

# **General Concepts on Numerical Optimization**

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## **Outline**

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- Unconstrained optimization (terminology)
- Types of minimizers
- Examples of objective functions
- Constrained optimization (mathematical formulations)
- Linear and non-linear programming

## Unconstrained Optimization Problem

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} u(\mathbf{x})$$

where  $u: \mathcal{R}^n \rightarrow \mathcal{R}$  is the **objective function** (or cost function), and  $\mathbf{x}$  contains the **optimization variables**

$\mathbf{x}^*$  is a **global minimizer**  $\Leftrightarrow u(\mathbf{x}^*) \leq u(\mathbf{x})$  for all  $\mathbf{x} \in \mathcal{R}^n$

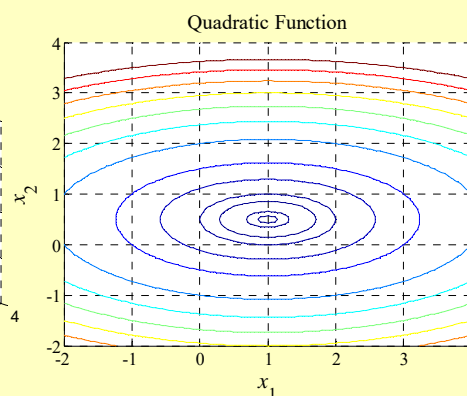
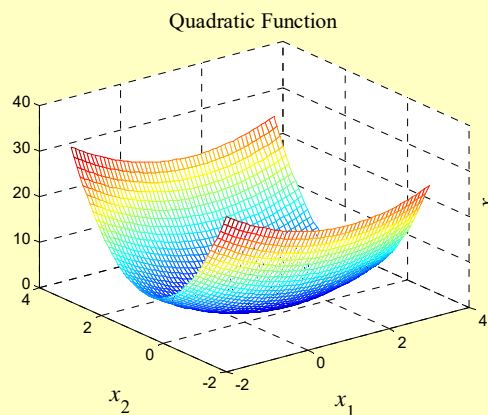
$\mathbf{x}^*$  is a **local minimizer**  $\Leftrightarrow u(\mathbf{x}^*) \leq u(\mathbf{x})$  for all  $\mathbf{x} \in \mathcal{N}$   
 $\mathcal{N} = \{\mathbf{x} \in \mathcal{R}^n : \|\mathbf{x} - \mathbf{x}^*\|_2 < \varepsilon\}$

Replacing  $\leq$  by  $<$  we have a **strict global minimizer** and a **strict local minimizer**, respectively

If  $u(\mathbf{x})$  is convex, a local minimizer is also the global minimizer

## Example 1 – Quadratic

$$u(\mathbf{x}) = (x_1 - 1)^2 + (2x_2 - 1)^2 \quad \text{where} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



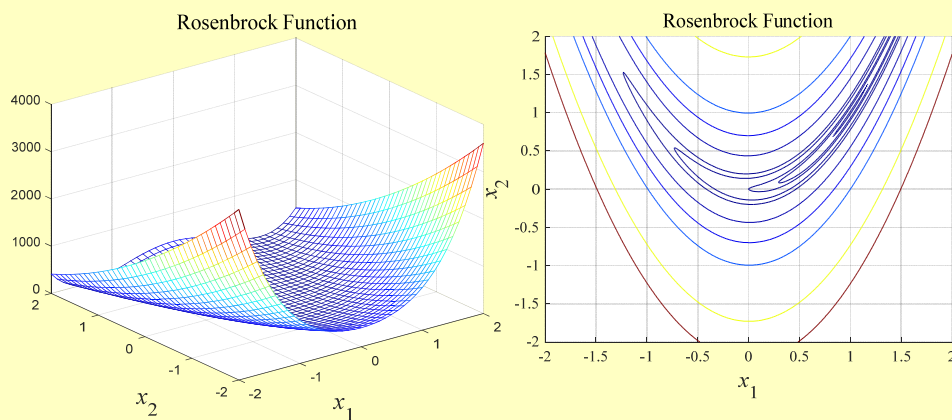
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### Example 2 – Rosenbrock

$$u(\mathbf{x}) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2 \quad \text{where} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

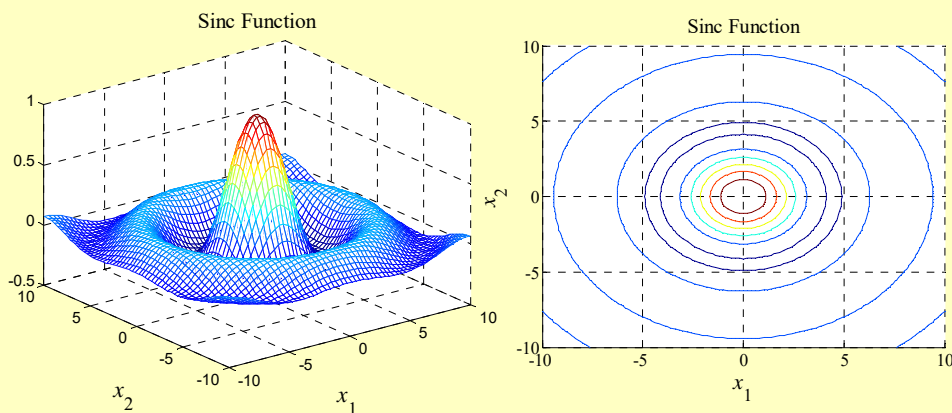


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### Example 3 – Sinc

$$u(\mathbf{x}) = \frac{\sin(r)}{r} \quad \text{where} \quad r = \sqrt{x_1^2 + x_2^2} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



