

# LECTURE 7

GKA 6035

EIVIND EKIRSEN, OCT 3<sup>RD</sup> 2011

## REVIEW + EXTRA MATERIAL: CONVEX/CONCAVE FUNCTIONS

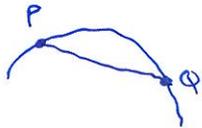
Assume that  $f(\underline{x}) = f(x_1, x_2, \dots, x_n)$  is defined on a convex set  $S = D_f$  in  $\mathbb{R}^n$ .

### DEFINITION:

$f$  convex on  $S \iff$  for any points  $P, Q$  on the graph of  $f$  the line segment  $[P, Q]$  is never under the graph



$f$  concave on  $S \iff$  for any points  $P, Q$  on the graph of  $f$ , the line segment  $[P, Q]$  is never over the graph



$S$  must be convex set, otherwise defn. of convex/concave functions will not make sense

$\mathbb{R}^n =$  all points  $\underline{x} = (x_1, \dots, x_n)$  in  $n$ -dim. space

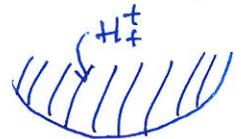
### Properties:

- (a)  $f$  convex  $\iff -f$  concave
- (b)  $f, g$  convex,  $a, b \geq 0 \implies af + bg$  convex  
 $f, g$  concave,  $a, b \geq 0 \implies af + bg$  concave

- (c)  $f$  convex function  $\iff H_f^+$  is a convex set  
 $f$  concave function  $\iff H_f^-$  is a convex set

Ex:  $f$  is convex

$$f = \underbrace{x^2 + y^2}_{\text{convex}} + \underbrace{x + y}_{\text{convex}}$$



= all points over or on the graph of  $f$



= all points under or on the graph of  $f$



### Useful result:

Let  $f$  be a function defined on a convex set  $S$ , and assume that  $f$  is continuous on  $S$  and  $C^2$  on the interior of  $S$ . Then we have:

- (a)  $f$  is convex on  $S \iff H(f)(\underline{x})$  is positive semidefinite for all interior pts  $\underline{x}$  in  $S$
- (b)  $f$  is concave on  $S \iff H(f)(\underline{x})$  is negative semidefinite for all interior points  $\underline{x}$  in  $S$

interior point of  $S =$  point in  $S$  that is not on the boundary

Ex:  $f(x,y) = xy$  defined on  $S = \{(x,y) : x \geq 0, y \geq 0\}$

Is  $f$  convex or concave?

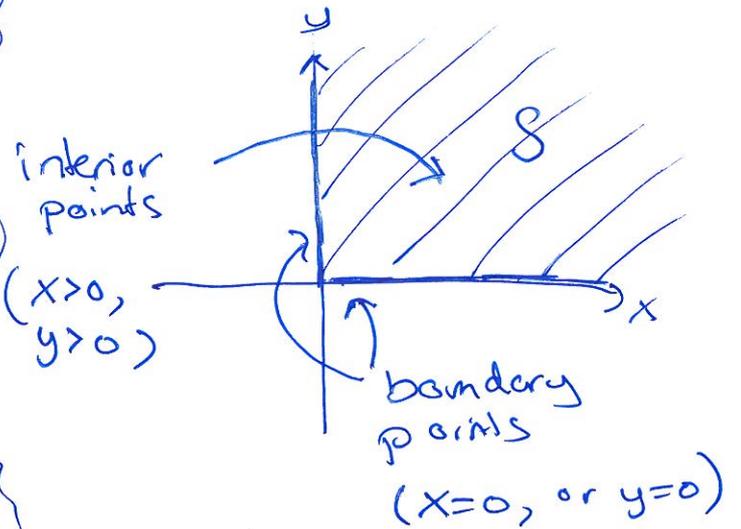
$$f'_x = y$$

$$f'_y = x$$

$$H(f) = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

$$\Delta_1 = 0, 0$$

$$\Delta_2 = -1$$



Condition for convexity:

