

• $f: X \rightarrow \mathbb{R}^m, x \in \mathbb{R}^n$

f is differentiable in $x_0 \in X$

if \exists a lin. rep $u: \mathbb{R}^n \rightarrow \mathbb{R}^m$

such that

$$f(x) = f(x_0) + u(x - x_0) + E(f; x, x_0)$$

with

$$\lim_{x \rightarrow x_0} \frac{E(f; x, x_0)}{\|x - x_0\|} = 0$$

u is called the difference of f

Thm If f is differentiable at x_0

then f is continuous at x_0 .

• If f is diff. at x_0 then

all of its partial derivatives

$\frac{\partial f_i}{\partial x_j}$ exist at x_0 $\begin{matrix} 1 \leq i \leq m \\ 1 \leq j \leq n \end{matrix}$

and the matrix that represents

the differential of f is

$$J_f(x_0) = \left(\frac{\partial f_i}{\partial x_j}(x_0) \right)_{1 \leq i \leq m, 1 \leq j \leq n}$$

($Df(x_0)$) : $\mathbb{R}^n \rightarrow \mathbb{R}^m$

$$\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \mapsto (J_f(x_0)) \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix}$$

• If $f: \mathbb{R}^n \rightarrow \mathbb{R}$ then

$$df(x_0) : \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \mapsto \frac{\partial f}{\partial x_1} x_1 + \dots + \frac{\partial f}{\partial x_n} x_n.$$

Defn If $f: \mathbb{R}^n \rightarrow \mathbb{R}$, then the gradient of f is $\nabla f(x_0) = (J_f(x_0))^t$

Thm If $f: X \rightarrow \mathbb{R}^m, x \in \mathbb{R}^n$ has all

partial derivatives $\frac{\partial f_i}{\partial x_j}$ on \overline{X} and

if the partial derivatives are continuous

then f is differentiable.

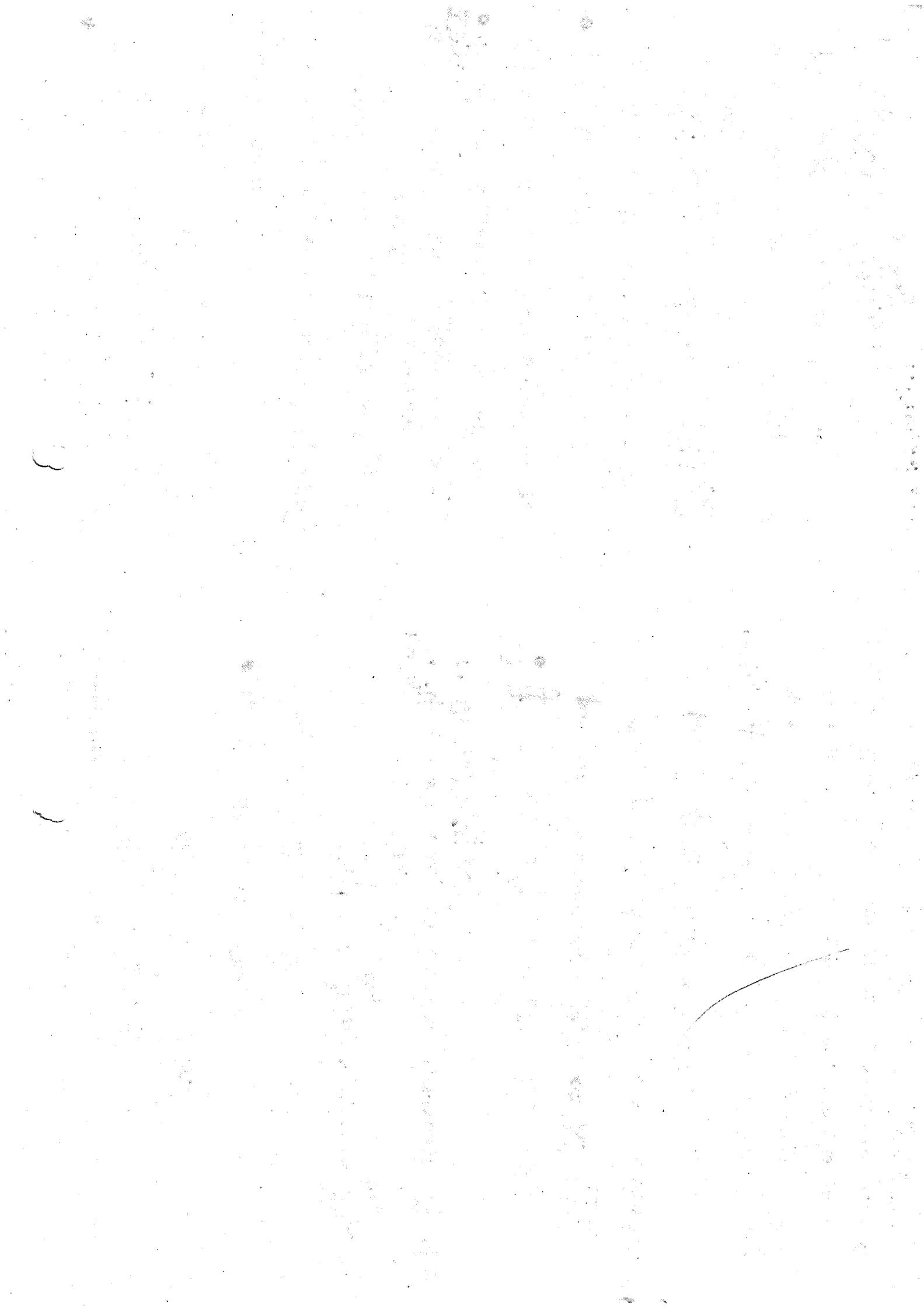
Defn $f: X \rightarrow \mathbb{R}^m$ diff. at x_0 - then the

graph of the affine lin. transformation

$g: \mathbb{R}^n \rightarrow \mathbb{R}^m, g(x) = f(x_0) + (df(x_0))(x - x_0)$

is called the tangent space at x_0 the

the graph of f . $G(f) = \{(x, f(x)) \in \mathbb{R}^{n+m} \mid$



Special case

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

$$\mathbb{X} \subset \mathbb{R}^2, x_0 \in \mathbb{X}$$

$$df(\bar{x}_0) : \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$(x, y) \mapsto \left(\frac{\partial f}{\partial x}(x_0), \frac{\partial f}{\partial y}(x_0) \right) \begin{pmatrix} x \\ y \end{pmatrix}$$

$$= \nabla f, (\bar{x}) >$$

$$= \frac{\partial f}{\partial x}(\bar{x}) \cdot x + \frac{\partial f}{\partial y}(\bar{x}) y.$$

and

$$g(x, y) = f(\bar{x}_0) + \nabla f(\bar{x}_0) \cdot (\bar{x} - \bar{x}_0)$$

$$\text{and } z = f(x_0) + \frac{\partial f}{\partial x}(\bar{x})(x - x_0) + \frac{\partial f}{\partial y}(\bar{x})(y - y_0)$$

is the equation of the tangent plane.

The Jacobi Matrices Schrift

$$\text{Thm } J_{fg}(x_0) = \overline{J_g}(f(x_0)) \cdot \overline{J_f}(x_0)$$

$$\text{then so is } f+g \text{ and } df(x_0) + dg(x_0) = d(f+g)(x_0)$$

$$2) \text{ if } f, g: \mathbb{R}^n \rightarrow \mathbb{R} \text{ are diff. in } x$$

then so is $f \cdot g$.

if $g \neq 0$ for any $x \in \mathbb{R}^n$, then f/g is also diff.

Thm (chain rule)

let $X \subset \mathbb{R}^n$ open

$Y \subset \mathbb{R}^m$ open. let $f: X \rightarrow Y$

$g: Y \rightarrow \mathbb{R}^p$ diff. functions.

