

Plan

- 1 Orthogonal diagonalization (continued from Lecture 5)
- 2 Unconstrained optimization
- 3 Convex and concave functions

Recall:

A $n \times n$ 1) An orthogonal diagonalization of A is a diagonalization $P^T A P = D$ such that P is an orthogonal matrix, i.e. $P^{-1} = P^T$.

$P = (v_1 | v_2 | \dots | v_n)$: $P^{-1} = P^T \iff \begin{cases} (a) v_i \cdot v_j = 0 \text{ for } i \neq j \\ (b) \|v_i\| = 1 \end{cases}$

ii) There is an orth. diag. of $A \iff A$ is symmetric

① Orthogonal diagonalization (cont'd)

Quadratic form in n variables: $f(\underline{x}) = \underline{x}^T A \underline{x}$ $\underline{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$ A $n \times n$ symm.

Fact: A has orth. diagonalization: $P^T A P = D$

Change of variables: $\underline{x} = P \underline{u}$ $| P^T$
 $P^T \underline{x} = \underline{u}$ $\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = P \cdot \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}$ or $\begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix} = P^T \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$

$$f(\underline{x}) = \underline{x}^T A \underline{x} = (P \underline{u})^T A (P \underline{u}) = \underline{u}^T \underbrace{P^T A P}_D \underline{u} = \underline{u}^T D \underline{u} = \lambda_1 u_1^2 + \lambda_2 u_2^2 + \dots + \lambda_n u_n^2$$

Ex: $f(x, y, z) = 4x^2 - 2xy - 6xz + 2y^2 - 2yz + 4z^2$

Eigenvalues: $-\lambda^3 + c_1 \lambda^2 - c_2 \lambda + c_3 = 0$
 $-\lambda^3 + 10\lambda^2 - 21\lambda + 0 = 0$

$$\underline{x} = \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

$$A = \begin{pmatrix} 4 & -1 & -3 \\ -1 & 2 & -1 \\ -3 & -1 & 4 \end{pmatrix}$$

$$\begin{cases} c_1 = \text{tr}(A) = 4 + 2 + 4 = 10 \\ c_2 = \text{sum of } 2 \times 2 \text{ minors} = 7 + 7 + 7 = 21 \\ c_3 = |A| = 0 \end{cases} \quad \begin{cases} -\lambda(\lambda^2 - 10\lambda + 21) \\ \lambda = 0 \quad \lambda_2 = 3 \quad \lambda_3 = 7 \end{cases}$$

$$R_1 + R_2 + R_3 = 0$$

Viete's formula:

$$\lambda^2 - a\lambda + b = 0$$

$\lambda = \lambda_1$ and λ_2 are the soln's

⇕

$$\lambda_1 + \lambda_2 = a, \lambda_1 \cdot \lambda_2 = b$$

Ex:

$$\lambda^2 - 10\lambda + 21 = 0$$

$$\lambda_1 + \lambda_2 = 10$$

$$\lambda_1 \cdot \lambda_2 = 21$$

Ex: (cont'd)

$$f(x,y,z) = 4x^2 - 2xy - 6xz + 2y^2 - 2yz + 4z^2 = \underline{0 \cdot u^2 + 3 \cdot v^2 + 7 \cdot w^2}$$

We immediately see that $f_{min} = 0$

How to compute P

$$F_0: \begin{pmatrix} 4 & -1 & -3 \\ -1 & 2 & -1 \\ -3 & -1 & 4 \end{pmatrix} \rightarrow \underline{v_1} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

$$F_3: \begin{pmatrix} 1 & -1 & -3 \\ -1 & -1 & -1 \\ -3 & -1 & 1 \end{pmatrix} \quad \underline{v_2} = \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix}$$

$$F_2: \begin{pmatrix} -3 & -1 & -3 \\ -1 & -5 & -1 \\ -3 & -1 & -3 \end{pmatrix} \quad \underline{v_3} = \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix}$$

(a) $\underline{v_i} \cdot \underline{v_j} = 0$ ($i \neq j$) → Always ok if $\underline{v_i}$ and $\underline{v_j}$ corr. to different eigenvalues

(b) $\|\underline{v_i}\| = 1$

$$\underline{v_1}' = \frac{1}{\|\underline{v_1}\|} \underline{v_1} = \frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

$$\underline{v_2}' = \frac{1}{\sqrt{6}} \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix}$$

$$\underline{v_3}' = \frac{1}{\sqrt{2}} \begin{pmatrix} 0 \\ 1 \\ -1 \end{pmatrix}$$

$$P = \begin{pmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{6}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & -\frac{2}{\sqrt{6}} & 0 \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

