

HW 2 Comments :

Problem 3: IF you have

$$\vec{r}(0) = \langle x_0, y_0 \rangle$$

$$\vec{v}(0) = \langle u_0, v_0 \rangle$$

$$\vec{a}(t) = \langle 0, -g \rangle$$

Then,

$$\vec{r}(t) = \left\langle x_0 + u_0 t, y_0 + v_0 t - \frac{1}{2} g t^2 \right\rangle$$

$$= \left\langle 0 + t \cos \theta, 0 + t \sin \theta - \frac{1}{2} g t^2 \right\rangle$$

HW 2 due tomorrow (Fri)

No class Mon.

Quiz 2 on Tues beginning of class.

Start Chapter 4 early.

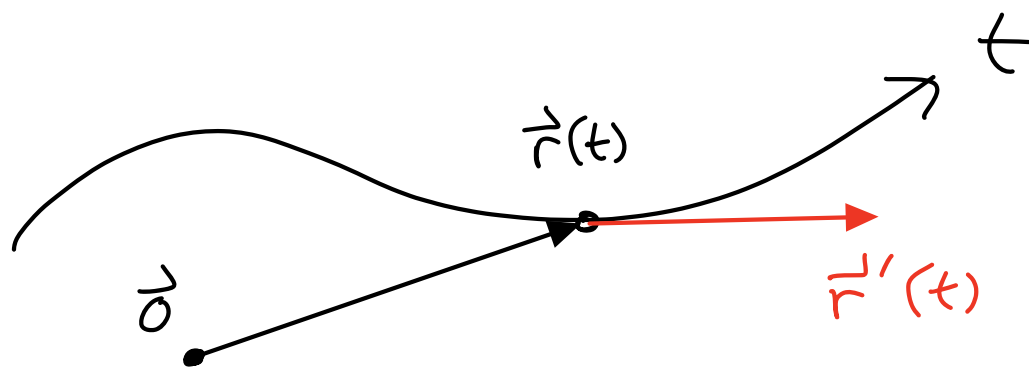
Chap 4: Differentiation of functions of several variables.

(i.e. "gradient vectors").

So far we have studied functions

$$\vec{r} : \mathbb{R} \rightarrow \mathbb{R}^n$$

Picture: Parametrized path



The derivative is velocity:

$$\vec{r}(t) = \langle x_1(t), x_2(t), \dots, x_n(t) \rangle$$

$$\vec{r}'(t) = \langle x_1'(t), x_2'(t), \dots, x_n'(t) \rangle$$

$$\frac{d\vec{r}}{dt} = \left\langle \frac{dx_1}{dt}, \frac{dx_2}{dt}, \dots, \frac{dx_n}{dt} \right\rangle.$$

Applications:

- Integrate  $\|\vec{r}'(t)\|$  to get arc length.
- Newton's 2nd Law.

$$\vec{v}(t) = \vec{r}'(t)$$

$$\vec{a}(t) = \vec{v}'(t) = \vec{r}''(t)$$

$$\vec{F}(t) = m \vec{a}(t) = m \vec{r}''(t).$$

Now we consider functions

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

To each point  $(x_1, \dots, x_n)$  in  $\mathbb{R}^n$   
we assign a number (i.e. scalar)

$$f(x_1, x_2, \dots, x_n).$$

Called a "scalar field".

e.g. temperature  
pressure  
density  
etc.

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

$$f(x, y) = \left(\frac{x}{2}\right)^2 + y^2$$

We can visualize this in 2 ways:

- Level Curves :

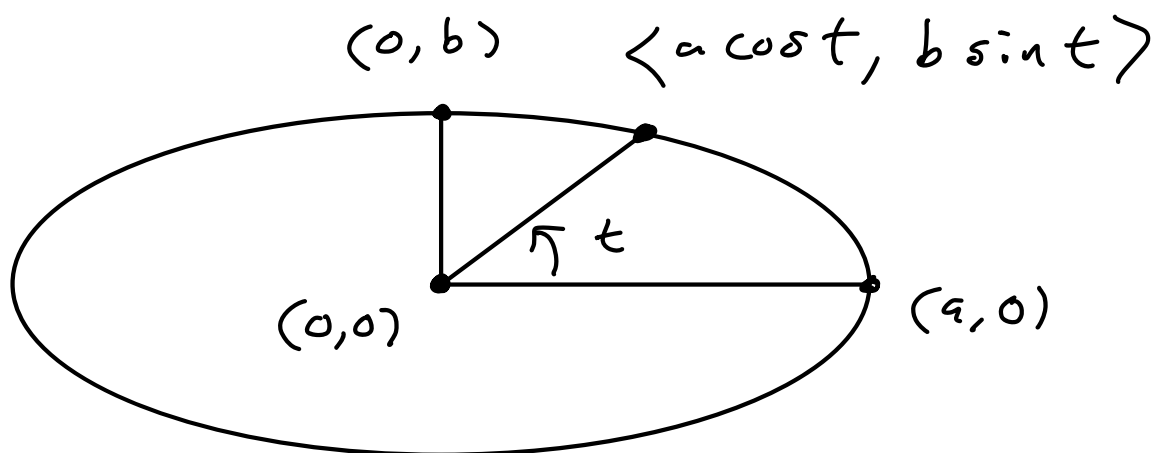
For each fixed constant  $c \in \mathbb{R}$   
we get a curve in  $\mathbb{R}^2$  defined by

$$f(x,y) = c.$$

In our case, each level curve  
is an ellipse

$$\left(\frac{x}{2}\right)^2 + y^2 = c$$

[Aside : Equation of an ellipse.



$$\left(\frac{x}{a}\right)^2 + \left(\frac{y}{b}\right)^2 = 1$$

Special case :  $a = b = r$

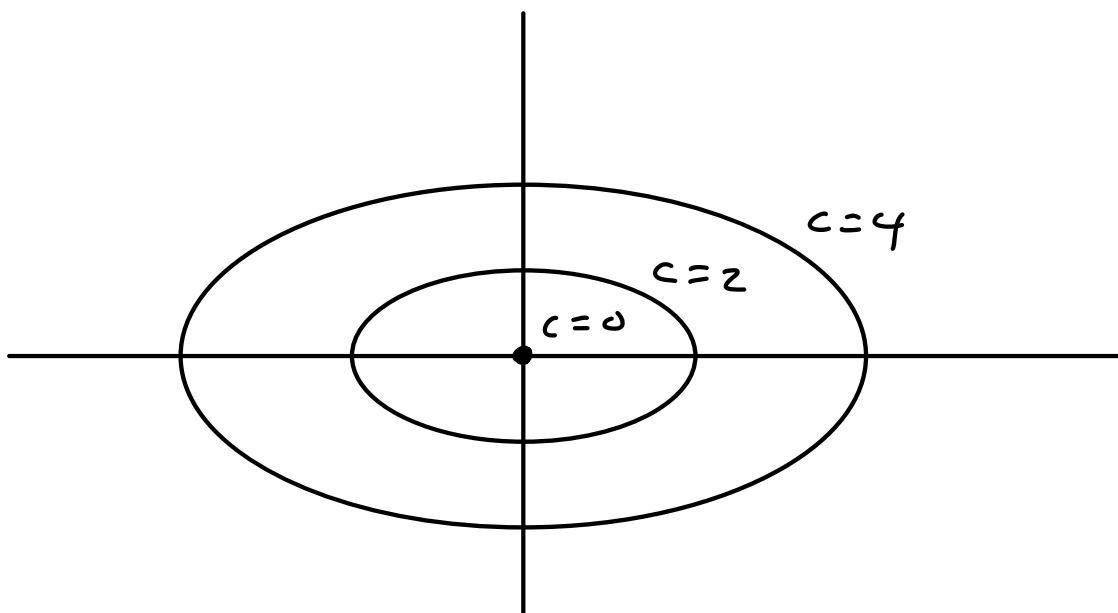
$$\left(\frac{x}{r}\right)^2 + \left(\frac{y}{r}\right)^2 = 1$$

$$x^2 + y^2 = r^2$$

Circle of radius  $r$ . ]

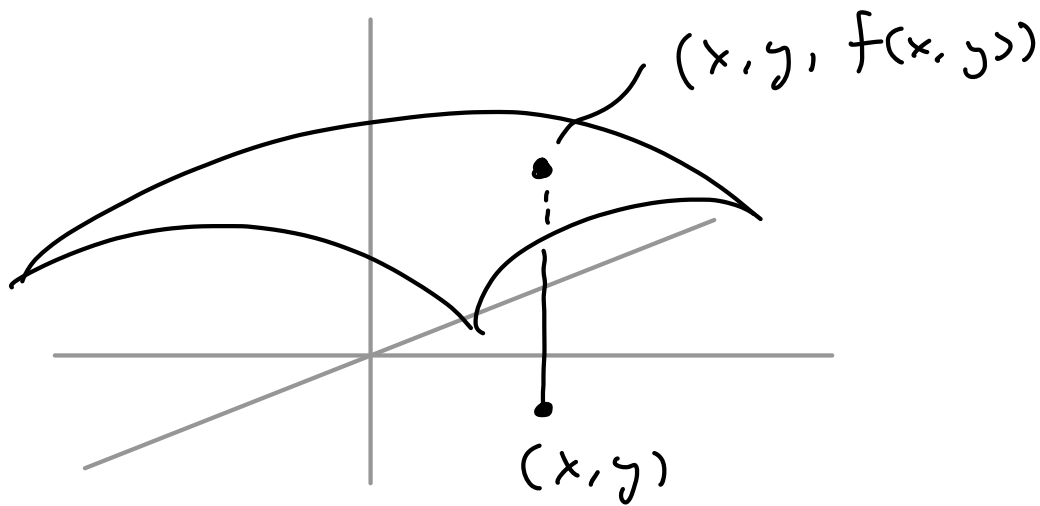
$$\text{So } \left(\frac{x}{2}\right)^2 + y^2 = c$$

$$\left(\frac{x}{2\sqrt{c}}\right)^2 + \left(\frac{y}{\sqrt{c}}\right)^2 = 1.$$



Infinitely many level curves. You have to imagine (or use color, heat map if  $c = \text{temperature}$ ).

- We can also visualize  $f(x,y)$  as the 2D surface  $z = f(x,y)$ .

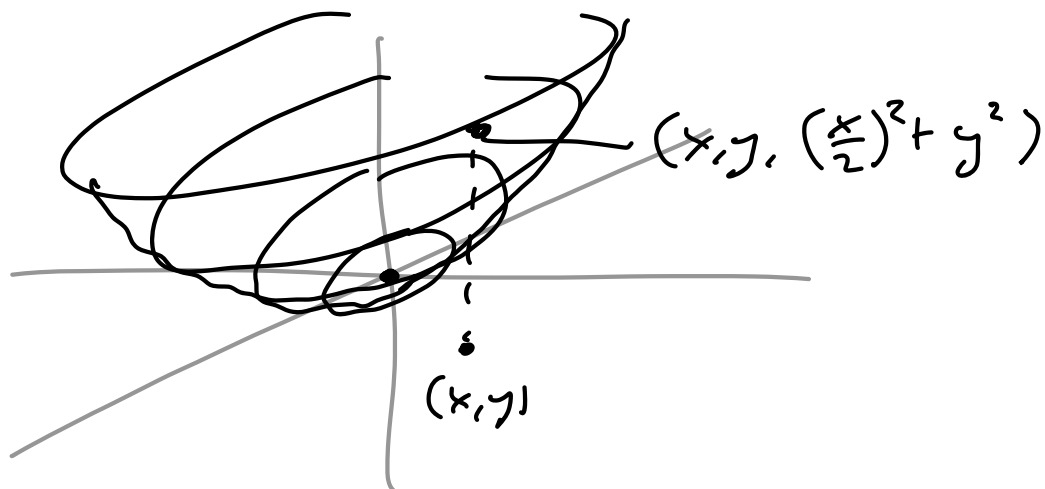


The height of the surface above the point  $(x,y)$  is the scalar  $f(x,y)$ .