Then $g \circ f: X \rightarrow \mathbb{R}^p$ is diff

on X . Find for any $x_0 \in X$

its differential is given by

the linear map which is the

composition of $d(g(f(x_0))) : \mathbb{R}^m \rightarrow \mathbb{R}^p$
and $df(x_0) : \mathbb{R}^n \rightarrow \mathbb{R}^m$ composition
of mps.

$$\text{i.e. } d(g \circ f)(x_0) = dg(f(x_0)) \circ df(x_0)$$

Thm

If $f: X \rightarrow \mathbb{R}^m$ is

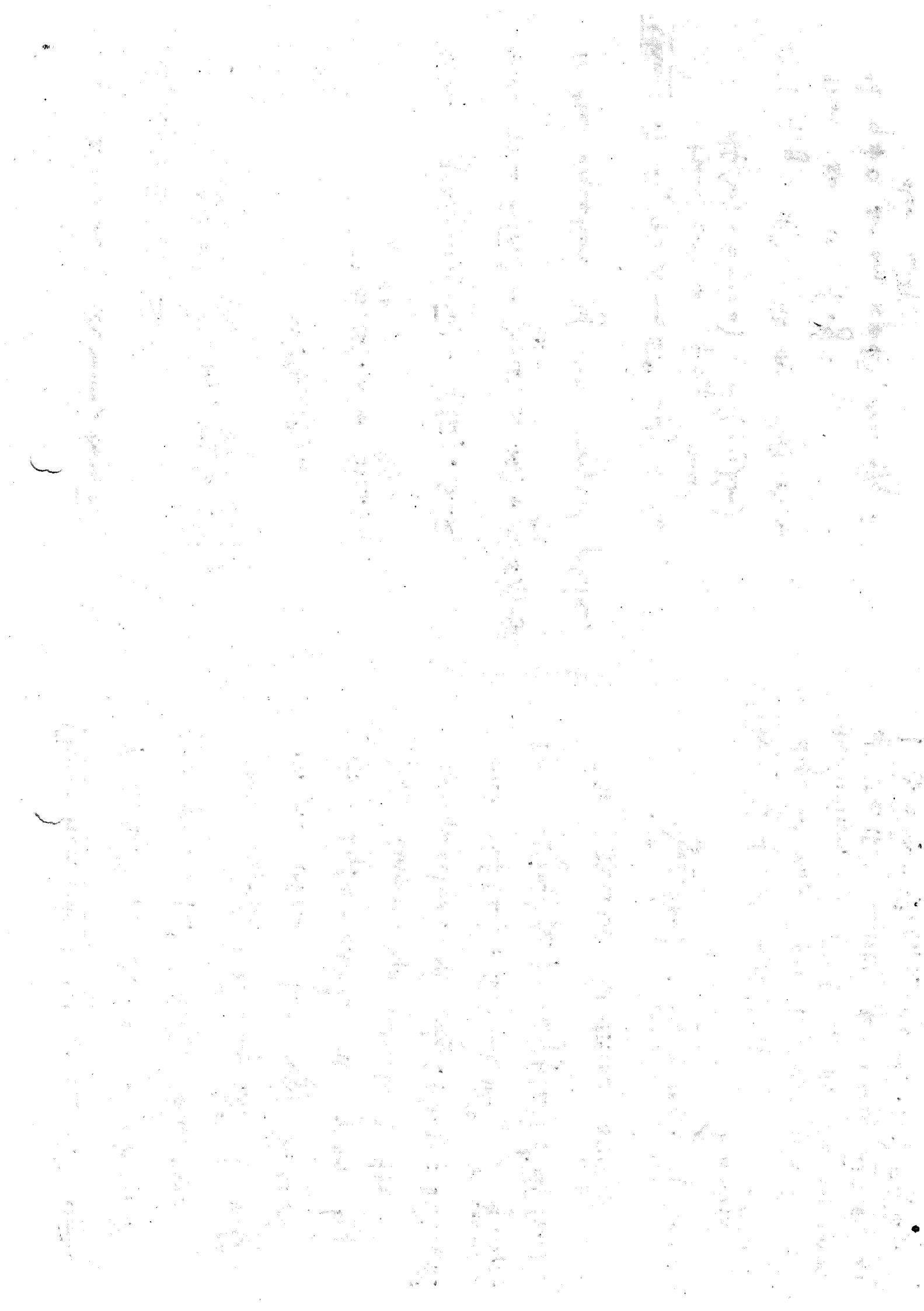
↑ multpx product

$$J_{gf}(x_0) = \overline{J_g}(f(x_0)) \cdot \overline{J_f}(x_0)$$

if $f: X \rightarrow \mathbb{R}^m$ is

diff at x_0 , then the directional derivative of f at x_0 in the direction of $v \in \mathbb{R}^n$ exists for every $v \in \mathbb{R}^n$ and

$$\left| \frac{d}{dt} f(x_0 + tv) \right|_{t=0} = J_f(x_0)v = \overline{J_f}(x_0) \cdot v$$



Rk. Geometric meaning
of the gradient

$$f: \mathbb{R}^n \rightarrow \mathbb{R} \text{ diff.}$$

We'll maximize the
direc. der. at x_0 , ie
 $\langle \nabla f(x_0), \vec{v} \rangle$ If we
maximize $\cos \theta$

ie when $\theta = 0$.

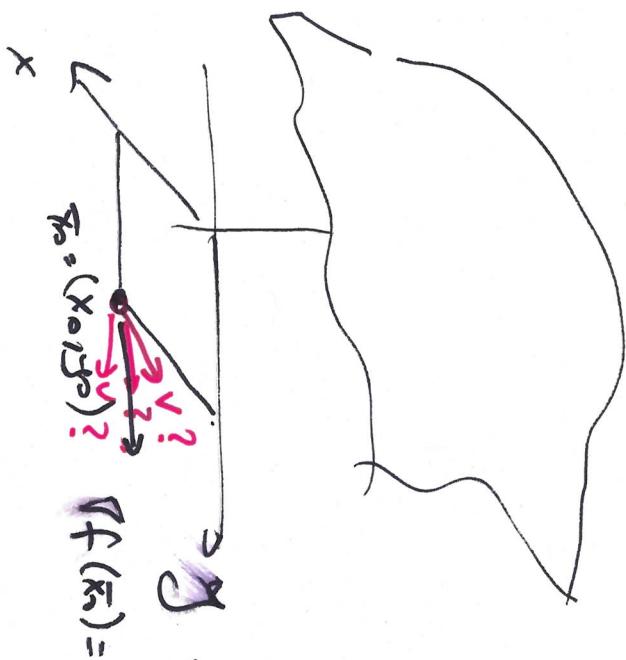
$$\nabla f(\bar{x}_0) = \left| \begin{array}{c} \frac{\partial f}{\partial x_1}(\bar{x}_0) \\ \vdots \\ \frac{\partial f}{\partial x_n}(\bar{x}_0) \end{array} \right|$$

Suppose $\nabla f(\bar{x}_0) \neq 0$.

Let \vec{v} be a unit vector, $\|\vec{v}\| = 1$.

dir. der. of f in the direc. of \vec{v}
at the point \bar{x}_0 is given by

$$\langle \nabla f(\bar{x}_0), \vec{v} \rangle = \underbrace{\|\nabla f(\bar{x}_0)\|}_{\text{when is this}} \underbrace{\|\vec{v}\| \cos \theta}_{\text{largest?}}$$



$$\nabla f(x_0) = \left(\frac{\partial f}{\partial x}(x_0), \frac{\partial f}{\partial y}(x_0) \right)$$





3 important examples
of diff. functions.

①

Polar coordinates.