Change of variables:

$$\begin{pmatrix} u \\ v \\ w \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & -\frac{2}{\sqrt{6}} & 0 \\ -\frac{1}{\sqrt{3}} & 0 & \frac{1}{\sqrt{2}} \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

"PT"

$$\begin{aligned} u &= \frac{1}{\sqrt{3}}(x + y + z) \\ v &= \frac{1}{\sqrt{6}}(x - 2y + z) \\ w &= \frac{1}{\sqrt{2}}(-x + z) \end{aligned}$$

If $\underline{v_1}, \underline{v_2}$ is in E_2 and $\underline{v_1} \cdot \underline{v_2} = 0$:



$$\underline{v_2}' = \underline{v_2} - \text{Proj}_{\underline{v_1}}(\underline{v_2}) = \underline{v_2} - \frac{\underline{v_2} \cdot \underline{v_1}}{\|\underline{v_1}\|^2} \cdot \underline{v_1}$$

② Unconstrained optimization

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

Ex: $f(x, y, z) = 4x^2 - 2xy - 6xz + 2y^2 - 2yz + 4z^2$
 $= 0 \cdot u^2 + 3 \cdot v^2 + 7w^2$

$$f'_x = 8x - 2y - 6z$$

$$f'_y = -2x + 4y - 2z$$

$$f'_z = -6x - 2y + 8z$$

first order
partial derivatives

$$H(f) = \begin{pmatrix} f''_{xx} & f''_{xy} & f''_{xz} \\ f''_{yx} & f''_{yy} & f''_{yz} \\ f''_{zx} & f''_{zy} & f''_{zz} \end{pmatrix} = \begin{pmatrix} 8 & -2 & -6 \\ -2 & 4 & -2 \\ -6 & -2 & 8 \end{pmatrix}$$

Hessian
matrix

Fact: $H(f)$ is symmetric (if f is "nice")

Assume that f is "nice"
(C^2 , i.e. all partial derivatives ad second order partial derivatives exists and are cont.)

Method:

Candidate pts

① Find all stationary pts of f : $f'_x = f'_y = f'_z = 0$ (Foc)

Fact: If $\underline{x}^* = (x^*, y^*, z^*)$ is max/min, then it is stationary

Ex: $f = x^3 + y^3 + z^3 - 3x - 3y - 3z + 5$

$$f'_x = 3x^2 - 3 = 0 \quad x^2 = 1 \quad \boxed{x = \pm 1}$$

$$f'_y = 3y^2 - 3 = 0 \quad y^2 = 1 \quad \boxed{y = \pm 1}$$

$$f'_z = 3z^2 - 3 = 0 \quad z^2 = 1 \quad \boxed{z = \pm 1}$$

Stationary pts:

$$(1, 1, 1) \quad f = -1 \quad \text{min?}$$

$$(1, 1, -1), (1, -1, 1), (-1, 1, 1) \quad f = 3$$

$$(1, -1, -1), (-1, 1, -1), (-1, -1, 1) \quad f = 7$$

$$(-1, -1, -1) \quad f = 11 \quad \text{max?}$$

Definitions:

$f(\underline{x}) = f(x_1, \dots, x_n)$ function in n variables

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

Defn.

\underline{x}^* is a maximum pt (global maximum point) for f if $f(\underline{x}^*) \geq f(\underline{x})$ for all points \underline{x} , and $f_{\max} = f(\underline{x}^*)$ is then the maximum value of f

