

# Lecture 31: Extrema of multivariable functions

Setup  $\vec{a} \in \mathcal{D} \xrightarrow{f} \mathbb{R}$  function of  $n$  variables  
point  $\mathbb{R}^n$  subset  $(x_1, \dots, x_n)$

Definition:  $f$  has a (global/absolute) maximum at  $\vec{a}$  <sup>minimum</sup>  
 if  $f(\vec{a}) \geq f(\vec{x})$  for all  $\vec{x} \in \mathcal{D}$ .

(Then  $f(\vec{a})$  is called the maximum value.) <sup>minimum</sup>

$f$  has a relative/local maximum at  $\vec{a}$  <sup>minimum</sup>

if  $f|_{B(\vec{a}, \epsilon) \cap \mathcal{D}}$  has a maximum at  $\vec{a}$  <sup>minimum</sup>

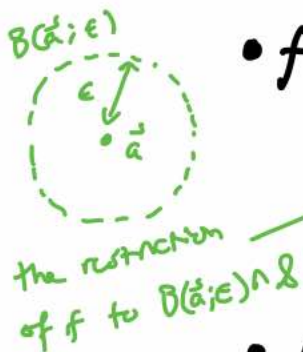
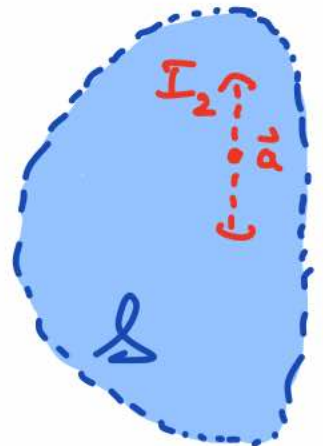
for  $\epsilon > 0$  sufficiently small.

• an extremum (global or local) of  $f$  means a maximum or minimum of  $f$  (global or local)

Theorem 1: Assume  $\vec{a} \in \text{int}(\mathcal{D})$ . If  $f$  has a local extremum at  $\vec{a}$ , then  $\vec{\nabla} f(\vec{a}) = \vec{0}$ , i.e.  $\vec{a}$  is a stationary point of  $f$ .

Proof: Write  $\vec{a} = (a_1, \dots, a_n)$ , and restrict  $f$  to the interval  $I_j = \{(a_1, \dots, x_j, \dots, a_n) \mid a_j - \epsilon < x_j < a_j + \epsilon\}$ :

This is a function of a single variable  $x_j$ , call it  $F(x_j) := f(a_1, \dots, x_j, \dots, a_n)$ , with max/min at  $(x_j =) a_j$ .



A theorem from Math 203 says that  $F'(a_j) = 0$ .

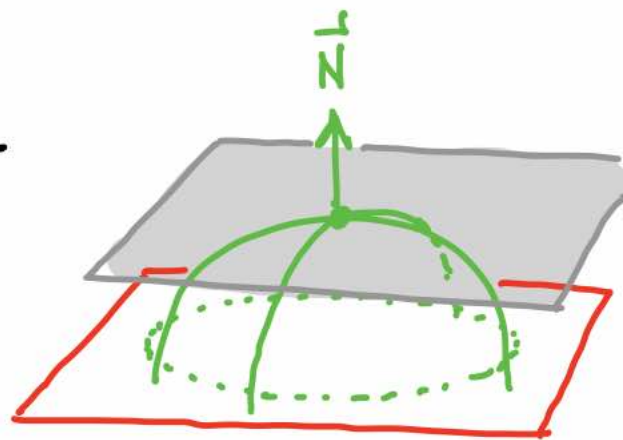
But  $F'(a_j)$  is  $\frac{\partial f}{\partial x_j}(\vec{a})$ , which is therefore 0 for each  $j$ .  $\square$

Remarks: (A) At a stationary point, the tangent plane to the graph of

$$(*) \quad z = f(x_1, \dots, x_n)$$

in  $\mathbb{R}^{n+1}$  is  $z = f(\vec{a})$  ("horizontal").

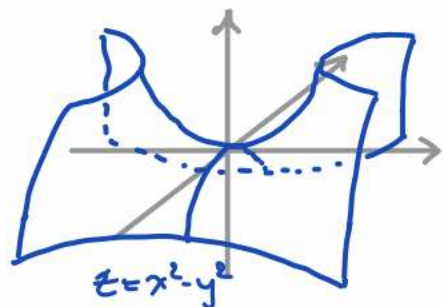
Why? The normal to (\*) is  $\vec{\nabla}(z - f(\vec{x})) = (-\vec{\nabla}f(\vec{a}), 1) = (\vec{0}, 1)$ .