Let $f: [0, \infty) \times [0, 2\pi) \rightarrow \mathbb{R}^2$

$$(r, \theta) \mapsto (x, y)$$

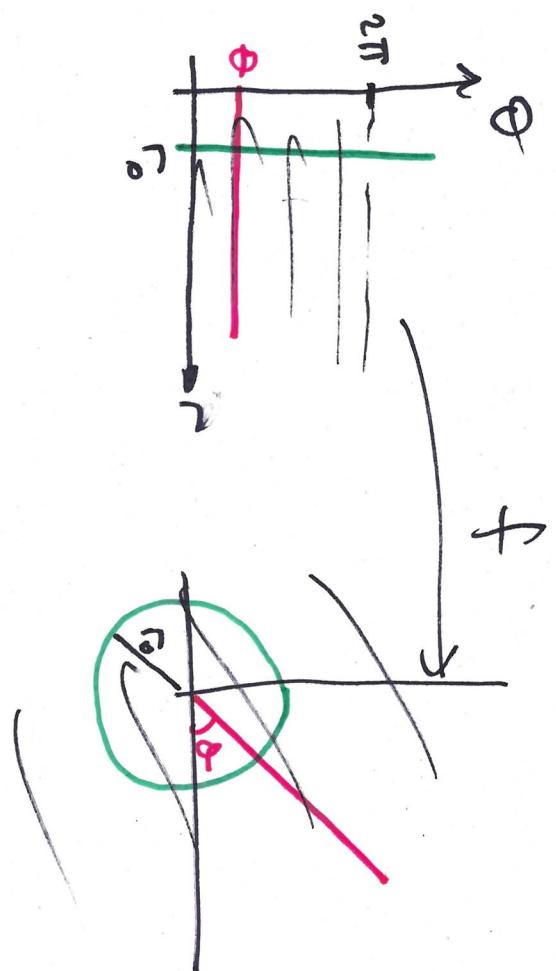
$$= (r \cos \theta, r \sin \theta)$$

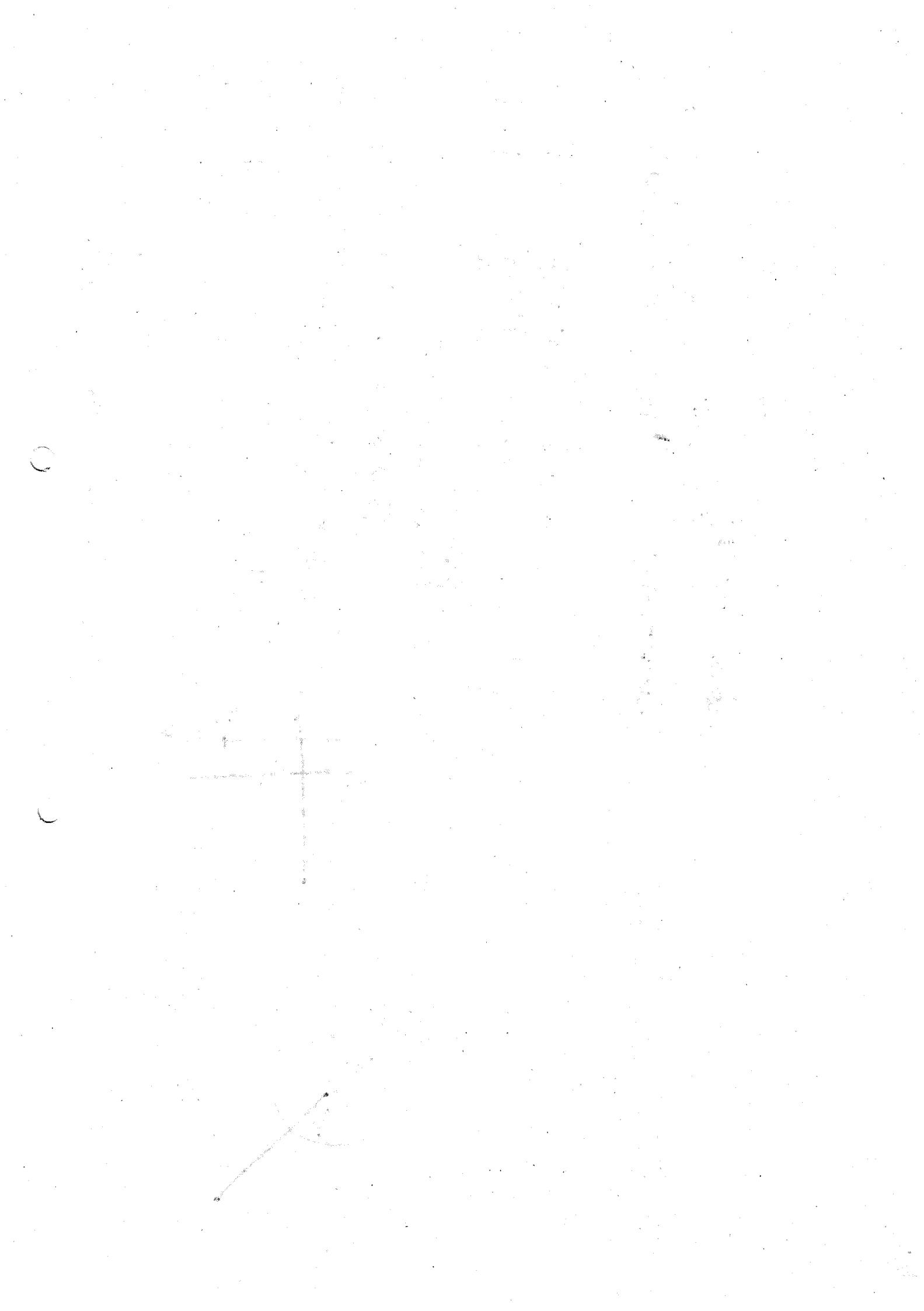
$$f = (f_1, f_2) \quad f_1(r, \theta) = r \cos \theta$$

$$f_2(r, \theta) = r \sin \theta.$$

$$\mathcal{J}_f(r, \theta) = \begin{pmatrix} \frac{\partial f_1}{\partial r} & \frac{\partial f_1}{\partial \theta} \\ \frac{\partial f_2}{\partial r} & \frac{\partial f_2}{\partial \theta} \end{pmatrix} = \begin{pmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{pmatrix}$$

$$\det \mathcal{J}_f(r, \theta) = 1.$$





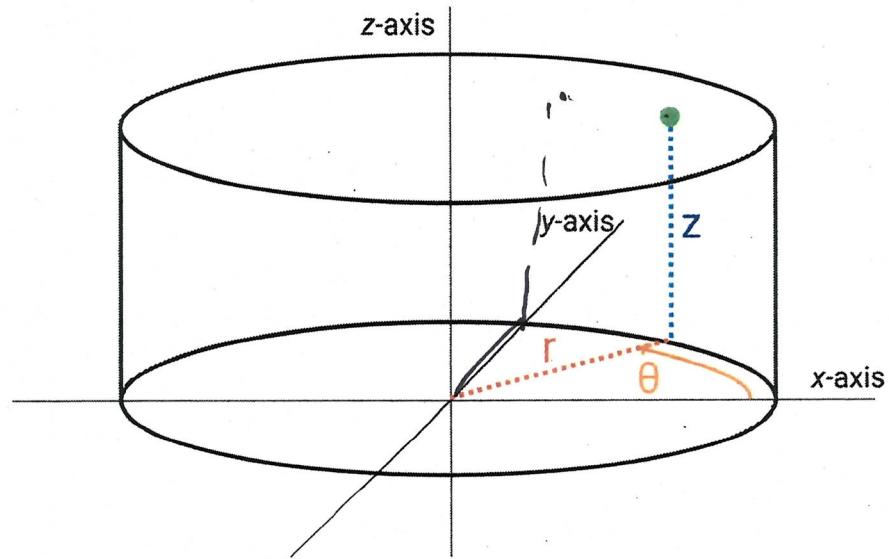


FIGURE 1. Cylindrical Coordinates

$$f: (0, \infty) \times (0, 2\pi) \times \mathbb{R} \rightarrow \mathbb{R}^3$$

$$(r, \theta, z) \mapsto \begin{pmatrix} r \cos \theta \\ r \sin \theta \\ z \end{pmatrix} = \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

$$J_f(r, \theta) = \begin{pmatrix} \cos \theta & -r \sin \theta & 0 \\ \sin \theta & r \cos \theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad \underline{\det J_f = r}$$



