

Recall

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

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$$f \in C^k \quad (\text{on } X \text{ open in } \mathbb{R}^n) \quad (k \geq 1)$$

every partial derivative of order $\leq k$ exists on X and is a continuous function on X

Then partial derivatives with respect to different variables commute:

$$\partial_{x_i} \partial_{x_j} f = \partial_{x_j} \partial_{x_i} f$$

$m = (m_1, \dots, m_n), \quad m_i \geq 0 \text{ integers } \textcircled{77}$
 $m_1 + \dots + m_n = k$

$$\frac{\partial^m f}{\partial x_1^{m_1} \dots \partial x_n^{m_n}} = \underbrace{\partial_{x_1} \dots \partial_{x_1}}_{m_1 \text{ times}} \underbrace{\partial_{x_2} \dots \partial_{x_2}}_{m_2 \text{ times}} \dots \underbrace{\partial_{x_n} \dots \partial_{x_n}}_{m_n \text{ times}} f$$

3.7. Taylor polynomials

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Motivation: $n = 1$

(I open) $f: I \longrightarrow \mathbb{R}, \mathbb{C}^k$

f is well-approximated
close $x_0 \in I$ by

$$f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2} f''(x_0)(x - x_0)^2 + \dots \\ + \frac{1}{k!} f^{(k)}(x_0)(x - x_0)^k$$

In ~~n~~ n variables:

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Def. (3.7.1) $k \geq 1$, $X \subset \mathbb{R}^n$ open \mathbb{R}
 $f: X \rightarrow \mathbb{R}$ class C^k

Taylor polynomial of degree k of f
at x_0 : functions of $\gamma = (x_1, \dots, x_n)$
given by:

$$T_k f(\gamma; x_0) = f(x_0) + \sum_{i=1}^n \frac{\partial f_i(x_0)}{\partial x_i} \gamma_i \\ + \dots + \dots +$$

$$\sum_{\substack{m_i \geq 0 \\ m_1 + \dots + m_n = k}} \frac{1}{m_1! \dots m_n!} \partial_{m_1}^{k_1} \dots \partial_{m_n}^{k_n} f(x_0) y_1^{m_1} \dots y_n^{m_n}$$

(m_1, \dots, m_n)

(Term of degree j , $0 \leq j \leq k$, is the same as \bigcirc with k replaced by j).

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Using multi-index notation:

$$m = (m_1, \dots, m_n), \quad m_i \geq 0$$

Write

$$\begin{cases} |m| = m_1 + \dots + m_n \\ m! = m_1! \dots m_n! \\ y^m = y_1^{m_1} \dots y_n^{m_n}, \quad y \in \mathbb{R}^n \end{cases}$$

$$\frac{1}{m_1! \dots m_n!} \frac{\partial^{|m|} f(x_0)}{\partial x_1^{m_1} \dots \partial x_n^{m_n}} = \frac{1}{m!} \partial_m^{|m|} f(x_0) y^m$$

With Here notation:

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$$\text{Tr } f(Y; x_0) = \sum_{|m| \leq R} \frac{1}{m!} \partial_m^{|m|} f(x_0) \gamma_m$$

sum over all (m_1, \dots, m_n)
 $m_i \geq 0, |m| \leq R$

$$\frac{n=1:}{\sum_{n=0}^R} \frac{1}{n!} f^{(n)}(x_0) \gamma_n$$

Example:

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$h=1$: $T_1 f(y; x_0) = f(x_0) + \nabla f(x_0) \cdot y$

scalars
product in \mathbb{R}^n

$h=2$: $f \in C^2 = f(x_0) + \sum \partial_{x_i} f(x_0) y_i$

$T_2 f(y; x_0) = f(x_0) + \nabla f(x_0) \cdot y$

$+ \frac{1}{2} \sum_{i=1}^n \partial_{x_i}^2 f(x_0) y_i^2 + \sum_{1 \leq i < j \leq n} \partial_{x_i} \partial_{x_j} f(x_0) y_i y_j$

