

# **EC 4101: Microeconomic Analysis III**

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All relevant details on EC4101 are in the [syllabus](#)

3 suggestions

- Please follow the textbook and lectures closely.
- Use the material on the slides to guide you through the material in the textbook.
- Try solving all the assignments even if you might not be the designated student.

What is the job of an economic theorist?



- [The Raft of Medusa](#) (1819) - Jean Louis Théodore Géricault
- Moment from the aftermath of the wreck of the French naval frigate *Méduse*, which ran aground off the coast of today's Mauritania on July 5, 1816
- Take a real situation or story or thought ... that exists and represent it in a useful manner



- Mars Rover Spirit (2004)
- The objective is to do something that is practically useful

# What is EC 4101 about?

- Microeconomic theory is about modeling individual consumer and firm behavior in a mathematically to allow technically mature analysis.
- EC 3101 gives some description of these models – focuses on covering many topics rather than details
  - This description not enough for serious analysis
- EC4101 focuses on giving you the full technical description of those models
  - This description is useful for serious analysis
- Of course, that means we cannot cover as many topics.

# Chapter 2

## Mathematics for Microeconomics

- This file is a summary of the basic maths that you should know (but we do not have the time to go over in lecture). So keep it handy for future consultation.
- You will notice at a few places parenthesis such as “(” and “)” not aligned properly. This is not my fault – it’s the slightly distorted pdf conversion.

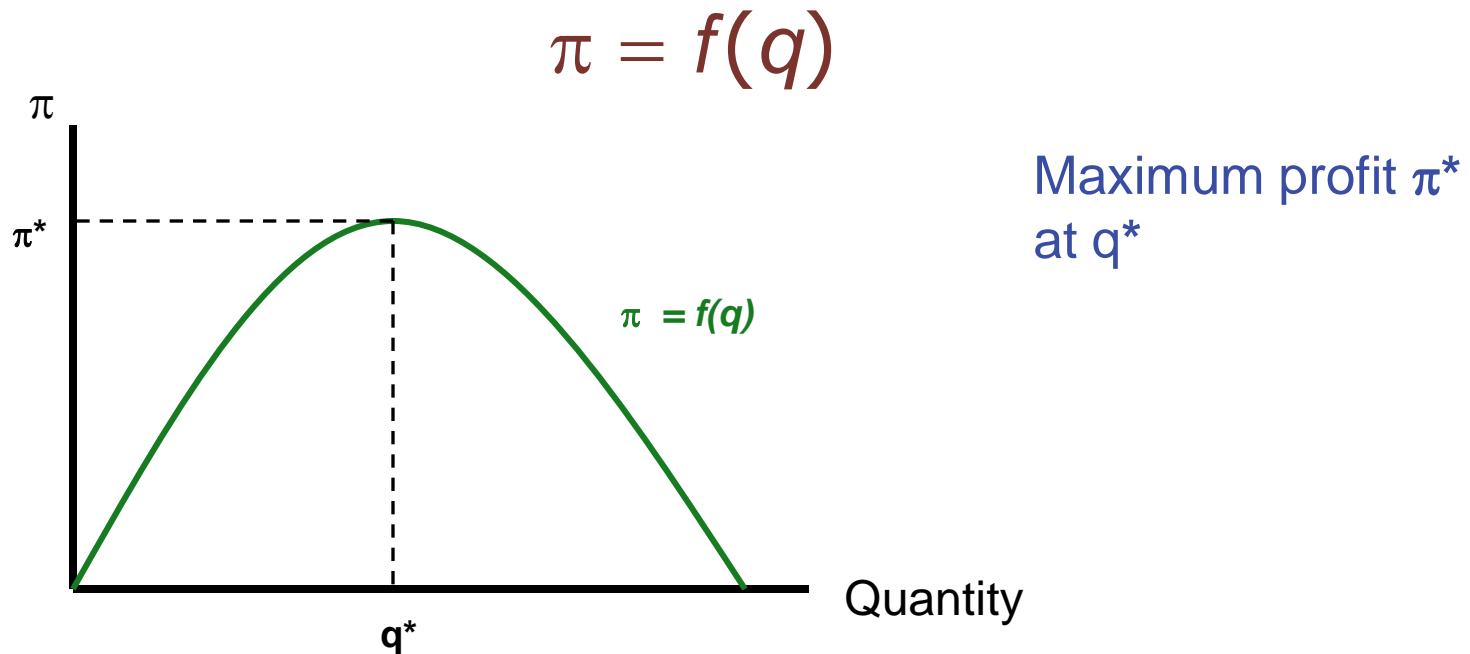
# The Mathematics of Optimization

- Economic theories assume that an economic agent is seeking to find the optimal value of some function
  - consumers seek to maximize utility
  - firms seek to maximize profit
- This chapter reviews the mathematics that go into these problems