[ Think: height = temperature ... ]

Our Example:  $z = \left(\frac{x}{2}\right)^2 + y^2$

is a parabolic bowl ("paraboloid")



Remark: The graph  $z = f(x, y)$  is a useful visualization but it does not work for scalar fields  $f: \mathbb{R}^3 \rightarrow \mathbb{R}$ .

Say  $f(x, y, z) =$  temperature at point  $(x, y, z)$  in  $\mathbb{R}^3$ .

Then the "graph"  $w = f(x, y, z)$  is a "curvy 3D shape" living in 4D space, which is NOT HELPFUL. In this case our only hope is to visualize the "level surfaces"

$$f(x, y, z) = c \text{ for fixed } c.$$

These are the points in  $\mathbb{R}^3$  with a given fixed temperature  $c$ .



# BIG QUESTION:

What is the "derivative" of a scalar field  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  ?

Ideas:

① If  $f$  is temperature at a point then derivative should be "rate of change of temperature".

Problem: Rate of change of temp depends on our velocity.

①' Given a point  $P$  and a velocity  $\vec{v}$ , what rate of change of temperature do you feel?

② Recall:  $df/dx$  is the slope of the tangent line to the curve  $y = f(x)$  in the plane.



So ... deriv of  $f(x,y)$  should be "slope of tangent plane" to the surface  $z = f(x,y)$ .

Problem: A plane is not determined by a slope; it is determined by a normal vector.

②' Derivative of  $f(x,y)$  should give the normal vector to the tangent plane to surface  $z = f(x,y)$  at a given point.



Good News: Turns out problems ①' & ②' are the same, determined by the GRADIENT VECTOR.

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

$$f(x_1, x_2, \dots, x_n)$$

we define the gradient vector

$$\nabla F = \left\langle \frac{dF}{dx_1}, \frac{dF}{dx_2}, \dots, \frac{dF}{dx_n} \right\rangle$$

Example:  $f(x, y) = \frac{1}{4}x^2 + y^2$

$$\nabla F(x, y) = \left\langle \frac{1}{2}x, 2y \right\rangle$$

$$\left[ \frac{d}{dx} \left( \frac{1}{4}x^2 + y^2 \right) = \frac{1}{4}2x + \bigcirc \right]$$

Because  $d/dx$  treats  $y$  as a constant. Most books write

$$\frac{\partial}{\partial x} \text{ instead of } \frac{d}{dx}$$

and call this a "partial derivative with respect to  $x$ ". ]

Remarks:

- $\nabla$  is called "nabla".

- The vector  $\nabla F(x, y)$  changes from point to point, so we can

think of  $\nabla f$  as a "vector field"

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

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

Called the "gradient vector field".

[ Examples of vector fields.

force fields (gravity, electric, ...)

velocity fields (wind) ]



The gradient vector to

$$f(x, y) = \frac{1}{4}x^2 + y^2$$

at the point  $(x_0, y_0)$  is

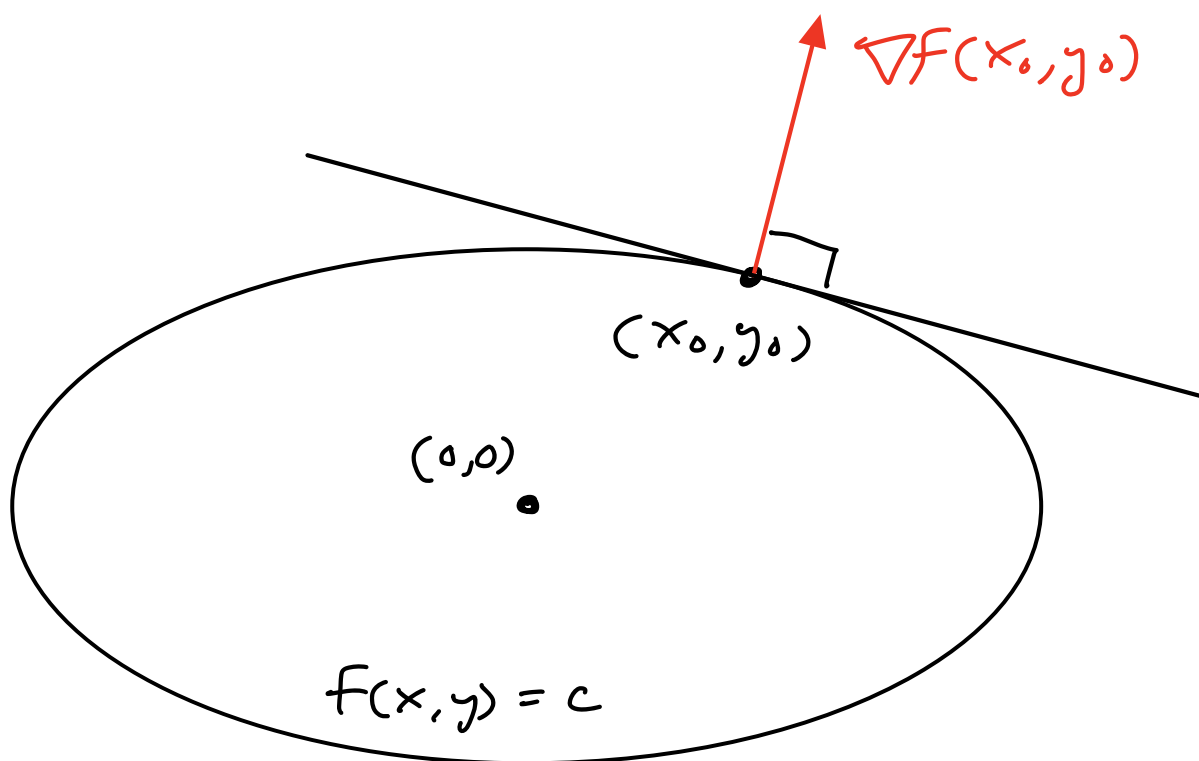
$$\nabla f(x_0, y_0) = \left\langle \frac{1}{2}x_0, 2y_0 \right\rangle.$$

MEANING: If  $c = f(x_0, y_0)$

is the temperature at this point

then  $\nabla f(x_0, y_0)$  is perpendicular

to the level curve :



Meaning :  $\nabla f(x_0, y_0)$  is the direction of maximum increase of temperature at the point  $(x_0, y_0)$ .




Two Rigorous Statements.


- The tangent line to the curve  $f(x, y) = \text{constant} = c$

at the point  $(x_0, y_0)$  is

$$\frac{dF}{dx}(x_0, y_0)(x - x_0) + \frac{dF}{dy}(x_0, y_0)(y - y_0) = 0.$$

$$\nabla f(x_0, y_0) \cdot (x - x_0, y - y_0) = 0$$

  
this is a  
normal vector

  
this is a point  
on the line.

In our case

$$\nabla F(x_0, y_0) \cdot (x - x_0, y - y_0) = 0$$

$$\left\langle \frac{1}{2}x_0, 2y_0 \right\rangle \cdot (x - x_0, y - y_0) = 0$$

$$\frac{1}{2}x_0(x - x_0) + 2y_0(y - y_0) = 0$$

The tangent line to the curve

$$\frac{1}{4}x^2 + y^2 = \text{constant}$$

at the point  $(x_0, y_0)$ .

e.g. The tangent line to ellipse

$$\frac{1}{4}x^2 + y^2 = 1$$

at point  $(\sqrt{2}, \sqrt{2}/2)$  has equation  
 $x_0$   $y_0$

$$\frac{1}{2}x_0(x-x_0) + 2y_0(y-y_0) = 0$$

$$\frac{1}{2}\sqrt{2}(x-\sqrt{2}) + 2\frac{\sqrt{2}}{2}(y-\frac{\sqrt{2}}{2}) = 0$$

$$\frac{\sqrt{2}}{2}x - 1 + \sqrt{2}y - 1 = 0$$

$$\frac{\sqrt{2}}{2}x + \sqrt{2}y = 2$$

$$\frac{1}{2}x + y = \frac{2}{\sqrt{2}} = \sqrt{2}.$$



Example: Find equation of the tangent line to circle

$$x^2 + y^2 = 25$$

at the point  $(x, y) = (3, 4)$ .

$$\text{Let } f(x, y) = x^2 + y^2.$$

$$\text{Then } \nabla f(x, y) = \langle 2x, 2y \rangle.$$

$$\nabla f(3, 4) = \langle 6, 8 \rangle.$$

So tangent line is

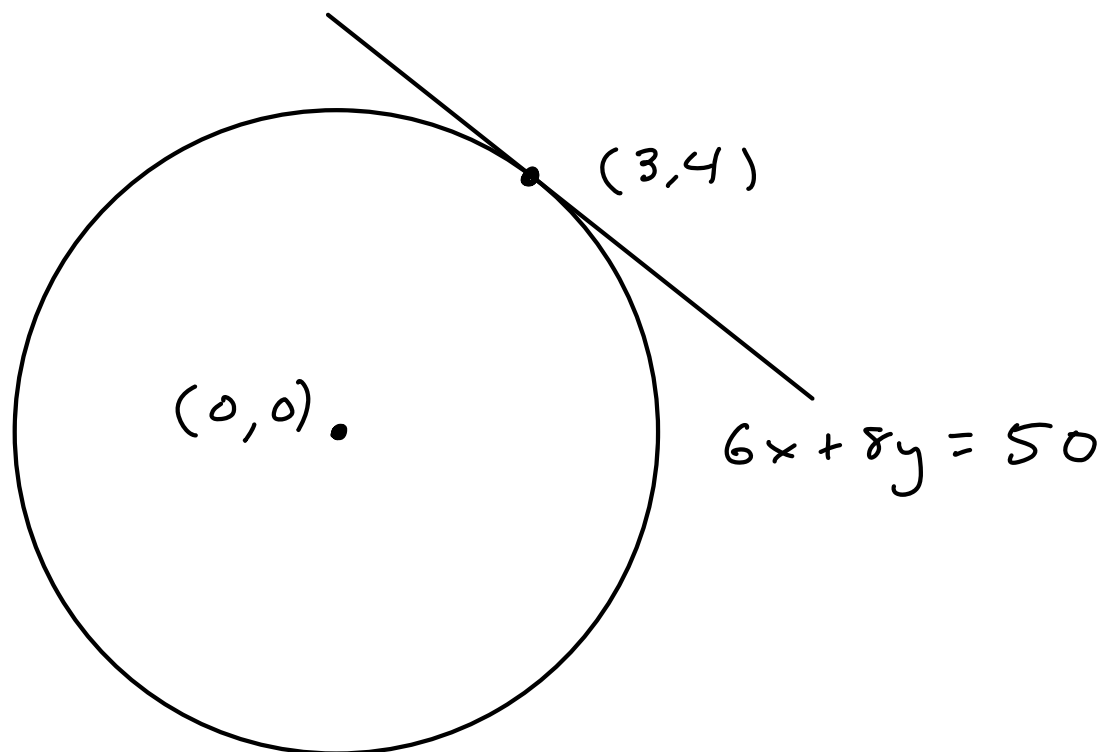
$$\nabla f(3, 4) \cdot \langle x-3, y-4 \rangle = 0$$

$$\langle 6, 8 \rangle \cdot \langle x-3, y-4 \rangle = 0$$

$$6(x-3) + 8(y-4) = 0.$$

$$6x + 8y - 18 - 32 = 0$$

$$6x + 8y = 50$$



This Week: Gradients.

