

# MIE 524/624

## Parametric Optimization with Analytical solution methods

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# Reference

- Chapter 8 – Murphy, 2023(Book 1)

# Optimization - What?

- What is optimization modeling?

# Optimization modeling – How?

- **Formulate problem- determine**
  - Objective function
  - Exogenous (decision) variables
  - Endogenous (input) variables
  - Constraints (if any)
- **Apply suitable solution algorithms**
  - dependent on form of objective function and constraints - linear, integer, nonlinear
    - simplex, interior point method (Linear Programming)
    - branch and bound (Integer programming)
    - Newton's (analytical algorithms; non-linear programming)
    - gradient descent (numerical optimization; non-linear programming)

# Problem: Find optimal routing of drones between $n$ cities for aerial assessment of damage after a natural disaster

- Problem formulation
  - **Objective function**
    - $\min \sum_{i=0}^n \sum_{j=0}^n c_{ij} x_{ij}$
  - **Endogenous variables**
    - $n$  = number of cities to visit
    - $c_{ij}$  = cost of travel from location  $i$  to location  $j$
  - **Exogenous (decision) variables**
    - $x_{ij}$  = (binary with value 1 if drone should travel directly from location  $i$  to location  $j$ )
  - **Constraints:**
    - s.t,  $\sum_{i=0}^n x_{ij} = 1, \forall j; \sum_{j=0}^n x_{ij} = 1, \forall i;$
- Solution algorithm?

# Problem: Find optimal routing of drones between $n$ cities for aerial assessment of damage after a natural disaster

- Problem formulation

- Objective function

- $\min \sum_{i=0}^n \sum_{j=0}^n c_{ij} x_{ij}$  ← Linear

- Endogenous variables

- $n$  = number of cities to visit
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- Exogenous (decision) variables

- $x_{ij}$  = (binary with value 1 if drone should travel directly from location  $i$  to location  $j$ ) ← Binary/Integer

- Constraints: s.t,  $\sum_{i=0}^n x_{ij} = 1, \forall j; \sum_{j=0}^n x_{ij} = 1, \forall i;$  ← Linear/combinatorial



- Solution algorithm?

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- Solution algorithm (combinatorial)
  - Branch and bound



# Non-linear programming/ continuous

- $\text{Min } f(\mathbf{x})$ ,
- $\mathbf{x} \in R^n$   Continuous variable
- $f(\mathbf{x}) = -x_1(70 - 4x_1) - x_2(150 - 15x_2) + 100 + 15x_1 + 15x_2$   
 Non-linear objective function



# Analytic gradient-based solution

- First and second order necessary and sufficient conditions
- Suppose  $f: R^n \rightarrow R$  is twice differentiable at  $\vec{x}^*$ . If  $\vec{x}^*$  is a **local** minimum then
  - $\nabla f(\vec{x}^*) = 0$  (**first-order necessary condition**)
  - $H(\vec{x}^*)$  is positive semi-definite (**second-order necessary**)
  - $H(\vec{x}^*)$  is positive definite (**second-order sufficient**)
- If  $f$  is **convex** and  $\vec{x}^*$  is a local optima then,  $\vec{x}^*$  is also a **global** optima
- (note: the arrow in  $\vec{x}$  implies  $x$  is a vector; typical notation is to use a bold  $x$  to indicate a vector; when writing by hand on the board I may use  $\vec{x}$ )

# Calculus- basics

- Hessian ( $H$ ): Suppose  $f: R^n \rightarrow R$  is twice differentiable at some point  $\mathbf{x}$ , then (**note:**  $R^n$  implies **vector**  $\mathbf{x}$  is n-dimensional)

- $$H(\mathbf{x}) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1 \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_n} \end{bmatrix}_{\mathbf{x}}$$