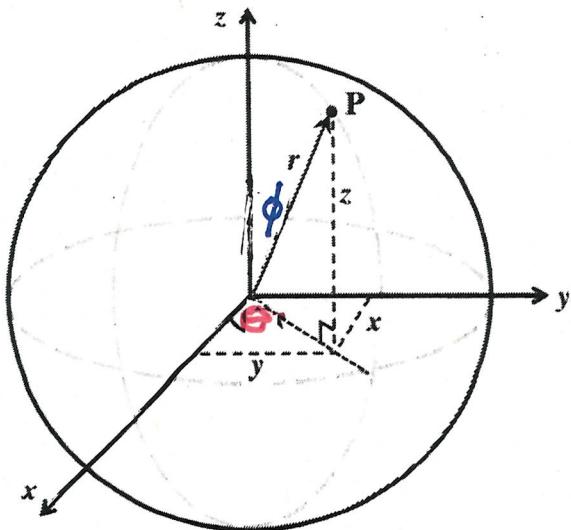


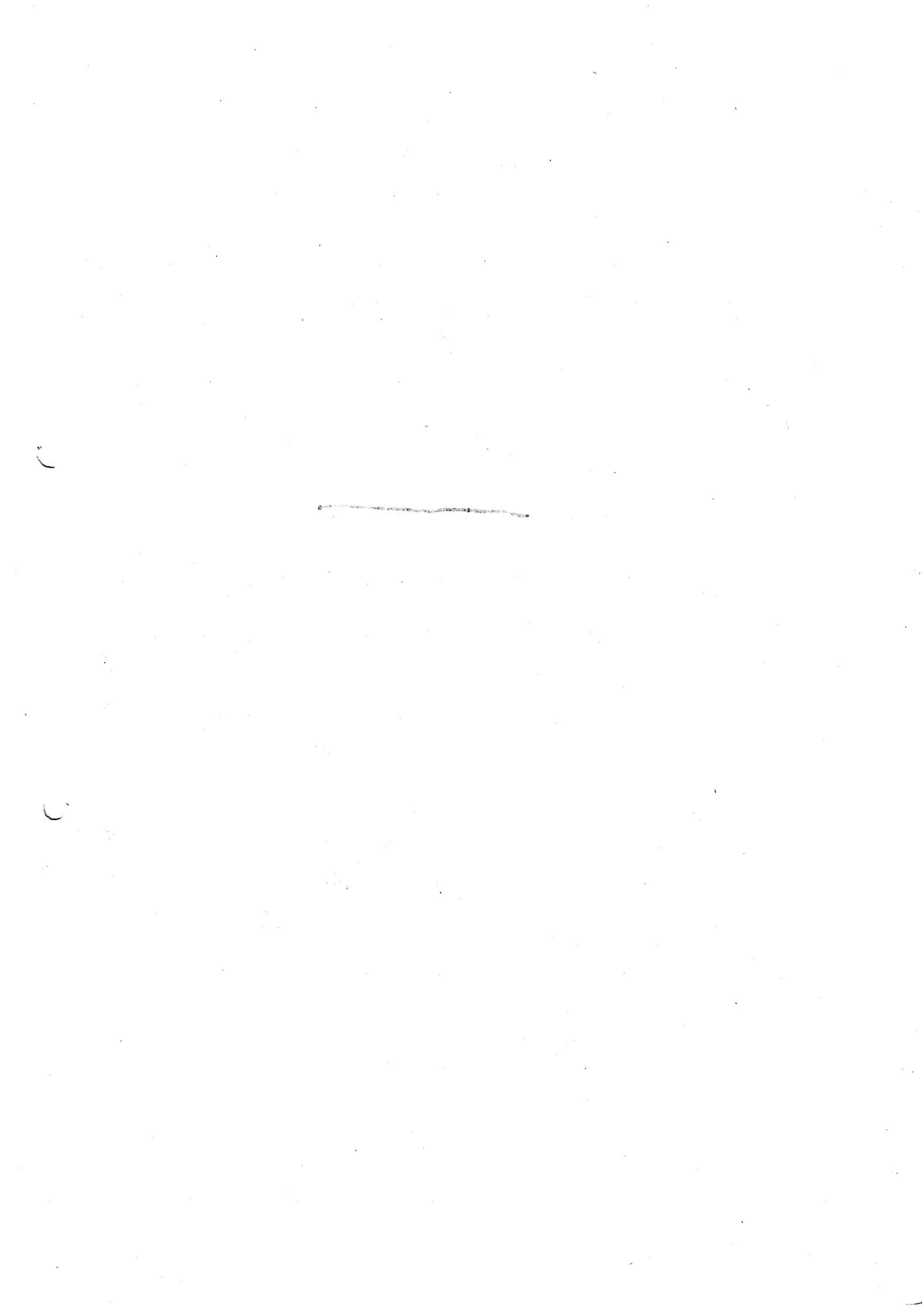
FIGURE 2. Spherical Coordinates

$$f : (0, \infty) \times (0, 2\pi) \times (0, \pi) \rightarrow \mathbb{R}^3$$

$$(r, \theta, \phi) \mapsto \begin{pmatrix} r \cos \theta \sin \phi \\ r \sin \theta \sin \phi \\ r \cos \phi \end{pmatrix} = \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$

$$J_f(r, \theta, \phi) = \begin{pmatrix} \cos \theta \sin \phi & -r \sin \theta \sin \phi & r \cos \theta \cos \phi \\ \sin \theta \sin \phi & r \cos \theta \sin \phi & r \sin \theta \cos \phi \\ \cos \phi & 0 & -r \sin \phi \end{pmatrix}$$

$$\det J_f = -r^2 \sin \phi$$



Defn. Let $X \subset \mathbb{R}^n$ an open set

and $f: X \rightarrow \mathbb{R}^n$ diff.

We say f is a change

of variables around x_0 if

there is a radius $R > 0$ such that

the restriction of f to

the ball around x_0 of radius R

$$B = \{x \in \mathbb{R}^n \mid \|x - x_0\| < R\}$$

so that the image $Y = f(B)$

is open in \mathbb{R}^n and \exists

a diff map $g: Y \rightarrow B$

such that $g \circ f = \text{id}_Y$. $f \circ g = \text{id}_B$

re. $f|_{B(x_0)}$ is a bijection to the

image with a
inverse g which is
also differentiable.

Thm

(Inverse function thm):

Let $X \subseteq \mathbb{R}^n$ open, $f: X \rightarrow \mathbb{R}^n$

diff. If $x_0 \in X$ is such that

$$\det(\bar{\mathcal{J}}_f(x_0)) \neq 0 \quad \text{ie } \bar{\mathcal{J}}_f(x_0)$$

is invertible then f is a

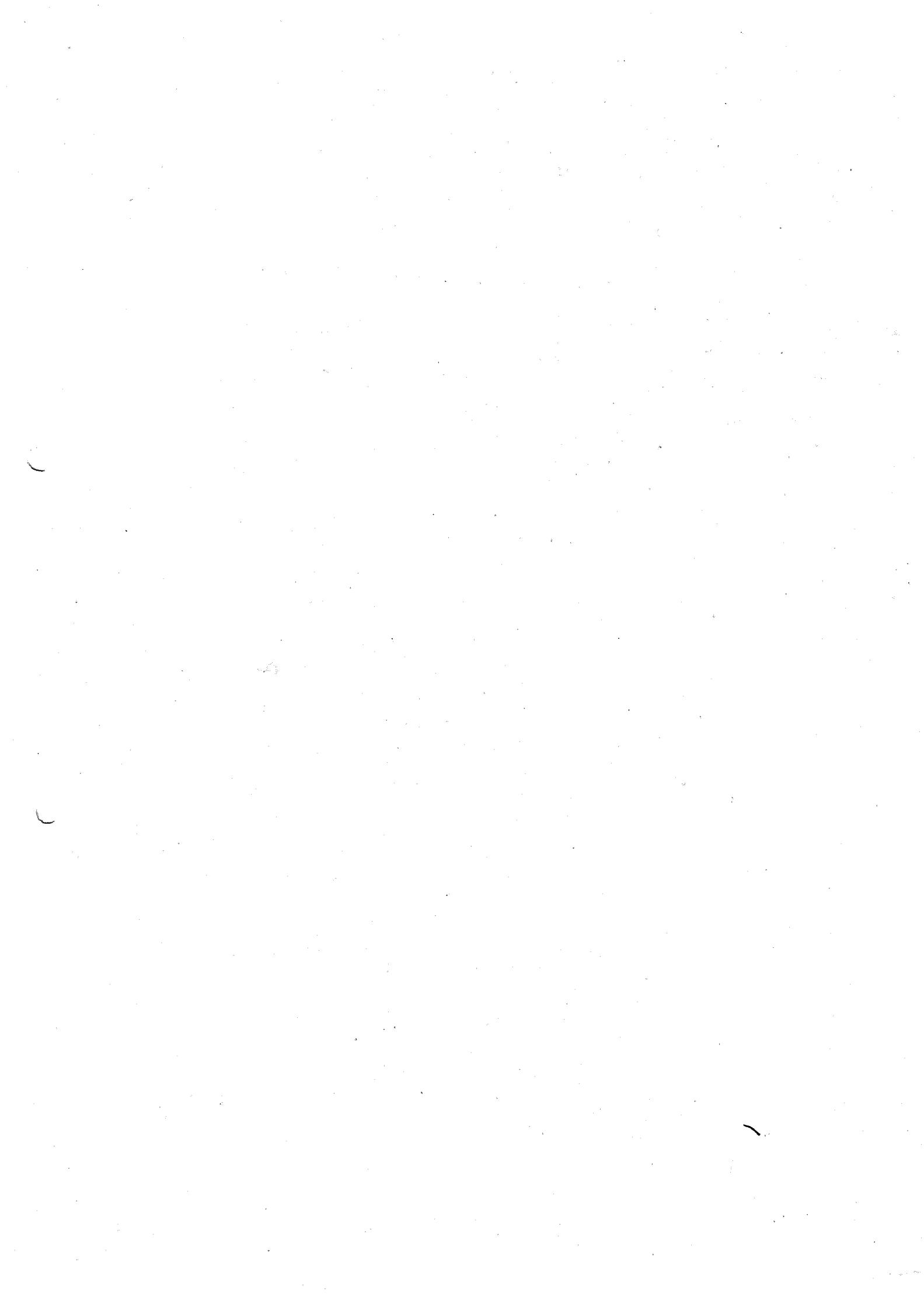
change of variables around x_0 .