$$\Delta_1 \geq 0, \Delta_2 \geq 0$$

for all points  $x > 0, y > 0$

not convex

Concavity:

$$\Delta_1 \leq 0, \Delta_2 \geq 0$$

for all points  $x > 0, y > 0$

not concave

Ex:  $f(x,y,z) = xyz$  defined on  $S = \{(x,y,z) : x \geq 0, y \geq 0, z \geq 0\}$

$$f'_x = yz$$

$$f'_y = xz$$

$$f'_z = xy$$

$$H(x) = \begin{pmatrix} 0 & z & y \\ z & 0 & x \\ y & x & 0 \end{pmatrix}$$

$$\Delta_1 = 0, 0, 0$$

$$\Delta_2 = -z^2, -x^2, -y^2$$

$$\Delta_3 = -z(-xy) + y(zx)$$

$$= 2xyz$$

Convex:  $\Delta_1 \geq 0, \Delta_2 \geq 0, \Delta_3 \geq 0$  for all  $x > 0, y > 0, z > 0$

$-z^2 < 0 \Rightarrow$  not convex

Concave:  $\Delta_1 \leq 0, \Delta_2 \geq 0, \Delta_3 \neq 0$  ——— || ———

$-z^2 < 0 \Rightarrow$  not concave

## Plan: Lecture 7

- ① Extremal points
- ② Lagrange problems

} [FMEA] 3.1-3.3  
(except envelope thm.)

Keep in mind: We want to solve the following problems:

Ⓐ  $\max/\min f(x_1, \dots, x_n)$

Unconstrained optimization  
( $S = D_f = \mathbb{R}^n$ )

Ⓑ  $\max/\min f(x_1, \dots, x_n)$

subject to  $\left\{ \begin{array}{l} \text{one or} \\ \text{more} \\ \text{equality/ineq.} \\ \text{constraints} \end{array} \right.$

Constrained optimization

( $S$  is the subset of  $\mathbb{R}^n$  of points that satisfy the constraints)

### ① Extremal points:

We assume that all functions are  $C^2$ .

Definition:  $f(x_1, \dots, x_n)$  a function defined on  $S$

$\underline{x}^*$  is a global maximum for  $f$  if

$\underline{x}^* \in S$  and  $f(\underline{x}^*) \geq f(\underline{x})$  for all  $\underline{x} \in S$

$\underline{x}^*$  is a global minimum for  $f$  if

$\underline{x}^* \in S$  and  $f(\underline{x}^*) \leq f(\underline{x})$  for all  $\underline{x} \in S$

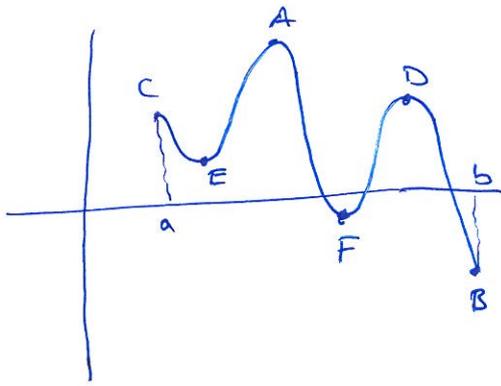
$\underline{x}^*$  is a local maximum for  $f$  if

$\underline{x}^* \in S$  and  $f(\underline{x}^*) \geq f(\underline{x})$  for all  $\underline{x} \in S$  close to  $\underline{x}^*$

$\underline{x}^*$  is a local minimum for  $f$  if

$\underline{x}^* \in S$  and  $f(\underline{x}^*) \leq f(\underline{x})$  for all  $\underline{x} \in S$  close to  $\underline{x}^*$

