

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

is called differentiable

at x_0 , with differential

$$u: \mathbb{R}^n \rightarrow \mathbb{R}^m, \text{ if}$$

\exists a linear map $u: \mathbb{R}^n \rightarrow \mathbb{R}^m$

such that

$$\lim_{x \rightarrow x_0} \frac{f(x) - f(x_0) - u(x - x_0)}{\|x - x_0\|} = 0.$$

ie. The affine linear map

$$g(x) = f(x_0) + u(x - x_0)$$

approximates f well around x_0

in the sense that

$f(x) - g(x) = \text{Error}$ goes to 0
faster than $\|x - x_0\| \rightarrow 0$.

The differential is denoted by

$$\frac{d}{dx} f: \mathbb{R}^n \rightarrow \mathbb{R}^m \quad \text{or}$$

$$(df)_{(x_0)}$$

Thm If f is diff at x_0

then ① f is continuous at x_0

② $\frac{\partial f_i}{\partial x_j}(x_0)$ exists $\forall i \leq m, j \leq n$.

③ The matrix of the
lin. map $df(x_0): \mathbb{R}^n \rightarrow \mathbb{R}^m$
 $x \rightarrow Ax$

is given by the Jacobian matrix

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

Thm If $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$

has all partial derivatives

defined and $\frac{\partial f_i}{\partial x_j}: \mathbb{R}^n \rightarrow \mathbb{R}^m$

are continuous. Then f is differentiable.

Thm 1) If $f, g: \mathbb{R}^n \rightarrow \mathbb{R}^m$
diff then so is $f \pm g$

$$\text{and } d_{x_0} f \pm d_{x_0} g = d_{x_0} (f \pm g)$$

2) If $f, g: \mathbb{R}^n \rightarrow \mathbb{R}$ diff

then so is fg and f/g (if $g \neq 0$)

$$d_{x_0} (fg) = \left(d_{x_0} f \right) g(x_0) + f(x_0) d_{x_0} g$$

The tangent space

at x_0 is the graph of the affine linear map

$$g(x) = f(x_0) + (d_{x_0} f)(x - x_0).$$

ie. $\left\{ (x, g(x)) \in \mathbb{R}^n \times \mathbb{R}^m \mid g(x) = f(x_0) + d_{x_0} f(x - x_0) \right\}$

Ex: If $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ diff at $\bar{x} = (a, b)$. Then

$$d_{(a,b)} f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$\begin{pmatrix} x \\ y \end{pmatrix} \mapsto \begin{pmatrix} \frac{\partial f}{\partial x}(a,b) & \frac{\partial f}{\partial y}(a,b) \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$(d_{(a,b)} f) \begin{pmatrix} x \\ y \end{pmatrix} = A_1 x + A_2 y$$

$$\text{where } A_1 = \frac{\partial f}{\partial x}(a,b) \quad A_2 = \frac{\partial f}{\partial y}(a,b)$$

$$g(x, y) = f(a, b) + A_1(x - a) + A_2(y - b)$$

Ex: $f: \mathbb{R}^2 \rightarrow \mathbb{R}$
 $(x, y) \mapsto \sqrt{x^2 + y^2}$

$$(x_0, y_0) = (3, 4)$$

$$f(3, 4) = 5$$

$$\nabla f(3, 4) = \begin{pmatrix} \frac{\partial f}{\partial x}(3, 4) \\ \frac{\partial f}{\partial y}(3, 4) \end{pmatrix} = \begin{pmatrix} 3/5 \\ 4/5 \end{pmatrix}$$

$$\frac{\partial f}{\partial x} = \frac{1}{2} \cdot \frac{2x}{\sqrt{x^2 + y^2}}$$

$$\frac{\partial f}{\partial y} = \frac{1}{2} \cdot \frac{2y}{\sqrt{x^2 + y^2}}$$

$$g(x, y) = f(x_0, y_0) +$$

$$\nabla f \cdot (x - 3, y - 4)$$

$$g(x, y) = 5 + \frac{3}{5}(x - 3) + \frac{4}{5}(y - 4)$$

What is the analog
of the chain rule

Thm. (Chain rule) let $X \subseteq \mathbb{R}^m$
open, $Y \subseteq \mathbb{R}^m$ open

and $f: X \rightarrow Y$

and $g: Y \rightarrow \mathbb{R}^p$

diff. functions. Then

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

is differentiable.

