# **Optimization: Quadratic Programming**

## **Quadratic programming**

#### Quadratic programming (QP):

TYPE 1:

$$\min_{x} f(x) = \min_{x} \frac{1}{2} x^{T} H x + c^{T} x$$

$$Ax \leq b$$

$$x \geq 0$$

#### TYPE 2: Standard form

$$\min_{x} f(x) = \min_{x} \frac{1}{2} x^{T} H x + c^{T} x$$

$$Ax = b$$

$$x \ge 0$$

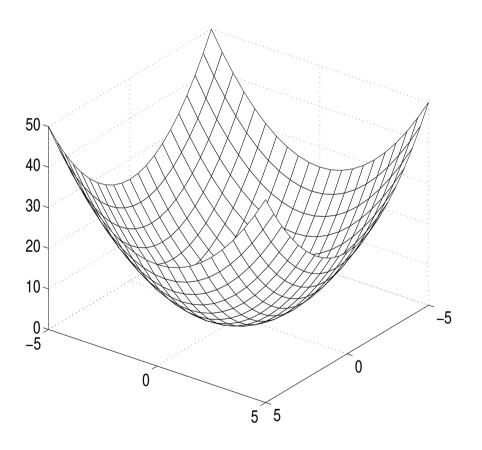
TYPE 1  $\implies$  TYPE 2 (see later)

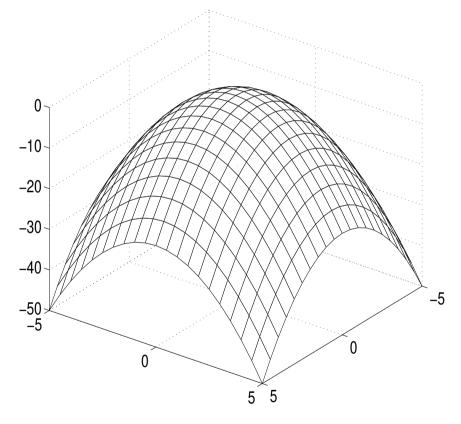
Unconstrained QP: Analytic solution:  $x = -H^{-1}c$ 

## Plot of $x^T H x$

$$H = egin{bmatrix} 1 & 0 \ 0 & 1 \end{bmatrix}$$
, positive definite

$$H=egin{bmatrix} 1 & 0 \ 0 & 1 \end{bmatrix}$$
, positive definite  $H=egin{bmatrix} -1 & 0 \ 0 & -1 \end{bmatrix}$ , negative definite

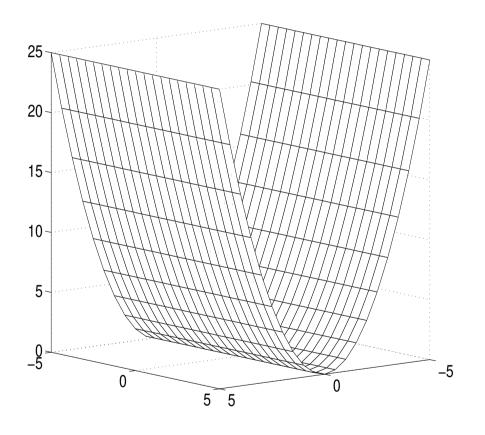


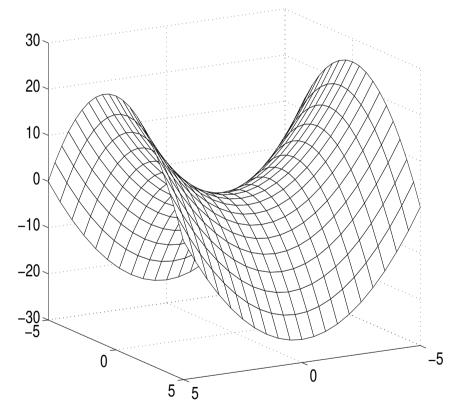


### Plot of $x^T H x$

$$H=\begin{bmatrix}1&0\\0&0\end{bmatrix}$$
, positive semi-definite  $H=\begin{bmatrix}1&0\\0&-1\end{bmatrix}$ , indefinite

$$H = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$
, indefinite





## Type 1 $\rightarrow$ Type 2 (= standard form)

• Type 1: 
$$Ax \le b$$
,  $x \ge 0$ 

$$\Rightarrow Ax + Is = b, \quad x, s \ge 0$$

$$\Rightarrow [A I] \begin{bmatrix} x \\ s \end{bmatrix} = b, \quad \begin{bmatrix} x \\ s \end{bmatrix} \ge 0 \quad \text{Type 2!}$$