(Chapter 4: Differentiation of multi variable functions)

A function  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  is called a "scalar field". To each point  $P = (x_1, x_2, \dots, x_n)$  in  $\mathbb{R}^n$  it associates a scalar

$f(P)$  or  $f(x_1, x_2, \dots, x_n)$ .

Think:  $f(P)$  is temperature at the point  $P$ .

The derivative of  $f$  defined as

$$\nabla f = \left\langle \frac{df}{dx_1}, \frac{df}{dx_2}, \dots, \frac{df}{dx_n} \right\rangle$$

$$\left( \text{or } \left\langle \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right\rangle \right)$$

Notation:  $\frac{\partial f}{\partial x_i}$  means we take

deriv. with respect to variable  $x_i$ , pretend that the other vars. are constant.



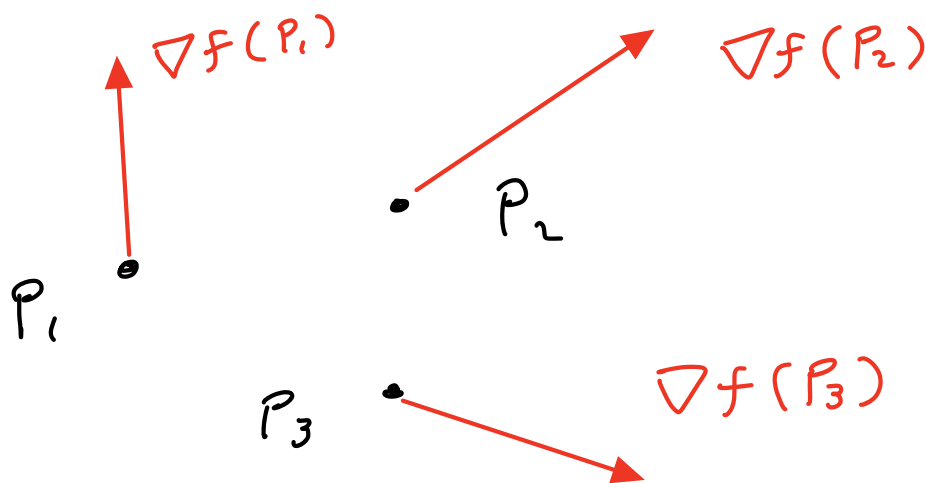
e.g.  $f(x, y) = xy.$

$$\nabla f = \left\langle \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right\rangle$$

$$\nabla f(x, y) = \langle y, x \rangle$$

To each point  $P$  in  $\mathbb{R}^n$  the derivative  $\nabla f$  associates a vector.

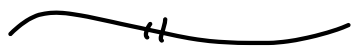
Picture:



Can think of  $\nabla f: \mathbb{R}^n \rightarrow \mathbb{R}^n$   
as a "vector field".

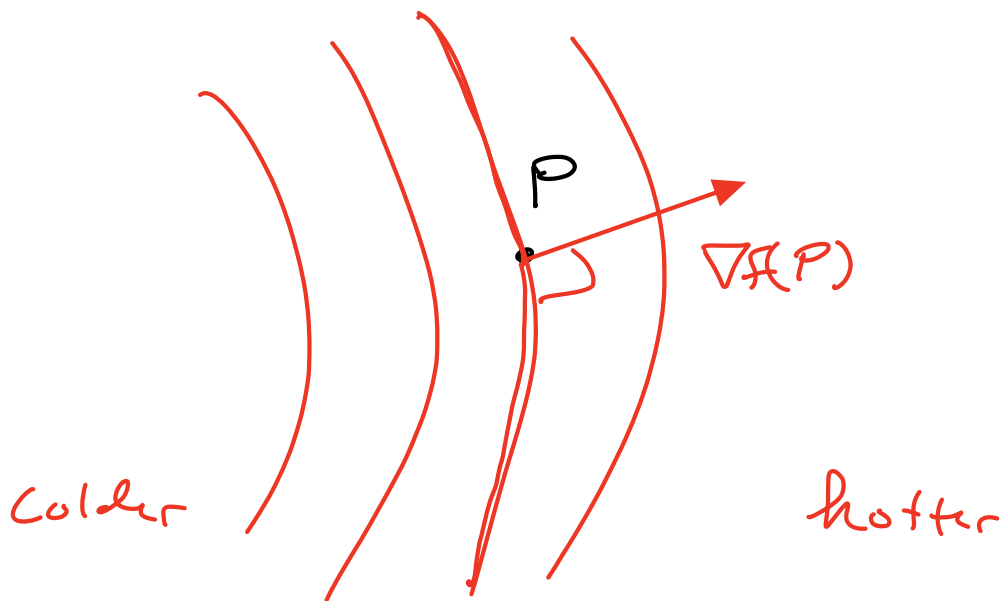
So

" $\nabla(\text{scalar field}) = \text{vector field}.$ "



Meaning: At a point  $P$  in  $\mathbb{R}^n$ ,  
the vector  $\nabla f(P)$  tells us the  
direction where  $f$  is increasing  
fastest.

e.g.  $f$  is temperature



curves of constant temp.

$\nabla f(P)$  points in the direction of  
increasing temperature & is  $\perp$  to  
the "level curve" at  $P$ .

e.g.  $f(x,y) = xy$ . defined at  
any point

$$\nabla f(x,y) = \langle y, x \rangle.$$

pick this point

Consider point  $P = (3, 1)$ .

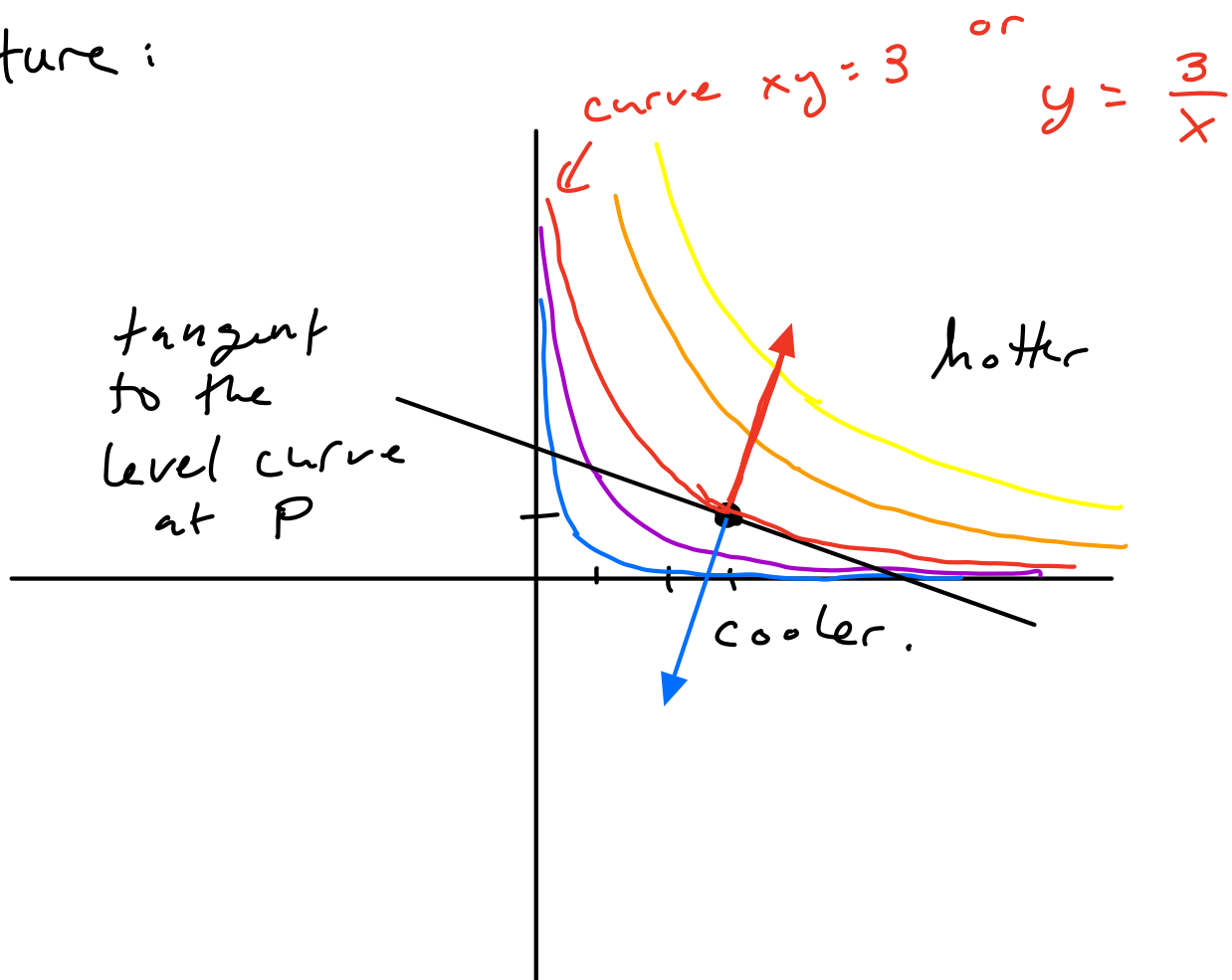
$$f(P) = 3 \cdot 1 = 3.$$

"temperature at  $P$  is 3".

Temperature increases fastest  
in the direction  $\nabla f(P) =$

$$\nabla f(3, 1) = \langle 1, 3 \rangle$$

Picture:



-  $\nabla f(P)$  is the direction in which

$f$  decreases most rapidly at  $P$ .



The "same story" in 3D.

$$\text{Say } f(x, y, z) = 5x^2 - 3xy + xyz$$

is temperature at point  $P = (x, y, z)$ .

$$\nabla f = \left\langle \frac{df}{dx}, \frac{df}{dy}, \frac{df}{dz} \right\rangle$$

$$df/dx = 10x - 3y + yz$$

$$df/dy = 0 - 3x + xz$$

$$df/dz = 0 - 0 + xy$$

$$\nabla f(x, y, z)$$

$$= \langle 10x - 3y + yz, -3x + xz, xy \rangle$$

e.g. Temperature at  $P = (1, 1, 1)$  is

$$f(1, 1, 1) = 5(1)^2 - 3(1)(1) + (1)(1)(1)$$

$$= 5 - 3 + 1 = 3$$

and increases most rapidly in  
the direction

$$\begin{aligned}\nabla f(1,1,1) &= \langle 10-3+1, -2+1, 1 \rangle \\ &= \langle 8, -2, 1 \rangle.\end{aligned}$$



Why does it work?

KEY: Multivariable Chain Rule.

Recall the good old chain rule.