If $x_0 \in X$, $f(x_0) = y_0$

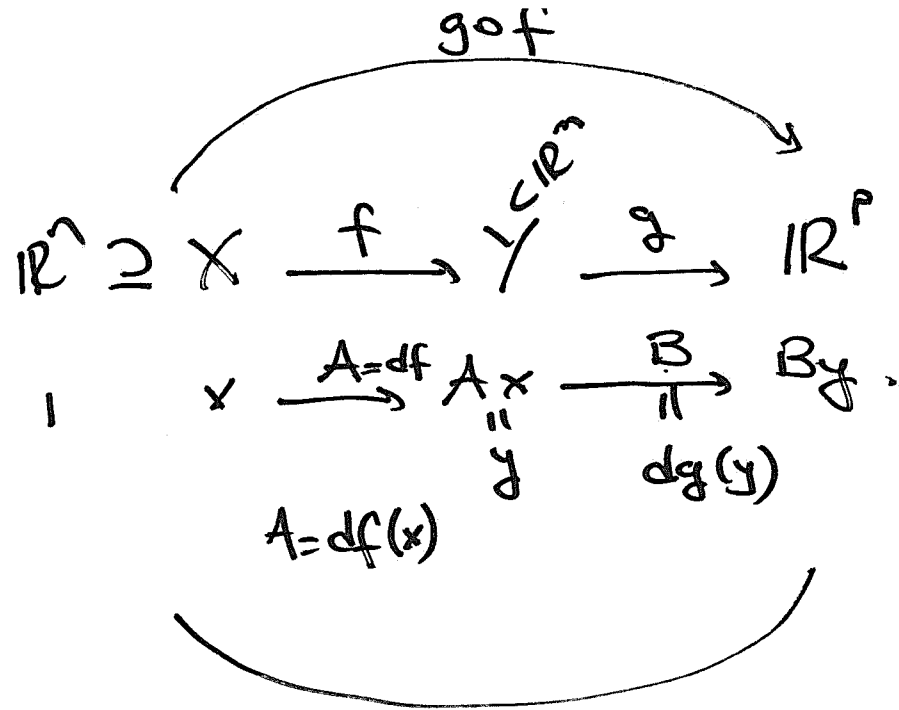
$$d_{x_0}(g \circ f) = dg(f(x_0)) \circ df(x_0).$$

$$\parallel \\ d(g \circ f)(x_0).$$

↓
composition
of the 2
linear maps
corresponding
to the differentials

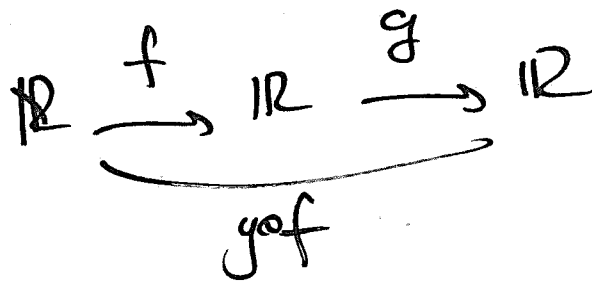
In particular for the Jacobi
Matrix of $g \circ f$ satisfies

