

# LECTURE 5

GKA 6035

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## REVIEW LECTURE 4 + ADDITIONAL EXAMPLE

- Eigenvalues
- Eigenvectors
- Diagonalization
- How to compute  $A^n$

A symmetric  $\Rightarrow$  A diagonalizable

Ex: Is  $A = \begin{pmatrix} 3 & 1 & 1 \\ 1 & 2 & 1 \\ -1 & -1 & 1 \end{pmatrix}$  diagonalizable?

① A is not symmetric.

② Eigenvalues

$$\begin{vmatrix} 3-\lambda & 1 & 1 \\ 1 & 2-\lambda & 1 \\ -1 & -1 & 1-\lambda \end{vmatrix} = \begin{matrix} (3-\lambda) \cdot ((2-\lambda)(1-\lambda) + 1) \\ -1 \cdot ((1-\lambda) + 1) \\ -1 \cdot (1 - (2-\lambda)) \end{matrix}$$

~~$= (3-\lambda)(\lambda^2 - 3\lambda + 3) - (2-\lambda) - (-1+\lambda)$~~  ← this didn't work

$= (3-\lambda) \cdot ((2-\lambda)(1-\lambda)) + (3-\lambda) + (-1)$

$= (3-\lambda)(2-\lambda)(1-\lambda) + (2-\lambda) = (2-\lambda) \cdot ((3-\lambda)(1-\lambda) + 1)$

$= (2-\lambda)(\lambda^2 - 4\lambda + 4) = 0$

$\lambda = 2$  or,  $\lambda^2 - 4\lambda + 4 = 0$

$\lambda = 2$

Solution:  $\lambda = 2$  (mult. 3)

$\lambda_1 = 2 \quad \lambda_2 = 2 \quad \lambda_3 = 2$

③ If there are  $n$  distinct eigenvalues,  
 then there are  $n$  lin. independent eigenvectors.  
 Not the case here, we have to compute:

Eigenvectors for  $\lambda=2$ :

$$\begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ -1 & -1 & -1 \end{pmatrix} \xrightarrow{\left[ \begin{array}{l} -1 \\ -1 \end{array} \right]} \begin{pmatrix} 1 & 1 & 1 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \xrightarrow{\left[ \begin{array}{l} 1 \\ 1 \end{array} \right]} \begin{pmatrix} 1 & 0 & 1 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Coefficient  
matrix  
with  $\lambda=2$

rank = 2  
 degrees of freedom  
 = 1

$$\begin{aligned} x+z &= 0 \\ -y &= 0 \end{aligned}$$

$$\begin{aligned} x &= -z \\ y &= 0 \\ z &\text{ free} \end{aligned}$$

$z$  free

It is not diagonalisable since we do not have more than one linearly independent eigenvector.

Remember:

A Diagonalizable means

$$P^{-1}AP = D, \text{ with}$$

$$D = \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{pmatrix} \text{ diagonal}$$

$$P = \left( \begin{array}{c|c|c} \underline{v_1} & \underline{v_2} & \dots & \underline{v_n} \end{array} \right) \text{ invertible} \\ \updownarrow \\ \{v_1, \dots, v_n\} \text{ lin. independent}$$

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} -z \\ 0 \\ z \end{pmatrix} = z \cdot \underline{\underline{\begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix}}}$$

$$\underline{v_1} = \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix} \text{ eigenvector} \\ \lambda = 2.$$

## PLAN: LECTURE 5

- ① INTRODUCTION TO OPTIMIZATION (LECTURE 5-8)
- ② QUADRATIC FORMS AND DEFINITENESS
- ③ BORDERED HESSIANS FOR QUADRATIC FORMS

[FMEA] 1.7-1.8

It may be smart to review material about functions, for example

[FMEA] Ch. 4, Ch. 11  
for those who need it.

## ① INTRO TO OPTIMIZATION

$$f(x_1, x_2, \dots, x_n) = f(\underline{x})$$

function in  $n$  variables

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

unconstrained optimization

max/min of  $f(\underline{x})$  with no constraints on  $\underline{x}$ .

constrained optimization

max/min of  $f(\underline{x})$  subject to constraints

Ex:

$$\max x_1^2 - 7x_1x_2 + 3x_2^2$$

$$\max_{f''} xyz \quad \text{subject to} \quad \underbrace{x^2 + y^2 + z^2}_{D_f} \leq 1$$

domain of definition

$$D_f = \{(x, y, z) : x^2 + y^2 + z^2 \leq 1\}$$

## ② Quadratic forms

A quadratic form  $Q(\underline{x})$  is a polynomial function where all terms have degree two.