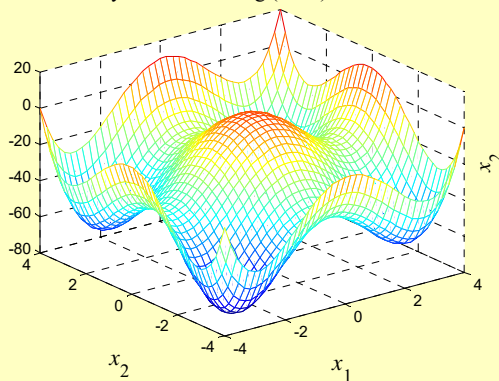
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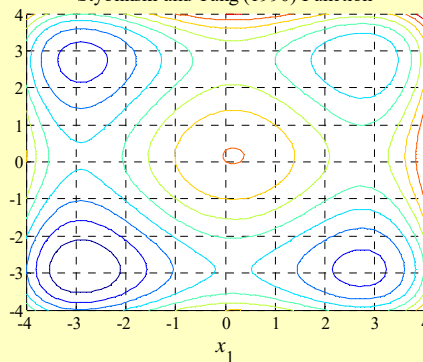
## Example 4 – Styblinski and Tang

$$u(\mathbf{x}) = 0.5(x_1^4 - 16x_1^2 + 5x_1 + x_2^4 - 16x_2^2 + 5x_2) \quad \text{where } \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Styblinski and Tang (1990) Function



Styblinski and Tang (1990) Function



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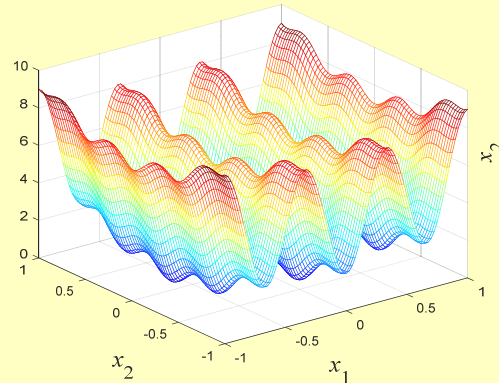
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## Example 5 – Venkataraman

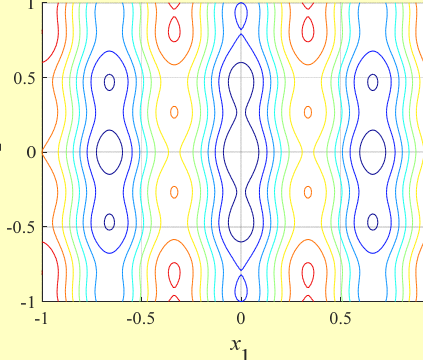
$$u(\mathbf{x}) = ax_1^2 + bx_2^2 - c \cos(px_1) - d \cos(qx_2) + c + d$$

$$\text{where } a = 1, b = 2, c = 0.3, d = 0.4, p = 3\pi, q = 4\pi \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Venkataraman (2002) Function



Venkataraman (2002) Function



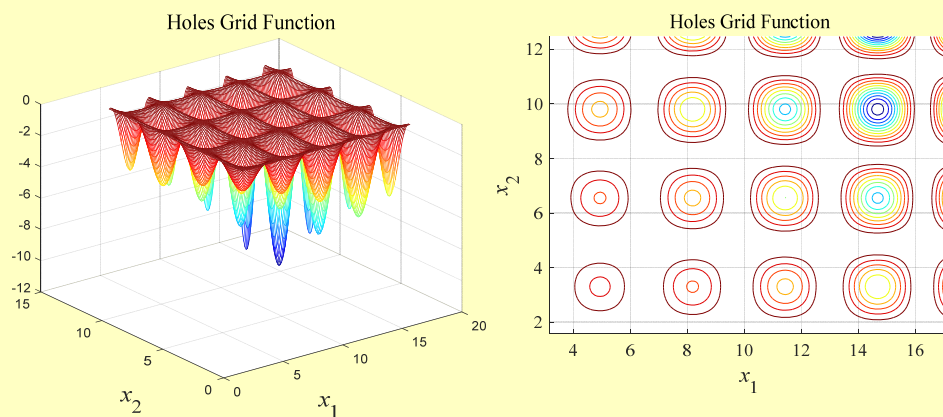
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## Example 6 – Holes Grid Function

$$u(\mathbf{x}) = -\sin^2\left(\frac{a\pi x_1}{b}\right)\cos^2\left(\frac{a\pi x_2}{b}\right)e^{\left(\frac{x_1+x_2}{c}\right)} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

where  $a = 4$ ,  $b = 13$ , and  $c = 10$



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## Constrained Optimization Problem