$$J_{g \circ f}(x_0) = J_g(f(x_0)) \cdot J_f(x_0).$$



$$d(\text{gof}) = BA$$

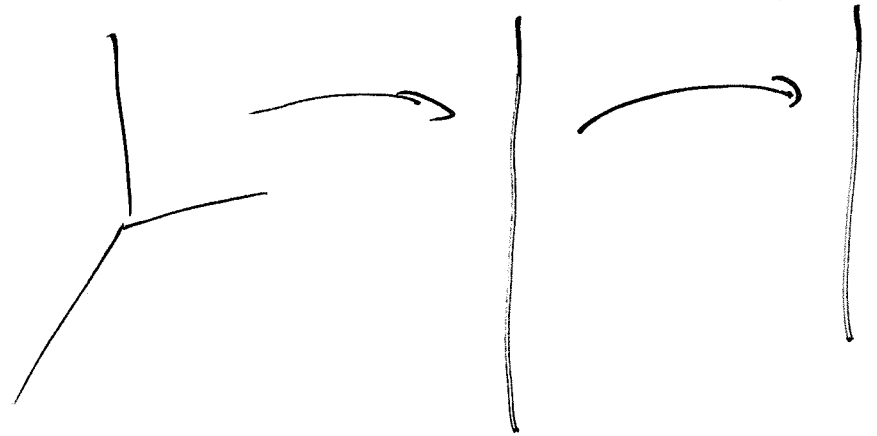
Ex. ① $n = m = p = 1$.



$$(\text{gof})'(x) = g'(f(x)) \cdot f'(x)$$

② $\mathbb{R}^n \xrightarrow{f} \mathbb{R} \xrightarrow{g} \mathbb{R}$

$\text{gof} = \mathbb{R}^n \rightarrow \mathbb{R}$



$\mathbb{R}^3 \rightarrow \mathbb{R} \rightarrow \mathbb{R}$

$$d(\text{gof})(x_0) = dg(f(x_0)) \cdot f'(x_0)$$

Ex ② $h: \mathbb{R}^2 \rightarrow \mathbb{R}$

$$(x, y) \mapsto e^{xy}$$

$$dh(x, y) = (y e^{xy}, x e^{xy})$$

or we can view h
as a composition of 2

functions

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$(x, y) \rightarrow xy$$

$$g: \mathbb{R} \rightarrow \mathbb{R}$$

$$t \rightarrow e^t$$

$$(g \circ f)(x, y) = e^{xy}$$

Using chain rule

$$d(g \circ f) = dg(f(x, y)) \cdot df(x, y)$$

$$e^{xy} \cdot (y, x)$$

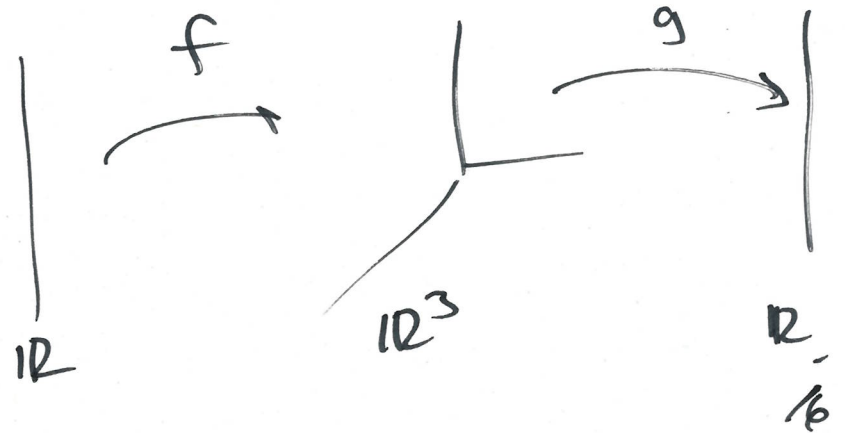
$$= \begin{pmatrix} e^{xy} & y \\ x & e^{xy} \end{pmatrix}$$

③.

$$t \rightarrow (f_1(t), f_2(t), \dots, f_n(t))$$

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

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



$$g \circ f: \mathbb{R} \rightarrow \mathbb{R}$$

$$d(g \circ f) = \underbrace{dg(f(t_0))}_{\text{matrix}} \cdot f'(t_0)$$

$$\left(\frac{\partial g}{\partial x_1}(f(t)), \frac{\partial g}{\partial x_2}, \dots, \frac{\partial g}{\partial x_n} \right) \cdot \begin{pmatrix} f_1'(t) \\ f_2'(t) \\ \vdots \\ f_n'(t) \end{pmatrix}$$