$m = (0, \dots, 0, 2, 0, \dots, 0)$
↑
 $m!$ = 2! 1-th variable

$m = (0, \dots, 0, 1, 0, \dots, 1, 0, \dots, 0)$
↑
 $m!$ = 1 i-th j-th

Recall: $f \in C^2$

$$\text{Hess}_f(x_0) = \left(\frac{\partial^2 f}{\partial x_i \partial x_j} (x_0) \right)_{1 \leq i, j \leq n}$$

"Hessian"; symmetric matrix

The quadratic term in T_2 is

$$\frac{1}{2} Y^*$$

transpose = row vector

$$\text{Hess}_f(x_0)$$

$n \times n$

$$Y \in \mathbb{R}^n$$

column vector

[Linear algebra]

So :

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$$T_2 f(x; x_0) = f(x_0) + \nabla f(x_0) \cdot Y + \frac{1}{2} Y^t \text{Hess}_f(x_0) Y$$

Ex: $n=2$

$$\text{Hess}_f(x_0) = \begin{pmatrix} a & b \\ b & d \end{pmatrix} = H$$

$$\begin{aligned} (Y_1 \ Y_2) H \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} &= (Y_1 \ Y_2) \begin{pmatrix} aY_1 + bY_2 \\ bY_1 + dY_2 \end{pmatrix} \\ &= aY_1^2 + bY_1Y_2 + bY_1Y_2 + dY_2^2 \end{aligned}$$

So

$$\frac{1}{2} Y^T H Y = \frac{1}{2} a Y_1^2 + b Y_1 Y_2 + \frac{1}{2} d Y_2^2$$

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Compare with:

$$\frac{1}{2} \partial_{x_1}^2 f(x_0) Y_1^2 + \frac{1}{2} \partial_{x_2}^2 f(x_0) Y_2^2$$

$$H = \begin{pmatrix} \partial_{x_1}^2 f & \partial_{x_1 x_2}^2 f \\ \partial_{x_1 x_2}^2 f & \partial_{x_2}^2 f \end{pmatrix} = \text{Hess } f(x_1, x_2)$$

Prop. 3.7.3

$k \geq 1$, $X \subset \mathbb{R}^n$ open C^k
 $f: X \rightarrow \mathbb{R}$ class C^k

Write

$$f(x) = T_R f(x - x_0; x_0) + E_R f(x; x_0)$$

Then

$$\lim_{\substack{x \rightarrow x_0 \\ x \neq x_0}} \frac{E_R f(x; x_0)}{\|x - x_0\|^k} = 0$$

Ex. (3. 7. 4)

