

# LECTURE 6

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MATHEMATICS

## Plan:

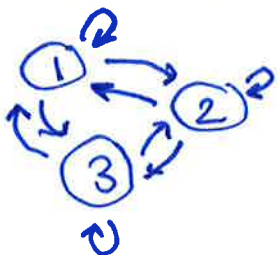
- ① Determiniteness of symmetric matrices
- ② Unconstrained optimization in  $n$  variables
- ③ Convex and concave functions

## Reading:

[MEJ] 14.1-14.4,  
14.8, 17.1-17.5

## Review:

### Markov chains



$\underline{x}$ : state vector  
col. sum = 1

$A = (a_{ij})$   
transition matrix

$$A \cdot \underline{x}_t = \underline{x}_{t+1}$$

$a_{ij}$ :  $j \rightarrow i$   
col. sums = 1

### Equilibrium:

$$\lim_{t \rightarrow \infty} \underline{x}_t = \lim_{t \rightarrow \infty} A^t \cdot \underline{x}_0$$

### Thm:

If  $A$  is regular, then

- \* there is a unique eigenvector  $\underline{u}$  with  $\lambda=1$  st.  $\underline{u}$  is a state vector
- \*  $\underline{u}$  is the equilibrium state

Defn.  $A$  regular if  $A^n$  has non-zero entries for  $n$  big enough

$A$  non-zero entries  $\Rightarrow A$  regular

## Quadratic forms:

$f(\underline{x}) = f(x_1, \dots, x_n) = \underline{x}^T \cdot A \cdot \underline{x}$  for a unique symmetric  $n \times n$ -matrix  $A$   
polynomial with all terms of degree 2.

Ex:  $f(x, y, z) = x^2 + 6xz - y^2 = (x \ y \ z) \cdot \begin{pmatrix} 1 & 0 & 3 \\ 0 & -1 & 0 \\ 3 & 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ z \end{pmatrix}$  the symm. matrix of  $f$ .

$\uparrow$   $\uparrow$   $\uparrow$   
 $\underline{x}^T$   $A$   $\underline{x}$

$g(x, y, z) = 2x^2 + y^2 + 3z^2 = \underline{x}^T \cdot \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{pmatrix} \cdot \underline{x}$

Defn: A symm matrix of  $f$  and  $\lambda_1, \dots, \lambda_n$  are eigenvalues of  $A$

$f$  pos. semidefn.  $\Leftrightarrow f(\underline{x}) \geq 0$  for all  $\underline{x} \Leftrightarrow \lambda_1, \lambda_2, \dots, \lambda_n \geq 0$

$f$  pos. defn.  $\Leftrightarrow f(\underline{x}) > 0$  for all  $\underline{x} \neq \underline{0} \Leftrightarrow \lambda_1, \lambda_2, \dots, \lambda_n > 0$

$f$  neg. semidefn.  $\Leftrightarrow f(\underline{x}) \leq 0$  for all  $\underline{x} \Leftrightarrow \lambda_1, \lambda_2, \dots, \lambda_n \leq 0$

$f$  neg. defn.  $\Leftrightarrow f(\underline{x}) < 0$  for all  $\underline{x} \neq \underline{0} \Leftrightarrow \lambda_1, \lambda_2, \dots, \lambda_n < 0$

$f$  indefinite  $\Leftrightarrow f(\underline{x})$  has pos. and neg. values  $\Leftrightarrow$  we have both pos. and neg. eigenvalues

$\uparrow$   
defn.

$\uparrow$   
result

Ex:  $g(x, y, z) = 2x^2 + y^2 + 3z^2 \geq 0$   $A = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{pmatrix}$   $\lambda_1 = 2 \geq 0$   $\lambda_2 = 1 \geq 0$   $\lambda_3 = 3 \geq 0$  pos. semidefinite (pos. definite also)

$h(x, y, z) = 2x^2 - y^2 + z^2$   $\lambda_1 = 2, \lambda_2 = -1, \lambda_3 = 1$  indefinite

$h(1, 0, 0) = 2$   
 $h(0, 1, 0) = -1$

Result is based on the fact that any quadratic form can be re-written as

$$f(\underline{x}) = \lambda_1 \cdot u_1^2 + \lambda_2 \cdot u_2^2 + \dots + \lambda_n \cdot u_n^2$$

where  $u_1, \dots, u_n$  is linear expressions in  $x_1, \dots, x_n$ .