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

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

$$(f \circ g)(t) = f(g(t)).$$

$$(f \circ g)'(t) = f'(g(t)) \cdot g'(t)$$

$$= (f' \circ g)(t) \cdot g'(t)$$

In Chapter 3 we had a new version.

$$\vec{r} : \mathbb{R} \rightarrow \mathbb{R}^n$$

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

$$(\vec{r} \circ f)(t) = \vec{r}(f(t)).$$

$$(\vec{r} \circ f)'(t) = \underbrace{\vec{r}'(f(t))}_{\text{vector}} \cdot \underbrace{f'(t)}_{\text{scalar}}.$$

Now we have something new.

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

$$\vec{r} : \mathbb{R} \rightarrow \mathbb{R}^n$$

Say  $\vec{r}(t)$  is a parameterized path in  $\mathbb{R}^n$ , say  $f$  is temperature.

So  $f(\vec{r}(t))$  is the temperature we feel at time  $t$ . We can

think of this as a composition:

$$(f \circ \vec{r})(t) = f(\vec{r}(t))$$

$$f \circ \vec{r} : \mathbb{R} \rightarrow \mathbb{R}.$$

$t \mapsto$  our temp. at time  $t$

as we travel the curve.

Question: What temperature change do we feel?

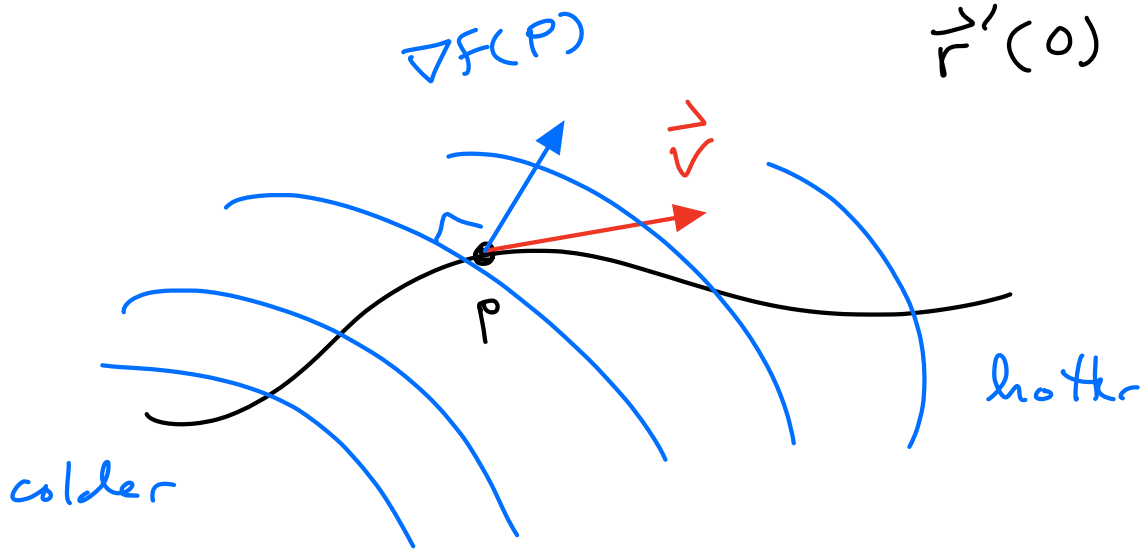
$$(f \circ \vec{r})'(t) = ?$$

Theorem: dot product.

$$\underbrace{(f \circ \vec{r})'(t)}_{\text{scalar}} = \underbrace{\nabla f(\vec{r}(t))}_{\text{vector}} \bullet \underbrace{\vec{r}'(t)}_{\text{vector}}$$

e.g. The rate of change of  $f$  at the point  $P$  in the direction of vector  $\vec{v}$ . Suppose  $\vec{r}(0) = P$

$$\vec{r}'(0) = \vec{v}$$



Our rate of change of temp at time  $t=0$  is

$$(F \circ \vec{r})'(0)$$

$$= \nabla F(\vec{r}(0)) \cdot \vec{r}'(0)$$

$$= \nabla F(P) \cdot \vec{v}$$

$$= \underbrace{(\text{gradient}) \cdot (\text{velocity})}$$

maximized when our velocity points in direction of gradient.

Another consequence: The gradient vector at  $P$  is  $\perp$  to the level set of  $f$  at  $P$ .

e.g. Consider  $f(x,y,z) = (2x)^2 + y^2 + z^2$ .

Temperature at point  $P = (2,3,5)$  is

$$f(2,3,5) = (2 \cdot 2)^2 + 3^2 + 5^2 = 50.$$



Gradient vector is

$$\nabla F(x, y, z) = \langle 8x, 2y, 2z \rangle.$$

$$\nabla F(2, 3, 5) = \langle 16, 6, 10 \rangle.$$

The level set  $F(x, y, z) = 50$   
is the set of points where  
temperature = 50.

$$(2x)^2 + y^2 + z^2 = 50.$$

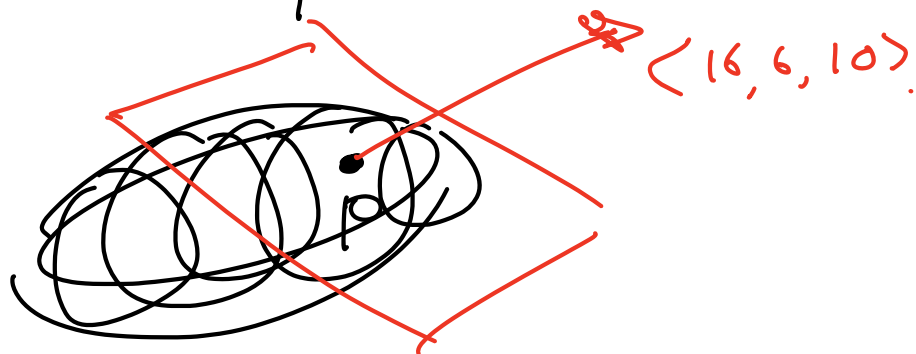
What kind of shape?

Fixed  $x \rightarrow$  circle in  $y, z$ .

Fixed  $y \rightarrow$  ellipse in  $x, z$

Fixed  $z \rightarrow$  ellipse in  $x, y$ .

Called an "ellipsoid"



Theorem:  $\langle 16, 6, 10 \rangle$  is normal  
to the tangent plane to the  
level surface at  $P = (2, 3, 5)$ .

Conclusion:

Equation of tangent plane to  
ellipsoid  $(2x)^2 + y^2 + z^2 = 50$   
at the point  $(2, 3, 5)$  is

$$\nabla f(2, 3, 5) \cdot \langle x-2, y-3, z-5 \rangle = 0.$$

$$\langle 16, 6, 10 \rangle \cdot \langle x-2, y-3, z-5 \rangle = 0$$

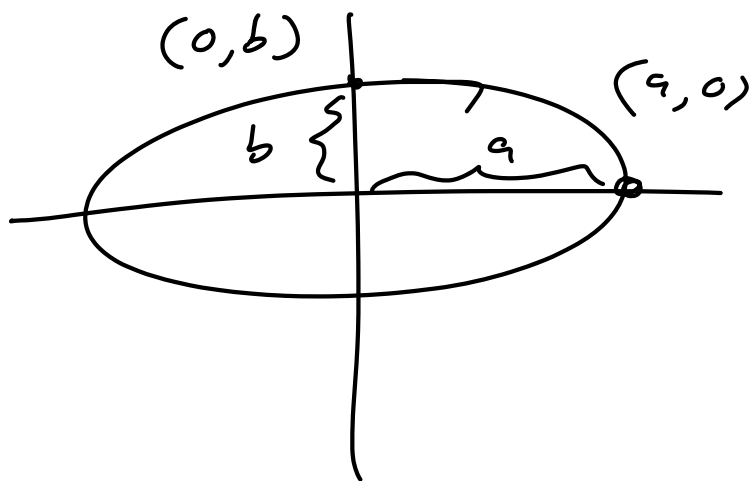
$$16(x-2) + 6(y-3) + 10(z-5) = 0$$

:

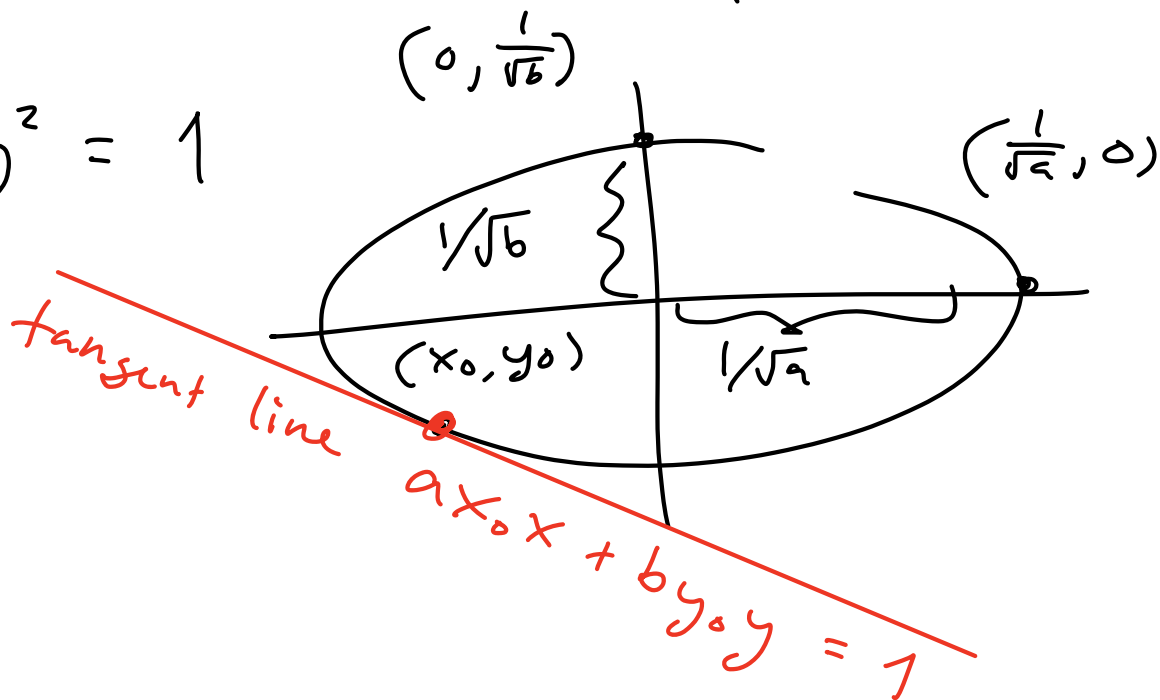
$$8x + 3y + 5z = 50.$$

HW 3 Problem 1:

$$\left(\frac{x}{a}\right)^2 + \left(\frac{y}{b}\right)^2 = 1$$



$$ax^2 + by^2 = 1$$



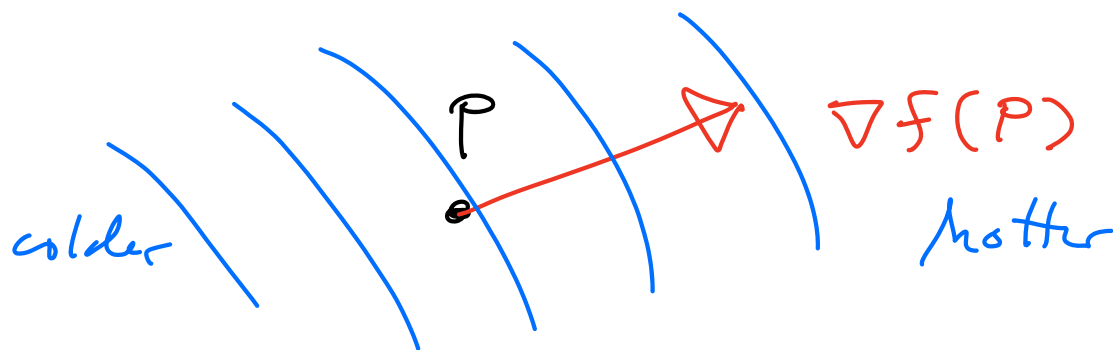
HW 3 due Friday.