General form in three variables:

$$Q(x_1, x_2, x_3) = a_{11}x_1^2 + a_{12}x_1x_2 + a_{13}x_1x_3 \\ + a_{22}x_2^2 + a_{23}x_2x_3 \\ + a_{33}x_3^2$$

Ex:  $Q(\underline{x}) = x_1^2 + 2x_1x_2 + x_2^2 + x_3^2$

Facts: For any Quadratic form  $Q(\underline{x})$

i)  $Q(\underline{0}) = Q(0, 0, \dots, 0) = 0$

ii)  $\underline{x} = \underline{0}$ ,  $(x_1, \dots, x_n) = (0, \dots, 0)$ , is a stationary point

Ex:  $Q(\underline{x}) = x_1^2 - 2x_2^2$

$$Q'_{x_1} = 2x_1 = 0 \quad x_1 = 0 \\ Q'_{x_2} = -4x_2 = 0 \quad x_2 = 0$$

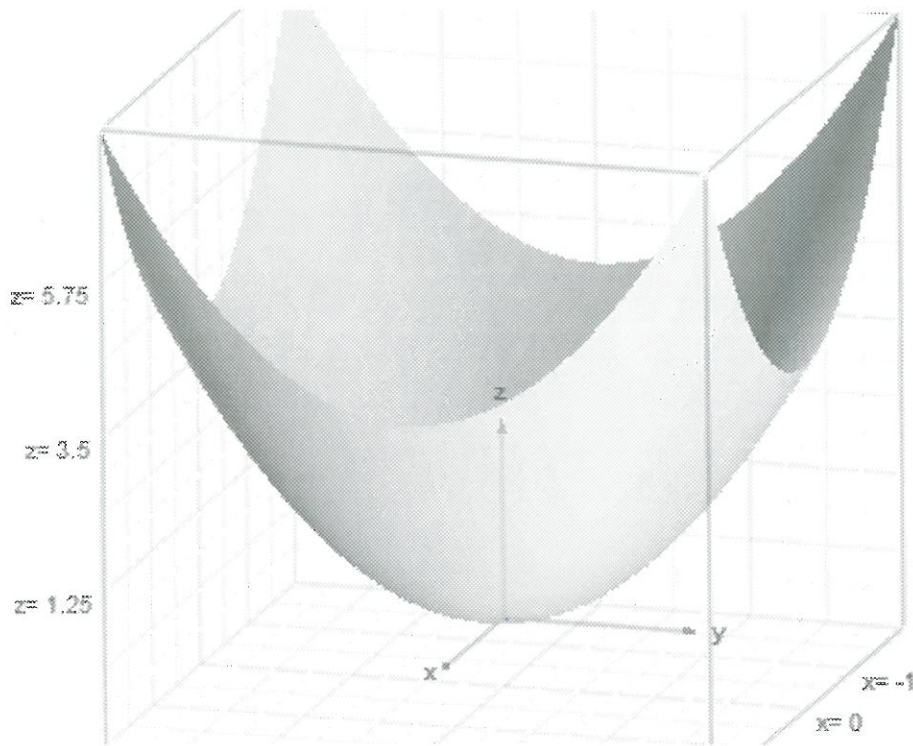
$\underline{x} = (0, 0)$  is  
stationary point

Remember:

Stationary point

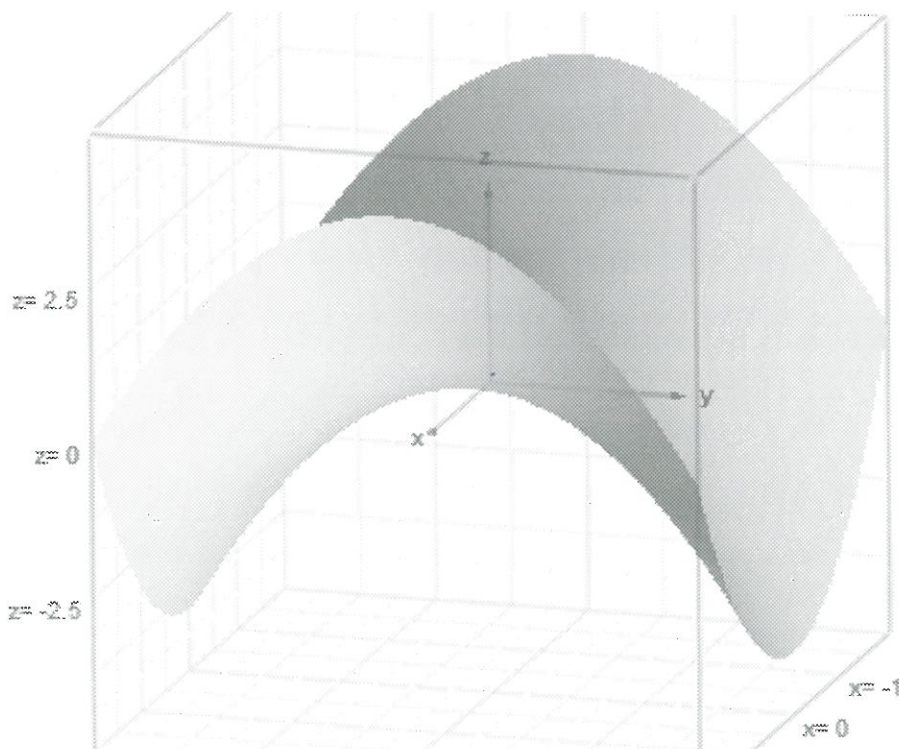


$$Q'_1 = Q'_2 = \dots = Q'_n = 0$$



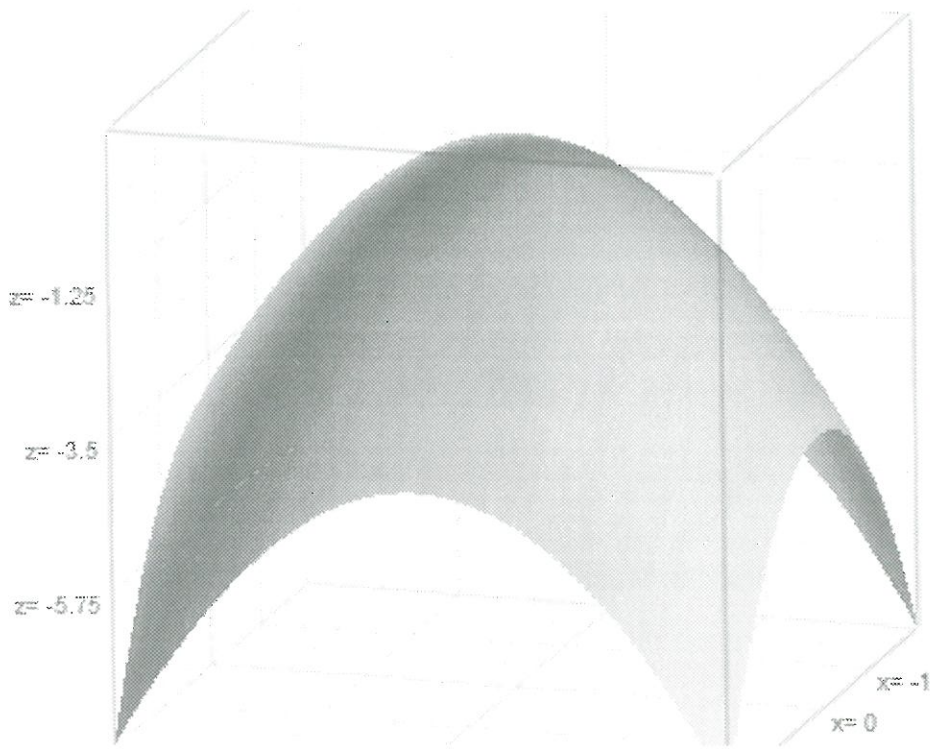
$$z = x^2 + y^2$$

positive  
definite



$$z = x^2 - y^2$$

indefinite



$$z = -x^2 - y^2$$

negative  
definite

Defn:  $Q(\underline{x})$  quadratic form

We say that  $Q$  is

\* positive definite if  $Q(\underline{x}) > 0$  for all  $\underline{x} \neq \underline{0}$