Ex:  $f$  defined on  $[a, b]$   
with graph



A: global max

B: global min

C, A, D: local max

E, F, B: local min

Definition:  $f(x_1, \dots, x_n)$  defined on  $S$

A stationary point  $\underline{x}^*$  is a point in the interior of  $S$  such that

$$f'_1(\underline{x}^*) = f'_2(\underline{x}^*) = \dots = f'_n(\underline{x}^*) = 0$$

Ex:  $f(x, y) = 2x - y - x^2 + xy - y^2$  defined on  $S = \mathbb{R}^2$

$$f'_x = 2 - 2x + y = 0$$

$$f'_y = -1 + x - 2y = 0$$

$$\begin{aligned} 2x - y &= 2 \\ -x + 2y &= -1 \end{aligned} \quad \begin{matrix} \uparrow \\ \downarrow \end{matrix} \cdot 2$$

$$\begin{aligned} 3y &= 0 \Rightarrow y = 0 \\ x &= 1 \end{aligned}$$

Stationary pts: (1, 0)

(1, 0) is an interior point of  $S = \mathbb{R}^2$

Thm:  $f(x_1, \dots, x_n)$  defined on  $S$

If  $\underline{x}^*$  is a (local or global) extremal point in the interior of  $S$ , then  $\underline{x}^*$  is a stationary point.

(local or global)  
extremal point =  
(local or global)  
min or max

Conclusion:

A local or global extremal point of  $f$  is either

- i) stationary point (in the interior)
- ii) boundary point

Ex:  $f(x,y) = 2x - y - x^2 + xy - y^2$  defn. on  $S = \mathbb{R}^2$

- Boundary pts: none

- Stationary pts:  $\underline{x} = (1, 0)$

Convex/concave functions:

$f(\underline{x})$  defined on  $S$

~~Ex~~

$\underline{x}^*$   $\left\{ \begin{array}{l} \text{interior} \\ \text{stationary} \\ \text{point} \end{array} \right.$

$f$  convex  $\Rightarrow \underline{x}^*$  global min

$f$  concave  $\Rightarrow \underline{x}^*$  global max

Ex:  $\left. \begin{array}{l} f'_x = 2 - 2x + y \\ f'_y = -1 + x - 2y \end{array} \right\}$

$$H(f) = \begin{pmatrix} -2 & 1 \\ 1 & -2 \end{pmatrix}$$

$$D_1 = -2 < 0$$

$$D_2 = 3 > 0$$

} negative  
definite  
for all  $\underline{x}$

$\Downarrow$

$f$  is concave

Conclusion:  $\underline{x}^* = (1, 0)$  is a global maximum

# Classification of local extremal points

Thm:  $f$  defined on  $S$ ,  $\underline{x}^*$  interior stationary point

$$\begin{cases} H(f)(\underline{x}^*) \text{ pos. definite} \implies \underline{x}^* \text{ local minimum} \\ H(f)(\underline{x}^*) \text{ neg. definite} \implies \underline{x}^* \text{ local maximum} \\ H(f)(\underline{x}^*) \text{ indefinite} \implies \underline{x}^* \text{ is neither local min.} \\ \hspace{15em} \text{nor local max.} \\ \hspace{15em} \text{(saddle point)} \end{cases}$$

Second derivative test

Remark:

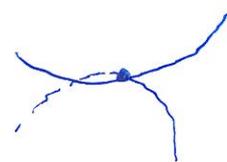
\* A saddle point is a stationary point that is neither local min nor local max.

\* If  $H(f)(\underline{x}^*)$  is

- ① pos. semidefinite but not positive definite

or

- ② neg. semidefinite but not negative definite



then the test is inconclusive.