- Type 2: Ax = b,  $x \geqslant 0$
- Type 3:  $Ax \le b$ ,  $x \in \mathbb{R}^n$ Define  $x = x^+ - x^-$  with  $x^+, x^- \ge 0$  $\Rightarrow Ax^+ - Ax^- + Is = b, \quad x^+, x^-, s \ge 0$   $\Rightarrow [A - A I] \begin{bmatrix} x^+ \\ x^- \\ s \end{bmatrix} = b, \quad \begin{bmatrix} x^+ \\ x^- \\ s \end{bmatrix} \ge 0 \quad \text{Type 2!}$

In general: for constrained problem:

$$\min_{x} f(x)$$
 ,  $h(x) = 0$  ,  $g(x) \leq 0$ 

Karush-Kuhn-Tucker conditions:

$$abla f(x) + 
abla g(x) \mu + 
abla h(x) \lambda = 0$$

$$h(x) = 0 \quad , \quad g(x) \leq 0$$

$$\mu^T g(x) = 0 \quad , \quad \mu \geqslant 0$$

QP-problem:

$$f(x) = \frac{1}{2}x^{T}Hx + c^{T}x$$
$$h(x) = Ax - b , g(x) = -x$$

Karush-Kuhn-Tucker conditions:

$$Ax = b$$
 ,  $x \geqslant 0$   
 $Hx + A^{T}\lambda - \mu = -c$   
 $\mu^{T}x = 0$  ,  $\mu \geqslant 0$ 

## Modified simplex method

$$Ax + u_1 = b$$

$$Hx + A^T \lambda - \mu + u_2 = -c$$

$$x, \mu \geqslant 0$$

$$\mu^T x = 0$$

Extended linear programming problem:

$$\min_{u_1,u_2} \sum_{i} (u_1)_i + \sum_{j} (u_2)_j$$

$$\begin{bmatrix} A & 0 & 0 & I & 0 \\ H & A^T & -I & 0 & I \end{bmatrix} \begin{bmatrix} x \\ \lambda \\ \mu \\ u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} b \\ -c \end{bmatrix}, \quad x, \mu, u_1, u_2 \geqslant 0$$

and so:

$$\min_{x_0} c_0^T x_0$$
 ,  $A_0 x_0 = b_0$  ,  $x_0 \ge 0$ 

but with additional nonlinear constraint  $x^T \mu = 0$ 

## Modified simplex method

$$x^{T}\mu = 0$$
  $x, \mu \geqslant 0$   
 $\Rightarrow \sum_{i} x_{i} \mu_{i} = 0$   $x_{i}, \mu_{i} \geqslant 0$   
 $\Rightarrow x_{i} \mu_{i} = 0$  for all  $i$   
 $\Rightarrow x_{i} = 0$  or  $\mu_{i} = 0$  for all  $i$ 

- → extra feasibility constraint for basic solutions
- → modified simplex method (Wolfe, Lemke)

Finite number of steps!!!

### **Example**

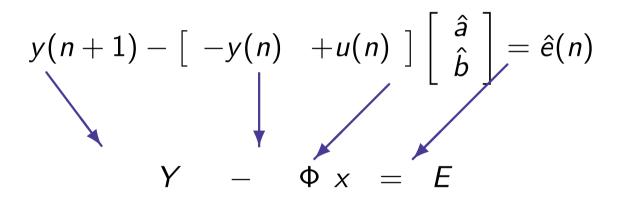
ARX (Auto Regressive eXogenous input) model:

$$y(n+1) + ay(n) = bu(n) + e(n)$$

e: zero-mean white noise

Given: y(n), u(n), n = 1, 2, ..., N

 $\Rightarrow$  a, b?



Best estimate for a and  $b \rightarrow$  minimize energy of  $\hat{e}$ 

## **Example (continued)**

$$Y - \Phi x = E$$

$$\min_{x} \sum_{n=1}^{N} \hat{e}^{2}(n) = \min_{x} E^{T}E$$

$$= \min_{x} (Y - \Phi x)^{T} (Y - \Phi x)$$

$$= \min_{x} Y^{T}Y + x^{T}\Phi^{T}\Phi x - x^{T}\Phi^{T}Y - Y^{T}\Phi x$$

$$= \min_{x} d + \frac{1}{2}x^{T}Hx + c^{T}x$$

 $\rightarrow$  quadratic objective function

Stable model  $\rightarrow -0.99 \leqslant \hat{a} \leqslant 0.99$ 

- → linear constraint
- ⇒ Quadratic Programming problem

## **Summary**

Quadratic programming: Standard form

$$\min_{x} \frac{1}{2} x^{T} H x + c^{T} x$$
s.t.  $Ax = b$ 

$$x \ge 0$$

- Alternative standard forms & conversion
- Modified simplex method
  - $\rightarrow$  finds exact solution in finite number of steps