We can apply this to the following

$$f: \mathbb{R} \rightarrow \mathbb{R}^2 \\ t \rightarrow (f_1(t), f_2(t))$$

$$M: \mathbb{R}^2 \rightarrow \mathbb{R} \\ (x, y) \rightarrow xy$$

$$dM(x, y) = (y, x)$$

$$(M \circ f)(t) = f_1(t) f_2(t)$$

$$d(M \circ f)(t) = \underbrace{dM(f(t))}_{\text{matrix}} \cdot f'(t)$$

$$= dM(f_1(t), f_2(t)) \cdot \begin{pmatrix} f_1'(t) \\ f_2'(t) \end{pmatrix}$$

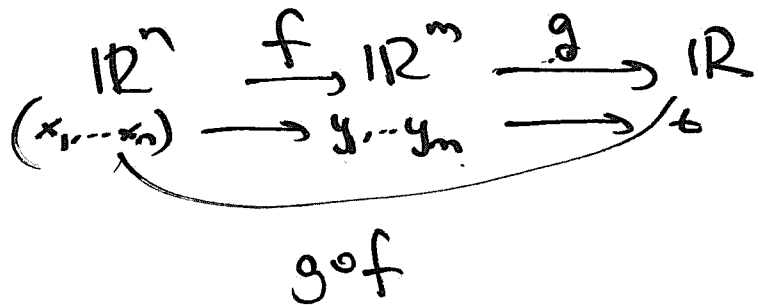
$$= (f_2(t), f_1(t)) \cdot \begin{pmatrix} f_1'(t) \\ f_2'(t) \end{pmatrix}$$

$$= f_1'(t) \cdot f_2(t) + f_1(t) \cdot f_2'(t)$$

Product rule of f-variable analysis.

$$f(x_0) = y_0$$

(4)



$$J_{g \circ f}(x_0) = \left(\frac{\partial(g \circ f)}{\partial x_1}, \frac{\partial(g \circ f)}{\partial x_2}, \dots \right)$$

$$\dots \frac{\partial(g \circ f)}{\partial x_n} \Bigg)$$

$$= \underbrace{J_g(f(x_0))}_{1 \times m} \cdot J_f(x_0)$$

$$\left(\frac{\partial g}{\partial y_1}(y_0), \dots, \frac{\partial g}{\partial y_m}(y_0) \right)_{1 \times m} \cdot \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_n} \\ \vdots & & \vdots \\ \frac{\partial f_m}{\partial x_1} & \dots & \frac{\partial f_m}{\partial x_n} \end{pmatrix}$$

This gives for example

$$\frac{\partial(g \circ f)}{\partial x_1} = \frac{\partial g}{\partial y_1}(y_0) \cdot \frac{\partial f_1}{\partial x_1}$$

$$+ \frac{\partial g}{\partial y_2}(y_0) \cdot \frac{\partial f_2}{\partial x_1}(x_0)$$

+ ...

$$+ \frac{\partial g}{\partial y_m}(y_0) \cdot \frac{\partial f_m}{\partial x_1}(x_0)$$

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

Rk If f is diff at x_0

\Rightarrow partial derivatives of f exists to write each variable -

Defn

In general given any

$v \in \mathbb{R}^n$, we define

the directional derivative

of f at x_0 in the

direction of v as the

derivative at $t=0$ of

$g(t) := f(x_0 + tv)$
if it exists.

we write

$$d_f(x_0), \quad d_f(v; x_0)$$

$$= \lim_{t \rightarrow 0} \frac{f(x_0 + tv) - f(x_0)}{t}$$

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

$X \subseteq \mathbb{R}^n$ diff at $x_0 \in X$

and $v \in \mathbb{R}^n, v \neq 0$

Then the directional derivative of f at x_0

in the direction of v

exists and

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

Ex $f(x, y) = \begin{pmatrix} x^2 + y^2 \\ 2x \\ 2y \end{pmatrix}$

$$J_f(1, 2) = \begin{pmatrix} 2 & 4 \\ 0 & 2 \\ 2 & 0 \end{pmatrix}$$

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}^3$$

$$df(1, 2): \mathbb{R}^2 \rightarrow \mathbb{R}^3$$

$$\begin{pmatrix} x \\ y \end{pmatrix} \mapsto J_f(1, 2) \begin{pmatrix} x \\ y \end{pmatrix}$$

$$J_f(x, y) = \begin{pmatrix} 2x & 2y \\ 2 & 0 \\ 0 & 2 \end{pmatrix}$$

Hence

$df(1, 2)$ is the lin.