Moreover the Jacobian of

g at x_0 is defined by

$$\bar{\mathcal{J}}_g(f(x_0)) = \bar{\mathcal{J}}_f(x_0)^{-1}$$

Proof.



Higher derivatives.

For all polys, big functions, exponentials are smooth.

Defn. $X \subset \mathbb{R}^n$, $f: X \rightarrow \mathbb{R}^m$, class C^1

we say ~~f~~ is diff or x and
if f is diff on X and
all of its partial derivatives
are continuous.

$C^1(X; \mathbb{R}^m)$.

Let $k \geq 2$, we say f is C^k

if ~~the~~ it is diff and
each $\partial_{x_i}^k f: X \rightarrow \mathbb{R}^m$ is

of class C^{k-1} .

$C^k(X, \mathbb{R}^m)$.

f is smooth or C^∞ if
it is ~~smooth~~ or C^∞

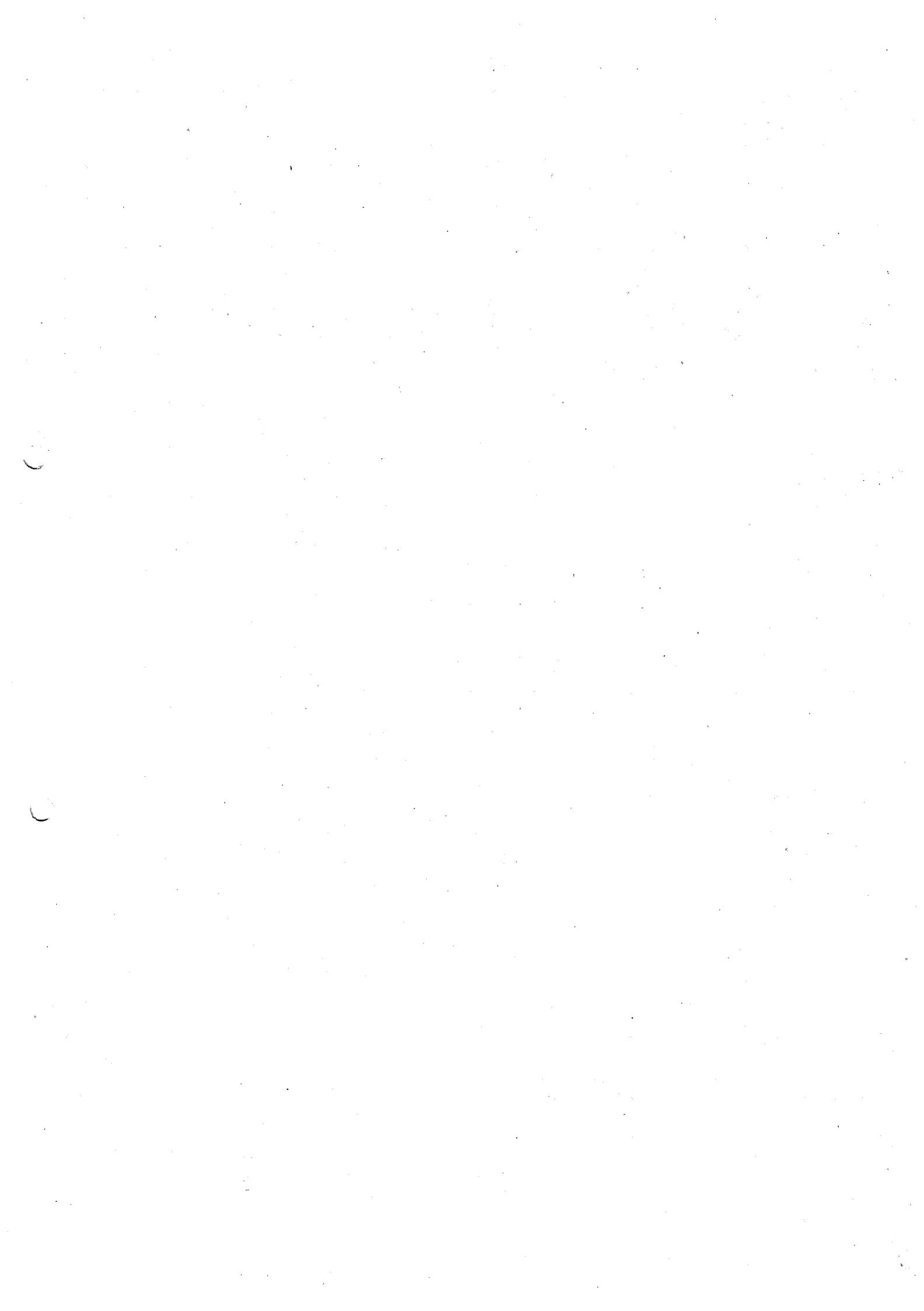
Thm For $f \in C^k$, $k \geq 2$

~~partial~~ then the partial
derivatives of order $\leq k$
are indep of order of
differentiation.

(i.e. Mixed partial derivatives
(up to order k) all commute.

e.g. $\partial_x^2 f$ if $k=2$, $f \in C^2$

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$$



2) If $f \in C^4$

$$\frac{\partial^3 f}{\partial x_i \partial x_j \partial x_k} = \frac{\partial^3 f}{\partial x_j \partial x_i \partial x_k} = \dots$$

Defn. If $f \in C^2(X \rightarrow \mathbb{R})$,
 $X \subset \mathbb{R}^n$, then the $n \times n$
Matrix $\left(\frac{\partial^2 f}{\partial x_i \partial x_j}(x_0) \right) =: \text{Hess}_f(x_0)$

$$\frac{\partial^4 f}{\partial x_1 \partial x_2 \partial x_3 \partial x_4} = \frac{\partial^4 f}{\partial x_3 \partial x_1 \partial x_2 \partial x_4} = \dots$$

is called the Hessian of f .