# ① Determinants of symmetric matrices: A symmetric $n \times n$ matrix

Method: Principal minors

(a) Leading principal minors:

$$D_1 = M_{1,1}$$

$$D_2 = M_{12,12}$$

$$D_3 = M_{123,123}$$

$\vdots$

$$D_n = M_{12\dots n,12\dots n} = |A|$$

$$A = \begin{pmatrix} 1 & 0 & 3 \\ 0 & -1 & 0 \\ 3 & 0 & 0 \end{pmatrix}$$

$$\begin{aligned} D_1 &= 1 \\ D_2 &= -1 \\ D_3 &= 3 \cdot 3 \end{aligned}$$

$$\begin{aligned} f(x,y,z) &= x^2 + 6xz - y^2 = 9 \\ &= (x+3z)^2 - y^2 - 9z^2 \\ &\quad \uparrow \quad \quad \uparrow \quad \quad \uparrow \\ &\quad \quad \quad -1 \quad \quad -9 \end{aligned} \Rightarrow \text{indefinite}$$

Result:

$$A \text{ pos. definite} \iff \overset{\text{defn.}}{x^T A \cdot x > 0 \text{ for } x \neq 0} \iff D_1, D_2, \dots, D_n > 0$$

$$A \text{ neg. definite} \iff x^T A \cdot x < 0 \iff D_1 < 0, D_2 > 0, D_3 < 0, \dots$$

Ex:  $f(x) = -x^2 - y^2 - z^2$

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

$$\lambda_1 = -1 \quad \lambda_2 = -1 \quad \lambda_3 = -1 < 0$$

neg. definite

$$\begin{aligned} D_1 &= -1 & \leftarrow \lambda_1 \\ D_2 &= 1 & \leftarrow \lambda_1 \cdot \lambda_2 \\ D_3 &= -1 & \leftarrow \lambda_1 \cdot \lambda_2 \cdot \lambda_3 \end{aligned}$$

What if A is neither pos. or neg. definite?

fails  $\begin{cases} \text{wrong sign} \Rightarrow \text{indefinite} \\ \text{zero} \Rightarrow \text{indefinite or pos/neg. semidefn.} \end{cases}$

In general, we try to determine the definiteness using leading principal minors  $\Delta_1, \dots, \Delta_n$ . If this is not possible, we

All principal minors ← look at

$\Delta_i$ : minor of order  $i$  obtained by choosing  $i$  rows, and the same  $i$  columns.

= deleting all other rows and columns.

Result:

A pos. semidefn.  $\Leftrightarrow \Delta_1, \Delta_2, \dots, \Delta_n \geq 0$

A neg. semidefn.  $\Leftrightarrow \Delta_1 \leq 0, \Delta_2 \geq 0, \Delta_3 \leq 0, \dots$

A indefinite  $\Leftrightarrow$  all other cases

Typical examples:

$\Delta_2 < 0$  or  $\Delta_2 < 0$  : indefinite

$\Delta_1$  and  $\Delta_3$  opposite signs : indefinite

Ex:

~~$A = \begin{pmatrix} 1 & 2 & 1 \\ 2 & 0 & 2 \\ 1 & 2 & 0 \end{pmatrix}$~~

$A = \begin{pmatrix} 1 & 2 & 1 \\ 2 & 0 & 2 \\ 1 & 2 & 0 \end{pmatrix}$

$\Delta_1 = 1$

$\Delta_2 = 0$

$\Delta_3 = 1 \cdot 0 - 2 \cdot 0 = 0$

either pos. semid.  
or indefinite

$\Delta_1 = 1, 4, 0 \geq 0$   
 $\Delta_2 = 0, -4, -1$   
 $\Delta_3 = 0$

$\Rightarrow$  indefinite

$\uparrow$   
 $\Delta_i$

The case of  $|A|=0$ :

Thm: (New result, 2016)

If  $\text{rk } A = r < n$ , ~~then~~ we have:

$D_1 > 0, D_2 > 0, \dots, D_r > 0$  : A pos. semidefinite

$D_1 < 0, D_2 > 0, \dots, (-1)^r D_r > 0$  : A neg. semidefinite

Ex:

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

$$\begin{aligned} D_1 &= 1 \\ D_2 &= 1 \\ D_3 &= 0 \\ D_4 &= 0 \end{aligned} \Rightarrow A \text{ pos. semidefn.} \\ (\text{using new result})$$

What is  $\text{rk } A$ ?  $\text{rk } A = 2$

$$\begin{pmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{pmatrix} \xrightarrow{J-1} \begin{pmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\text{rk } A = 2 \Rightarrow$$

All minors  
of order 3  
and 4 are  
zero!

Alt:

Using principal minors:

"old method"

$$\Delta_1 = 1, 1, 1, 1 \geq 0$$

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

$$\Delta_3 = 0, 0, 0, 0 \geq 0$$

$$\Delta_4 = 0 \geq 0$$

pos. semidefinite

(6 2-minors, 4 3-minors,  
1 4-minor = determinant to compute!)



## ② Unconstrained optimization in $n$ vars.

max/min  $f(x_1, \dots, x_n)$  (no constraints)  
"  $f(\underline{x})$

max = global max  
min = global min

Method:

① Find all stationary pts:

$f'_1 = f'_2 = \dots = f'_n = 0$  FOC

② Compute the Hessian matrix

$$H(f) = \begin{pmatrix} f''_{x_1x_1} & f''_{x_1x_2} & \dots & f''_{x_1x_n} \\ \vdots & \vdots & \ddots & \vdots \\ f''_{x_nx_1} & f''_{x_nx_2} & \dots & f''_{x_nx_n} \end{pmatrix}$$

first order cond.

$n \times n$  Symmetric matrix

Second derivative test:

and classify the stationary pts  $\underline{x}^*$ :

$H(f)(\underline{x}^*)$  pos. defn.  $\Rightarrow \underline{x}^*$  is local min  
 $H(f)(\underline{x}^*)$  neg. defn.  $\Rightarrow \underline{x}^*$  is local max  
 $H(f)(\underline{x}^*)$  indefinite  $\Rightarrow \underline{x}^*$  is saddle pt

↑  
true if  $f$  is "nice",  
i.e.  $C^2$  = all second order partial derivatives exist and are cont.

inconclusive if pos. semidefn. but not pos. defn.  
neg. — | — neg. — | —

Ex:  $f(x,y) = x^3 - 3xy + y^3$

$f'_x = 3x^2 - 3y = 0$

$3x^2 = 3y \quad y = x^2$

$f'_y = -3x + 3y^2 = 0$

$-3x + 3 \cdot (x^2)^2 = 0$

$-3x + 3x^4 = 0$

$x=0: y=0 \rightarrow (0,0)$

$-3x(1 - x^3) = 0$

$x=1: y=1 \rightarrow (1,1)$

$x=0$  or  $x^3=1$   
 $x=1$

Stat. points:  $(0,0), (1,1)$

$$f(x,y) = x^3 - 3xy + y^3$$

$$f'_x = 3x^2 - 3y$$

$$f'_y = -3x + 3y^2$$

$$f''_{xx} = 6x$$

$$f''_{xy} = -3$$

$$f''_{yx} = -3$$

$$f''_{yy} = 6y$$

$$H(f) = \begin{pmatrix} 6x & -3 \\ -3 & 6y \end{pmatrix}$$

Stat. pt: (0,0), (1,1)

Classification as local max, local min or saddle pts

$$(x,y)=(1,1): H(f)(1,1) = \begin{pmatrix} 6 & -3 \\ -3 & 6 \end{pmatrix} = \begin{pmatrix} A & B \\ B & C \end{pmatrix}$$

$$D_1 = 6 > 0$$

$$D_2 = 36 - 9 = 27 > 0$$

$\Downarrow$   
(1,1) is local min.  $f(1,1) = -1$   
 $H(f)(1,1)$  pos. defn.

$$(x,y)=(0,0): H(f)(0,0) = \begin{pmatrix} 0 & -3 \\ -3 & 0 \end{pmatrix}$$

$$\left. \begin{matrix} D_1 = 0 \\ D_2 = -9 \end{matrix} \right\} H(f)(0,0) \text{ indefinite}$$

$\Downarrow$   
(0,0) is saddle pt.