map which sends

$$\begin{pmatrix} x \\ y \end{pmatrix} \text{ to } \begin{pmatrix} 2 & 4 \\ 0 & 2 \\ 2 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 2x + 4y \\ 2x \\ 2y \end{pmatrix}$$

$$\text{Say } v = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

Directional der. of f at $(1, 2)$

in the direction of v is

$$\left. \frac{d}{dt} f((1, 2) + t(1, 1)) \right|_{t=0}$$

$$= (df(1, 2))(v) = \begin{pmatrix} 2 & 4 \\ 2 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 6 \\ 2 \\ 2 \end{pmatrix}$$

Can verify from

$$\frac{d}{dt} (f(1+t, 2+t))$$

$$\frac{d}{dt} \begin{pmatrix} (1+t)^2 + (2+t)^2 \\ 2(1+t) \\ 2(2+t) \end{pmatrix}$$

$$= \begin{pmatrix} 2(1+t) + 2(2+t) \\ 2 \\ 2 \end{pmatrix}$$

at $t=0$ this also

gives $\begin{pmatrix} 6 \\ 2 \\ 2 \end{pmatrix}$

The gradient of a
 function $f: \mathbb{R}^n \rightarrow \mathbb{R}$
 $(x_1, \dots, x_n) \rightarrow f(x_1, \dots, x_n)$

(I) $\nabla f(x_0) = \begin{pmatrix} \frac{\partial f}{\partial x_1}(x_0) \\ \vdots \\ \frac{\partial f}{\partial x_n}(x_0) \end{pmatrix}$

points in the direction
 of "greatest increase"!

For any
 derivative $v = v_1, \dots, v_n \in \mathbb{R}^n$, the directional
 derivative $(df)_{x_0}(v) = \nabla f(x_0) \cdot v$ is

$$= \begin{pmatrix} \frac{\partial f}{\partial x_1}(x_0) \\ \vdots \\ \frac{\partial f}{\partial x_n}(x_0) \end{pmatrix} \cdot (v_1, \dots, v_n) = \langle \nabla f, v \rangle$$

Suppose $\|v\| = 1$

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}$$



$$P = f(x_0, y_0)$$

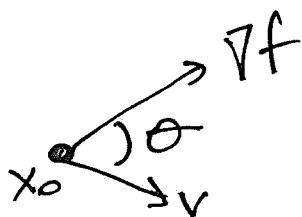
$$\nabla f(x_0, y_0) = \begin{pmatrix} \frac{\partial f}{\partial x}(x_0, y_0) \\ \frac{\partial f}{\partial y}(x_0, y_0) \end{pmatrix}$$

$$J_f(x_0)(v) = \langle \nabla f, v \rangle$$

$$= \|\nabla f\| \|v\| \cos \theta$$

we used
 $\|v\| = 1$

$$\rightarrow \|\nabla f\| \cos \theta$$

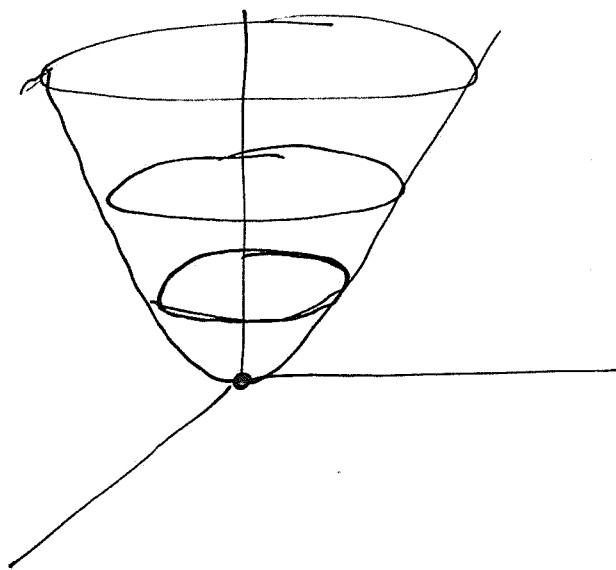


↓
 maximized
 when $\theta = 0$.