Generic notation:

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in \Omega} u(\mathbf{x})$$

$u: \mathcal{R}^n \rightarrow \mathcal{R}$  is the objective function (or cost function),  
 $\mathbf{x}$  contains the optimization variables,  $\Omega$  is the  
**feasible set or feasible region**

$\mathbf{x}^*$  is a global minimizer  $\Leftrightarrow u(\mathbf{x}^*) \leq u(\mathbf{x}), \mathbf{x} \in \Omega$

$\mathbf{x}^*$  is a local minimizer  $\Leftrightarrow u(\mathbf{x}^*) \leq u(\mathbf{x})$  for all  $\mathbf{x} \in \mathcal{N}$   
 $\mathcal{N} = \{\mathbf{x} \in \Omega : \|\mathbf{x} - \mathbf{x}^*\|_2 < \varepsilon\}$

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## Constrained Optimization Problem (cont)

More explicit notation:

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} u(\mathbf{x}) \quad \text{subject to} \quad \begin{cases} \mathbf{h}(\mathbf{x}) = \mathbf{0} \\ \mathbf{g}(\mathbf{x}) \leq \mathbf{0} \\ \mathbf{x}^{\text{lb}} \leq \mathbf{x} \leq \mathbf{x}^{\text{ub}} \end{cases}$$

$\mathbf{h}: \mathcal{R}^n \rightarrow \mathcal{R}^E$  has  $E$  **equality constraints**, and

$\mathbf{g}: \mathcal{R}^n \rightarrow \mathcal{R}^I$  has  $I$  **inequality constraints**

$\mathbf{x}^{\text{lb}} \in \mathcal{R}^n$  contains the **lower bounds** for  $\mathbf{x}$ , and

$\mathbf{x}^{\text{ub}} \in \mathcal{R}^n$  the **upper bounds**

The last inequalities are known as **side or box constraints**

## Constrained Optimization Problem (cont)

Other form:

$$\begin{aligned} \mathbf{x}^* &= \arg \min_{\mathbf{x}} u(\mathbf{x}) \\ &\text{subject to} \\ &\quad \mathbf{h}(\mathbf{x}) = \mathbf{0} \\ &\quad \mathbf{g}(\mathbf{x}) \leq \mathbf{0} \\ &\quad \mathbf{x}^{\text{lb}} \leq \mathbf{x} \leq \mathbf{x}^{\text{ub}} \end{aligned}$$

- Equality constraints ( $\mathbf{h}$ ) are rarely used in practical problems
- In general, the number of equality constraints ( $E$ ) should be smaller than the number of optimization variables ( $n$ )
- Side constraints define an hypercube (the search region)

## Linear and Nonlinear Optimization Problems

- If  $u(\mathbf{x})$  and all the constraints are linear functions of  $\mathbf{x}$ , the problem is a **linear programming problem**
- If the objective function or at least one of the constraints is nonlinear, then the problem is a **nonlinear programming problem**
- Linear programming problems are very common in decision disciplines (marketing, sales, production planning, transportation, operational research)
- Nonlinear programming problems are very common in engineering (modeling and design)

## Linear Programming Problems

Standard form:

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} \mathbf{c}^T \mathbf{x}$$

subject to

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

$$\mathbf{x} \geq \mathbf{0}$$

- $\mathbf{x}, \mathbf{c} \in \mathcal{R}^n$ ,  $\mathbf{A} \in \mathcal{R}^{m \times n}$ ,  $\mathbf{b} \in \mathcal{R}^m$
- It is assumed that  $\mathbf{b}$  is non-negative ( $\mathbf{b} \geq \mathbf{0}$ , element wise), and that the rank of  $\mathbf{A}$  is  $m$

## Non-Linear Programming Problems

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Standard form:

$$\mathbf{x}^* = \arg \min_{\mathbf{x}} u(\mathbf{x})$$

subject to

$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$

$$\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$$

$$\mathbf{x}^{\text{lb}} \leq \mathbf{x} \leq \mathbf{x}^{\text{ub}}$$

- $\mathbf{x}, \mathbf{x}^{\text{lb}}, \mathbf{x}^{\text{ub}} \in \mathcal{R}^n$
- $u: \mathcal{R}^n \rightarrow \mathcal{R}, \mathbf{h}: \mathcal{R}^n \rightarrow \mathcal{R}^E, \mathbf{g}: \mathcal{R}^n \rightarrow \mathcal{R}^I$
- It is assumed  $n > E$