Ex:  $f = x^2y - xy^2 - x + y$

$$f'_x = 2xy - y^2 - 1 = 0$$

$$2xy = y^2 + 1$$

$$f'_y = x^2 - 2xy + 1 = 0$$

$$x^2 - (y^2 + 1) + 1 = 0$$

$$x^2 - y^2 = 0$$

$$(x-y)(x+y) = 0$$

$$\underline{y=x} \text{ or } \underline{y=-x}$$

$y=x$ :  $\left. \begin{matrix} 2x^2 = x^2 + 1 \\ x^2 = 1 \end{matrix} \right\} \begin{matrix} (1,1) \\ (-1,-1) \end{matrix}$

$y=-x$ :  $\left. \begin{matrix} -2x^2 = x^2 + 1 \\ -3x^2 = 1 \end{matrix} \right\} \begin{matrix} \text{no} \\ \text{soln.} \end{matrix}$

Conclusion:  $f$  has two stationary pts:  $(1,1), (-1,-1)$ .

Classification:

$$\left. \begin{aligned} f'_x &= 2xy - y^2 - 1 \\ f'_y &= x^2 - 2xy + 1 \end{aligned} \right\} \Rightarrow H(f) = \begin{pmatrix} 2y & 2x - 2y \\ 2x - 2y & -2x \end{pmatrix}$$

In  $(1,1)$ :  $H(f)(1,1) = \begin{pmatrix} 2 & 0 \\ 0 & -2 \end{pmatrix} \quad \left. \begin{aligned} D_1 &= 2 \\ D_2 &= -4 \end{aligned} \right\} \text{indefinite}$

$\Rightarrow (1,1)$  is saddle point

In  $(-1,-1)$ :  $H(f)(-1,-1) = \begin{pmatrix} -2 & 0 \\ 0 & 2 \end{pmatrix} \quad \left. \begin{aligned} D_1 &= -2 \\ D_2 &= -4 \end{aligned} \right\} \text{indefinite}$

$\Rightarrow (-1,-1)$  is saddle point

Ex:  $f(x_1, x_2, x_3) = x_1^3 + x_2^3 + \frac{1}{3}x_3^3$  defined on  $\mathbb{R}^3$

$$\left. \begin{aligned} f'_{x_1} &= 3x_1^2 = 0 \\ f'_{x_2} &= 3x_2^2 = 0 \\ f'_{x_3} &= x_3^2 = 0 \end{aligned} \right\} \begin{array}{l} \text{Stationary} \\ \text{pts:} \\ \underline{(0,0,0)} \end{array} \quad H(f) = \begin{pmatrix} 6x_1 & 0 & 0 \\ 0 & 6x_2 & 0 \\ 0 & 0 & 2x_3 \end{pmatrix}$$

$$H(f)(0,0,0) = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \begin{array}{l} \text{positive semidefinite} \\ \text{negative semidefinite} \end{array}$$

$\Rightarrow$  test inconclusive

$$\left. \begin{array}{l} f(a,0,0) = a^3 > 0 \text{ if } a > 0 \\ a^3 < 0 \text{ if } a < 0 \end{array} \right\} \Rightarrow (0,0,0) \text{ saddle point.}$$



## How to solve Lagrange - problems:

Problem:

$$\max/\min f(x_1, \dots, x_n) \quad \text{subject to} \quad \begin{cases} g_1(x_1, \dots, x_n) = b_1 \\ \vdots \\ g_m(x_1, \dots, x_n) = b_m \end{cases}$$

i) Form the Lagrangian function

$$L(x_1, \dots, x_n; \lambda_1, \dots, \lambda_m) = f(x_1, \dots, x_n) - \lambda_1 \cdot g_1(x_1, \dots, x_n) - \lambda_2 \cdot g_2(x_1, \dots, x_n) - \dots - \lambda_m \cdot g_m(x_1, \dots, x_n)$$

Lagrange  
multipliers

ii) Solve the Lagrange equations:

$$\left. \begin{array}{l} \frac{dL}{dx_1} = 0 \\ \frac{dL}{dx_2} = 0 \\ \vdots \\ \frac{dL}{dx_n} = 0 \end{array} \right\} \begin{array}{l} \text{first order} \\ \text{equations} \\ (n \text{ equations}) \end{array}$$
  
$$\left. \begin{array}{l} g_1(x_1, \dots, x_n) = b_1 \\ \vdots \\ g_m(x_1, \dots, x_n) = b_m \end{array} \right\} \begin{array}{l} \text{constraints} \\ (m \text{ equations}) \end{array}$$