Warning!

$$f(x,y) = \begin{cases} \frac{xy(x^2-y^2)}{x^2+y^2} & (x,y) \neq (0,0) \\ 0 & \text{at } (0,0) \end{cases}$$

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

$H^t = H$.

$$\text{Ex: } f: \mathbb{R}^3 \rightarrow \mathbb{R}$$

$$(x, y, z) \mapsto x^2y + y^2$$

$$\frac{\partial^2 f}{\partial x^2}(0,0) = 1$$

$$\frac{\partial^2 f}{\partial y^2}(0,0) = -1$$

$$\frac{\partial^2 f}{\partial x \partial y}(0,0) = 2y$$

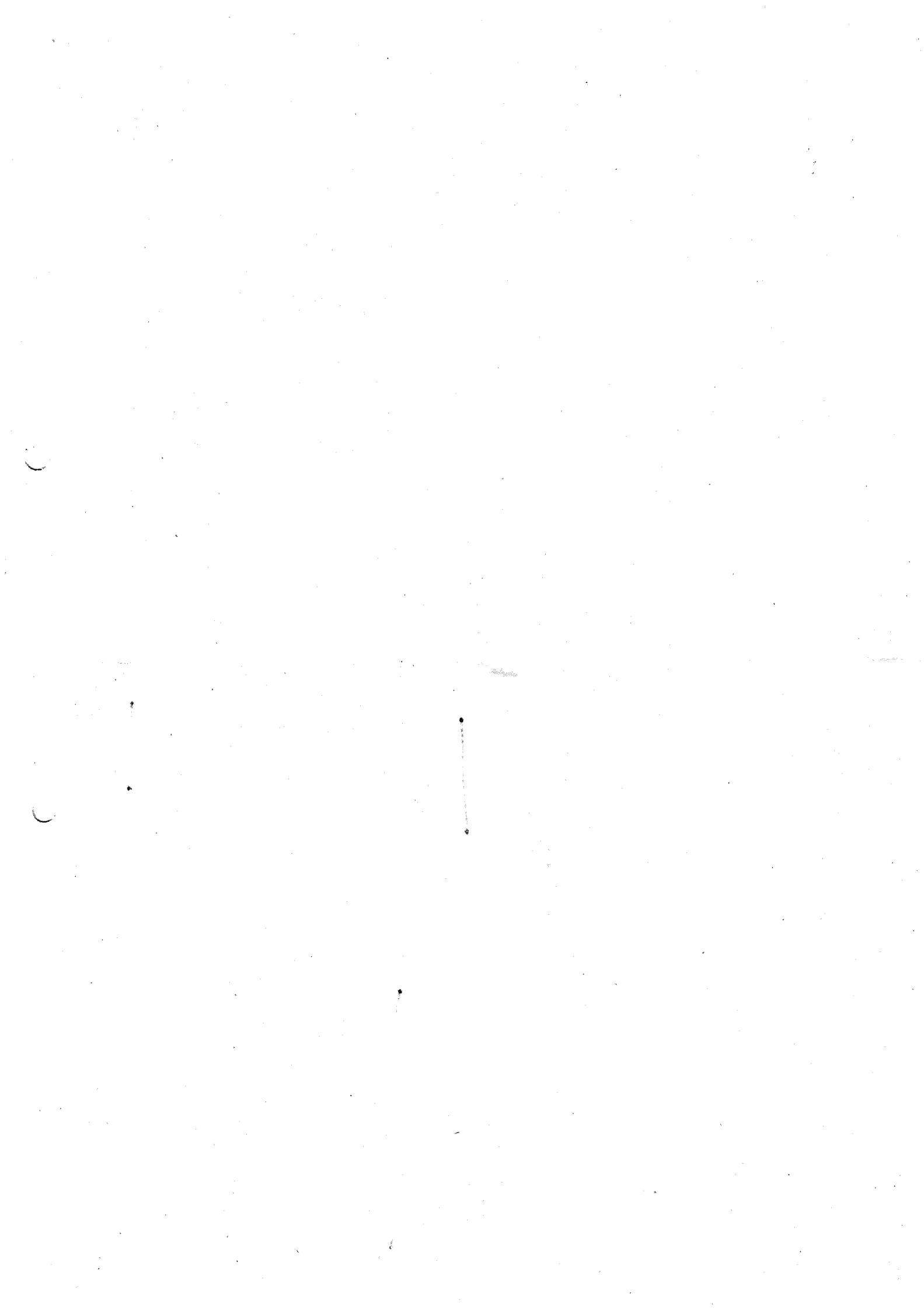
$$\frac{\partial^2 f}{\partial y \partial z}(0,0) = x^2 + z^2$$

$$\frac{\partial^2 f}{\partial z^2}(0,0) = 0$$

$$\frac{\partial^2 f}{\partial x^2}(0,0) = 2y$$

$$\frac{\partial^2 f}{\partial y^2}(0,0) = 0$$

$$\frac{\partial^2 f}{\partial z^2}(0,0) = 0$$



$$\frac{\partial^2 f}{\partial x \partial y} = 2x = \frac{\partial^2 f}{\partial y \partial x}$$

$$\frac{\partial^2 f}{\partial x^2} = 0 = \frac{\partial^2 f}{\partial z^2 \partial x}$$

$$\frac{\partial^2 f}{\partial y \partial z} = 1 = \frac{\partial^2 f}{\partial z \partial y}$$

$$\text{Hess}_f(x, y, z) = \begin{pmatrix} 2y & 2x & 0 \\ 2x & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

for the partial derivative for
 $\frac{\partial^{|\mathbf{m}|}}{\partial x_1^{m_1} \partial x_2^{m_2} \dots \partial x_n^{m_n}} f$
 we

$$\text{write } \frac{\partial^{|\mathbf{m}|}}{\partial x^n} f$$

x^n means $(x_1^{m_1}, x_2^{m_2}, \dots, x_n^{m_n})$

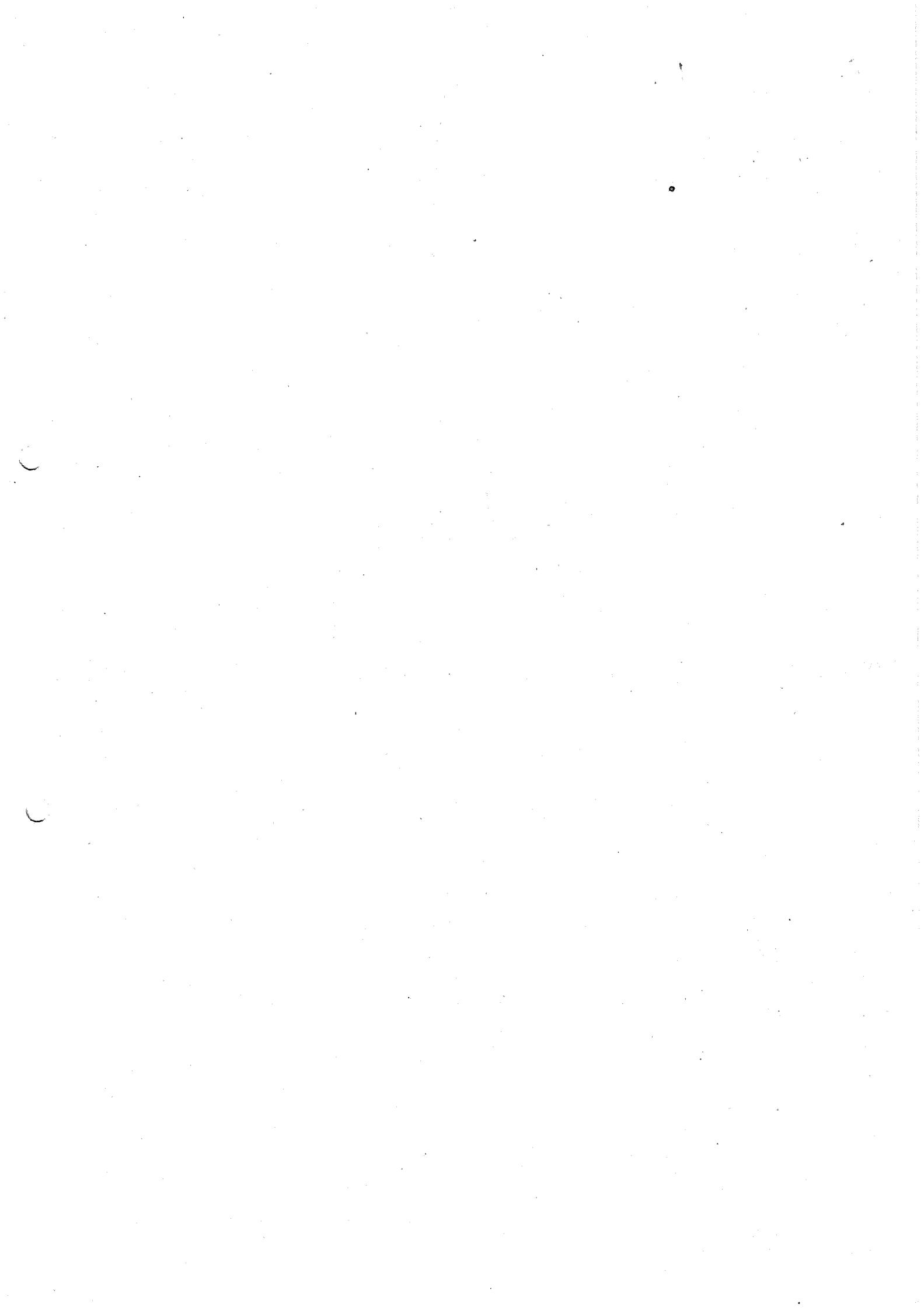
$$m! := m_1! m_2! \dots m_n!$$

Notation: When we are
 dealing w/ partial derivatives
 of higher order we use
 multi index notation.

