

# Functions of Several Variables

Hayk Aprikyan, Hayk Tarkhanyan

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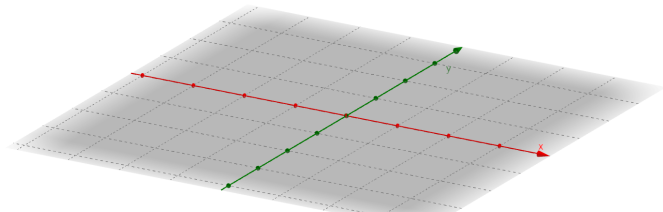
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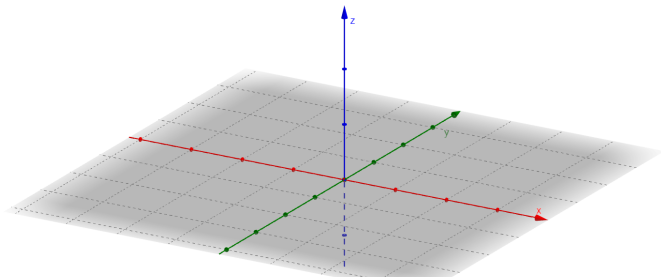
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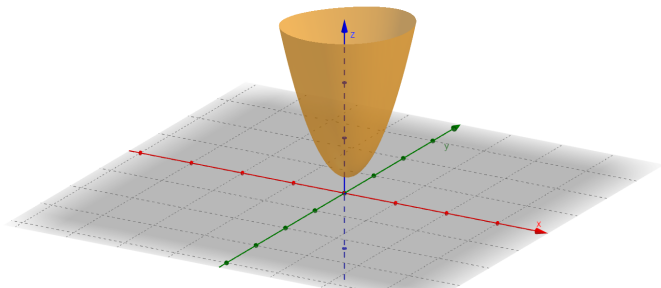
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How can you measure the effect of increasing the cost of apple by a little (i.e. how quickly will  $f$  change if  $x$  changes)?

By fixing  $y$  and then doing the usual derivative stuff with  $x$ !

## Definition

If there exists a finite limit

$$f_x = \lim_{h \rightarrow 0} \frac{f(x+h, y) - f(x, y)}{h}$$

then it is called the **partial derivative** of  $f(x, y)$  with respect to  $x$ , and denoted by  $f_x$  or  $\frac{\partial f}{\partial x}$ .

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## Example

If  $f(x, y) = x^2 + y^2$ , then:

$$f_x = 2x \quad \text{and} \quad f_y = 2y$$

# Partial Derivative

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## Definition

The vector consisting of the partial derivatives of  $f(x, y)$ :

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}$$

is called the **gradient** of  $f(x, y)$ .

In the previous example,  $\nabla f = [2x \quad 2y]$ .

# Partial Derivative

Similarly, for a function of  $n$  variables,  $f(x_1, \dots, x_n) = f(\mathbf{x})$  we define partial derivatives as:

$$f_{x_1}(\mathbf{x}) = \frac{\partial f}{\partial x_1}(\mathbf{x}) = \lim_{h \rightarrow 0} \frac{f(x_1 + h, x_2, \dots, x_n) - f(x_1, x_2, \dots, x_n)}{h},$$

$$f_{x_2}(\mathbf{x}) = \frac{\partial f}{\partial x_2}(\mathbf{x}) = \lim_{h \rightarrow 0} \frac{f(x_1, x_2 + h, \dots, x_n) - f(x_1, x_2, \dots, x_n)}{h},$$

$\vdots$

$$f_{x_n}(\mathbf{x}) = \frac{\partial f}{\partial x_n}(\mathbf{x}) = \lim_{h \rightarrow 0} \frac{f(x_1, x_2, \dots, x_n + h) - f(x_1, x_2, \dots, x_n)}{h}.$$

And the gradient of  $f(\mathbf{x})$  as:

$$\nabla f = \frac{df}{d\mathbf{x}} = \left[ \frac{\partial f(\mathbf{x})}{\partial x_1} \quad \frac{\partial f(\mathbf{x})}{\partial x_2} \quad \dots \quad \frac{\partial f(\mathbf{x})}{\partial x_n} \right] \in \mathbb{R}^{1 \times n}$$



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$$\frac{\partial}{\partial x_i}(f(\mathbf{x}) \cdot g(\mathbf{x})) = \frac{\partial f(\mathbf{x})}{\partial x_i} \cdot g(\mathbf{x}) + f(\mathbf{x}) \cdot \frac{\partial g(\mathbf{x})}{\partial x_i}$$

## Example

Let  $f(x, y) = 2x^2$  and  $g(x, y) = 4x + 6y$ .

$$(f \cdot g)_x = 2x^2(4) + (4x + 6y)(4x) = 24x^2 + 24xy$$

$$(f \cdot g)_y = 2x^2(6) + (4x + 6y)(0) = 12x^2$$

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Assume you're running a supermarket with the profit function

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How does a change of temperature affect your profit?