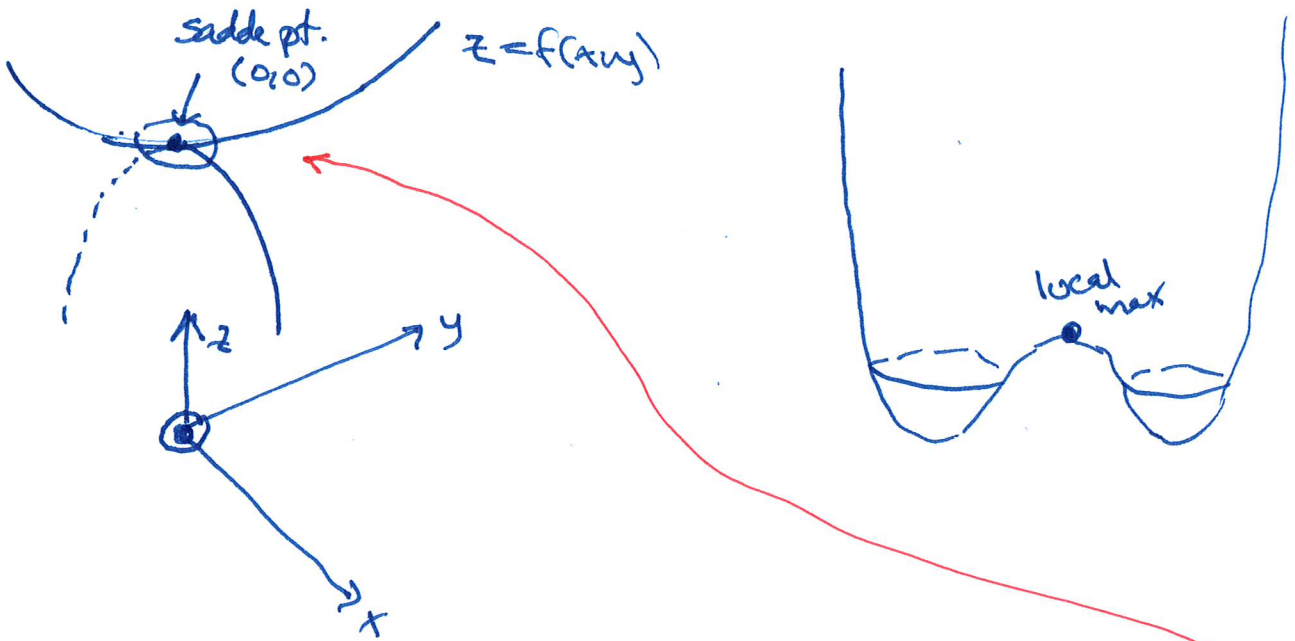
\underline{x}^* is a local maximum pt. for f if $f(\underline{x}^*) \geq f(\underline{x})$ for all points \underline{x} close to \underline{x}^*

\underline{x}^* is a minimum pt (global minimum pt) for f if $f(\underline{x}^*) \leq f(\underline{x})$ for all points \underline{x} , and $f_{\min} = f(\underline{x}^*)$ is then the minimum value of f

\underline{x}^* is a local minimum pt for f if $f(\underline{x}^*) \leq f(\underline{x})$ for all pts. \underline{x} close to \underline{x}^* .

\underline{x}^* is a saddle pt for f if \underline{x}^* is a stationary pt. of f that is neither a local max nor a local min.

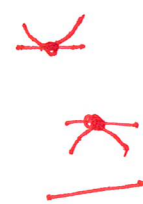
The range V_f of f is the set of all function values $f(\underline{x})$ of f , that is; $V_f = \{f(\underline{x}) : \underline{x} \text{ in } D_f = \text{domain of defn. of } f\}$.



② Classify the stationary points as local max, local min, or saddle pts using the second derivative test:

Result: Let x^* be a stationary pt of f . Then we have:

$H(f)(x^*)$	pos. defn.	\Rightarrow	x^*	local min
$H(f)(x^*)$	neg defn.	\Rightarrow	x^*	local max
$-11-$	indefn.	\Rightarrow	x^*	saddle pt.



Ex: (cont'd) $f = x^3 + y^3 + z^3 - 3x - 3y - 3z + 5$

$f'_x = 3x^2 - 3$
 $f'_y = 3y^2 - 3$
 $f'_z = 3z^2 - 3$

$$H(f) = \begin{pmatrix} 6x & 0 & 0 \\ 0 & 6y & 0 \\ 0 & 0 & 6z \end{pmatrix}$$

$(1,1,1): H(f)(1,1,1) = \begin{pmatrix} 6 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 6 \end{pmatrix}$ pos. defn. \downarrow $(1,1,1)$ local min
 $(-1,-1,-1): = \begin{pmatrix} -6 & & \\ & -6 & \\ & & -6 \end{pmatrix}$ neg. defn. \downarrow $(-1,-1,-1)$ local max
 all other stat. pts } saddle pts

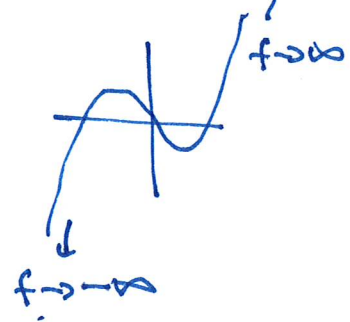
③ Determine if best candidate for max/min is actually max/min.

