# Introduction to Classical Optimization Methods

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## Example

A farmer has 2400 m of fencing and wants to fence off a rectangular field that borders a straight river. He needs no fence along the river. What are the dimensions of the field that has the largest area?



## Example

A manufacturer needs to make a cylindrical can that will hold 1.5 liters of liquid. Determine the dimensions of the can that will minimize the amount of material used in its construction.



Constraint:  $\pi r^2 h = 1500$ 

## An Example

#### Objectives

Topology: Optimal connectivity of the structure Minimum cost of material: optimal cross section of all the members



We will consider the second objective only

The design variables are the cross sectional area of the members, i.e. A1 to A7

Using symmetry of the structure A7=A1, A6=A2, A5=A3

You have only four design variables, i.e., A1 to A4

# **Optimization formulation**

### Objective

Minimize  $1.132A_1\ell + 2A_2\ell + 1.789A_3\ell + 1.2A_4\ell$ 

What are the constraints?

One essential constraint is non-negativity of design variables, i.e. A1, A2, A3, A4 >= 0

Is it complete now?



### First set of constraints

Another constraint may be the minimization of deflection at C  $\frac{P\ell}{E} \left( \frac{0.566}{A_1} + \frac{0.500}{A_2} + \frac{2.236}{A_2} + \frac{2.700}{A_4} \right) \le \delta_{\max}$ Another constraint is buckling of compression members  $\frac{P}{2}(\cot\theta + \cot\alpha) \le \frac{\pi E A_4^2}{5.76\ell^2}$ 

 $\frac{P\csc\theta}{2A_1} \le S_{yc},$  $\frac{P\cot\theta}{2A_2} \le S_{yt},$ 

 $\frac{P\csc\alpha}{2A_3} \le S_{yt},$ 

Minimize  $1.132A_1\ell + 2A_2\ell + 1.789A_3\ell + 1.2A_4\ell$ 

subject to

$$\begin{split} S_{yc} &- \frac{P}{2A_1 \sin \theta} \ge 0, \\ S_{yt} &- \frac{P}{2A_2 \cot \theta} \ge 0, \\ S_{yt} &- \frac{P}{2A_3 \sin \alpha} \ge 0, \\ S_{yc} &- \frac{P}{2A_4} (\cot \theta + \cot \alpha) \ge 0, \\ \frac{\pi E A_1^2}{1.281\ell^2} &- \frac{P}{2 \sin \theta} \ge 0, \\ \frac{\pi E A_4^2}{5.76\ell^2} &- \frac{P}{2} (\cot \theta + \cot \alpha) \ge 0, \\ \delta_{\max} &- \frac{P\ell}{E} \left( \frac{0.566}{A_1} + \frac{0.500}{A_2} + \frac{2.236}{A_3} + \frac{2.700}{A_4} \right) \ge 0, \\ 10 \times 10^{-6} \le A_1, A_2, A_3, A_4 \le 500 \times 10^{-6}. \end{split}$$

## An optimization problem

Minimize  $F = (x - p)^2 + (y - q)^2$  $a_2x + b_2y \le d_2$   $x, y \ge 0$  Shattacharita KSubject to  $a_1x + b_1y \le d_1$ 





# Single variable optimization

### **Stationary points**

For a continuous and differentiable function f(x), a stationary point  $x^*$  is a point at which the slope of the function is zero, i.e. f'(x) = 0 at  $x = x^*$ ,



# Relative minimum and maximum

- A function is said to have a relative or local minimum at x = x\* if f(x\*)≤ f(x\*+h) for all sufficiently small positive and negative values of h, i.e. in the near vicinity of the point x\*.
- Similarly, a point x\* is called a relative or local maximum if f(x\*) ≥ f(x\*+h) for all values of h sufficiently close to zero.
- A point x\* is said to be an inflection point if the function value increases locally as x\* increases and decreases locally as x\* reduces



# Global minimum and maximum

- A function is said to have a global or absolute minimum at  $x = x^*$  if f  $(x^*) \le f(x)$  for all x in the domain over which f(x) is defined.
- A function is said to have a global or absolute maximum at  $x = x^*$  if f  $(x^*) \ge f(x)$  for all x in the domain over which f(x) is defined.



### Necessary and sufficient conditions for optimality

#### **Necessary condition**

If a function f(x) is defined in the interval  $a \le x \le b$  and has a relative minimum at  $x = x^*$ , Where  $a \le x^* \le b$  and if f'(x) exists as a finite number at  $x = x^*$ , then  $f'(x^*) = 0$ 

#### Proof

$$f'(x^*) = \lim_{h \to 0} \frac{f(x^* + h) - f(x^*)}{h}$$

Since  $x^*$  is a relative minimum

$$f(x^*) \le f(x^* + h)$$

For all values of h sufficiently close to zero, hence

$$\frac{f(x^*+h) - f(x^*)}{h} \ge 0 \qquad \text{if } h \ge 0$$
$$\frac{f(x^*+h) - f(x^*)}{h} \le 0 \qquad \text{if } h \le 0$$

Thus

 $f'(x^*) \ge 0$  If *h* tends to zero through +ve value  $f'(x^*) \le 0$  If *h* tends to zero through -ve value

The only way to satisfy both the conditions is to have

$$f^{/}(x^{*})=0$$

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Note:

- This theorem can be proved if  $x^*$  is a relative maximum
- Derivative must exist at  $x^*$
- The theorem does not say what happens if a minimum or maximum occurs at an end point of the interval of the function
- It may be an inflection point also.