(B) The converse to Theorem 1 is FALSE:

$f(x, y) = x^2 - y^2$  has  $\vec{\nabla}f(0, 0) = \vec{0}$ , but is

(instead of  $x_1, x_2$ ) concave  $\begin{cases} \text{up} \\ \text{down} \end{cases}$  in the  $\begin{cases} x \\ y \end{cases}$ -direction.



A saddle-point is a stationary point which is not a local extremum.

**EXAMPLE**

$$z = f(x, y) = x^2 + 4xy + y^2 \quad (\text{what can we say about it?})$$

- $xz$ -cross-section:  $f(x, 0) = x^2 \rightsquigarrow$  concave up
- $yz$ -cross-section:  $f(0, y) = y^2 \rightsquigarrow$  also concave up

$$\bullet \text{ Also } D_{\hat{u}}f = \vec{\nabla}f \cdot \hat{u} = u_x f_x + u_y f_y = u_x(2x+4y) + u_y(2y+4x)$$

is 0 at  $\vec{0}$ , so  $(0, 0)$  is certainly a stationary point of  $f$   
 $\rightsquigarrow$  suggests local minimum at  $(0, 0)$ ? Just to be sure, let's

- differentiate twice in the "SE-direction":

$$D_{\hat{u}}^2 f = D_{\hat{u}}(D_{\hat{u}}f) = D_{\hat{u}} \left\{ \frac{\sqrt{2}}{2} (2x+4y - (2y+4x)) \right\} = D_{\hat{u}} \left\{ \sqrt{2} (y-x) \right\}$$

$$= \vec{\nabla}(\sqrt{2}(y-x)) \cdot \frac{\sqrt{2}}{2}(1, -1) = (-\sqrt{2}, \sqrt{2}) \cdot \frac{1}{\sqrt{2}}(1, -1) = \underline{\underline{-2}} (!!)$$

Moral: finding the concavities in the  $x$ - &  $y$ -directions may not tell you much about the directions of greatest or least concavity, or what these greatest & least concavities are!

To explore further, let  $\vec{a}$  be a stationary point of a function  $f(x, y)$ , and set  $\hat{u} = (\overset{u_x}{\cos \theta}, \overset{u_y}{\sin \theta})$ . Then

$$\begin{aligned} D_{\hat{u}}^2 f &= D_{\vec{a}} (u_x f_x + u_y f_y) = \vec{\nabla} (u_x f_x + u_y f_y) \cdot \hat{u} \\ &= (u_x f_{xx} + u_y f_{yx}, u_x f_{xy} + u_y f_{yy}) \cdot (u_x, u_y) \\ &= (u_x, u_y) \begin{pmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{pmatrix} \begin{pmatrix} u_x \\ u_y \end{pmatrix} =: \hat{u}^T H \hat{u} = \hat{u} \cdot H \hat{u}, \end{aligned}$$

where the  $2 \times 2$ -matrix-valued function  $H(x, y)$  is called the Hessian of  $f$ . Write  $H_0$  for  $H(\vec{a})$ .

So  $\hat{u} \cdot H \hat{u}$  is the concavity at  $\vec{a}$  in the direction  $\hat{u}$ , which depends on  $\theta$ . We want the directions of extreme concavity:

$$\begin{aligned} 0 &= \frac{d}{d\theta} \hat{u} \cdot H_0 \hat{u} = \hat{u}' \cdot H_0 \hat{u} + \hat{u} \cdot H_0 \hat{u}' = 2 \hat{u}' \cdot H_0 \hat{u} \\ \Rightarrow \hat{u}' \perp H_0 \hat{u} &\stackrel{\uparrow}{\Rightarrow} \hat{u} \parallel H_0 \hat{u} \Rightarrow \underline{\hat{u} \text{ is an eigenvector of } H_0!} \end{aligned}$$

If  $\hat{u} = \vec{v} :=$  eigenvector w/ eigenvalue  $\lambda$ , then

$$D_{\hat{u}}^2 f = \vec{v} \cdot H_0 \vec{v} = \vec{v} \cdot \lambda \vec{v} = \lambda \|\vec{v}\|^2 = \underline{\lambda \text{ is the concavity!}}$$

$$\uparrow \hat{u}' = \frac{d}{d\theta} (\cos \theta, \sin \theta) = (-\sin \theta, \cos \theta) \text{ is } \perp \text{ to } \hat{u} = (\sin \theta, \cos \theta)$$

Writing  $\lambda_1 \leq \lambda_2$  for the 2 eigenvalues, these are the minimum of maximum concavities of  $f$  at  $\vec{a}$   $\Rightarrow$

**FACT 1**  $\Delta := \det \begin{pmatrix} f_{xx}(\vec{a}) & f_{xy}(\vec{a}) \\ f_{yx}(\vec{a}) & f_{yy}(\vec{a}) \end{pmatrix}$  is the product of max + min concavities at  $\vec{a}$ .