$$n=2, \quad f(x,y) = e^{3x - \sin(xy)}$$

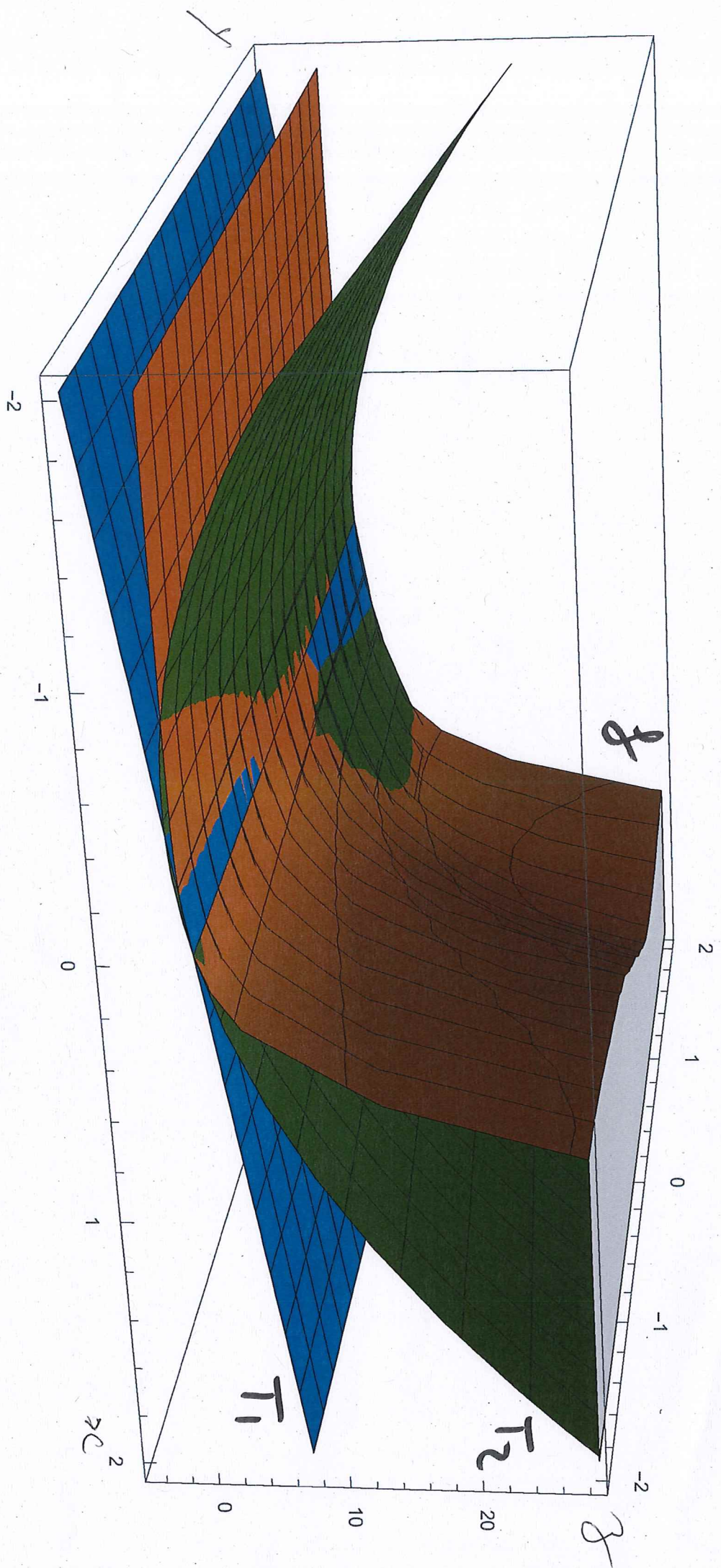
$$(x_0, y_0) = (0, 0), \quad f(0,0) = 1$$

$$T_2 f(x,y) \Big|_{(0,0)} = 1 + \underbrace{3x}_{\text{gradient}} + \underbrace{\frac{9x^2}{2} - xy}_{\text{Hessian}} \Big|_{(x_1, y_1)}$$

$$f(-0,0015) \approx 0,9993; \quad f(0,003) \approx 0,9955145896\dots$$

$$T_1 f(\dots) = 0,9955$$

$$T_2 f(\dots) = 0,995514625$$



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3.8 - Critical points

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Goal: analogue of

(1) if $f: I \xrightarrow{\text{open}} \mathbb{R}$ is differentiable, and f max./min. at $x_0 \in I$ (local extremum) then

$$f'(x_0) = 0$$

(2) if f is C^2 , $f'(x_0) = 0$,

$f''(x_0) > 0$, then f has a local minimum at x_0

Prop. 3.8.1. Let $X \subset \mathbb{R}^n$ (91)

$f: X \rightarrow \mathbb{R}$ open differentiable on X

If $x_0 \in X$ satisfies:

(1) $f(x) \leq f(x_0)$ if x close to x_0
(local maximum at x_0)