# Functions with One Variable

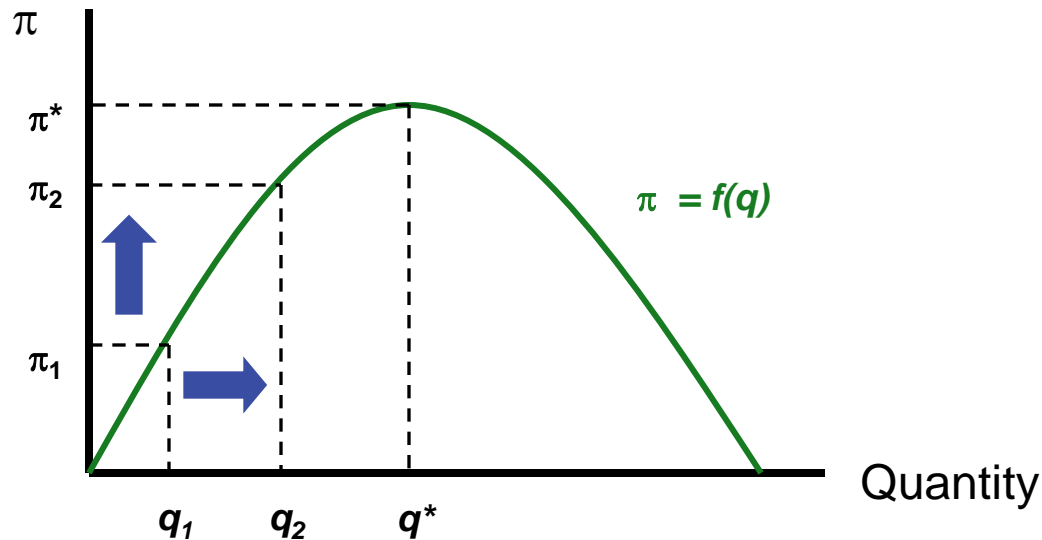
- Simple example: Manager of a firm wants to maximize profits





# Functions with One Variable

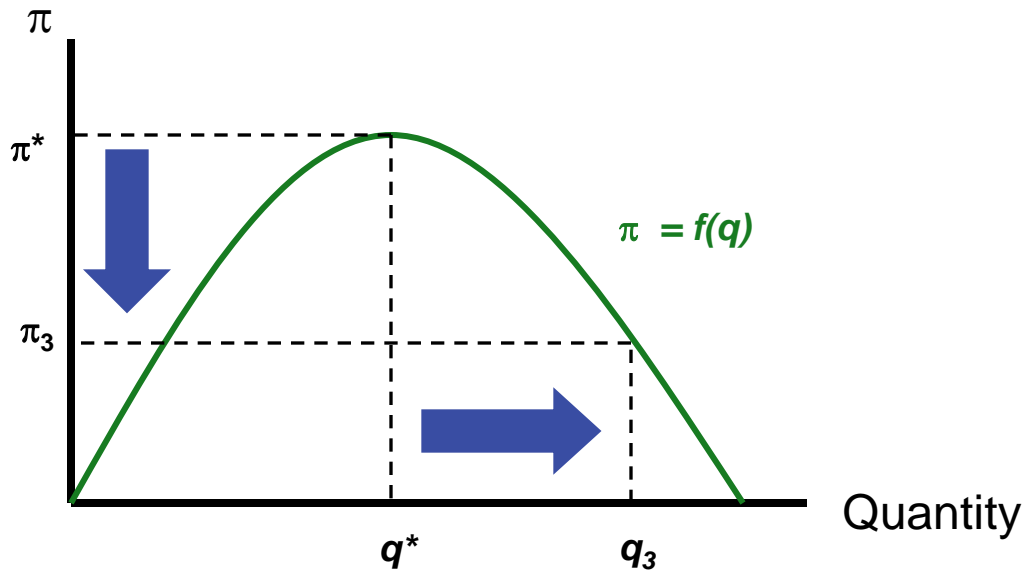
- Vary  $q$  to see where maximum profit occurs
  - an increase from  $q_1$  to  $q_2$  leads to a rise in  $\pi$



$$\frac{\Delta \pi}{\Delta q} > 0$$

# Functions with One Variable

- If output is increased beyond  $q^*$ , profit will decline
  - an increase from  $q^*$  to  $q_3$  leads to a drop in  $\pi$



$$\frac{\Delta \pi}{\Delta q} < 0$$

# Derivatives

- The derivative of  $\pi = f(q)$  is the limit of  $\Delta\pi/\Delta q$  for very small changes in  $q$

$$\frac{d\pi}{dq} = \frac{df}{dq} = \lim_{h \rightarrow 0} \frac{f(q_1 + h) - f(q_1)}{h}$$

