch

Michigan State University

::

Dept of Computational Mathematics, Science & Engineering

Weds, April 15, 2026

## Topics:

- Dual for strictly convex quadratic programming - Dual for convex quadratic programming

## Announcements:

- Homework 6 is due on Friday, April 17, 2026 at 11:59pm.

# Section 1

Last Time

# Dual objective function

Consider the general model referred to as the **primal model**

$$f^* = \min f(\mathbf{x})$$

such that  $g_i(\mathbf{x}) \leq 0, i = 1, 2, \dots, m,$

$$h_j(\mathbf{x}) = 0, j = 1, 2, \dots, p,$$

$\mathbf{x} \in X$ , where  $X \subseteq \mathbb{R}^n$ ,

and  $f, g_i, h_j$  are functions defined on  $X$ .

The Lagrangian of the problem is

$$L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = f(\mathbf{x}) + \sum_{i=1}^m \lambda_i g_i(\mathbf{x}) + \sum_{j=1}^p \mu_j h_j(\mathbf{x}),$$

**The dual objective function**

$q : \mathbb{R}_+^m \times \mathbb{R}^p \rightarrow \mathbb{R} \cup \{-\infty\}$  is

$$q(\boldsymbol{\lambda}, \boldsymbol{\mu}) = \min_{\mathbf{x} \in X} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}),$$

# Weak duality theorem

## Primal Problem

$$f^* = \min f(\mathbf{x})$$

such that  $g_i(\mathbf{x}) \leq 0, i = 1, 2, \dots, m,$

$$h_j(\mathbf{x}) = 0, j = 1, 2, \dots, p,$$

$\mathbf{x} \in X$ , where  $X \subseteq \mathbb{R}^n$ ,

and  $f, g_i, h_j$  are functions defined on  $X$ .

## Dual Problem

$$q^* = \max q(\boldsymbol{\lambda}, \boldsymbol{\mu})$$

such that  $(\boldsymbol{\lambda}, \boldsymbol{\mu}) \in \text{dom}(q),$

where  $\text{dom}(q) = \{(\boldsymbol{\lambda}, \boldsymbol{\mu}) \in \mathbb{R}_+^m \times \mathbb{R}^p : q(\boldsymbol{\lambda}, \boldsymbol{\mu}) > -\infty\}$ , and

$$q(\boldsymbol{\lambda}, \boldsymbol{\mu}) = \min_{\mathbf{x} \in X} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}).$$

## Theorem (Weak duality theorem)

Consider the primal problem and its dual. Then  $q^* \leq f^*$ , where  $q^*, f^*$  are the optimal *dual* and *primal* values, respectively.

▶ Desmos example

# Strong duality of convex problems with equality & inequality constraints

## Primal Problem (P)

$$\begin{aligned} f^* &= \min f(\mathbf{x}) \\ \text{such that } & g_i(\mathbf{x}) \leq 0, i = 1, 2, \dots, m, \\ & h_j(\mathbf{x}) \leq 0, j = 1, 2, \dots, p, \\ & s_k(\mathbf{x}) = 0, k = 1, 2, \dots, q, \\ & \mathbf{x} \in X, \end{aligned}$$

- For (P):  $X$  is a convex set and  $f, g_1, \dots, g_m$  are convex functions over  $X$ . The functions  $h_1, \dots, h_p, s_1, \dots, s_q$  are affine.

## Dual Problem (D)

$$\begin{aligned} q^* &= \max q(\boldsymbol{\lambda}, \boldsymbol{\mu}) \\ \text{such that } & (\boldsymbol{\lambda}, \boldsymbol{\mu}) \in \text{dom}(q), \end{aligned}$$

$$\begin{aligned} \text{where } \text{dom}(q) &= \{(\boldsymbol{\lambda}, \boldsymbol{\mu}) \in \mathbb{R}_+^m \times \mathbb{R}^p : \\ & q(\boldsymbol{\lambda}, \boldsymbol{\mu}) > -\infty\}, \text{ and} \\ & q(\boldsymbol{\lambda}, \boldsymbol{\mu}) = \min_{\mathbf{x} \in X} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}). \end{aligned}$$

## Theorem (Strong duality under equality & inequality constraints)

*If the generalized Slater's condition is satisfied in (P) and  $f^*$  has a finite optimal value, then the optimal value of (D) is attained, and the optimal values of the primal and dual problems are the same  $f^* = q^*$ .*

# Dual for linear programming

## Primal

$$f^* = \min \quad \mathbf{c}^\top \mathbf{x}$$

such that  $A\mathbf{x} \leq \mathbf{b}$ ,

## Dual

$$q^* = \max \quad -\mathbf{b}^\top \boldsymbol{\lambda}$$

such that  $A^\top \boldsymbol{\lambda} = -\mathbf{c}$ ,  
 $\boldsymbol{\lambda} \geq 0$ .