But if  $\Delta > 0$ , this tells me only that  $\lambda_1, \lambda_2 > 0$  OR  $\lambda_1, \lambda_2 < 0$ . Which is it?

Consider  $f_{xx}(\vec{a})$ , the concavity in the  $x$ -direction — as such, clearly in between the max/min concavities:

$$\lambda_1 \leq f_{xx}(\vec{a}) \leq \lambda_2.$$

So if  $f_{xx}(\vec{a}) > 0$ , then  $\lambda_2 > 0$ ; and since we assumed  $\Delta = \lambda_1 \lambda_2 > 0$ ,  $\lambda_1 > 0$  too!  $\Rightarrow$

<b>FACT 2</b>	$\Delta$	$f_{xx}(\vec{a})$	Consequence
(2nd derivative test)	① $> 0$	$> 0$	local min
	② $> 0$	$< 0$	local max
	③ $< 0$	—	<u>Saddle</u> = stationary point which is not a local extremum
	$0$	—	inconclusive

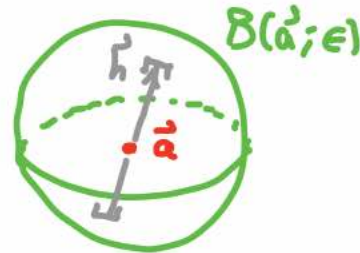
To recap: the 2 facts are for use in the case where  $f$  is twice continuously differentiable in a neighborhood of  $\vec{a}$ , with  $\vec{\nabla} f(\vec{a}) = \vec{0}$ . ①②③ correspond to the quadratic form  $Q(\vec{h}) = \vec{h}^T H(\vec{a}) \vec{h}$  being ① positive definite / ② negative definite / ③ indefinite.

**EXAMPLE (cont'd.)**

$\vec{a} = \vec{0}, f(x,y) = x^2 + 4xy + y^2$

$H(x,y) = \begin{pmatrix} 2 & 4 \\ 4 & 2 \end{pmatrix}, \Delta = 4 - 16 = -12 < 0$   
 $\rightarrow$  saddle point.

Now we generalize to  $n$  variables and examine  $f(x)$  on the gray axis in the picture:



$g(u) := f(\vec{a} + u\vec{h})$  for  $u \in [-1, 1]$ .

$\downarrow$  Chain rule

$g'(u) = \nabla f(\vec{a} + u\vec{h}) \cdot \vec{h} = \sum_{j=1}^n h_j f_{x_j}(\vec{a} + u\vec{h})$

$\downarrow$  Chain rule

$g''(u) = \nabla \left( \sum_j h_j f_{x_j}(\vec{a} + u\vec{h}) \right) \cdot \vec{h} = \sum_{i,j} h_i h_j f_{x_i x_j}(\vec{a} + u\vec{h})$

$= \vec{h}^T H(\vec{a} + u\vec{h}) \vec{h},$  where  $H = \left[ \frac{\partial^2 f}{\partial x_i \partial x_j} \right] =: \underline{\text{Hessian of } f}$

$\downarrow$

Taylor remainder  $\zeta \in (0, 1)$

$f(\vec{a} + \vec{h}) - f(\vec{a}) = g(1) - g(0) = g'(0) + \frac{1}{2} g''(\zeta)$

$= \nabla f(\vec{a}) \cdot \vec{h} + \frac{1}{2} \vec{h}^T H(\vec{a} + \zeta \vec{h}) \vec{h}$

$(**)$   $\swarrow$

$= \nabla f(\vec{a}) \cdot \vec{h} + \frac{1}{2} \vec{h}^T H(\vec{a}) \vec{h} + \|\vec{h}\|^2 E_2(\vec{a}; \vec{h})$   $(†)$

$(†)$  where  $E_2(\vec{a}; \vec{h}) = \begin{cases} \vec{h}^T \frac{H(\vec{a} + \zeta \vec{h}) - H(\vec{a})}{2\|\vec{h}\|^2} \vec{h}, & \vec{h} \neq \vec{0} \\ 0, & \vec{h} = \vec{0} \end{cases}$