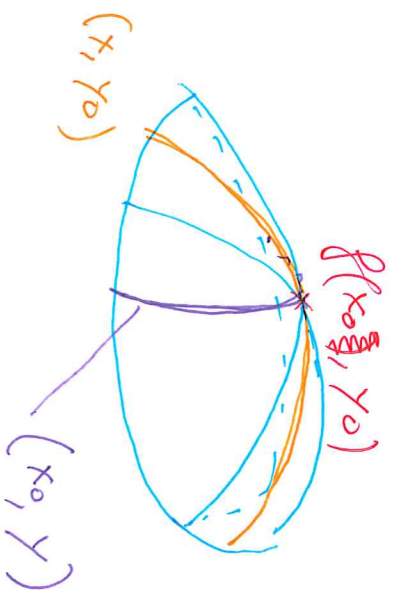
or

(2) $f(x) \geq f(x_0)$
(local minimum)

Then $\nabla f(x_0) = 0$ ($\Leftrightarrow \frac{df}{dx_i}(x_0) = 0$
if $1 \leq i \leq n$)

Proof. $n=2$

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$$g(t) = f(x_0, y_0 + t)$$

(t small enough
so that $(x_0, y_0 + t) \in X$)

$$g(0) = f(x_0, y_0)$$

(Analysis I) g has local max. at $t=0$

$$\Rightarrow g'(0) = 0$$

$$\frac{\partial f}{\partial y}(x_0, y_0) = 0$$

Def. 3.8.2 -

$f: X \rightarrow \mathbb{R}$ differentiable.

A point x_0 such that $\nabla f(x_0) = 0$ is called a critical point of f .

So if f has a local extremum at a point x_0 , this must be a critical point.

(Converse is false, already for $n=1$.)

How to find where $f: X \rightarrow \mathbb{R}$ (94)
is maximal / minimal? ($f \in C^1$)

(1) f might not have a max./min
(because X is ~~usually~~ not compact)

(2) Typically, \bar{X} compact is given,

$f: \bar{X} \rightarrow \mathbb{R}$ continuous closed

(\Rightarrow There is a max./min, Prop. 3.8.1) bounded

(3) Write $\bar{X} = X \cup B$ "boundary"
open

(4) if f is differentiable on X , (95)
then the point(s) x_0 where $f(x_0)$
is maximal (or minimal) are either

(4i) a critical point of
 f on X

(4ii) a point of B

(5) So : we solve for $\nabla f(x_0) = 0$,
evaluate f at those critical points,
and evaluate f on B , and compare.

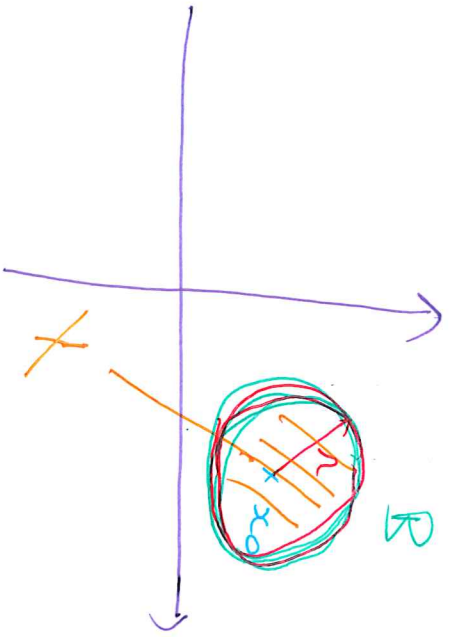
Ex.

$$x_0 \in \mathbb{R}^n, r > 0$$

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$$(1) \quad \overline{X} = \{x \mid \|x - x_0\| \leq r\}$$

(ball, closed, around x_0 , of radius r)



$$\overline{X} = X \cup B$$

$$X = \{x \mid \|x - x_0\| < r\}$$

$$B = \{x \mid \|x - x_0\| = r\}$$

(2) [3.8.4]