\* positive semidefinite if  $Q(\underline{x}) \geq 0$  for all  $\underline{x}$

\* negative definite if  $Q(\underline{x}) < 0$  for all  $\underline{x} \neq \underline{0}$

\* negative semidefinite if  $Q(\underline{x}) \leq 0$  for all  $\underline{x}$

\* indefinite if  $Q(\underline{x}) > 0$  for some values of  $\underline{x}$   
and  $Q(\underline{x}) < 0$  for other values of  $\underline{x}$

Note:

positive (semi)definite  $\iff \underline{x} = \underline{0}$  is global minimum

negative (semi)definite  $\iff \underline{x} = \underline{0}$  is global maximum

indefinite  $\iff \underline{x} = \underline{0}$  is saddle point

Matrix form:

$$Q(x_1, x_2, \dots, x_n) = a_{11}x_1^2 + a_{12}x_1x_2 + \dots \\ + a_{22}x_2^2 + \dots \\ \vdots \\ + a_{nn}x_n^2$$

$$= \sum_{\substack{1 \leq i \leq n \\ 1 \leq j \leq n \\ i \leq j}} a_{ij} x_i x_j$$

$$= (x_1 \ x_2 \ \dots \ x_n) \cdot \begin{pmatrix} a_{11} & a_{12}/2 & \dots \\ a_{12}/2 & a_{22} & \dots \\ \vdots & \vdots & \ddots \\ & & & a_{nn} \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

$$= \underline{x}^T \cdot A \cdot \underline{x}, \text{ where } A \text{ is a symmetric matrix.}$$

Ex:  $Q(\underline{x}) = x_1^2 + 3x_2^2 = (x_1 \ x_2) \cdot \begin{pmatrix} 1 & 0 \\ 0 & 3 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \underline{x}^T A \underline{x}$

$$\underline{Q}(\underline{x}) = x_1^2 + \underline{2x_1x_2} + x_2^2 + x_3^2$$

$$= (x_1 \ x_2 \ x_3) \cdot \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \underline{x}^T A \underline{x}$$

Any quadratic form  $Q(\underline{x}) = \underline{x}^T A \underline{x}$  for a unique symmetric matrix  $A$ . — the symmetric matrix of the quadratic form.



Thm:  $Q$  quadratic form,  $A$  its symmetric matrix  
( $n$  variables) ( $n \times n$ ,  $Q(\underline{x}) = \underline{x}^T A \underline{x}$ )

$Q$  positive definite  $\Leftrightarrow$  all eigenvalues of  $A$  are positive ( $\lambda_i > 0$ )

positive semidefinite  $\Leftrightarrow$  — | | —  
non-negative ( $\lambda_i \geq 0$ )

negative definite  $\Leftrightarrow \lambda_i < 0$  (all eigenvalues)

negative semidefinite  $\Leftrightarrow \lambda_i \leq 0$  (all eigenvalues)

indefinite  $\Leftrightarrow$  there are both positive and negative eigenvalues  
( $\lambda_i > 0$ ,  $\lambda_j < 0$ )

quadratic form  $\rightarrow$  symmetric matrix  $\rightarrow$  eigenvalues  $\rightarrow$   $\left\{ \begin{array}{l} \text{Sign of } \lambda_i \\ \text{determines} \\ \text{definiteness} \end{array} \right.$

Ex:  $Q(\underline{x}) = x_1^2 + 2x_1x_2 + x_2^2 + x_3^2$

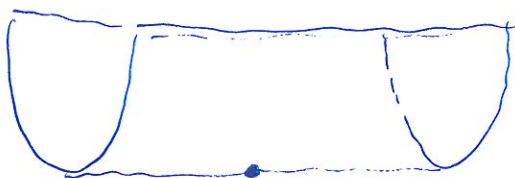
$$A = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad \left| \begin{array}{ccc} 1-\lambda & 1 & 0 \\ 1 & 1-\lambda & 0 \\ 0 & 0 & 1-\lambda \end{array} \right| = (1-\lambda) \cdot ((1-\lambda)(1-\lambda) - 1) = 0$$

$$(1-\lambda) \cdot (\lambda^2 - 2\lambda) = 0$$

$$\lambda = 1, \lambda = 0, \lambda = 2$$

$Q$  is positive semidefinite.