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

$$\text{let } \mathbf{m} = (m_1, m_2, \dots, m_n)$$

$$\text{let } |\mathbf{m}| = m_1 + m_2 + \dots + m_n$$



We've already seen

a first order approximation

$$f = \mathbb{R}^n \rightarrow \mathbb{R} \text{ at } \bar{x}_0$$

It is given by affine lin. approx.
to f

$$f(x) = f(\bar{x}_0) + \nabla f(\bar{x}_0) \cdot (x - \bar{x}_0)$$

$$+ E_x(f; x_0).$$

Ex: Find an approx. value

for the number

$$\alpha := \sqrt{(3.03)^2 + (3.95)^2}$$

$$\begin{aligned} f &: \mathbb{R}^2 \rightarrow \mathbb{R} \\ (x,y) &\mapsto \sqrt{x^2 + y^2} \\ f(x_0) &= 5 \end{aligned}$$

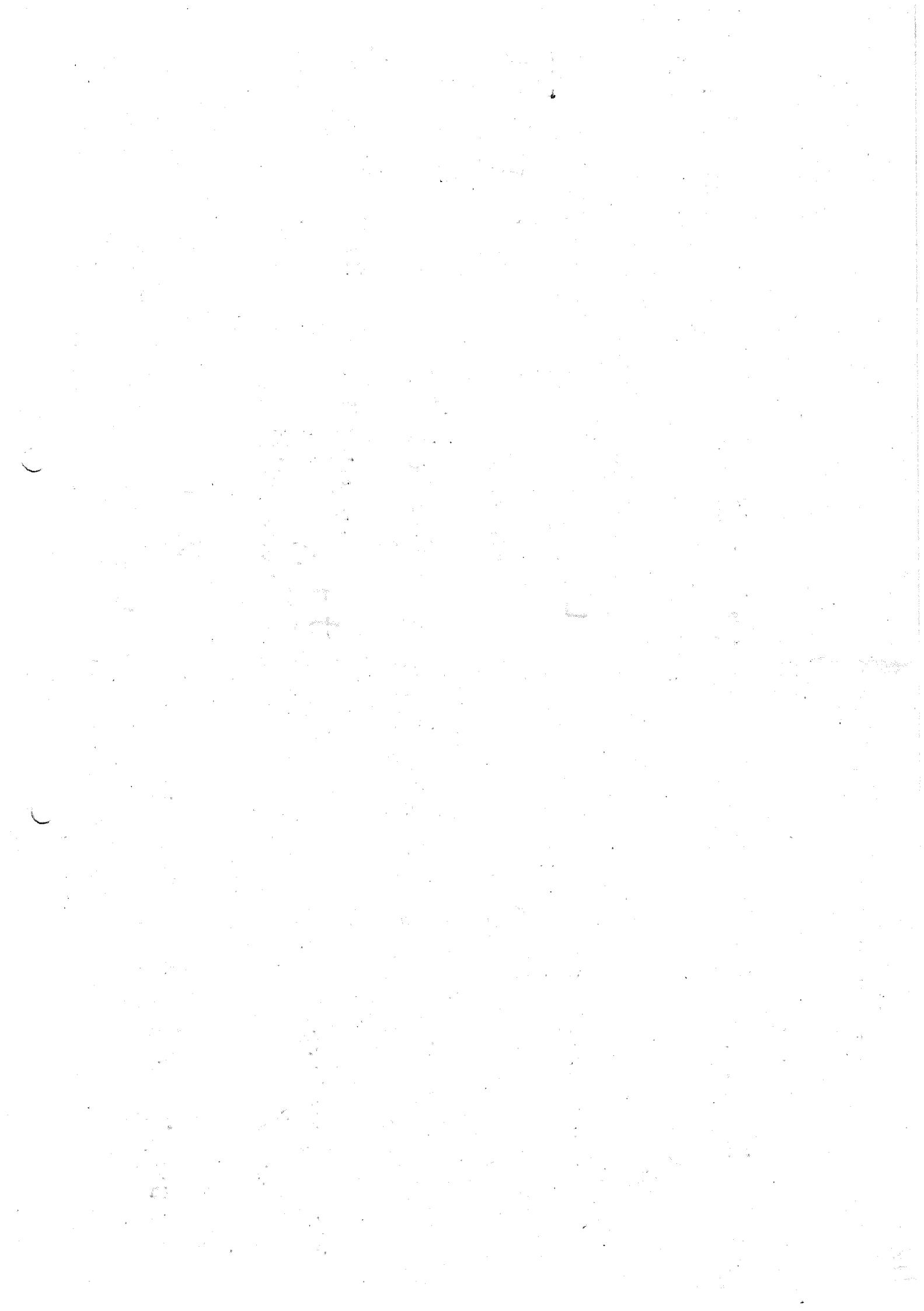
$$\begin{aligned} \nabla f(3,4) &= \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right) \\ &= \left(\frac{x}{\sqrt{x^2 + y^2}}, \frac{y}{\sqrt{x^2 + y^2}} \right) \\ &\stackrel{(x,y) = (3,4)}{=} \left(\frac{3}{5}, \frac{4}{5} \right) \end{aligned}$$

$$\begin{aligned} \alpha &= 5 + \frac{3}{5} \cdot 0.03 + \frac{4}{5} \cdot (-0.05) \\ &= 4.978 \end{aligned}$$

$$f(3.03, 3.95)$$

$$\approx f(3,4) + (\nabla f(3,4)) \cdot (0.03, -0.05)$$

$$\text{actual value} = 4.97829 \dots$$



for $f: \mathbb{R}^n \rightarrow \mathbb{R}$ $y = (y_1, \dots, y_n)$

let $T_k f(y; x_0) :=$

$$f(x_0) + \nabla f(x_0) \cdot y$$

$T_k f$ is called the Taylor poly of order k of f at x_0

$T_1 f(x - x_0; x_0)$ gives the

first order approx to f at x_0 . (This is a poly in 1 variable.)

What about higher order approximations?

$x_0 \in X$. The k -th Taylor polynomial of f at x_0 is a poly in n -variables of degree $\leq k$ given by