Ex: $f = x^3 + y^3 + z^3 - 3x - 3y - 3z + 5$

$f(1,1,1) = -1$ local min \rightarrow Best cand. for min Not min

$f(-1,-1,-1) = 11$ local max \rightarrow Best cand. for max Not max

Min: Try $f(x,0,0) = x^3 - 3x + 5$
 $f(-10,0,0) = -1000 + 30 + 5 = -965$
 $f(10,0,0) = 1000 - 30 + 5 = 975$



Concl: No (global) max/min.

③ Convex / concave functions



Convex



Concave

Criterion for convex / concave function:

If $H(f)(\underline{x})$ is positive semidef. for all \underline{x} , then f is convex
 If $H(f)(\underline{x})$ is negative semidef. for all \underline{x} , then f is concave

In fact:

$H(f)(\underline{x})$ pos. semidef. $\iff f$ convex
 for all \underline{x}
 $H(f)(\underline{x})$ neg. semidef. $\iff f$ concave
 — || —

Ex: $f = x^2 + y^2 + z^2 - 3x - 3y - 3z + 5$

$H(f) = \begin{pmatrix} 6x & 0 & 0 \\ 0 & 6y & 0 \\ 0 & 0 & 6z \end{pmatrix}$ pos. defn. at $(1,1,1)$
 neg. defn. at $(-1,-1,-1)$

not convex,
 not concave

$f(x,y,z) = \begin{pmatrix} 4x^2 - 2xy - 6xz \\ + 2y^2 - 2yz + 4z^2 \end{pmatrix} = \underline{x}^T A \underline{x}$

$H(f) = 2A = \begin{pmatrix} 8 & -2 & -6 \\ -2 & 4 & -2 \\ -6 & -2 & 8 \end{pmatrix}$

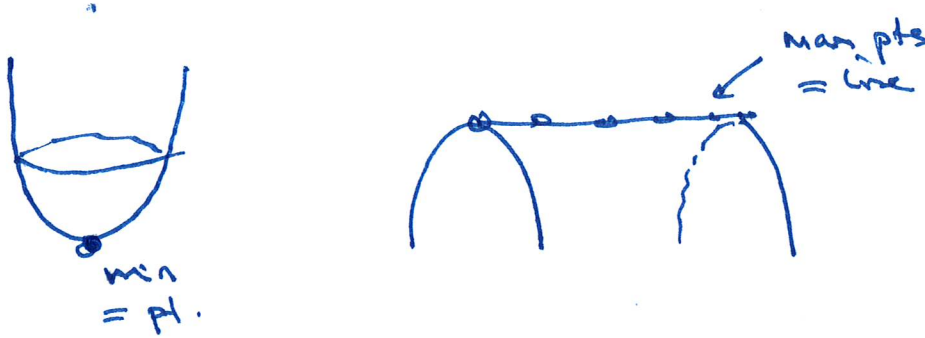
A pos. semidef. $\lambda = 0, 3, 7$

$H(f) = 2A$ pos. semidef. $\lambda = 0, 6, 14$

f convex

Result: convex optimization

i) If f is convex and x^* stationary pt of f , then it is min
 if —||— concave —||— then it is max



Ex: $f(x, y, z) = 4x^2 - 2xy - 6xz + 2y^2 - 2yz + 4z^2 + 14x - 14z + 5$ } = $\underline{x}^T \underline{A} \underline{x} + \underline{B} \underline{x} + C$

$$\underline{B} = (14 \ 0 \ -14)$$

$$\underline{B} \underline{x} = (14 \ 0 \ -14) \cdot \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

In this case:

$$H(x) = 2A$$

$$f'(\underline{x}) = \begin{pmatrix} f'_1 \\ f'_2 \\ \vdots \\ f'_n \end{pmatrix} = 2A \underline{x} + \underline{B}^T$$

More on defn. of convex/concave fn's:

Let $f(x_1, x_2, \dots, x_n)$ be a fn. defined on a subset D_f of \mathbb{R}^n . Then D_f is called a convex set if the line segment $[P, Q]$ from a point $P = (p_1, \dots, p_n)$ in D_f to a pt $Q = (q_1, \dots, q_n)$ in D_f is contained in D_f for all P, Q in D_f .

