



# Lagrange multiplier and KKT condition

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# Toy example

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- Maximize  $5x_1x_2$  subject to  $2x_1 + x_2 = 100$
- Can we solve the optimization problem by gradient descent/ascent?
- Probably not, because we have extra constraints



# Toy example

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- Maximize  $5x_1x_2$  subject to  $2x_1 + x_2 = 100$

- Sol 1

$$f(x_1, x_2) = 5x_1x_2 = 5x_1(100 - 2x_1)$$

$$\rightarrow \frac{\partial f(x_1, x_2)}{\partial x_1} = 500 - 20x_1 := 0$$

$$\rightarrow (x_1, x_2) = (25, 50)$$

$$\rightarrow \text{The maximum value of } 5x_1x_2 \text{ is } 6250$$

- If the constraints are not complicated, such a method is manageable



# Lagrange multiplier

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- Lagrange multipliers is a strategy for finding the extreme value of a function **subject to equality constraints**
- Finding the maximum value of  $y = f(\mathbf{x})$  subject to  $g_i(\mathbf{x}) = 0, i = 1, 2, \dots, m$
- Lagrange function (a.k.a. Lagrangian)
  - $y_\lambda = f(\mathbf{x}) + \lambda_1 g_1(\mathbf{x}) + \lambda_2 g_2(\mathbf{x}) + \dots + \lambda_m g_m(\mathbf{x})$
- $\lambda_i$ 's are called “Lagrange multipliers”



# Solving the problem

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- Lagrange function:  $\mathcal{L}(x_1, \dots, x_n, \lambda_1, \dots, \lambda_m) = f(\mathbf{x}) + \sum_{i=1}^m \lambda_i g_i(\mathbf{x})$
- Take the derivative of the Lagrange function to every variable (i.e., all the  $x$ 's and the  $\lambda$ 's)  
$$\Rightarrow \begin{cases} \frac{\partial \mathcal{L}(x_1, \dots, x_n, \lambda_1, \dots, \lambda_m)}{\partial x_j} = 0 \quad \forall j \\ \frac{\partial \mathcal{L}(x_1, \dots, x_n, \lambda_1, \dots, \lambda_m)}{\partial \lambda_i} = 0 \quad \forall i \end{cases}$$
- Test each solution set. Whichever gives the greatest (or the smallest) value is the maximum (or minimum) point



# Solving the toy example

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- Maximize  $5x_1x_2$  subject to  $2x_1 + x_2 = 100$

$$f(x_1, x_2) = 5x_1x_2, g(x_1, x_2) = 2x_1 + x_2 - 100$$

$$\mathcal{L}(x_1, x_2, \lambda_1) = 5x_1x_2 + \lambda_1(2x_1 + x_2 - 100)$$

$$\left\{ \begin{array}{l} \frac{\partial \mathcal{L}(x_1, x_2, \lambda_1)}{\partial x_1} = 5x_2 + 2\lambda_1 := 0 \\ \frac{\partial \mathcal{L}(x_1, x_2, \lambda_1)}{\partial x_2} = 5x_1 + \lambda_1 := 0 \\ \frac{\partial \mathcal{L}(x_1, x_2, \lambda_1)}{\partial \lambda_1} = 2x_1 + x_2 - 100 := 0 \end{array} \right.$$

$$\Rightarrow (x_1, x_2, \lambda_1) = (25, 50, -125)$$



# Generalized Lagrange multiplier

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- Lagrange multipliers is generalized to include the **inequality constraints** under the Karush–Kuhn–Tucker (KKT) condition
- Standard form problem

**Minimize**  $f(\mathbf{x})$  subject to  $g_i(\mathbf{x}) \leq 0$  ( $i = 1, \dots, p$ ) and  $h_j(\mathbf{x}) = 0$  ( $j = 1, \dots, m$ )

- If the task is to maximize  $f(\mathbf{x})$ , transform the problem into minimize  $-f(\mathbf{x})$
- Lagrangian

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





# Necessary (not sufficient!) optimal condition (KKT condition)

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- If  $\mathbf{x}^*$  is the optimal solution to the standard form problem, then there exist KKT multipliers  $\lambda$  and  $\mu$  such that

- Lagrangian optimality in  $\mathbf{x}$

$$\nabla \mathcal{L}(\mathbf{x}^*, \lambda, \mu) = 0 \text{ ----- (1)}$$

- Primal feasibility

$$g_i(\mathbf{x}^*) \leq 0 \quad \forall i \text{ ----- (2)}$$

$$h_j(\mathbf{x}^*) = 0 \quad \forall j \text{ ----- (3)}$$

- **Dual feasibility**

$$\lambda_i \geq 0 \quad \forall i \text{ ----- (4)}$$

- **Complementary slackness**

$$\lambda_i g_i(\mathbf{x}^*) = 0 \quad \forall i \text{ ----- (5)}$$



# Example

- Minimize  $f(x_1, x_2) = x_1^2 + 2x_2^2$  subject to  $x_1 + x_2 \geq 3$  and  $x_2 - x_1^2 \geq 1$

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = x_1^2 + 2x_2^2 + \lambda_1(3 - x_1 - x_2) + \lambda_2(1 + x_1^2 - x_2)$$

$$\Rightarrow \begin{cases} \frac{\partial \mathcal{L}}{\partial x_1} = 0 \\ \frac{\partial \mathcal{L}}{\partial x_2} = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda_1} = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda_2} = 0 \end{cases} \Rightarrow (x_1, x_2, \lambda_1, \lambda_2) = (-2, 5, 12, -8) \text{ or } (1, 2, 6, 2)$$

$\Rightarrow (-2, 5, 12, -8)$  does not follow the KKT condition (4)

( $\because \lambda_2 = -8 < 0$ )

$$\Rightarrow \min f(x_1, x_2) = f(1, 2) = 1^2 + 2 \cdot 2^2 = 9$$



# Summary

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- When we have constraints on an optimization problem, gradient descent/ascent may not be applicable
- Lagrange multiplier is a useful tool to solve the optimization problem with equality and inequality constraints