$$T_k f(y; x_0) = f(x_0) +$$

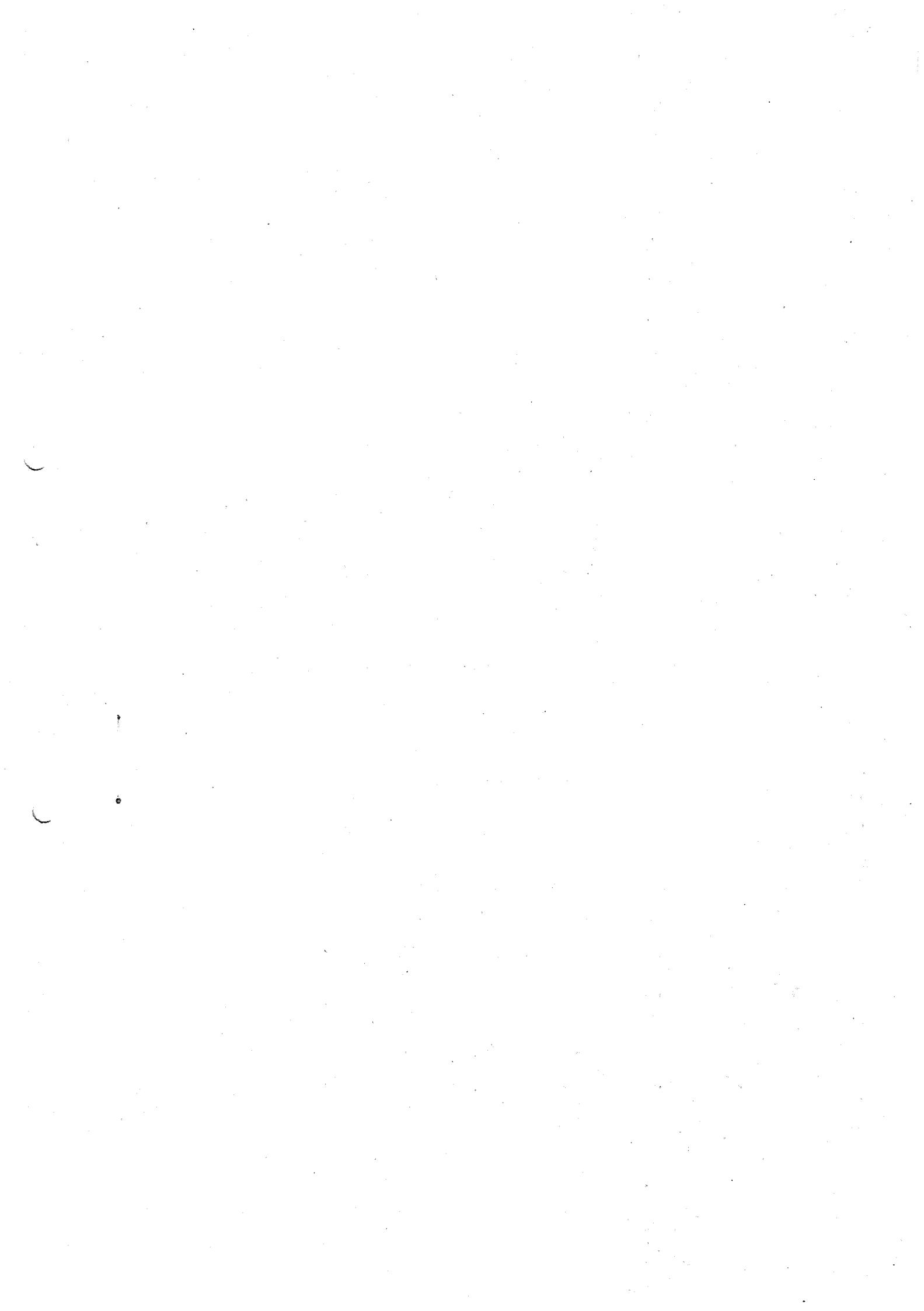
$$\sum_{i=1}^n \frac{\partial f}{\partial x_i}(x_0) y_i +$$

$$\dots + \sum_{m_1+ \dots + m_n = k} \frac{1}{m_1! \dots m_n!} \frac{\partial^k f}{\partial x_1^{m_1} \dots \partial x_n^{m_n}}(x_0) y^m.$$

$$= \sum_{|m| \leq k} \frac{1}{m!} \partial_x^m f(x) y^m.$$

Defn. Let $f: X \rightarrow \mathbb{R}$

$f \in C^k$ $X \subset \mathbb{R}^n$



eg. $f: \mathbb{R}^2 \rightarrow \mathbb{R}$, $f \in C^2$

$x_0 \in \mathbb{R}^2$ $y = (y_1, y_2)$

Thm. Let $f \in C^k(X, \mathbb{R})$
 $x_0 \in X$. Then we have

$$T_2 f(y, x_0) = f(x_0) + \nabla f(x_0) \cdot \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$

$$+ \frac{1}{2!} (y_1, y_2) \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}.$$

$$\frac{f(x) - f(x_0) - \nabla f(x_0) \cdot (x - x_0)}{\|x - x_0\|^k} \rightarrow 0 \quad x \rightarrow x_0.$$

$$= f(x_0) + \frac{\partial f}{\partial x_1}(x_0) y_1 + \frac{\partial f}{\partial y}(x_0) y_2$$

$$+ \frac{1}{2!} \left(\frac{\partial^2 f}{\partial x_1^2} y_1^2 + 2 \frac{\partial^2 f}{\partial x_1 \partial x_2} y_1 y_2 + \frac{\partial^2 f}{\partial x_2^2} y_2^2 \right).$$

$$\frac{\partial f}{\partial y} \Big|_{(0,0)} = 1.$$

$$\frac{\partial f}{\partial x} \Big|_{(0,0)} = 1$$

$$f(0,0) = 1$$

$$\frac{\partial f}{\partial x} \Big|_{(0,0)} = e^x \cdot e^y \cos x - e^{x+y} \sin x = 1.$$



$$\left. \frac{\partial^2 f}{\partial x^2} \right|_{(0,0)} = 0$$

$$\left. \frac{\partial^2 f}{\partial y^2} \right|_{(0,0)} = 0$$

$$\Delta = 1$$

$$\left. \frac{\partial^2 f}{\partial xy} \right|_{(0,0)} = 1$$

$$T_1 f = f(0,0) + \nabla f(0,0)(x,y) - (0,0)$$

$$T_1 f = 1 + x + y$$

$$T_2 f = 1 + x + y + \frac{1}{2}(xy)(0,1) \\ T_2 f = 1 + x + y + xy + \frac{1}{2}y^2$$

$$T_3 f = 1 + x + y + xy + \frac{1}{2}y^2$$

$$-\frac{1}{3}x^3 + \frac{1}{6}y^3 + \frac{1}{2}xy^2$$

$$T_3 f(x,y) = 1 + xy + xy + \frac{1}{2}y^2$$

$$+ \frac{1}{6}(-2)x^3$$

$$+ \frac{1}{6} \cdot 1 \cdot y^3$$

$$+ 0 \cdot x^2y$$

$$+ \frac{1}{2!1!} xy^2$$

$$C^k(X,Y) = \{ f : X \rightarrow Y \}$$

$$\frac{\partial^2 f}{\partial y^2} \frac{\partial^3 f}{\partial x^3}$$

$$= 1$$

$$\frac{\partial^3 f}{\partial x^3} = 0$$

$$\frac{\partial^3 f}{\partial y^3} = -2$$

$$(0,0) \left(\frac{\partial^3 f}{\partial x^3} \right) = 0$$

$$\left(\frac{\partial^2 f}{\partial x^2} \right)_{(0,0)} = 0$$

$f \in \mathcal{G}$ class C^k

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S 3.8: Critical points

and extreme of functions

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

$$f'(x_0) = 0.$$

Recall $f: \mathbb{R} \rightarrow \mathbb{R}$.
 If f has a local min or max at x_0 then

$$\underline{\text{Defn } f: X \subset \mathbb{R}^n \rightarrow \mathbb{R}}$$

def: we say $x_0 \in X$

is a local maximum (min)

if we can find a nbhd

$$B_r(x_0) = \{x \in \mathbb{R}^n \mid \|x - x_0\| < r\}$$

such $B_r(x_0) \subset \Sigma$ and

$$\text{set } \forall x \in B_r(x_0)$$

$$f(x) \leq f(x_0) \quad (\text{resp } f(x) \geq f(x_0)).$$

$$\text{ie } \frac{\partial f}{\partial x_1}(x_0) = \frac{\partial f}{\partial x_2}(x_0) = \dots = \frac{\partial f}{\partial x_n}(x_0) = 0.$$



Defn A pt $x_0 \in X$

is called a critical

point of f if $\nabla f(x_0) = 0$.

Critical points are candidates for loc. extremes.

Def A critical pt which is not a loc. min or max is called a saddle point.

Recall. If $f: [a, b] \rightarrow \mathbb{R}$

global extreme of f is either at an interior

pt $x_0 \in (a, b)$ for which $f'(x_0) = 0$ or at $x=a$, $x=b$

Thm. If $f: \bar{X} \rightarrow \mathbb{R}$

diff on the interior of X

where \bar{X}

is closed and bounded. Then ~~suff~~ global

extreme of f exists and it is either at a critical point of f or on the boundary of \bar{X} .

$$\bar{X} = \text{int}(X) \cup \text{bd}(\bar{X})$$