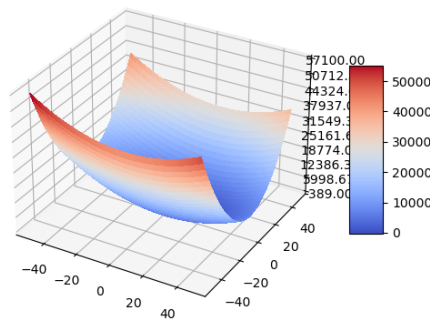
- Matrix  $H$  is positive semidefinite, iff (if and only if)
  - $\mathbf{z}H\mathbf{z}^T \geq 0$ ;  $\mathbf{z}$  is any non-zero vector;  $\mathbf{z}^T$  is transpose of  $\mathbf{z}$  ;
  - OR, all leading principal minors are  $\geq 0$ ; A  $k^{th}$  principal minor of a  $n \times n$  matrix is the determinant of any  $k \times k$  matrix obtained by deleting  $n - k$  rows and corresponding  $n - k$  columns
- Matrix  $H$  is positive definite, iff
  - $\mathbf{z}H\mathbf{z}^T > 0$ ;  $\mathbf{z}$  is any non-zero vector;  $\mathbf{z}^T$  is transpose of  $\mathbf{z}$ ;
  - OR, all leading principal minors are  $> 0$
- $f(\mathbf{x})$  is convex iff  $H(\mathbf{x})$  is positive semidefinite for ‘every’ point  $\mathbf{x}$  in the domain of  $f$
- $f(\mathbf{x})$  is strictly convex iff  $H(\mathbf{x})$  is positive definite for ‘every’ point  $\mathbf{x}$  in the domain of  $f$

# Non-linear programming/ continuous

- $\text{Min } f(\mathbf{x}), \mathbf{x} \in R^n$
- $f(\mathbf{x}) = -x_1(70 - 4x_1) - x_2(150 - 15x_2) + 100 + 15x_1 + 15x_2$
- $f(\mathbf{x}) = 8x_1 + 12x_2 + x_1^2 - 2x_2^2$

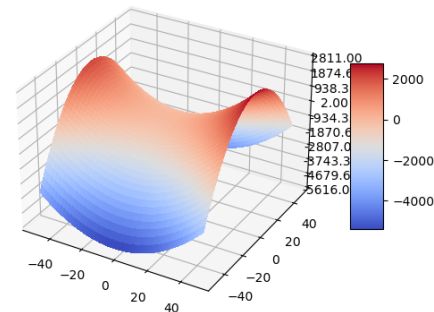
# Example of analytic method

- $f(\mathbf{x}) = -x_1(70 - 4x_1) - x_2(150 - 15x_2) + 100 + 15x_1 + 15x_2$
- Solve for  $\mathbf{x}$  using first order necessary condition, by setting the partial derivatives equal to zero
- $\frac{\partial f}{\partial x_1} = -70 + 8x_1 + 15 = 0 \Rightarrow x_1 = \frac{55}{8}$
- $\frac{\partial f}{\partial x_2} = -150 + 30x_2 + 15 = 0 \Rightarrow x_2 = \frac{9}{2}$
- Test for the second order necessary and sufficient conditions, by checking if the Hessian at  $\left(\frac{55}{8}, \frac{9}{2}\right)$  is positive semidefinite or positive definite
- $H = \begin{bmatrix} 8 & 0 \\ 0 & 30 \end{bmatrix}$  (notice it is independent of  $\mathbf{x}$ )
- 1<sup>st</sup> leading principal minor:  $8 > 0$
- 2<sup>nd</sup> leading principal minor=determinant  $\begin{vmatrix} 8 & 0 \\ 0 & 30 \end{vmatrix} > 0 \Rightarrow H$  is positive definite
- Solution:  $\left(\frac{55}{8}, \frac{9}{2}\right)$  is a strict local minimum of  $f(\mathbf{x})$
- Is it global optima?
  - $f(\mathbf{x})$  is convex because  $H(\mathbf{x})$  is positive definite for ‘every’ point  $\mathbf{x}$  in the domain of  $f \Rightarrow$  above solution is a global optima



## Example 2

- $f(x) = 8x_1 + 12x_2 + x_1^2 - 2x_2^2$
- Solve for  $x$  using first order necessary condition, by setting the partial derivatives equal to zero
- $\frac{\partial f}{\partial x_1} = 8 + 2x_1 = 0 \Rightarrow x_1 = -4$
- $\frac{\partial f}{\partial x_2} = 12 - 4x_2 = 0 \Rightarrow x_2 = 3$
- Test for the second order necessary and sufficient conditions, by checking if the Hessian at  $(-4,3)$  is positive semidefinite or positive definite
- $H = \begin{bmatrix} 2 & 0 \\ 0 & -4 \end{bmatrix}$
- 1<sup>st</sup> leading principal minor:  $2 > 0$
- 2<sup>nd</sup> leading principal minor=determinant  $\begin{vmatrix} 2 & 0 \\ 0 & -4 \end{vmatrix} < 0 \Rightarrow H$  is not positive definite or semi definite
- **Solution:  $(-4,3)$  is a stationary point but not a minima for  $f(x)$ .**



This analytic method is insufficient for this problem

## If objective function is a maxima

- **Is it a maxima?** Convert max to min (  $\text{Max } f(x) \sim \text{Min } -f(x)$  )

# Questions?



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