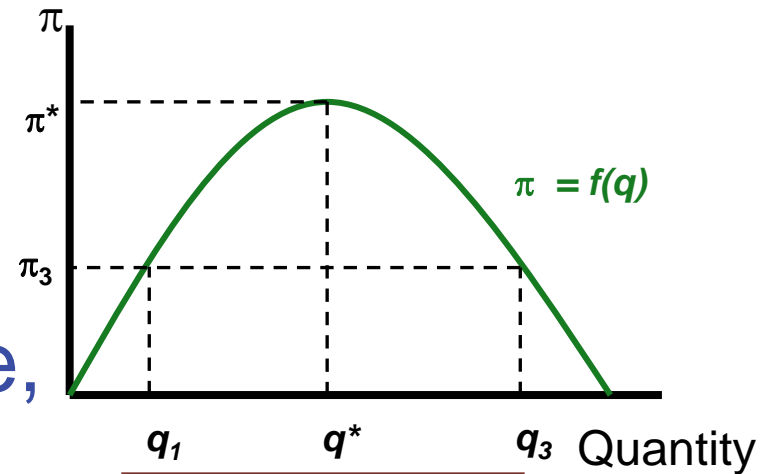
- The value depends on the value of  $q_1$

# Value of a Derivative at a Point

- The evaluation of the derivative at the point  $q = q_1$  can be denoted

$$\left. \frac{d\pi}{dq} \right|_{q=q_1}$$

- In our previous example,



$$\left. \frac{d\pi}{dq} \right|_{q=q_1} > 0$$

$$\left. \frac{d\pi}{dq} \right|_{q=q_3} < 0$$

$$\left. \frac{d\pi}{dq} \right|_{q=q^*} = 0$$

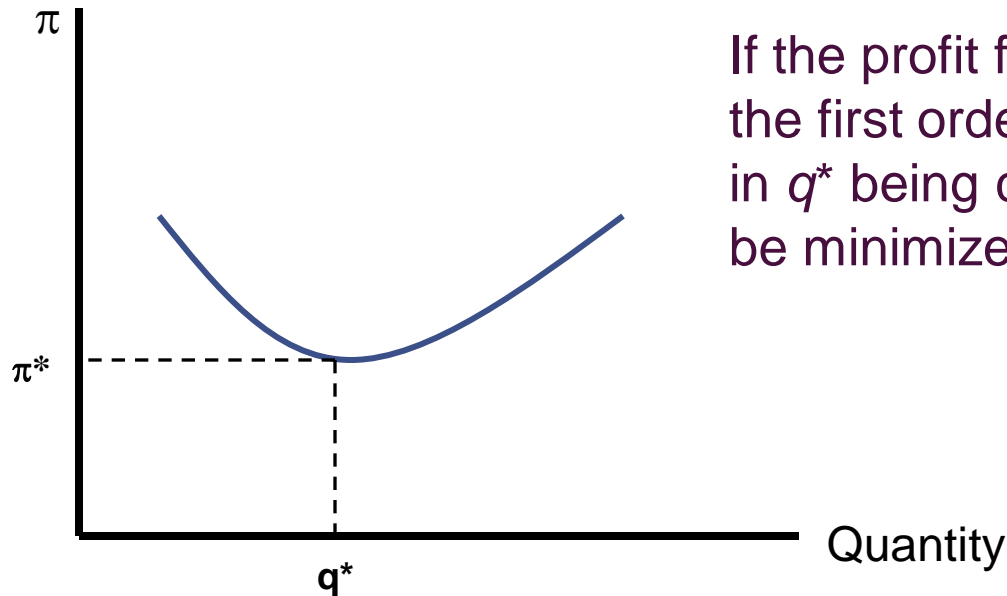
# First Order Condition for a Maximum

- For a function of one variable to attain its maximum value at some point, the derivative at that point must be zero

$$\left. \frac{df}{dq} \right|_{q=q^*} = 0$$

# Second Order Conditions

- The first order condition ( $d\pi/dq$ ) is a necessary condition for a maximum, but it is not a sufficient condition



