

Convex Optimization

Lecture 8: Lagrange Multiplier

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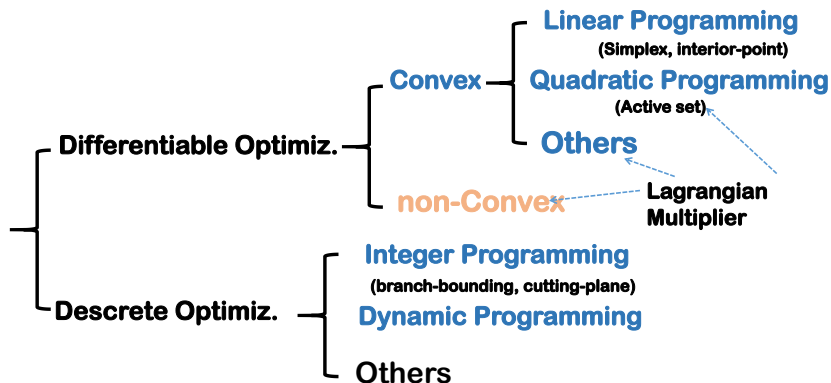
Outline

1 Lagrangian Multiplier

Opening Discussion

- 1 So far we have seen various optimization problems
- 2 We know how to judge whether a problem is convex
- 3 Optimization problems can be divided into different categories
- 4 The problem now is how to solve these problems
- 5 Namely, how to find the extreme values for an objective function under several constraints

The Popularity of Lagrangian Multiplier



Opening Example (1)

$$\begin{aligned} \text{Min.}_{x_1, x_2} \quad & x_1 + x_2 \\ \text{s.t.} \quad & x_1^2 + x_2^2 - 1 \leq 0 \end{aligned} \tag{1}$$

- Given there is no constraint, the problem is easy to address
- So we should consider how to remove the constraint
- While still being in line with the constraint
- We introduce the constraint as a penalty term into the objective

$$\text{Min.}_{x_1, x_2} \quad x_1 + x_2 + P(x_1^2 + x_2^2 - 1) \tag{2}$$

- If x_1, x_2 is out of the constraint, big value will be assigned to P

Opening Example (2)

$$\begin{aligned} & \underset{x_1, x_2}{\text{Min.}} \quad x_1 + x_2 \\ & \text{s.t.} \quad x_1^2 + x_2^2 - 1 \leq 0 \end{aligned} \tag{3}$$

$$\Downarrow$$

$$\underset{x_1, x_2}{\text{Min.}} \quad x_1 + x_2 + P(x_1^2 + x_2^2 - 1) \tag{4}$$

- If x_1, x_2 is out of the constraint, big value will be assigned to P
- Namely, P is given as

$$P(y) = \begin{cases} +\infty & y > 0 \\ 0 & y \leq 0 \end{cases}$$

- However, the objective function is no longer differentiable
- We need a smooth penalty function

Opening Example (3)

$$\text{Min.}_{x_1, x_2} \quad x_1 + x_2 + P(x_1^2 + x_2^2 - 1) \quad (5)$$

- However, the objective function is no longer differentiable
- We need a smooth penalty function

$$P(y) = \lambda \cdot y$$

- The penalty takes higher value if y violates more
- If we take the maximum of λ , we still approximate the previous one

$$P(y) = \begin{cases} +\infty & y > 0 \\ 0 & y \leq 0 \end{cases}$$

Opening Example (4)

$$\text{Min.}_{x_1, x_2} \quad x_1 + x_2 + P(x_1^2 + x_2^2 - 1) \quad (6)$$

$$P(y) = \lambda \cdot y \Downarrow$$

$$\text{Min.}_{x_1, x_2} \quad x_1 + x_2 + \text{Max.}_{\lambda \geq 0} \quad \lambda(x_1^2 + x_2^2 - 1)$$

$$\Downarrow$$

$$\text{Min.}_{x_1, x_2} \text{Max.}_{\lambda \geq 0} \quad x_1 + x_2 + \lambda(x_1^2 + x_2^2 - 1)$$

- Maximize on λ first or later do not impact the overall, so we have

$$\text{Max.}_{\lambda \geq 0} \text{Min.}_{x_1, x_2} \quad x_1 + x_2 + \lambda(x_1^2 + x_2^2 - 1)$$

Opening Example (5)

$$\text{Max.}_{\lambda \geq 0} \text{Min.}_{x_1, x_2} x_1 + x_2 + \lambda(x_1^2 + x_2^2 - 1)$$