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In other words,

- if  $f$  depends on  $x$  and  $y$
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Turns out, there is a simple formula for that:

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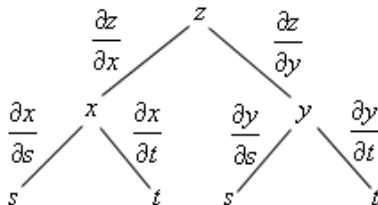
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$$\begin{aligned}\frac{dz}{dt} &= \frac{\partial z}{\partial x} \frac{dx}{dt} + \frac{\partial z}{\partial y} \frac{dy}{dt} = (2x \cos(x^2 + y^2)) \cdot (2t) + (2y \cos(x^2 + y^2)) \cdot (3t^2) \\ &= 4xt \cos(x^2 + y^2) + 6yt^2 \cos(x^2 + y^2)\end{aligned}$$

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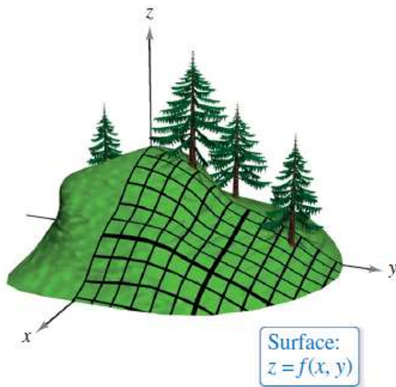
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Note that the directional derivative is a *number* (like partial derivatives), not a vector.

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The directional derivative shows how much our function changes if we "walk" not only along the  $x$  or  $y$ -axis, but by an arbitrary direction of our choice.



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For example, you might want to increase the price of coffee by  $h$  drams, but increase the price of tea two times more, i.e. by  $2h$  drams. In this case you would be considering the directional derivative along the vector  $\begin{bmatrix} 1 & 2 \end{bmatrix}$

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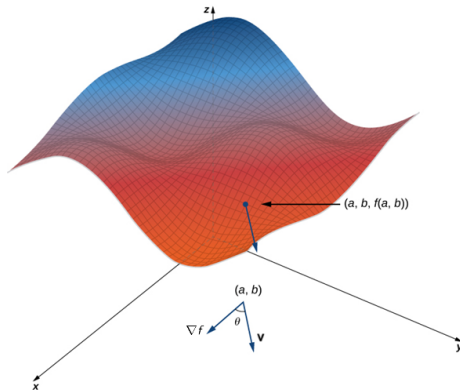
A particularly important question you might ask is:

## Question

By which direction should I move, so the function increases the most?

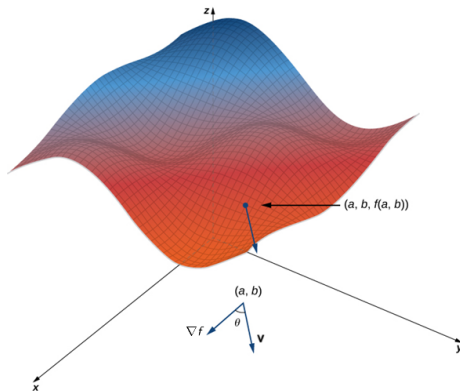
In other words, along which direction does  $\nabla_{\mathbf{v}} f$  take its highest value?

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Suppose  $\mathbf{v}$  is any vector (with  $\|\mathbf{v}\| = 1$ ).