If the profit function was u-shaped, the first order condition would result in  $q^*$  being chosen and  $\pi$  would be minimized

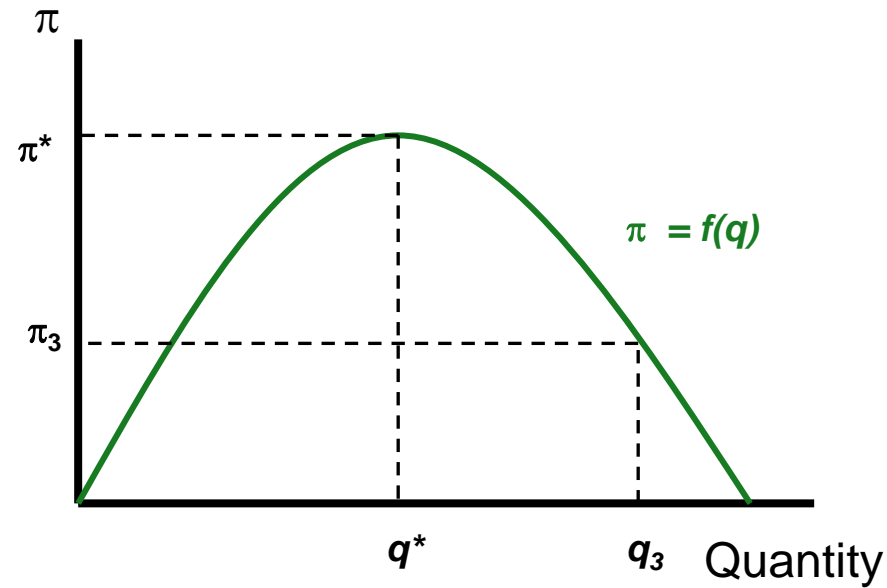
# Second Order Conditions

- This must mean that, in order for  $q^*$  to be the optimum,

$$\frac{d\pi}{dq} > 0 \text{ for } q < q^* \quad \text{and} \quad \frac{d\pi}{dq} < 0 \text{ for } q > q^*$$

- At  $q^*$ ,  $d\pi/dq$  must be decreasing

– the derivative of  $d\pi/dq$  must be negative at  $q^*$



# Second Derivatives

- The derivative of a derivative is called a second derivative
- The second derivative can be denoted by

$$\frac{d^2\pi}{dq^2} \text{ or } \frac{d^2f}{dq^2} \text{ or } f''(q)$$



# Second Order Condition

- The second order condition to represent a (local) maximum is

$$\left. \frac{d^2 \pi}{dq^2} \right|_{q=q^*} = f''(q) \Big|_{q=q^*} < 0$$

# Rules for Finding Derivatives

1. If  $b$  is a constant, then  $\frac{db}{dx} = 0$

2. If  $b$  is a constant, then  $\frac{d[bf(x)]}{dx} = bf'(x)$

3. If  $b$  is constant, then  $\frac{dx^b}{dx} = bx^{b-1}$

4.  $\frac{d \ln x}{dx} = \frac{1}{x}$

# Rules for Finding Derivatives

5.  $\frac{da^x}{dx} = a^x \ln a$  for any constant  $a$

– a special case of this rule is  $de^x/dx = e^x$

# Rules for Finding Derivatives

- Suppose that  $f(x)$  and  $g(x)$  are two functions of  $x$  and  $f'(x)$  and  $g'(x)$  exist
- Then

$$6. \frac{d[f(x) + g(x)]}{dx} = f'(x) + g'(x)$$

$$7. \frac{d[f(x) \cdot g(x)]}{dx} = f(x)g'(x) + f'(x)g(x)$$

# Rules for Finding Derivatives

$$8. \frac{d\left(\frac{f(x)}{g(x)}\right)}{dx} = \frac{f(x)g'(x) - f'(x)g(x)}{[g(x)]^2}$$

provided that  $g(x) \neq 0$

# Rules for Finding Derivatives

- If  $y = f(x)$  and  $x = g(z)$  [so  $y = f(g(z))$ ] and if both  $f'(x)$  and  $g'(x)$  exist, then:

$$9. \quad \frac{dy}{dz} = \frac{dy}{dx} \cdot \frac{dx}{dz} = \frac{df}{dx} \cdot \frac{dg}{dz}$$

- this is called the chain rule
- allows us to study how one variable ( $z$ ) affects another variable ( $y$ ) through its influence on some intermediate variable ( $x$ )