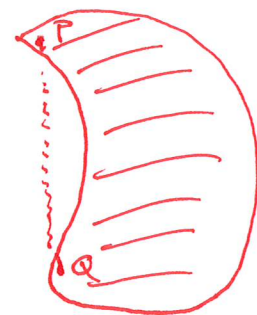
Ex:



convex



not convex

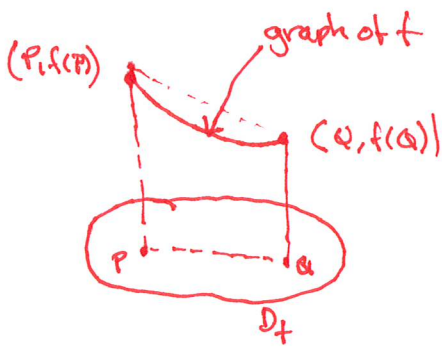


not convex

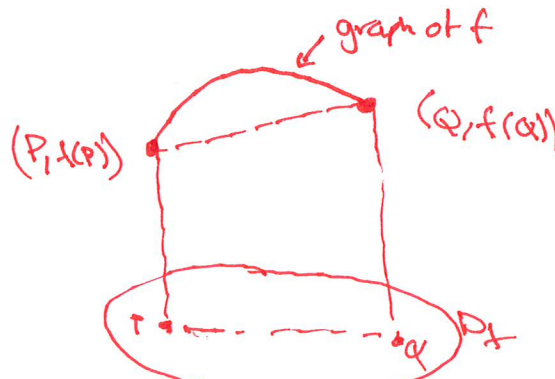
To define whether f is convex/concave, D_f must be a convex set.

Defn: Let $f(x)$ be defined on a convex set D_f .

We say that f is convex (concave) if for any pts P, Q in D_f , the line segment from $(P, f(P))$ to $(Q, f(Q))$ lies on or above (on or below) the graph of f .



convex



concave

Ex: $f(x,y,z) = 4x^2 - 2xy - 6xz + 7y^2 - 2yz + 4z^2 + 14x - 14z + 3$
 $= \underline{x^T A x} + \underline{B x} + C$

$$A = \begin{pmatrix} 4 & -1 & -3 \\ -1 & 2 & -1 \\ -3 & -1 & 4 \end{pmatrix}$$

$$B = (14 \ 0 \ -14)$$

$$C = (3)$$

Stat. pts: $f'(x) = \begin{pmatrix} f'_x \\ f'_y \\ f'_z \end{pmatrix} = 2Ax + B^T = \underline{0}$
 $2Ax = -B^T$
 $Ax = -\frac{1}{2}B^T$

$$\begin{array}{c} A \\ \downarrow \\ \left(\begin{array}{ccc|c} 4 & -1 & -3 & -7 \\ -1 & 2 & -1 & 0 \\ -3 & -1 & 4 & 7 \end{array} \right) \end{array}$$

$$\begin{aligned} -x + 2y - z &= 0 \\ 7y - 7z &= -7 \end{aligned}$$

$$\Rightarrow 7y = 7z - 7 \Rightarrow y = z - 1$$

$$-x + 2(z - 1) - z = 0 \Rightarrow x = z - 2$$

$$\begin{array}{c} \downarrow \\ \left(\begin{array}{ccc|c} \textcircled{-1} & 2 & -1 & 0 \\ 4 & -1 & -3 & -7 \\ -3 & -1 & 4 & 7 \end{array} \right) \begin{array}{l} \uparrow 4 \\ \downarrow -3 \end{array} \end{array}$$

$$\begin{array}{c} \downarrow \\ \left(\begin{array}{ccc|c} \textcircled{-1} & 2 & -1 & 0 \\ 0 & \textcircled{7} & -7 & -7 \\ 0 & -7 & 7 & 7 \end{array} \right) \end{array}$$

Stat. pts: $(x,y,z) = (z-2, z-1, z)$, (z free)

convex/concave: $H(f) = 2A$, $A = \begin{pmatrix} 4 & -1 & -3 \\ -1 & 2 & -1 \\ -3 & -1 & 4 \end{pmatrix}$, f convex

$$\left. \begin{array}{l} D_1 = 4 \\ D_2 = 7 \\ D_3 = 0 \end{array} \right\} \Rightarrow \text{A pos. semidef. by REC (rk A = 2)}$$

$\Rightarrow (z-2, z-1, z)$ are min. pts of f

$$f(z-2, z-1, z) = f(-2, -1, 0) = 16 - 4 + 2 - 28 + 3 = \underline{\underline{-11}} \quad (z=0)$$

$$\left. \begin{array}{l} f_{\min} = \underline{\underline{-11}} \quad \text{min. value} \\ \text{at} \\ (x,y,z) = (z-2, z-1, z) \\ \text{for all } z \end{array} \right\}$$

min. pts