Defn:

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

Stationary pt:

$\underline{x}^*$  local max:

$$f(\underline{x}^*) \geq f(\underline{x}) \text{ for all } \underline{x} \text{ near } \underline{x}^*$$

$\underline{x}^*$  local min:

$$f(\underline{x}^*) \leq f(\underline{x}) \text{ for all } \underline{x} \text{ near } \underline{x}^*$$

$\underline{x}^*$  saddle pt:

otherwise

Max/min = global max/min:

global max/min  $\Rightarrow$  local max/min  $\Rightarrow$  stationary pt.

$$\text{Ex: } f(x,y) = x^3 - 3xy + y^3$$

$(x,y)=(1,1)$  may be global min  
no global max.

In fact, no global min either.

$$f(-2,0) = -8 < -1$$

### ③ Convex and concave functions

f convex: any local min is a global min  
any stationary pt. is a global min



f concave: any stationary pt is a global max



Defn:

f is convex if



$\iff H(f)(\underline{x})$  is pos.  
semidefinite for all  $\underline{x}$ .

f is concave if



$\implies H(f)(\underline{x})$  is neg.  
semidefinite for all  $\underline{x}$ .

Ex:  $H(f) = \begin{pmatrix} 6x & -3 \\ -3 & 6y \end{pmatrix}$

$D_1 = 6x$

$D_2 = 36xy - 9$



## General defn. in full details:

$f$  is convex if :



For any two points on the graph of  $f$ , the line segment joining these pts are on or over the graph of  $f$ .

$f$  is concave if :

For any two points on the graph of  $f$ , the line segment joining these pts are on or under the graph of  $f$ .

These defn. can be used in all cases. When  $f$  is a nice function with derivatives ( $f$  is  $C^2$ ), then we use  $H(f)$  to test if  $f$  is convex/concave.

Ex:  $f(x,y) = e^{2x-3y}$

$$f'_x = 2 \cdot e^{2x-3y}$$

$$f'_y = -3 \cdot e^{2x-3y}$$

$$\Delta_1 = 4e^4, 9e^4 > 0$$

$$\Delta_2 = 0$$

pos. semidefn. for all  $x \Rightarrow f$  is convex

$$u = 2x - 3y$$



$$\Rightarrow H(f) = \begin{pmatrix} 4e^{2x-3y} & -6e^{2x-3y} \\ -6e^{2x-3y} & 9e^{2x-3y} \end{pmatrix} = \begin{pmatrix} 4e^u & -6e^u \\ -6e^u & 9e^u \end{pmatrix}$$

$$\Delta_1 = 4e^u > 0$$

$$\Delta_2 = 36e^{2u} - 36e^{2u} = 0 \geq 0$$

## An Example

Let  $f(x,y) = x^2y^3 + y^2 - 2y$ . Then  $f$  has just one stationary pt, which is a local min. However,  $f$  has no global min.

$$f'_x = 2xy^3 = 0$$

$$f'_y = 3x^2y^2 + 2y - 2 = 0$$

FOC: ~~1~~  $x=0$  or  $y=0$

If  $x=0$ , then (2) gives

$$2y - 2 = 0 \Rightarrow \underline{y=1}$$

If  $y=0$ , then (2) gives

$$-2 = 0 \quad \text{no solution}$$

$$H(f) = \begin{pmatrix} 2y^3 & 6xy^2 \\ 6xy^2 & 6x^2y + 2 \end{pmatrix}$$

$$H(f)(0,1) = \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \quad D_1 = 2 > 0$$

$$D_2 = 4 > 0$$

pos. defn.  $\Rightarrow (0,1)$  local min

Conclusion:  $(0,1)$  is the only stationary pt, with  $\underline{f(0,1) = -1}$

But  $(x,y) = (0,1)$  with  $f(0,1) = -1$  is not global min

For example,

$$f(3,-1) = -9 + 1 + 2 = -6 < -1$$

Conclusion:  $f$  has no global min even if  $(0,1)$  is local min and this is the only stationary point.