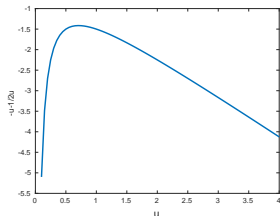
- Now let's solve the minimization first, treating λ as a constant
- We have

$$1 + 2\lambda x_1 = 0 \Rightarrow x_1 = \frac{-1}{2\lambda}$$

$$1 + 2\lambda x_2 = 0 \Rightarrow x_2 = \frac{-1}{2\lambda}$$

$$x_1 = \frac{-1}{2\lambda} \Downarrow x_2 = \frac{-1}{2\lambda}$$

$$\text{Max.}_{\lambda \geq 0} -\lambda - \frac{1}{2\lambda}$$



- $x_1 = x_2 = -\frac{\sqrt{2}}{2}$, $\lambda = \frac{\sqrt{2}}{2}$, the objective value is $-\sqrt{2}$

Lagrange Multiplier (1)

- Given (x_0, y_0) is the extreme point for function $z = f(x, y)$ under the constraint of $\phi(x, y) = 0$
- We can solve y out from $\phi(x, y) = 0$, that is $y = y(x)$
- Then we plug $y = y(x)$ into $f(x, y)$, we have

$$z = f(x, y(x))$$

$x = x_0$ is the extrema

- We take derivative on $f(x, y(x))$ w.r.t x

$$\frac{dz}{dx}\bigg|_{x=x_0} = f_x(x_0, y_0) + f_y(x_0, y_0) \cdot \frac{dy}{dx}\bigg|_{x=x_0} = 0$$

$$\frac{dy}{dx} = -\frac{\phi_x(x_0, y_0)}{\phi_y(x_0, y_0)} \Downarrow$$

$$\frac{dz}{dx}\bigg|_{x=x_0} = f_x(x_0, y_0) + f_y(x_0, y_0) \cdot \left(-\frac{\phi_x(x_0, y_0)}{\phi_y(x_0, y_0)}\right)\bigg|_{x=x_0} = 0$$

Lagrange Multiplier (2)

- We take derivative on $f(x, y(x))$ w.r.t x

$$\frac{dz}{dx}\bigg|_{x=x_0} = f_x(x_0, y_0) + f_y(x_0, y_0) \cdot \frac{dy}{dx}\bigg|_{x=x_0} = 0$$

$$\frac{dy}{dx} = -\frac{\phi_x(x_0, y_0)}{\phi_y(x_0, y_0)} \Downarrow$$

$$\frac{dz}{dx}\bigg|_{x=x_0} = f_x(x_0, y_0) + f_y(x_0, y_0) \cdot \left(-\frac{\phi_x(x_0, y_0)}{\phi_y(x_0, y_0)}\right)\bigg|_{x=x_0} = 0$$

$$\frac{f_y(x_0, y_0)}{\phi_y(x_0, y_0)} = -\mu \Downarrow$$

$$\begin{cases} f_x + \mu\phi_x = 0 \\ f_y + \mu\phi_y = 0 \\ \phi(x, y) = 0 \end{cases}$$

Noted that the derivative for implicit function $\phi(x, y)$ is $\frac{dy}{dx} = -\frac{\phi_x(x, y)}{\phi_y(x, y)}$

Lagrange Multiplier (3)

- Given an optimization problem

$$\begin{aligned} \text{Min. } z &= f(x, y) \\ \text{s.t. } \phi(x, y) &= 0 \end{aligned} \tag{7}$$

\Downarrow

$$\begin{cases} f_x + \mu\phi_x = 0 \\ f_y + \mu\phi_y = 0 \\ \phi(x, y) = 0 \end{cases} \tag{8}$$

Summarize these necessary \Downarrow conditions into one equation

$$L(x, y) = f(x, y) + \mu\phi(x, y) \tag{9}$$

- This is called **Lagrange function**

Lagrange Multiplier (4)

- Given an optimization problem

$$\begin{aligned} \text{Min. } z &= f(x, y) \\ \text{s.t. } \phi(x, y) &= 0 \end{aligned} \tag{10}$$

\Downarrow

$$L(x, y) = f(x, y) + \mu\phi(x, y) \tag{11}$$

- Take partial derivative on x, y and μ

$$\begin{cases} L_x = 0 \Rightarrow f_x + \mu\phi_x = 0 \\ L_y = 0 \Rightarrow f_y + \mu\phi_y = 0 \\ L_\mu = 0 \Rightarrow \phi(x, y) = 0 \end{cases} \tag{12}$$

Lagrange Multiplier (5)

- Given an optimization problem under multiple constraints

$$\begin{aligned}
 \text{Min. } & z = f(x, y) \\
 \text{s.t. } & h(x, y) = 0 \\
 & g(x, y) \leq 0
 \end{aligned} \tag{13}$$