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$$\bar{X} = [0, 1]^2$$

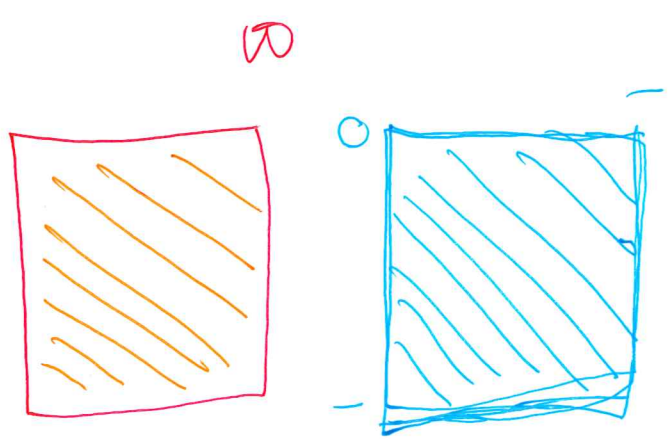
$$X =]0, 1[^2$$

$B =$ union of four segments

$(x, 0), (x, 1)$ or $(0, y), (1, y)$

$$0 \leq x \leq 1$$

$$0 \leq y \leq 1$$



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$$f(x, y) = x^2 - 2y^2$$

$$\nabla f(x, y) = \begin{pmatrix} 2x \\ -4y \end{pmatrix}$$

$(0, 0)$ is the only critical point
and $f(0, 0) = 0$ (will not be max. or min.)

Evaluate on B :

$$0 \leq x \leq 1$$

$$f(x, 1) = x^2 - 2$$

$$f(x, 0) = x^2,$$

$$f(0, y) = -2y^2,$$

$$f(1, y) = 1 - 2y^2$$

$$0 \leq y \leq 1$$

Max. of f on each of the line 99

segments:

1

-1

0

1

Min : 0

-2

-2

-1

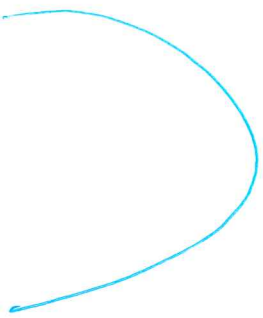
maximal value of f at $(1,0)$

minimal value at $(0,1)$

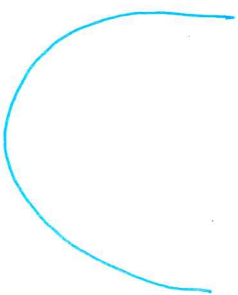
Q. when does f , C^2 , have a local extremum at a critical point x_0 ?

(100)

$$f''(x_0) < 0$$



$$f''(x_0) > 0$$

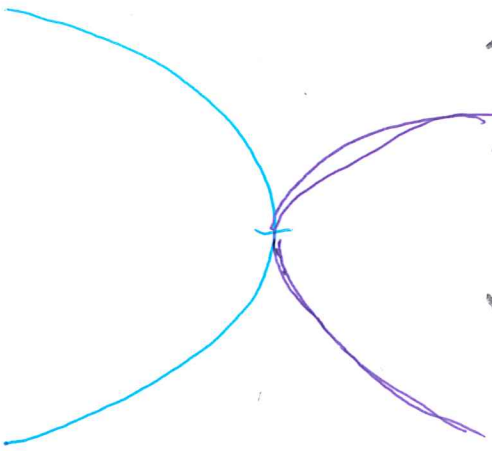


$$\underline{n=1}$$

Naive analogue: "if $\text{Hess}f(x_0)$ is $\neq 0$, we can say that f has a local extremum".

(101)

THIS IS FALSE!