Recall: A scalar field is a function

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

Assigns scalar  $f(P)$  to each point  $P$ .

Derivative  $\nabla F$  assigns a vector  
 $\nabla F(P)$  to each point  $P$



$F(P)$  = temperature at  $P$   
 $\nabla F(P)$  = direction of greatest  
increase of temperature.

Definition:

$$F(x_1, \dots, x_n)$$

$$\nabla F = \left\langle \frac{dF}{dx_1}, \frac{dF}{dx_2}, \dots, \frac{dF}{dx_n} \right\rangle.$$

Gradient is  $\perp$  to the level curves  
(curves of constant temperature).

Why?

Multivariable Chain Rule:

$f(P)$  is temperature at point  $P$ .

You travel path  $\vec{r}(t)$ .

Your temperature at time  $t$  is

$$T(t) = f(\vec{r}(t)).$$

Your rate of change of temperature at time  $t$  is

$$T'(t) = \underbrace{\nabla f(\vec{r}(t))}_{\text{vector}} \cdot \underbrace{\vec{r}'(t)}_{\text{vector}}$$

dot product.

OR

$$\begin{aligned} (f \circ \vec{r})'(t) &= \nabla f(\vec{r}(t)) \cdot \vec{r}'(t) \\ &= (\nabla f \circ \vec{r})(t) \cdot \vec{r}'(t) \end{aligned}$$

composition of functions      dot product.

$$(f \circ \vec{r})' = (\nabla f \circ \vec{r}) \cdot \vec{r}'$$

Consequence: Suppose you travel  
on a level curve / level surface:

$$f(\vec{r}(t)) = \text{constant}.$$

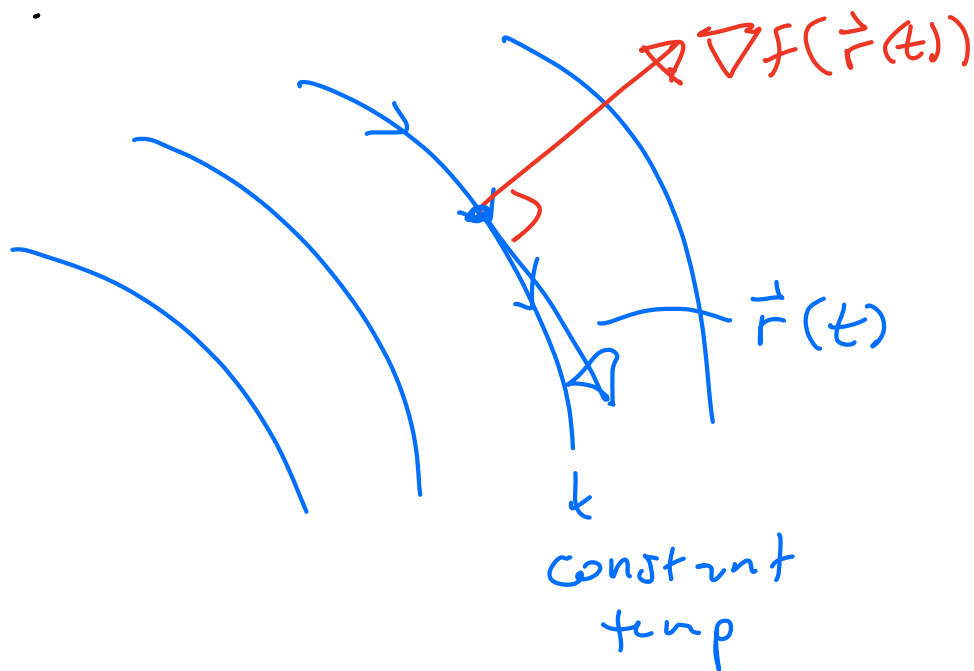
Then

$$\frac{d}{dt} [f(\vec{r}(t))] = 0$$

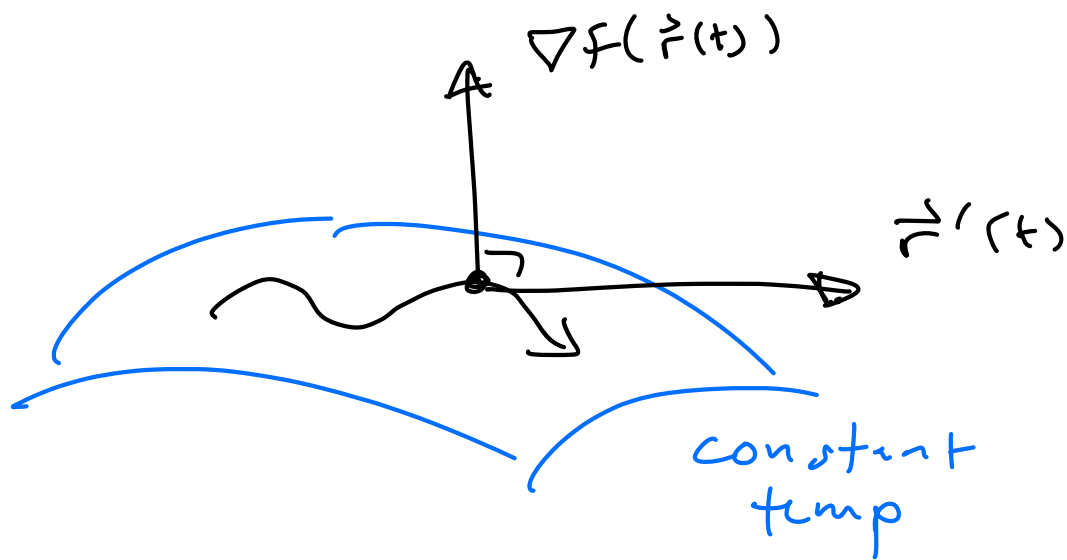
$$\nabla f(\vec{r}(t)) \cdot \vec{r}'(t) = 0$$

perpendicular vectors.

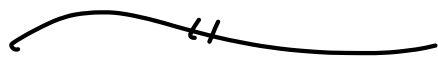
Picture:



Picture in 3D: level surfaces



So  $\nabla F(P)$  is  $\perp$  to the level surface through any point  $P$ .



Example: Consider scalar field

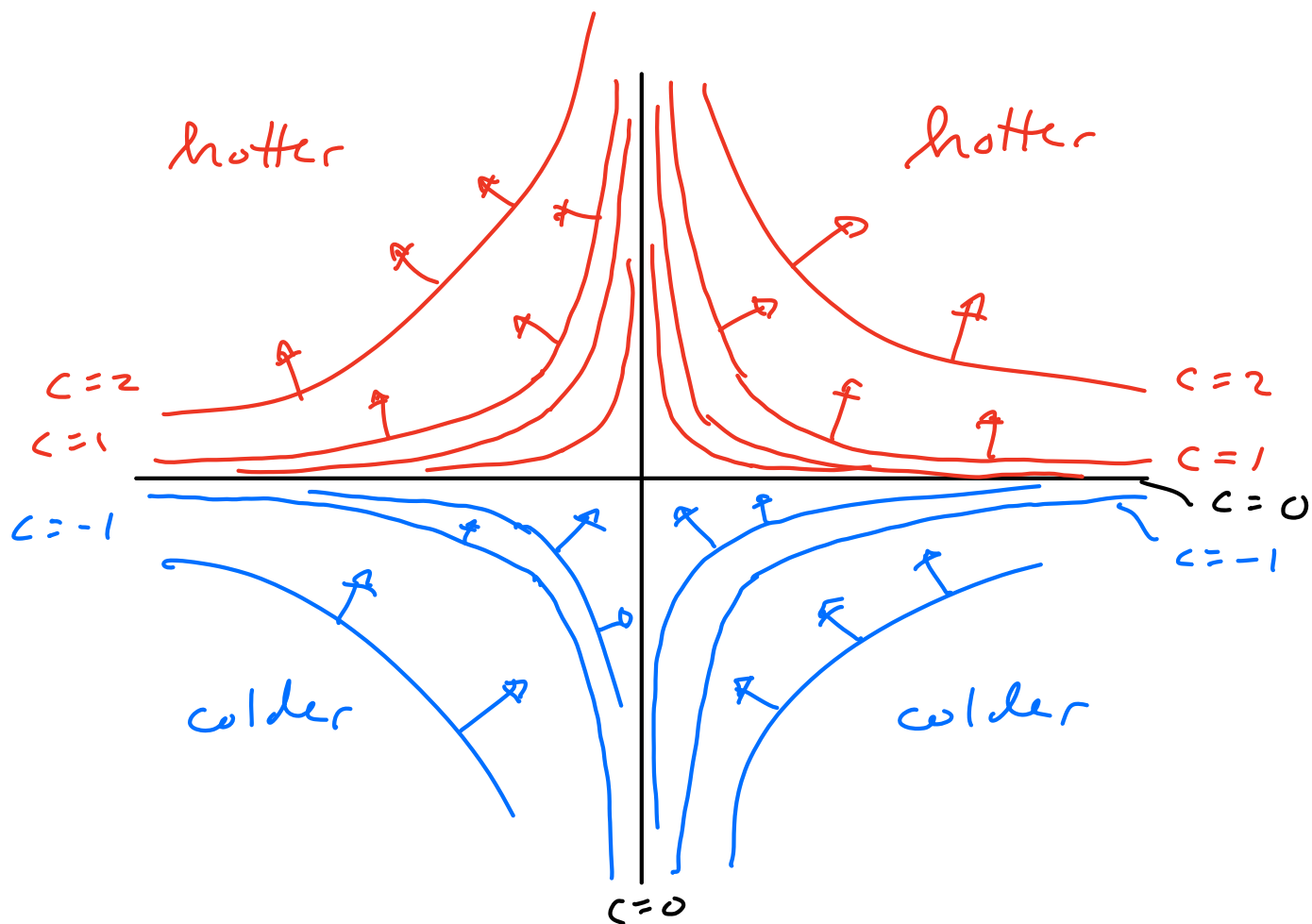
$$F(x, y) = x^2 y.$$

Level curves  $F(x, y) = c$  (constant)

$$x^2 y = c$$

$$y = \frac{c}{x^2}$$

What do these curves look like?