### Strong duality holds

If the primal problem is feasible (*meaning the constraint set is not empty*) and has a finite solution, then the **optimal dual value** is equal to the **optimal primal value**:

$$q^* = f^*.$$

## Section 2

# Quadratic Linear Programming

# Strictly Convex Quadratic Programming

## Primal

$$f^* = \min \quad \mathbf{x}^\top Q \mathbf{x} + 2\mathbf{c}^\top \mathbf{x}$$

such that  $A\mathbf{x} \leq \mathbf{b}$ ,

## Dual

$$q^* = \max q(\boldsymbol{\lambda})$$

such that  $\boldsymbol{\lambda} \geq 0$ .

- $Q \in \mathbb{R}^{n \times n}$  is **positive definite**,  $\mathbf{c} \in \mathbb{R}^n$ , and  $\mathbf{b} \in \mathbb{R}^m$ .

- 
- Strong duality holds
  - $L(\mathbf{x}, \boldsymbol{\lambda}) = \mathbf{x}^\top Q \mathbf{x} + 2\mathbf{c}^\top \mathbf{x} + 2\boldsymbol{\lambda}^\top (A\mathbf{x} - \mathbf{b})$
  - $\nabla_{\mathbf{x}} L(\mathbf{x}^*, \boldsymbol{\lambda}) = 2Q\mathbf{x}^* + 2(A^\top \boldsymbol{\lambda} + \mathbf{c}) = \mathbf{0}$
  - $\mathbf{x}^* = -Q^{-1}(\mathbf{c} + A^\top \boldsymbol{\lambda})$

The objective function becomes

$$q(\boldsymbol{\lambda}) = -\boldsymbol{\lambda}^\top A Q^{-1} A^\top \boldsymbol{\lambda} - 2(A Q^{-1} \mathbf{c} + \mathbf{b})^\top \boldsymbol{\lambda} - \mathbf{c}^\top Q^{-1} \mathbf{c}.$$

# Dual for strictly convex quadratic programming

## Convex Quadratic Program

$$\begin{aligned} \min \quad & \mathbf{x}^\top Q \mathbf{x} + 2\mathbf{c}^\top \mathbf{x} \\ \text{such that} \quad & A\mathbf{x} \leq \mathbf{b}, \end{aligned}$$

where  $Q \in \mathbb{R}^{n \times n}$  is **positive semi-definite**,  $\mathbf{c} \in \mathbb{R}^n$ , and  $\mathbf{b} \in \mathbb{R}^m$ .

Since  $Q \succeq 0$

- $Q$  is not necessarily invertible
- The dual problem formulated for the **strictly** convex case is not possible in the convex case.
- A new formulation for the convex case is needed.
- The trick: write  $Q = D^\top D$  for some matrix  $D$ , and make a new variable  $\mathbf{z} = D\mathbf{x}$ .

# Dual for convex quadratic programming

## Reformulated primal problem

$$\begin{aligned} \min \quad & \|z\|^2 + 2\mathbf{c}^\top \mathbf{x} \\ \text{such that} \quad & A\mathbf{x} \leq \mathbf{b}, \\ & z = D\mathbf{x}. \end{aligned}$$

## Dual Problem

$$\begin{aligned} \max \quad & -\|\boldsymbol{\mu}\|^2 - 2\mathbf{b}^\top \boldsymbol{\lambda} \\ \text{such that} \quad & \mathbf{c} + A^\top \boldsymbol{\lambda} - D^\top \boldsymbol{\mu} = 0, \\ & \boldsymbol{\lambda} \in \mathbb{R}_+^m, \boldsymbol{\mu} \in \mathbb{R}^n. \end{aligned}$$

# Groups - Round 5

## **Group 1**

Michal, Kyle, Daniel,  
Purvi

## **Group 2**

Joseph, Jack, Scott,  
Breena

## **Group 3**

Saitej, Dori, Noah,  
Tianjian

## **Group 4**

Dev, Shanze, Lowell,  
Andrew

## **Group 5**

Lora, Aidan, Arjun,  
Monirul Amin

## **Group 6**

Anthony, Abigail,  
Atticus, Yousif

## **Group 7**

Luis, Vinod, Morgan,  
Dominic

## **Group 8**

Jay, Jonid, Alice, Aaron

## **Group 9**

Arya, Jake, K M Tausif,  
Lauryn

## **Group 10**

Maye, Ha, Zheng, Sai

## **Group 11**

Jamie, Karen, Brandon,  
Quang Minh

## **Group 12**

Long, Sanskaar,  
Braedon, Igor