Sufficient conditions for optimality

### **Sufficient condition**

Suppose at point  $x^*$ , the first derivative is zero and first nonzero higher derivative is denoted by n, then

- 1. If n is odd, x\* is an inflection point
- 2. If n is even,  $x^*$  is a local optimum
  - 1. If the derivative is positive,  $x^*$  is a local minimum
  - 2. If the derivative is negative, x\* is a local maximum

### Proof

Apply Taylor's series

$$f(x^* + h) = f(x^*) + hf'(x^*) + \frac{h^2}{2!}f''(x^*) + \dots + \frac{h^{n-1}}{(n-1)!}f^{n-1}(x^*) + \frac{h^n}{n!}f^n(x^*)$$
  
Since  $f'(x^*) = f''(x^*) = \dots = f^{n-1}(x^*) = 0$   
$$f(x^* + h) - f(x^*) = \frac{h^n}{n!}f^n(x^*)$$
  
When  $n$  is even  $\frac{h^n}{n!} \ge 0$   
Thus if  $f^n(x^*)$  is positive  $f(x^* + h) - f(x^*)$  is positive Hence it is local minimum  
Thus if  $f^n(x^*)$  negative  $f(x^* + h) - f(x^*)$  is negative Hence it is local maximum

When *n* is odd  $\frac{h^n}{n!}$  changes sign with the change in the sign of h. Hence it is an inflection point

#### Multivariable optimization without constraints

Minimize f(X)

Where 
$$X = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

#### Necessary condition for optimality

If f(X) has an extreme point (maximum or minimum) at  $X = X^*$  and if the first partial Derivatives of f(X) exists at  $X^*$ , then

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$$\frac{\partial f(X^*)}{\partial x_1} = \frac{\partial f(X^*)}{\partial x_2} = \dots = \frac{\partial f(X^*)}{\partial x_n} = 0$$

#### Sufficient condition for optimality

The sufficient condition for a stationary point  $X^*$  to be an extreme point is that the matrix of second partial derivatives of f(X) evaluated at  $X^*$  is

(1) positive definite when  $X^*$  is a relative minimum

- (2) negative definite when  $X^*$  is a relative maximum
- (3) Neither positive nor negative definite when  $X^*$  is neither a minimum nor a maximum

#### Proof

Taylor series of two variable function

**Proof**  
Taylor series of two variable function  

$$f(x + \Delta x, y + \Delta y) = f(x, y) + \Delta x \frac{\partial f}{\partial x} + \Delta y \frac{\partial f}{\partial y} + \frac{1}{2!} \left( \Delta x^2 \frac{\partial^2 f}{\partial x^2} + 2\Delta x \Delta y \frac{\partial^2 f}{\partial x \partial y} + \Delta y^2 \frac{\partial^2 f}{\partial y^2} \right) + \cdots$$

$$f(x + \Delta x, y + \Delta y) = f(x, y) + \left[ \Delta x \quad \Delta y \right] \left[ \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \right] + \frac{1}{2!} \left[ \Delta x \quad \Delta y \right] \left[ \frac{\partial^2 f}{\partial x \partial y} - \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} - \frac{\partial^2 f}{\partial y^2} \right] \left[ \Delta x \\ \frac{\partial^2 f}{\partial y} - \frac{\partial^2 f}{\partial y^2} \right] \left[ \Delta x \\ \Delta y \right] \left[ \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \frac{\partial f}{\partial y} - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial y} - \frac{\partial f}{\partial y} - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y \right] \left[ \Delta x \\ \frac{\partial f}{\partial y} - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} + \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x \\ \Delta y - \frac{\partial f}{\partial y} \right] \left[ \Delta x$$

$$f(X^* + h) = f(X^*) + h^T \nabla f(X^*) + \frac{1}{2!} h^T H h + \cdots$$

Since  $X^*$  is a stationary point, the necessary condition gives that  $\nabla f(X^*) = 0$ Thus

$$f(X^* + h) - f(X^*) = \frac{1}{2!}h^T H h + \cdots$$

Now,  $X^*$  will be a minima, if  $h^T H h$  is positive

 $X^*$  will be a maxima, if  $h^T H h$  is negative

 $h^{T}Hh$  will be positive if H is a positive definite matrix

 $h^T H h$  will be negative if H is a negative definite matrix

A matrix H will be positive definite if all the eigenvalues are positive, i.e. all the  $\lambda$  values are positive which satisfies the following equation

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$$|A - \lambda I| = 0$$

Identify the optimal points of the function given below

$$f(x) = x^3 - 10x - 2x^2 + 10$$