Suppose we travel along the curve

$$\vec{r}(t) = \langle t, 2 - t^2 \rangle.$$

Our temperature at time  $t$  is

$$\begin{aligned} T(t) &= f(\vec{r}(t)) \\ &= f(t, 2 - t^2) \\ &= (t)^2(2 - t^2) \\ &= 2t^2 - t^4 \end{aligned}$$



When is our temperature maximized or minimized?

$$T'(t) = 0$$

$$4t - 4t^3 = 0$$

$$4t(1 - t^2) = 0$$

$$\Rightarrow t = 0 \text{ or } 1 - t^2 = 0 \\ t = \pm 1.$$

Second Derivative:

$$T''(t) = 4 - 12t^2$$

$$\text{So min at } t = 0 \quad [T''(0) > 0]$$

$$\text{max at } t = \pm 1 \quad [T''(\pm 1) < 0]$$

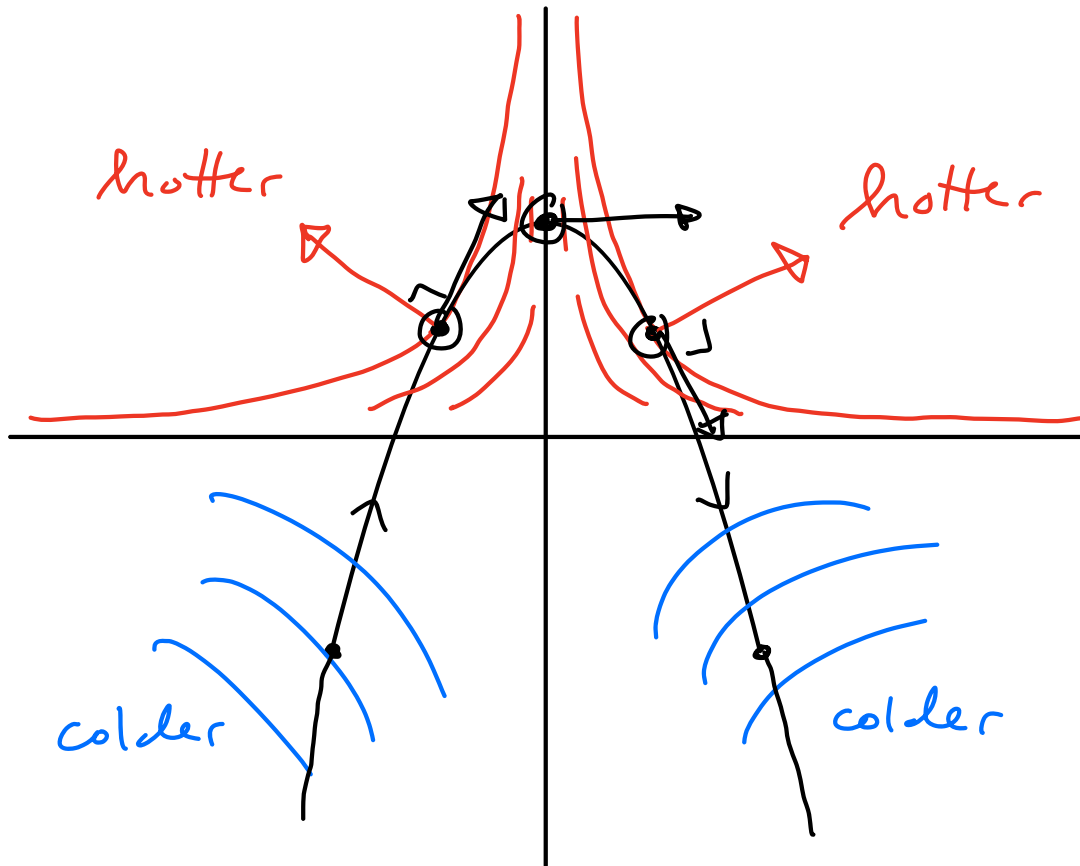
Where is temperature max or min?

$$\vec{r}(0) = \langle 0, 2 \rangle$$

$$\vec{r}(+1) = \langle +1, 2 - (+1)^2 \rangle = \langle 1, 1 \rangle$$

$$\vec{r}(-1) = \langle -1, 2 - (-1)^2 \rangle = \langle -1, 1 \rangle.$$

Picture :



Local maxima happened when our velocity is  $\perp$  to gradient.

Indeed, local max  $\Rightarrow T'(t) = 0$

$$T'(t) = \nabla f(\vec{r}(t)) \cdot \vec{r}'(t)$$

$$0 = \nabla f(\vec{r}(t)) \cdot \vec{r}'(t)$$

perpendicular!

$t=0$  a bit different because

$$\nabla f(\vec{r}(0)) = \langle 0, 0 \rangle.$$

Every vector is  $\perp$  to  $\langle 0, 0 \rangle$ .

So that case is "degenerate".

Another point of view.

Instead of  $\vec{r}(t) = \langle t, 2-t^2 \rangle$ ,

eliminate  $t$ . The parabola is

$$y = 2 - x^2$$

$$x^2 + y = 2$$

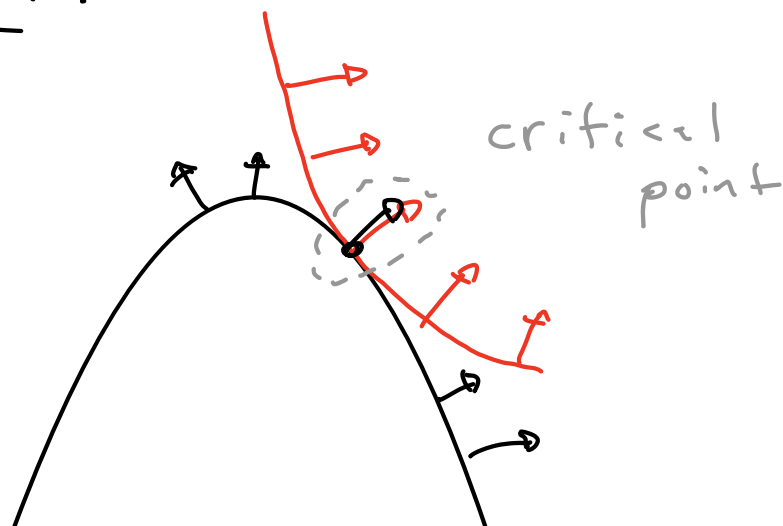
$$g(x, y) = 2$$

$$\text{for } f(x, y) = x^2 + y.$$

In this language, look for

points where  $\nabla f(x, y)$  &  $\nabla g(x, y)$

are parallel.



This is the method of "Lagrange Multipliers". Calculate:

IF  $\nabla F(x,y)$  &  $\nabla g(x,y)$  are parallel then

$$\nabla F(x,y) = \lambda \nabla g(x,y)$$

for some scalar  $\lambda$ .

In our case,

$$F(x,y) = x^2 y \quad (\text{temp.})$$

$$g(x,y) = x^2 + y \quad (\text{defines our parabola})$$

$$\nabla F(x,y) = \langle 2xy, x^2 \rangle$$

$$\nabla g(x,y) = \langle 2x, 1 \rangle$$

$$\text{Set } \langle 2xy, x^2 \rangle = \lambda \langle 2x, 1 \rangle$$

$$\langle 2xy, x^2 \rangle = \langle 2x\lambda, \lambda \rangle$$

$$\begin{cases} 2xy = 2x\lambda \\ x^2 = \lambda \end{cases}$$

And we are only interested in points on the parabola  $y = 2 - x^2$ .

So get 3 equations in 3 unknowns:

$$\begin{cases} \textcircled{1} & 2xy = 2x\lambda, \\ \textcircled{2} & x^2 = \lambda, \\ \textcircled{3} & y = 2 - x^2. \end{cases}$$

In general, VERY HARD to solve.

But this "textbook problem" is not bad.

If  $x = 0$  then  $y = 2$ .

And  $(x, y) = (0, 2)$  is a solution.

If  $x \neq 0$  then

$$\textcircled{1}: \quad \cancel{2x}y = \cancel{2x}\lambda \\ y = \lambda$$

$$\textcircled{2}: \quad x^2 = \lambda \\ x^2 = y$$

$$\textcircled{3}: \quad y = 2 - x^2.$$

$$\textcircled{2} \ \& \ \textcircled{3} : \quad x^2 = 2 - x^2$$

$$2x^2 = 2$$

$$x^2 = 1$$

$$x = \pm 1.$$

So two more critical points

$$(x, y) = (+1, +1) \text{ or } (-1, +1).$$

Same solution as before 😊

Three critical points

$$(0, 2), \quad (1, 1), \quad (-1, 1)$$

min  
of  $f$

max  
of  $f$

max  
of  $f$

Lagrange Multipliers in General:

Maximize  $f(x_1, x_2, \dots, x_n)$

subject to constraint

$$g(x_1, x_2, \dots, x_n) = k$$

Solution: Find all critical

points  $(x_1, \dots, x_n)$  such that

$$\begin{cases} \nabla f(x_1, \dots, x_n) = \lambda \nabla g(x_1, \dots, x_n) \\ g(x_1, \dots, x_n) = K \end{cases}$$

In general "impossible" to solve exactly, so use a computer to get numerical solutions.



Linear Approximation:

Another point of view on the chain rule.

$$\frac{d}{dt} [f(\vec{r}(t))] = \nabla f(\vec{r}(t)) \cdot \vec{r}'(t).$$

Let's write

$$f(x, y, z)$$

$$\vec{r}(t) = \langle x(t), y(t), z(t) \rangle.$$

$$\nabla f = \left\langle \frac{df}{dx}, \frac{df}{dy}, \frac{df}{dz} \right\rangle.$$

$$\vec{r}'(t) = \left\langle \frac{dx}{dt}, \frac{dy}{dt}, \frac{dz}{dt} \right\rangle.$$

Then the chain rule says:

$$\frac{dF}{dt} = \nabla F \cdot \vec{r}'$$

$$= \left\langle \frac{dF}{dx}, \frac{dF}{dy}, \frac{dF}{dz} \right\rangle \cdot \left\langle \frac{dx}{dt}, \frac{dy}{dt}, \frac{dz}{dt} \right\rangle.$$

$$\frac{dF}{dt} = \frac{dF}{dx} \cdot \frac{dx}{dt} + \frac{dF}{dy} \cdot \frac{dy}{dt} + \frac{dF}{dz} \cdot \frac{dz}{dt}$$

PURE ALGEBRA !

2D version:

$F(x, y)$  function of  $x$  &  $y$ .

$x(t), y(t)$  functions of  $t$ .

$$\frac{dF}{dt} = \frac{dF}{dx} \cdot \frac{dx}{dt} + \frac{dF}{dy} \cdot \frac{dy}{dt}.$$

Intuition:  $\frac{dF}{\cancel{dx}} \cdot \frac{\cancel{dx}}{dt} \approx \frac{dF}{dt}$

NOT correct with !



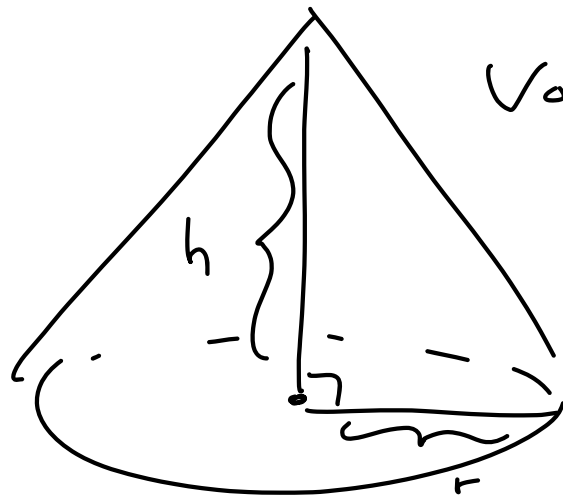
Application :

Consider a right circular cone with height  $h$  & radius  $r$ .

Volume is a function of  $h$  &  $r$  :

$$V(r, h) = \frac{1}{3} \pi r^2 h$$

Picture :



$$Vol = \frac{1}{3} \pi r^2 h.$$

Suppose  $h$  &  $r$  change with time :  $h(t)$ ,  $r(t)$ .