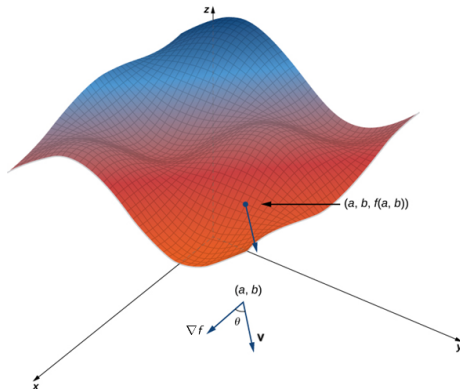
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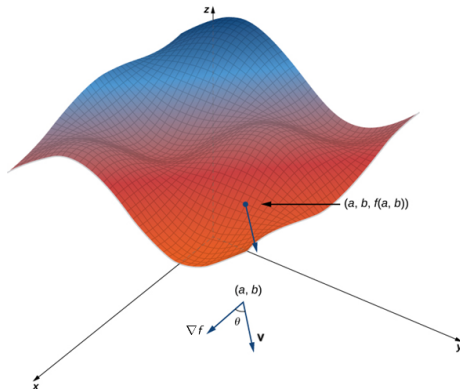
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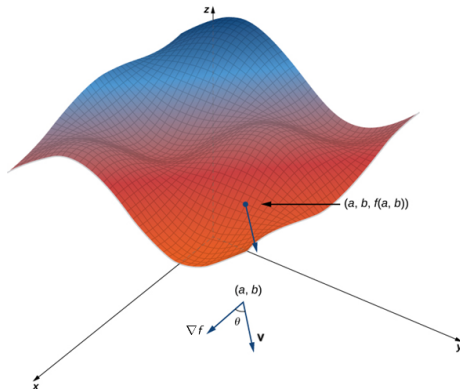


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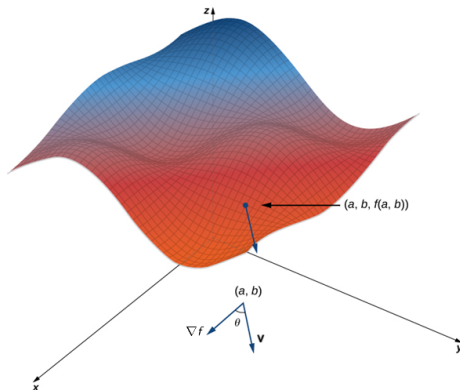
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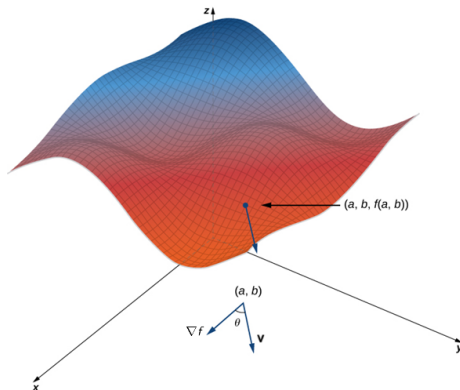


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*When the directions of  $\mathbf{v}$  and  $\nabla f$  coincide*

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$$\nabla_{\mathbf{v}} f = \|\nabla f\| \cos \theta$$

- When does this expression attain its maximum?

*When  $\cos \theta = 1$*

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## Theorem

The gradient is the **fastest increasing direction** of the function.

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## Theorem

The gradient is the **fastest increasing direction** of the function.

Similarly,  $-\nabla f$  is the fastest decreasing direction of the function.

# Extrema of a Function

Finally, how can we find the maximum and minimum values of a multivariable function  $f(\mathbf{x}) = f(x_1, \dots, x_n)$ ?

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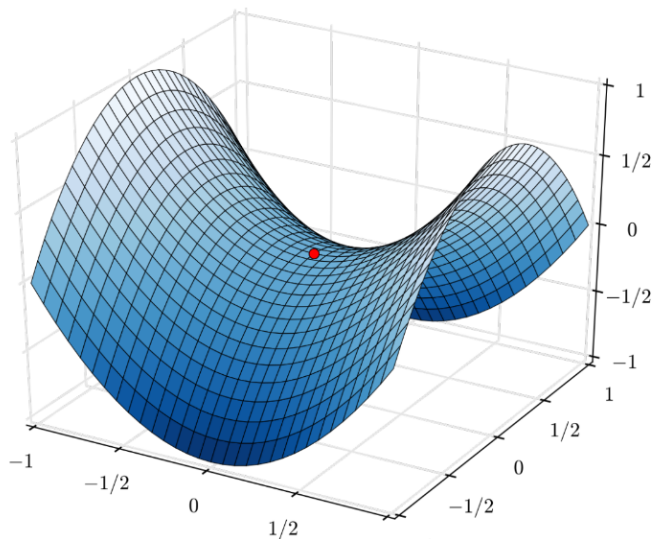
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$\mathbf{x}_0$  is called a **saddle point** of  $f$  if  $\nabla f(\mathbf{x}_0) = \mathbf{0}$  but it's not an extremum point.

# Extrema of a Function



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In case of two variables, we look at:

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## Theorem

If  $\nabla f(a, b) = \mathbf{0}$  at some point  $(a, b)$ , and

- $D > 0$  and  $f_{xx} > 0 \quad \Rightarrow \quad$  local minimum
- $D > 0$  and  $f_{xx} < 0 \quad \Rightarrow \quad$  local maximum
- $D < 0 \quad \Rightarrow \quad$  saddle point