has  $|E_2(\vec{a}; \vec{h})| = \frac{1}{2\|\vec{h}\|^2} \left| \sum_i \sum_j h_i h_j \left( \frac{\partial^2 f}{\partial x_i \partial x_j}(\vec{a} + \zeta \vec{h}) - \frac{\partial^2 f}{\partial x_i \partial x_j}(\vec{a}) \right) \right|$   
 $\leq \frac{1}{2\|\vec{h}\|^2} \sum_i \sum_j \|h_i\| \|h_j\| \left| \frac{\partial^2 f}{\partial x_i \partial x_j}(\vec{a} + \zeta \vec{h}) - \frac{\partial^2 f}{\partial x_i \partial x_j}(\vec{a}) \right|$   
 $\leq \frac{\|\vec{h}\|^2}{2\|\vec{h}\|^2} \sum_i \sum_j \left| \frac{\partial^2 f}{\partial x_i \partial x_j}(\vec{a} + \zeta \vec{h}) - \frac{\partial^2 f}{\partial x_i \partial x_j}(\vec{a}) \right| \xrightarrow{\text{as } \vec{h} \rightarrow \vec{0}} 0$

by continuity of 2nd partials.

where  $E_2(\vec{a}; \vec{h})$  is  $o(\|\vec{h}\|)$  ( $\rightarrow 0$  as  $\vec{h} \rightarrow \vec{0}$ ) assuming  $f$  is twice continuously differentiable on  $B(\vec{a}; \epsilon)$ .

Now recall from Lecture 15 the

Lemma on Quadratic Form: Let  $Q(\vec{h}) = \vec{h}^T A \vec{h}$ ,  $A$  symmetric  $n \times n$  with eigenvalues  $\lambda_1 \leq \dots \leq \lambda_n$ . Then

(i)  $Q(\vec{h}) > 0 \quad \forall \vec{h} \neq \vec{0} \iff$  all  $\lambda_j > 0 \iff$   $A$  positive-definite

(ii)  $Q(\vec{h}) < 0 \quad \forall \vec{h} \neq \vec{0} \iff$  all  $\lambda_j < 0 \iff$   $A$  negative-definite

(iii)  $Q(\vec{h})$  takes  $\pm$  values  $\iff \lambda_1 < 0 < \lambda_n \iff$   $A$  indefinite.

Theorem 2: If  $f$  is twice continuously differentiable, with a stationary point at  $\vec{x} = \vec{a}$ , then:

(i)  $H(\vec{a})$  pos. definite  $\implies$   $f$  has rel. minimum at  $\vec{a}$ .

(ii)  $H(\vec{a})$  neg. definite  $\implies$   $f$  has rel. maximum at  $\vec{a}$ .

(iii)  $H(\vec{a})$  indefinite  $\implies$   $f$  has saddle point at  $\vec{a}$ .

Proof: Since  $\nabla f(\vec{a}) = \vec{0}$  at a stationary point, **(\*\*)** becomes

$$f(\vec{a} + \vec{h}) - f(\vec{a}) = \vec{h}^T H(\vec{a}) \vec{h} + \underbrace{\|\vec{h}\|^2 E_2(\vec{a}; \vec{h})}_{\text{small term}}$$

The main idea is that this term doesn't matter, and so we are done by the lemma.

Here is how this works for (i):

• let  $0 \leq \lambda_1 \leq \dots \leq \lambda_n$  be eigenvalues of  $H(\vec{a})$ .

Pick  $\epsilon > 0$  s.t.  $|E_2(\vec{a}; \vec{h})| < \frac{1}{4} \lambda_1$  for  $0 < \|\vec{h}\| < \epsilon$ .

• let  $u \in (0, \lambda_1)$ , so that the eigenvalues  $\lambda_j - u$  of  $H(\vec{a}) - u\mathbb{I}_n$  are all positive. Lemma  $\Rightarrow \underbrace{\vec{h}^T [H(\vec{a}) - u\mathbb{I}_n] \vec{h}}_{Q(\vec{h})} > 0 \quad \forall \vec{h} \neq \vec{0}$ .

• so  $\vec{h}^T H(\vec{a}) \vec{h} > u \|\vec{h}\|^2 \quad \forall \vec{h} \neq \vec{0}$ , and taking  $u = \frac{1}{2} \lambda_1$  gives

$$\frac{1}{2} \vec{h}^T H(\vec{a}) \vec{h} > \frac{1}{4} \lambda_1 \|\vec{h}\|^2 > \|\vec{h}\|^2 |E_2(\vec{a}; \vec{h})| \geq 0$$

$$\Rightarrow f(\vec{a} + \vec{h}) - f(\vec{a}) = \frac{1}{2} \vec{h}^T H(\vec{a}) \vec{h} + \|\vec{h}\|^2 |E_2(\vec{a}; \vec{h})|$$

$$\geq \frac{1}{2} \vec{h}^T H(\vec{a}) \vec{h} - \|\vec{h}\|^2 |E_2(\vec{a}; \vec{h})| > 0 \quad \text{for } \vec{h} \neq \vec{0},$$

and  $f$  has a relative minimum at  $\vec{a}$ . □