Then the volume changes with time :

$$\frac{dV}{dt} = \frac{dV}{dr} \cdot \frac{dr}{dt} + \frac{dV}{dh} \cdot \frac{dh}{dt}$$

To simplify terminology, sometimes

We write

$$V_t = dV/dt$$
$$V_r = dV/dr$$
$$V_h = dV/dh.$$

$$V_t = V_r \cdot \frac{dr}{dt} + V_h \cdot \frac{dh}{dt}$$

Have  $V_r = \frac{1}{3} \pi 2rh$

$$V_h = \frac{1}{3} \pi r^2$$

So

$$\frac{dV}{dt} = \frac{1}{3} \pi 2rh \cdot \frac{dr}{dt} + \frac{1}{3} \pi r^2 \cdot \frac{dh}{dt}$$

But maybe it's not changing with time; it's changing for some other reason. So let's just say

$$dV = \frac{1}{3} \pi 2rh \cdot dr + \frac{1}{3} \pi r^2 \cdot dh$$

↑  
tiny change  
in  $V$

↑  
related to tiny  
changes in  $r$  &  $h$ .

Application : Error estimation.

Measure the radius & height :

$$r = 120 \pm 1.8 \text{ in}$$

$$h = 140 \pm 2.5 \text{ in}$$

$$\text{Then } V = \frac{1}{3} \pi r^2 h \pm dV$$

$$V = 2,111,500 \pm dV \quad \text{how big is the "error" ?}$$

Errors are related by chain rule :

$$dV = \frac{dV}{dr} \cdot dr + \frac{dV}{dh} \cdot dh$$

$$dV = \frac{1}{3} \pi 2rh \cdot dr + \frac{1}{3} \pi r^2 \cdot dh.$$

$$dV = \frac{1}{3} \pi 2 (120) (140) \cdot (1.8)$$

$$+ \frac{1}{3} \pi (120)^2 \cdot (2.5)$$

$$= 101,033 \text{ in}^3.$$

We conclude that

$$V = 2,111,150 \pm 101,033 \text{ in}^3$$
$$= 2.11 \pm 0.1 \text{ million in}^3.$$

HW3 Problem 3:

Convert  $\theta$  to radians.

HW3 Problem 2:

For any reasonable function  $f(x, y)$   
we will have

$$f_{xy} = f_{yx}$$

$$\frac{d}{dy} \left( \frac{df}{dx} \right) = \frac{d}{dx} \left( \frac{df}{dy} \right)$$

There are some pathological counterexamples, but we can ignore them.

Hint:  $f(x, y)$ ,  $x(r, \theta)$ ,  $y(r, \theta)$ .

$f$  is (indirectly) a function of  $r$  &  $\theta$ . Like to compute derivatives

$$f_r, f_\theta, f_{rr}, f_{r\theta}, f_{\theta\theta}.$$

For these we need chain rule.

$$f_r = f_x \cdot x_r + f_y \cdot y_r$$

$$f_{rr} = \frac{d}{dr} (f_x \cdot x_r + f_y \cdot y_r)$$

$$= \underbrace{\frac{d}{dr} (f_x \cdot x_r)}_{\text{product rule}} + \underbrace{\frac{d}{dr} (f_y \cdot y_r)}_{\text{product rule}}$$

$$= f_{xr} \cdot x_r + f_x \cdot x_{rr}$$

$$+ f_{yr} \cdot y_r + f_y \cdot y_{rr}$$

Also need to simplify  $f_{xr}$ ,  $f_{yr}$ .

Well,  $f_x(x, y)$  is a function of 2 variables  $x$  &  $y$ , so

$$f_{xr} = f_{xx} \cdot x_r + f_{xy} \cdot y_r.$$

$$\frac{df_x}{dr} = \frac{df_x}{dx} \cdot \frac{dx}{dr} + \frac{df_x}{dy} \cdot \frac{dy}{dr}.$$

∥

More on Linear Approximation.

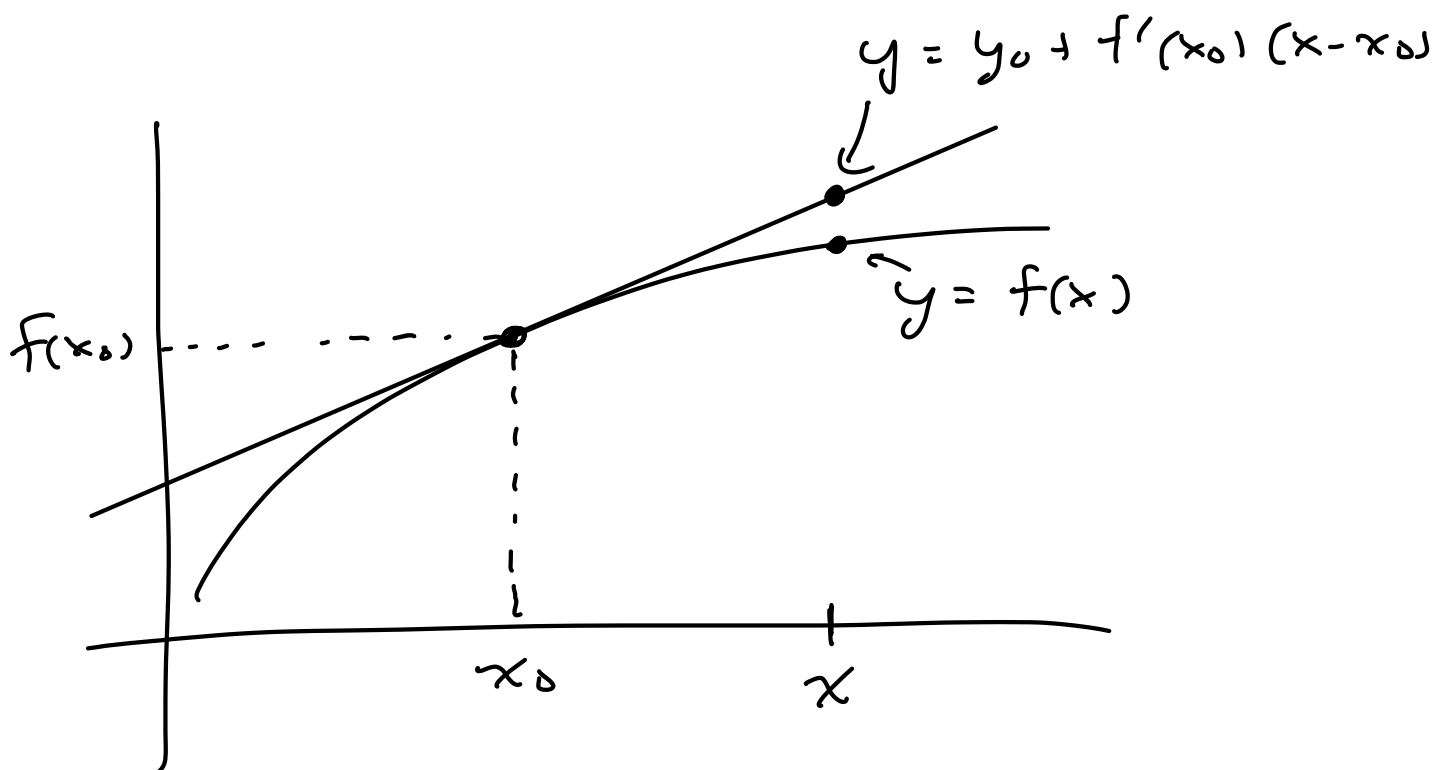
Given  $f: \mathbb{R} \rightarrow \mathbb{R}$  and  $x_0 \in \mathbb{R}$   
we have a Taylor expansion  
of  $f(x)$  near  $x = x_0$ :

$$\begin{aligned} f(x) &= f(x_0) + f'(x_0)(x - x_0) \\ &\quad + \frac{1}{2} f''(x_0)(x - x_0)^2 \\ &\quad + \frac{1}{6} f'''(x_0)(x - x_0)^3 \\ &\quad \vdots \\ &\quad + \frac{1}{n!} f^{(n)}(x_0)(x - x_0)^n \\ &\quad \vdots \end{aligned}$$

Get an approximation by stopping  
the series early. Linear approx:

$$f(x) \approx f(x_0) + f'(x_0)(x - x_0)$$

Picture:



Equation of the tangent line.

Slope  $f'(x_0)$ , point  $(x_0, y_0)$ .

Point-slope form:

$$y - y_0 = f'(x_0)(x - x_0)$$

$$y = y_0 + f'(x_0)(x - x_0)$$

Why do we care?

$$f(x) \approx \cancel{y_0} + f'(x_0)(x - x_0)$$

$f(x_0)$

EASIER TO CALCULATE!



Function of 2 variables  $f(x, y)$   
has a Taylor expansion near  
 $(x, y) = (x_0, y_0)$ :

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

$$+ f_x(x_0, y_0) (x - x_0) + f_y(x_0, y_0) (y - y_0)$$

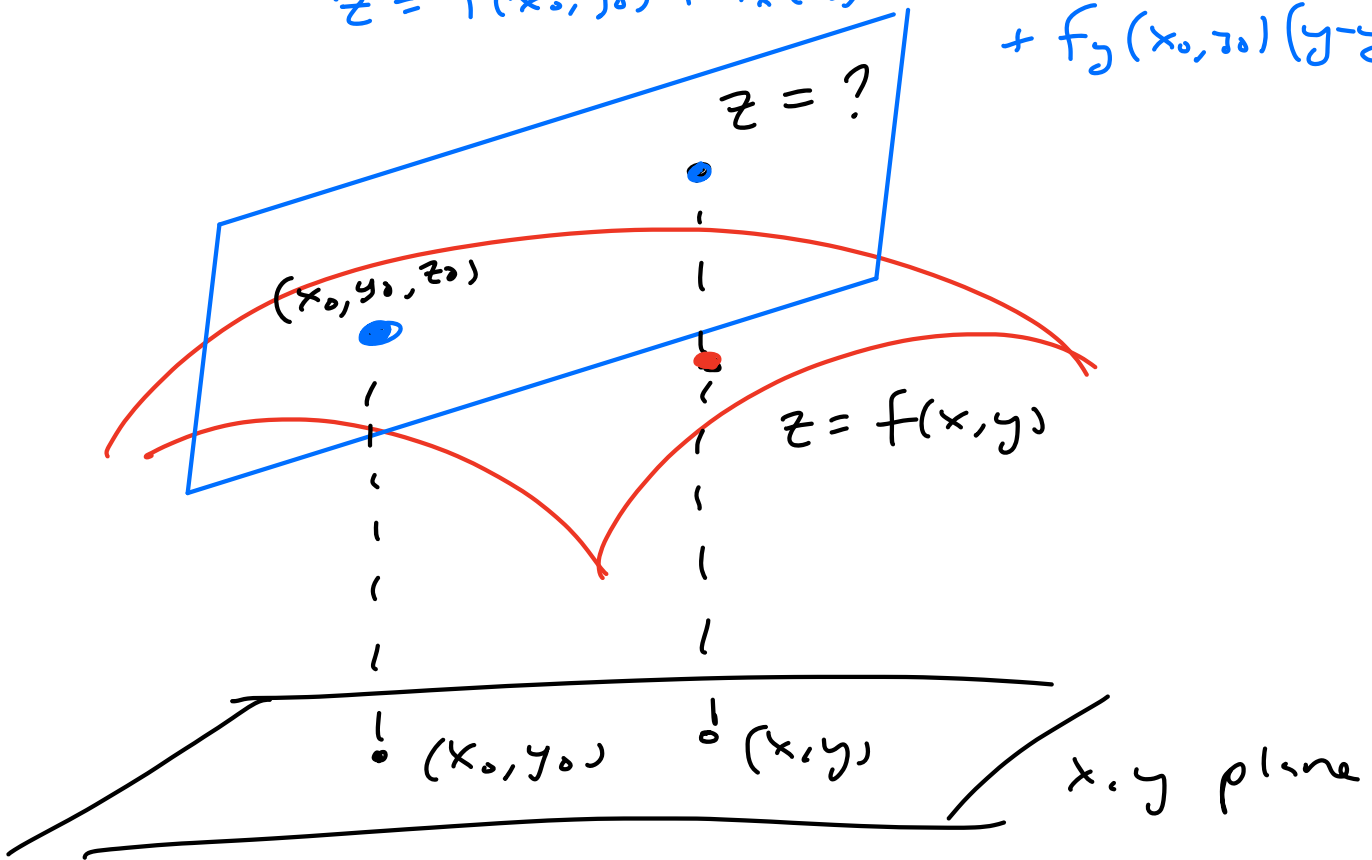
$$+ \frac{1}{2} \left[ f_{xx}(x_0, y_0) (x - x_0)^2 \right. \\ \left. + 2 f_{xy}(x_0, y_0) (x - x_0) (y - y_0) \right. \\ \left. + f_{yy}(x_0, y_0) (y - y_0)^2 \right]$$

$$+ \frac{1}{6} \left[ \text{stuff like} \right. \\ \left. f_{xyy}(x_0, y_0) (x - x_0) (y - y_0)^2 \dots \right]$$