}  $\begin{array}{l} (m+n) \text{ equations} \\ \text{in} \\ (m+n) \text{ variables} \end{array}$

Ex: max/min  $f(x,y) = x+3y$  subj. to  $g(x,y) = x^2+y^2 = 10$

$$L(x,y;\lambda) = x+3y - \lambda \cdot (x^2+y^2)$$

$$L'_x = \begin{cases} 1 - \lambda \cdot 2x = 0 \\ 3 - \lambda \cdot 2y = 0 \\ x^2 + y^2 = 10 \end{cases}$$

3 eqn. in 3 var's  
(not linear)

$$x = \frac{1}{2\lambda}$$

$$y = \frac{3}{2\lambda}$$

( $\lambda \neq 0$  since  $\lambda = 0$  does not give solutions)

— || —

$$x^2 + y^2 = \left(\frac{1}{2\lambda}\right)^2 + \left(\frac{3}{2\lambda}\right)^2 = \frac{1+9}{(2\lambda)^2} = 10$$

$$\frac{10}{(2\lambda)^2} = 10 \Rightarrow (2\lambda)^2 = 1 \Rightarrow 2\lambda = \pm 1 \\ \Rightarrow \lambda = \pm \frac{1}{2}$$

Solutions:

$$\lambda = \frac{1}{2} \text{ gives } x=1, y=3 \Rightarrow (x,y;\lambda) = \underline{(1,3;1/2)}$$

$$\lambda = -\frac{1}{2} \text{ gives } x=-1, y=-3 \Rightarrow (x,y;\lambda) = \underline{(-1,-3;-1/2)}$$

How can we use these solutions to solve the max/min - problem?

Thm:

If  $(\underline{x}^*; \underline{\lambda}^*)$  is a solution of the Lagrange equations, then we may fix the specific  $\underline{\lambda}^*$  and consider

$L(x_1, \dots, x_n; \lambda_1^*, \dots, \lambda_m^*)$  as a function of  $x_1, x_2, \dots, x_n$

Then we have:

$L(\underline{x}; \underline{\lambda}^*)$  convex function in  $\underline{x} \Rightarrow \underline{x}^*$  solves the min - problem

$L(\underline{x}; \underline{\lambda}^*)$  concave function in  $\underline{x} \Rightarrow \underline{x}^*$  solves the max - problem

Ex: We look at the solutions  $(x, y; \lambda) = (1, 3; 1/2), (-1, -3; -1/2)$ .

For  $(x^*, y^*; \lambda^*) = (1, 3; 1/2)$ : We fix  $\lambda^* = 1/2$  and let  $x, y$  vary

$$L(x, y) = x + 3y - \frac{1}{2}(x^2 + y^2) \quad \text{is } \underline{\text{concave}}; \quad L'' = \begin{pmatrix} -1/2 & 0 \\ 0 & -1/2 \end{pmatrix}$$

Hessian

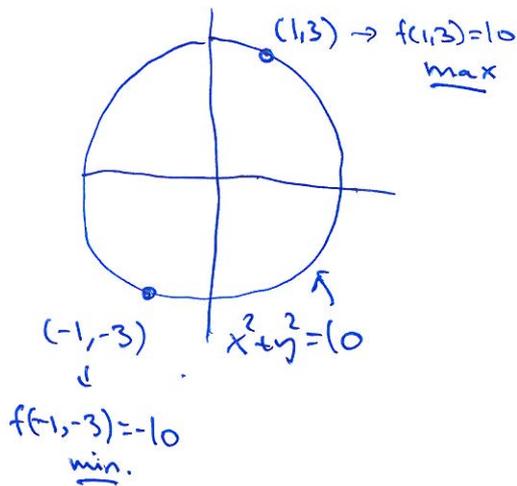
$\underline{x}^* = (x^*, y^*) = (1, 3)$  solves the max-problem;  $f(1, 3) = \underline{10}$  max value