=
 If we move in the direction
 of the gradient we
 maximize the directional
 derivative.

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$(x, y) \rightarrow x^2 + y^2$$



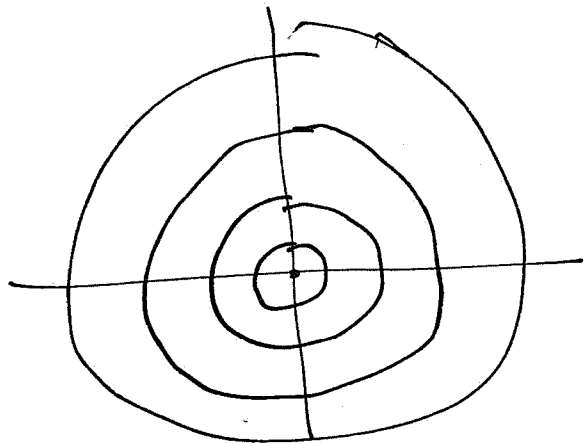
$$f(x, y) = \text{constant}$$

$$f(x, y) = 0 \Rightarrow (x, y) = (0, 0)$$

$$\{(x, y) : f(x, y) = 1\} = \{(x, y) \mid x^2 + y^2 = 1\}$$

(II) Consider the level sets of a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$.

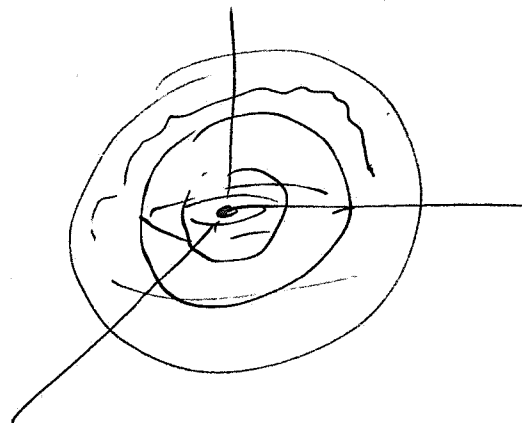
$$L_c := \{x \in \mathbb{R}^n \mid f(x) = c\}$$



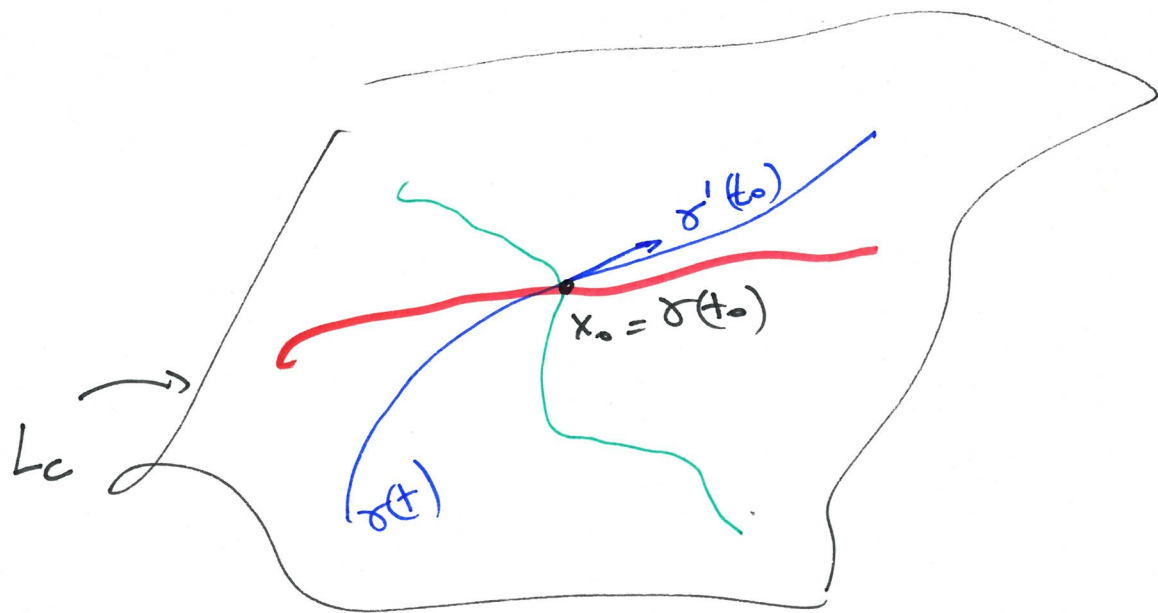
Ex: $f: \mathbb{R}^3 \rightarrow \mathbb{R}$
 $(x, y, z) \rightarrow x^2 + y^2 + z^2$