$$\partial_{y_2}^2 f(x_0) > 0$$

$$\partial_{x_1}^2 f(x_0) < 0$$

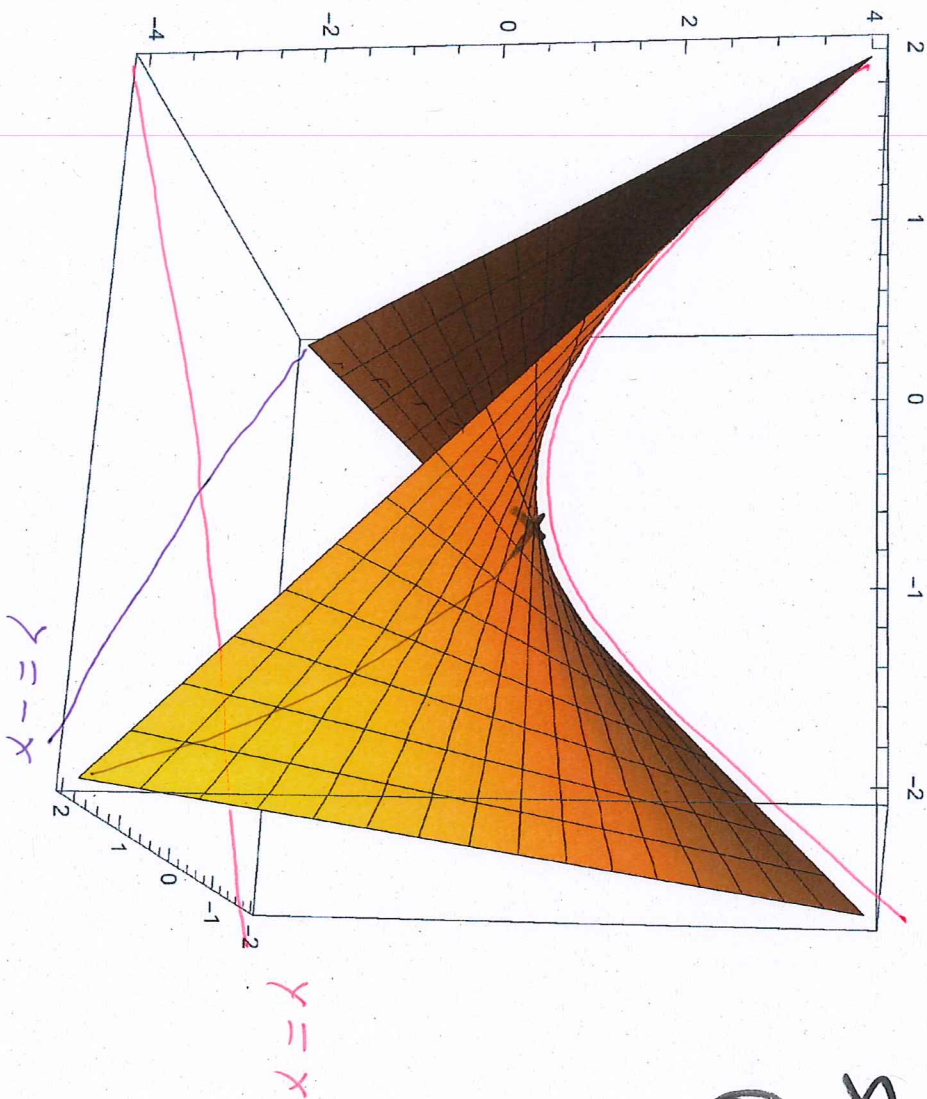
$x_0 = (0, 0)$ is a critical point

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$$f(x, y) = xy$$

$$f(x, x) = x^2$$

$$f(x, -x) = -x^2$$



" saddle point "

Def. (3.8.6) $f \in C^2$

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A critical point of f is non-degenerate if $\det \text{Hess}f(x_0) \neq 0$.

Remark: for degenerate critical points, the problem is much more complicated.

Ex: $f_1(x, y) = x^4 + y^4$, $f_2(x, y) = x^4 - y^4$
have $(0, 0)$ as degenerate critical point

Suppose x_0 is a non-degenerate critical point of f .

$H = \text{Hess}_f(x_0)$ is a symmetric invertible matrix

↳ (Linear algebra) H can be

diagonalized in an orthonormal basis (v_1, \dots, v_n)

$$y = t_1 v_1 + \dots + t_n v_n$$

$$\hookrightarrow y^t \text{Hess}_f(x_0) y = \lambda_1 t_1^2 + \dots + \lambda_n t_n^2$$

where λ_i is the eig. of v_i .