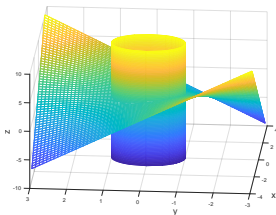
$$\Downarrow$$

$$L(x, y) = f(x, y) + \lambda g(x, y) + \mu h(x, y) \tag{14}$$

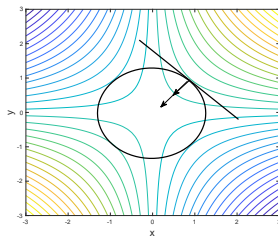
- Take partial derivative on x, y, λ and μ

$$\begin{cases}
 L_x = 0 \Rightarrow f_x + \lambda g_x + \mu h_x = 0 \\
 L_y = 0 \Rightarrow f_y + \lambda g_y + \mu h_y = 0 \\
 L_\lambda = 0 \Rightarrow g(x, y) = 0 \\
 L_\mu = 0 \Rightarrow h(x, y) = 0
 \end{cases} \tag{15}$$

Lagrange Multiplier (6)



(a)

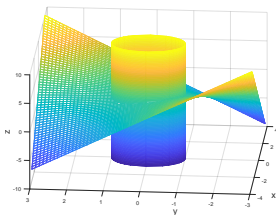


(b)

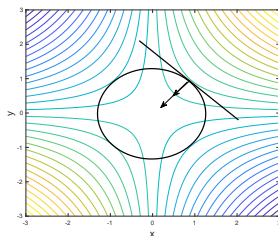
- Given an optimization problem under constraint
- On the potential extremal point, tangents from two functions parallel

$$\begin{aligned} \text{Max. } & z = f(x, y) \\ \text{s.t. } & h(x, y) = 0 \end{aligned}$$

Lagrange Multiplier (7)



(a)



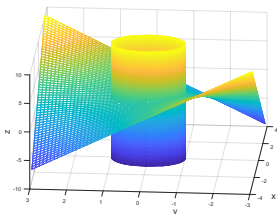
(b)

- Given an optimization problem under constraint
- The optimization searches for $(\frac{\partial f(x,y)}{\partial x}, \frac{\partial f(x,y)}{\partial y}) = \mu(\frac{\partial h(x,y)}{\partial x}, \frac{\partial h(x,y)}{\partial y})$

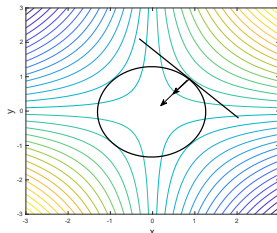
$$\text{Max. } z = f(x, y)$$

$$\text{s.t. } h(x, y) = 0$$

Lagrange Multiplier (8)



(a)



(b)

- The optimization searches for $(\frac{\partial f(x,y)}{\partial x}, \frac{\partial f(x,y)}{\partial y}) = \mu(\frac{\partial h(x,y)}{\partial x}, \frac{\partial h(x,y)}{\partial y})$
- Let us solve a concrete problem

$$\text{Max. } z = xy + 1$$

$$\text{s.t. } x^2 + y^2 - 1 = 0$$

Lagrange Multiplier (9)

- Let us solve a concrete problem

$$\begin{aligned} \text{Max. } z &= xy + 1 \\ \text{s.t. } x^2 + y^2 - 1 &= 0 \end{aligned}$$

$$\Downarrow$$

$$\begin{cases} z = xy + 1 \Rightarrow \left(\frac{\partial f(x,y)}{\partial x}, \frac{\partial f(x,y)}{\partial y} \right) = (y, x) \\ x^2 + y^2 - 1 = 0 \Rightarrow \left(\frac{\partial h(x,y)}{\partial x}, \frac{\partial h(x,y)}{\partial y} \right) = (2x, 2y) \end{cases} \quad (16)$$

$$\Downarrow$$

$$\begin{cases} y = \mu 2x \\ x = \mu 2y \\ x^2 + y^2 - 1 = 0 \end{cases}$$

Lagrange Multiplier (10)

- Let us solve a concrete problem

$$\begin{aligned} \text{Max. } z &= xy + 1 \\ \text{s.t. } x^2 + y^2 - 1 &= 0 \end{aligned}$$

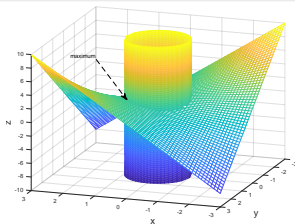
$$\Downarrow$$

$$\begin{cases} y = \mu 2x \\ x = \mu 2y \\ x^2 + y^2 - 1 = 0 \end{cases}$$

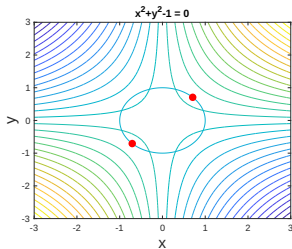
$$y = \mu 2x \Downarrow y = \frac{x}{2\mu}$$

$$\begin{cases} 4\mu^2 x^2 + x^2 - 4\mu^2 = 0 \\ x^2 + 4\mu^2 x^2 - 1 = 0 \end{cases}$$

- We have $x = \pm \frac{1}{\sqrt{2}}$, $\mu = \pm \frac{1}{2}$, $y = \pm \frac{1}{\sqrt{2}}$



(c)



(d)