Cut it off to get linear approx:

$$f(x, y) \approx f(x_0, y_0) + f_x(x_0, y_0) (x - x_0) \\ + f_y(x_0, y_0) (y - y_0)$$

$$z = f(x_0, y_0) + f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0)$$



$$z_0 = f(x_0, y_0)$$

Equation of Tangent Plane:

$$z - z_0 = f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0)$$

Linear Approx:

$$z \approx z_0 + f_x(x_0, y_0)(x - x_0) + f_y(x_0, y_0)(y - y_0)$$



Language:  $y = f(x)$

$$y - y_0 \approx f'(x_0) (x - x_0)$$

$$\Delta y \approx f'(x_0) \Delta x$$

$$\Delta y \approx \frac{dy}{dx} \Delta x$$

$$dy = \frac{dy}{dx} \cdot dx$$

Chain  
Rule

$$\left( \frac{dy}{dt} = \frac{dy}{dx} \cdot \frac{dx}{dt} \right)$$

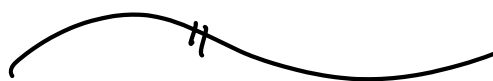
$$z = f(x, y)$$

$$z - z_0 \approx f_x(x_0, y_0) (x - x_0) + f_y(x_0, y_0) (y - y_0)$$

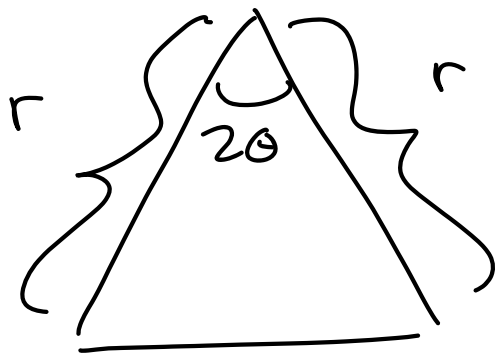
$$\Delta z \approx \frac{dz}{dx} \cdot \Delta x + \frac{dz}{dy} \cdot \Delta y$$

$$dz = \frac{dz}{dx} dx + \frac{dz}{dy} dy$$

Chain Rule!



Example: Estimate area of  
isocoles triangle



$$A(r, \theta) = \frac{1}{2} \text{base} \cdot \text{height}$$

$$= \frac{1}{2} (2r \sin \theta) (r \cos \theta)$$

$$= r^2 \sin \theta \cos \theta$$

$$= \frac{r^2}{2} \sin(2\theta)$$

$$A_r = r \sin(2\theta)$$

$$A_\theta = \frac{r^2}{2} \cos(2\theta) \cdot 2$$

$$= r^2 \cos(2\theta)$$

Linear Approximation

$$dA = A_r dr + A_\theta d\theta$$

$$= r \sin(2\theta) dr + r^2 \cos(2\theta) d\theta.$$

OR. Near  $r_0, \theta_0$ ,

$$A(r, \theta) - A(r_0, \theta_0) \approx$$

$$+ r_0 \sin(2\theta_0) (r - r_0)$$

$$+ r_0^2 \cos(2\theta_0) (\theta - \theta_0)$$



Unconstrained Optimization.

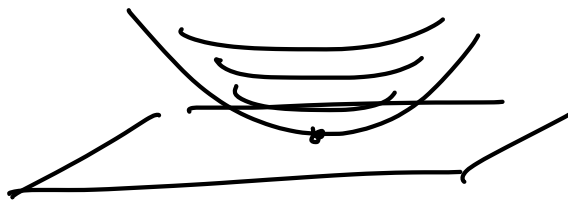
Find local max/min of a scalar field  $f(x, y)$ .

If we look at the graph

$z = f(x, y)$  these are places where

the tangent plane is horizontal:

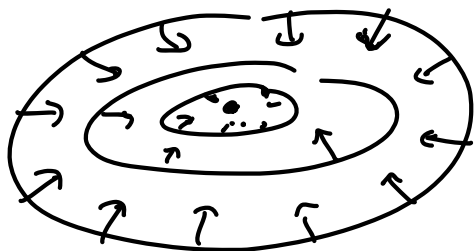
Local Max



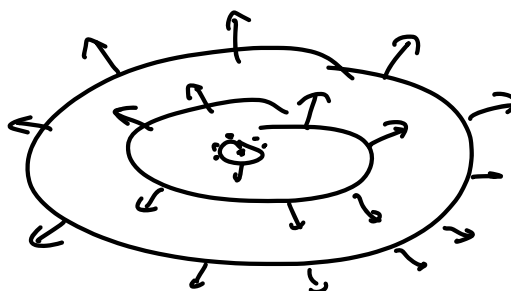
This happens when  $\nabla f(x,y)$  vanishes, i.e., equals  $\langle 0, 0 \rangle$ .

In 2D:

Local Max



Local Min



Example:  $f(x,y) = x^2 + y^2$ .

$$\nabla f(x,y) = \langle 2x, 2y \rangle = \langle 0, 0 \rangle.$$

"Critical point"  $(x,y) = (0,0)$ .

Turns out to be a min.

(Parabolic shaped valley).

Example:  $f(x, y) = xy$ .

$$\nabla f(x, y) = \langle y, x \rangle = \langle 0, 0 \rangle$$

Critical point  $(x, y) = (0, 0)$

Min or Max? NO!

It's a "saddle point".

[see Geogebra]

Example:  $f(x, y) = x^2y$

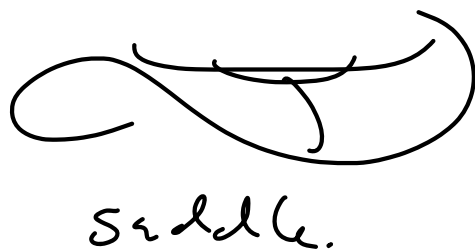
$$\nabla f(x, y) = \langle 2xy, x^2 \rangle = \langle 0, 0 \rangle.$$

Every point  $\langle 0, y \rangle$  is critical!

These turn out to be degenerate critical points.

[See Geogebra].

Summary:





degenerate  
(flat in some  
direction)

The "second derivative test"  
lets us distinguish between these.

Hessian Matrix of  $f(x, y)$ :

$$Hf = \begin{pmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{pmatrix}.$$

Hessian determinant

$$\begin{aligned} \det(Hf) &= f_{xx} \cdot f_{yy} - f_{xy} \cdot f_{yx} \\ &= f_{xx} \cdot f_{yy} - f_{xy}^2. \end{aligned}$$

Theorem:

let  $(x_0, y_0)$  be critical:

$$\nabla f(x_0, y_0) = \langle 0, 0 \rangle$$

i.e.  $f_x(x_0, y_0) = 0$  &  $f_y(x_0, y_0) = 0$

Then:



- IF  $\det(Hf)(x_0, y_0) < 0$  then  $(x_0, y_0)$  is a saddle point.
- IF  $\det(Hf)(x_0, y_0) = 0$  called "degenerate". [ Too flat for this test to work ... ]
- IF  $\det(Hf)(x_0, y_0) > 0$  then  $(x_0, y_0)$  is local max or min
  - Max when  $f_{xx}(x_0, y_0) < 0$
  - Min when  $f_{xx}(x_0, y_0) > 0$



Example:  $f(x, y) = x^2 - x^4 - y^2 + 1$

$$\nabla f(x, y) = \langle 2x - 4x^3, -2y \rangle = \langle 0, 0 \rangle$$

$$\begin{cases} 2x - 4x^3 = 0 \\ -2y = 0 \end{cases}$$

$$\longrightarrow y = 0$$

ALWAYS

$$2x(1-2x^2) = 0$$

$$x = 0 \text{ or } x = \pm \frac{1}{\sqrt{2}}.$$

3 critical points:

$$(0,0), \left(\frac{1}{\sqrt{2}}, 0\right), \left(-\frac{1}{\sqrt{2}}, 0\right)$$

$$f_{xx} = (2x - 4x^3)_x = 2 - 12x^2$$

$$f_{xy} = (2x - 4x^3)_y = 0$$

$$f_{yx} = (-2y)_x = 0$$

$$f_{yy} = (-2y)_y = -2$$

↑ SAME ☺

Hessian Matrix

$$Hf = \begin{pmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{pmatrix} = \begin{pmatrix} 2-12x^2 & 0 \\ 0 & -2 \end{pmatrix}$$

$$\det(Hf) = (2-12x^2)(-2) - 0$$

$$= -2 + 12x^2.$$

Evaluate  $\det(Hf)$  at our critical points:

$$\begin{aligned} \bullet \det(Hf)(0,0) &= -2 + 12 \cdot 0^2 \\ &= -2 < 0. \\ &\text{SADDLE.} \end{aligned}$$

$$\begin{aligned} \bullet \det(Hf)\left(\frac{1}{\sqrt{2}}, 0\right) &= -2 + 12\left(\frac{1}{\sqrt{2}}\right)^2 \\ &= -2 + 6 = 4 > 0 \end{aligned}$$

$$\begin{aligned} \bullet \det(Hf)\left(-\frac{1}{\sqrt{2}}, 0\right) &= -2 + 12\left(-\frac{1}{\sqrt{2}}\right)^2 \\ &= -2 + 6 = 4 > 0 \end{aligned}$$

Local max or min ...

To see which we look at  $f_{xx}$ .

$$f_{xx}(x,y) = 2 - 12x^2.$$

$$f_{xx}\left(\frac{1}{\sqrt{2}}, 0\right) = 2 - 12\left(\frac{1}{\sqrt{2}}\right)^2$$

$$= 2 - 6 = -4 < 0$$

MAX!

$$f_{xx}\left(-\frac{1}{\sqrt{2}}, 0\right) = 2 - 12\left(-\frac{1}{\sqrt{2}}\right)^2$$

$$= 2 - 6 = -4 < 0$$

MAX!

CALC II