For  $(x^*, y^*; \lambda^*) = (-1, -3; -1/2)$ : We fix  $\lambda^* = -1/2$  and let  $x, y$  vary

$$L(x, y) = x + 3y - (-1/2)(x^2 + y^2) = x + 3y + \frac{1}{2}(x^2 + y^2) \quad \text{is } \underline{\text{convex}}; \quad L'' = \begin{pmatrix} 1/2 & 0 \\ 0 & 1/2 \end{pmatrix}$$

Hessian

$\underline{x}^* = (x^*, y^*) = (-1, -3)$  solves the min-problem;  $f(-1, -3) = \underline{-10}$  min value



Conclusion:

max  $x + 3y$  subj. to  $x^2 + y^2 = 10$  is 10 at  $(1, 3)$   
 min  $x + 3y$  subj. to  $x^2 + y^2 = 10$  is -10 at  $(-1, -3)$

What if the functions are not convex or concave?

Consider the NDCQ (non-degenerate constraint qualification) for a point  $\underline{x}^*$  that is admissible:

$$\underline{\text{NDCQ}}: \quad \text{rk} \begin{pmatrix} \frac{\partial g_1}{\partial x_1}(\underline{x}^*) & \frac{\partial g_1}{\partial x_2}(\underline{x}^*) & \dots & \frac{\partial g_1}{\partial x_n}(\underline{x}^*) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial g_m}{\partial x_1}(\underline{x}^*) & \frac{\partial g_m}{\partial x_2}(\underline{x}^*) & \dots & \frac{\partial g_m}{\partial x_n}(\underline{x}^*) \end{pmatrix} = m$$

Ex: max/min  $x+3y$  subj. to  $x^2+y^2=10$

NDCQ:  $\text{rk} \begin{pmatrix} 2x & 2y \end{pmatrix} = 1$

Is NDCQ satisfied for all admissible points?

$(x,y)$  admissible  $\Leftrightarrow x^2+y^2=10$

$$\text{rk} \begin{pmatrix} 2x & 2y \end{pmatrix} = \begin{cases} 1, & x \neq 0 \text{ or } y \neq 0 \\ 0, & x=0 \text{ and } y=0 \end{cases}$$

Since  $(x,y)=(0,0)$  is not admissible ( $0^2+0^2 \neq 10$ ),  $\text{rk} \begin{pmatrix} 2x & 2y \end{pmatrix} = 1$  for all admissible points.

Thm:

If  $\underline{x}^*$  solves the min/max Lagrange problem, then one of the following conditions hold:

- i)  $(\underline{x}^*; \underline{\lambda})$  solves the Lagrange equations for some  $\underline{\lambda} = \lambda_1, \dots, \lambda_m$ .  
(and  $\underline{\lambda}$  is unique)
- ii)  $\underline{x}^*$  does not satisfy NDCQ

Conclusion:

We can make a list of possible candidates for max/min in a Lagrange problem, where we include both solutions of the Lagrange equations and admissible points that do not satisfy NDCQ.

Ex: In the example, if we choose not to use the method with convexity/concavity, we would:

(a) Make a list of candidate points:  $\{(1,3), (-1,-3)\}$

\*  $(1,3), (-1,-3)$  from Lagrange equations

\* no extra candidates since all admissible pts. satisfy NDCQ

(b) Argue that there must be max and min because of Extreme value thm.

(c) Compute  $f(1,3)=10$  and  $f(-1,-3)=-10$ , and conclude that  $(1,3)$  is max. and  $(-1,-3)$  is min.

I did not have time to go through the interpretation of the Lagrange multiplier. This will be done next week.