$$L_1 = \{(x, y, z) \mid x^2 + y^2 + z^2 = 1\}$$

sphere of radius 1



let $\gamma: [0, 1] \rightarrow \mathbb{R}^n$
be a diff. curve
on the level set of f
through x_0 s.t. $\gamma(t) \in L_c$
for some c .



$$L_c = \{x \in \mathbb{R}^n \mid f(x) = c\} = \text{level set}$$

$$f(\sigma(t)) = c \quad \text{since } \sigma(t) \subset L_c$$

Using the chain rule: we get

$$0 = (f(\sigma(t)))' = df(\sigma(t)) \cdot \sigma'(t)$$

$$\nabla_x f(x_0) \cdot \sigma'(t_0) = 0$$

$\Rightarrow \nabla f(x_0)$ is perpendicular to the tangent vector $\sigma'(t_0)$

This is true for any

curve that lies on L_c and goes through x_0

Hence $\nabla f(x_0)$ is perpendicular to the level set

(For $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ level sets are curves
 For $f: \mathbb{R}^3 \rightarrow \mathbb{R}$ level sets are surfaces)

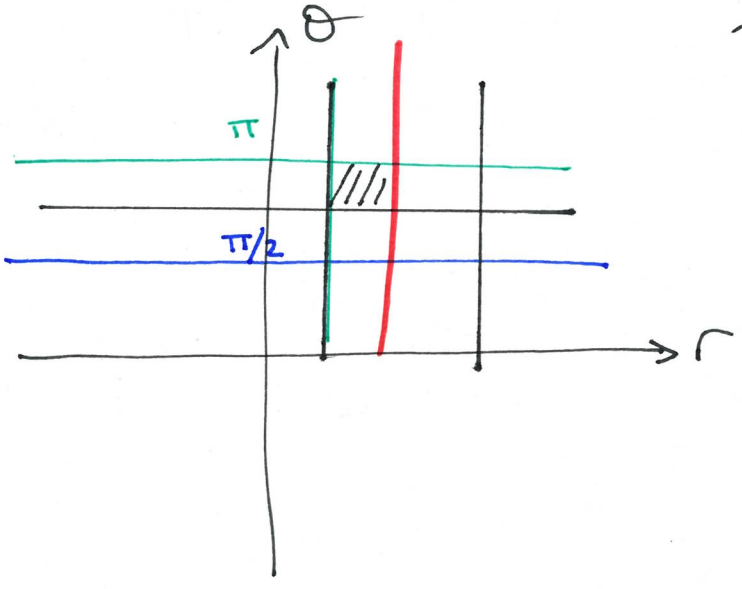
Polar coordinates

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

$$(r, \theta) \mapsto \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} r \cos \theta \\ r \sin \theta \end{pmatrix} = \begin{pmatrix} f_1(r, \theta) \\ f_2(r, \theta) \end{pmatrix}.$$

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

$$\det J_f(r, \theta) = r (\cos^2 \theta + \sin^2 \theta) = r$$



f