(since  $\lambda_i \geq 0$  for  $i=1,2,3$ )



## Principal minors:

A symmetric  
 $n \times n$ -matrix

A leading principal minor of order  $k$  is the minor you get when you keep the first  $k$  rows and the first  $k$  columns. It is called  $D_k$ .

Ex:  $A = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

$$D_1 = 1$$

$$D_2 = \begin{vmatrix} 1 & 1 \\ 1 & 1 \end{vmatrix} = 0$$

$$D_3 = \begin{vmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{vmatrix} = 0$$

row 1, 2  
col. 1, 2

A principal minor of order  $k$  is a minor of order  $k$  obtain when you keep the same numbered rows as columns. They are called  $\Delta_k$ .

Ex:  $\Delta_1 = 1, 1, 1$

$$\Delta_2 = \begin{vmatrix} 1 & 1 \\ 1 & 1 \end{vmatrix} = 0, \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} = 1, \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} = 1$$

$$\Delta_3 = \begin{vmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{vmatrix} = 0$$

row 2, 3  
col. 2, 3

$$\Delta_1 = 1, 1, 1$$

$$\Delta_2 = 0, 1, 1$$

$$\Delta_3 = 0$$

} Principal minors

$$D_1 = 1$$

$$D_2 = 0$$

$$D_3 = 0$$

} leading principal minors

Ex:  $Q(\underline{x}) = x_1^2 + 2x_2^2 + 7x_3^2$

$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 7 \end{pmatrix} \quad \begin{array}{l} \lambda = 1 \\ \lambda = 2 \\ \lambda = 7 \end{array}$$

$$D_1 = 1 \quad D_2 = 2 \quad D_3 = 1 \cdot 2 \cdot 7 = 14$$

$Q(\underline{x}) = -x_1^2 - 2x_2^2 - 7x_3^2$

$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & -7 \end{pmatrix} \quad \begin{array}{l} \lambda_1 = -1 \\ \lambda_2 = -2 \\ \lambda_3 = -7 \end{array}$$

$$D_1 = -1, \quad D_2 = (-1) \cdot (-2) = 2$$

$$D_3 = (-1) \cdot (-2) \cdot (-7) = -14$$

Result:  $Q$  quadratic form,  $A$  its symmetric matrix

$$\begin{cases} D_1, D_2, \dots, D_n & \text{leading principal m.} \\ \Delta_1, \Delta_2, \dots, \Delta_n & \text{principal minors} \\ & \text{all} \end{cases}$$

$Q$  positive definite  $\iff D_1, D_2, D_3, \dots, D_n > 0$

$Q$  negative definite  $\iff D_i$  has the same sign as  $(-1)^i$  for  $i=1, 2, \dots, n$ .

(i.e.  $(-1)^i D_i > 0$  for  $i=1, 2, \dots, n$ )

$Q$  positive semidefinite  $\iff \Delta_i \geq 0$  for all principal minors

$Q$  negative semidefinite  $\iff (-1)^i \Delta_i \geq 0$  — || —  
 $(\Delta_1 \leq 0, \Delta_2 \geq 0, \Delta_3 \leq 0, \dots)$

$Q$  indefinite  $\iff$  all cases that are neither positive semidefinite nor negative semidefinite

## Ex.

a)  $Q(x_1, x_2, x_3) = x_1^2 + 2x_1x_2 + x_2^2 + x_3^2$        $A = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

$D_1 = 1, D_2 = 0, D_3 = 0$       leading principal

$\Delta_1 = 1, \Delta_2 = 0, \Delta_3 = 0$       principal

$\Delta_i \geq 0$  for all principal minors }  $\Rightarrow$  positive semidefinite

b)  $Q(x_1, x_2, x_3) = x_1^2 + 2x_1x_2 + x_2^2 - x_3^2$        $A = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix}$

$D_1 = 1, D_2 = 0, D_3 = 0$

$\Delta_1 = 1, \Delta_2 = 0, \Delta_3 = 0$

$Q$  not positive semidefinite

$Q$  not negative semidefinite

$Q$  is indefinite

c)  $Q(x) = x^2 + 2yz$        $A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$

$D_1 = 1, D_2 = 0, D_3 = 1 \cdot (-1) = -1$

$\Delta_1 = \Delta_2 = \Delta_3$

Doesn't match pos/neg. semidefinite pattern

indefinite

### ③ Quadratic forms with linear constraints

Ex: Max/min  $Q(\underline{x}) = x^2 + 6xy - y^2$  subject to  $2x - y = 0$

$\underbrace{\hspace{10em}}$   
 quadratic form  
 in  $n$  variables  
 ( $n=2$ )

$\underbrace{\hspace{10em}}$   
 $m$  linear  
 constraints  
 ( $m=1$ )

Example of constraint optimization.

When  $A$  is the symmetric matrix of the quadratic form  $Q$  and  $B$  is the coefficient matrix of the constraints,

$$A = \begin{pmatrix} 1 & 3 \\ 3 & -1 \end{pmatrix} \quad B = \begin{pmatrix} 2 & -1 \end{pmatrix}$$

we form the bordered Hessian matrix

$$H = \begin{pmatrix} 0 & B \\ B^T & A \end{pmatrix}$$

Result: Assume that  $B$  has rank  $m$ .

Consider the last  $n-m$  leading principal minors of  $H$ ,

$$D_{2m+1}, D_{2m+2}, \dots, D_{m+n} = |H|_k$$

last principal minor is  $|H|$

All these leading principal minors  
have same sign as  $(-1)^m$

$\Leftrightarrow \left\{ \begin{array}{l} Q(\underline{x}) \text{ restricted to } \{\underline{x} : B\underline{x} = \underline{0}\} \\ \text{is } \underline{\text{positive definite}} \\ \text{and } \underline{x} = \underline{0} \text{ is global minimum} \end{array} \right.$

These leading principal minors  
alternate in sign and  $D_{m+n} = |H|$   
has the same sign as  $(-1)^n$

$\Leftrightarrow \left\{ \begin{array}{l} Q(\underline{x}) \text{ restricted to } \{\underline{x} : B\underline{x} = \underline{0}\} \\ \text{is } \underline{\text{negative definite}} \\ \text{and } \underline{x} = \underline{0} \text{ is global maximum.} \end{array} \right.$

In the example: Max/min  $Q(x) = x^2 + 6xy - y^2$  subject to  $2x - y = 0$

$$A = \begin{pmatrix} 1 & 3 \\ 3 & -1 \end{pmatrix}$$

$n = 2$   
(two var's)

$$B = (2 \ -1)$$

$m = 1$   
(one constraint)

}  $B$  has  $\text{rk } 1 = m$  ✓  
 $n - m = 2 - 1 = 1$   
 $\Rightarrow$  one leading principal minor to check,

$$D_3 = |H|$$

(the last one)

$$|H| = \left| \begin{array}{c|c} 0 & B \\ \hline B^T & A \end{array} \right| = \begin{vmatrix} 0 & 2 & -1 \\ 2 & 1 & 3 \\ -1 & 3 & -1 \end{vmatrix}$$

$$= -2(2 \cdot (-1) - 3 \cdot (-1)) + (-1)(2 \cdot 3 - 1 \cdot (-1)) = -2 - 7 = \underline{-9}$$

positive definite  $\Leftrightarrow |H|$  has same sign as  $(-1)^m = (-1)^1 = -1$

Yes, this condition is satisfied!

negative definite  $\Leftrightarrow |H|$  has same sign as  $(-1)^n = (-1)^2 = +1$

No, this condition is not satisfied

Conclusion:  $Q(x)$  restricted to  $\{2x - y = 0\}$  is positive definite  
 $(x, y) = (0, 0)$  is global minimum.

Alternative solution:

$$2x - y = 0 \Rightarrow y = 2x$$

$$Q(x, y) = x^2 + 6xy - y^2$$

$$= x^2 + 6x(2x) - (2x)^2 = 9x^2$$

↑  
positive definite

$x = 0$  global min.

$$x = 0 \Rightarrow y = 2x = 0$$

$$\Rightarrow (x, y) = (0, 0)$$