# Rules for Finding Derivatives

- Some examples of the chain rule include

$$10. \frac{de^{ax}}{dx} = \frac{de^{ax}}{d(ax)} \cdot \frac{d(ax)}{dx} = e^{ax} \cdot a = ae^{ax}$$

$$11. \frac{d[\ln(ax)]}{dx} = \frac{d[\ln(ax)]}{d(ax)} \cdot \frac{d(ax)}{dx} = \frac{1}{ax} \cdot a = \frac{1}{x}$$

$$12. \frac{d[\ln(x^2)]}{dx} = \frac{d[\ln(x^2)]}{d(x^2)} \cdot \frac{d(x^2)}{dx} = \frac{1}{x^2} \cdot 2x = \frac{2}{x}$$

# Example of Profit Maximization

- Suppose that the relationship between profit and output is

$$\pi = 1,000q - 5q^2$$

- The first order condition for a maximum is

$$d\pi/dq = 1,000 - 10q = 0$$

$$q^* = 100$$

- Since the second derivative is always  $-10$ ,  
 $q = 100$  is a global maximum



# Functions of Several Variables

- Most goals of economic agents depend on several variables
  - trade-offs must be made
- The dependence of one variable ( $y$ ) on a series of other variables ( $x_1, x_2, \dots, x_n$ ) is denoted by

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

# Partial Derivatives

- The partial derivative of  $y$  with respect to  $x_1$  is denoted by

$$\frac{\partial y}{\partial x_1} \text{ or } \frac{\partial f}{\partial x_1} \text{ or } f_{x_1} \text{ or } f_1$$

- in calculating the partial derivative, all of the other  $x$ 's are held constant

# Partial Derivatives

- A more formal definition of the partial derivative is

$$\left. \frac{\partial f}{\partial x_1} \right|_{\bar{x}_2, \dots, \bar{x}_n} = \lim_{h \rightarrow 0} \frac{f(\bar{x}_1 + h, \bar{x}_2, \dots, \bar{x}_n) - f(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n)}{h}$$

# Calculating Partial Derivatives

1. If  $y = f(x_1, x_2) = ax_1^2 + bx_1x_2 + cx_2^2$ , then

$$\frac{\partial f}{\partial x_1} = f_1 = 2ax_1 + bx_2 \quad \text{and}$$

$$\frac{\partial f}{\partial x_2} = f_2 = bx_1 + 2cx_2$$

2. If  $y = f(x_1, x_2) = e^{ax_1 + bx_2}$ , then

$$\frac{\partial f}{\partial x_1} = f_1 = ae^{ax_1 + bx_2} \quad \text{and} \quad \frac{\partial f}{\partial x_2} = f_2 = be^{ax_1 + bx_2}$$

# Calculating Partial Derivatives

3. If  $y = f(x_1, x_2) = a \ln x_1 + b \ln x_2$ , then

$$\frac{\partial f}{\partial x_1} = f_1 = \frac{a}{x_1} \quad \text{and} \quad \frac{\partial f}{\partial x_2} = f_2 = \frac{b}{x_2}$$

# Partial Derivatives

- Partial derivatives are the mathematical expression of the *ceteris paribus* assumption
  - show how changes in one variable affect some outcome when other influences are held constant

# Second-Order Partial Derivatives

- The partial derivative of a partial derivative is called a second-order partial derivative

$$\frac{\partial(\partial f / \partial x_i)}{\partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i} = f_{ij}$$

# Young's Theorem

- Under general conditions, the order in which partial differentiation is conducted to evaluate second-order partial derivatives does not matter

$$f_{ij} = f_{ji}$$



# Functions of Several Variables

- Suppose an agent wishes to maximize

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

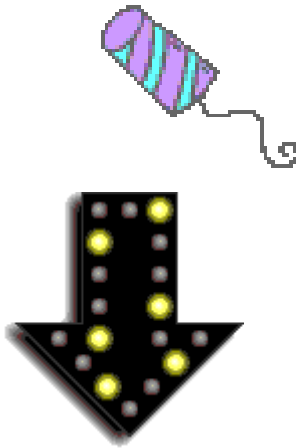
- The change in  $y$  from a change in  $x_1$  (holding all other  $x$ 's constant) is

$$dy = \frac{\partial f}{\partial x_1} dx_1 = f_1 dx_1$$

- the change in  $y$  is equal to the change in  $x_1$  times the slope (measured in the  $x_1$  direction)

# Party time! Let's make the change bigger

$$dy = \frac{\partial f}{\partial x_1} dx_1 = f_1 dx_1$$



$$\Delta y = \frac{\partial f}{\partial x_1} \Delta x_1 = f_1 \Delta x_1$$

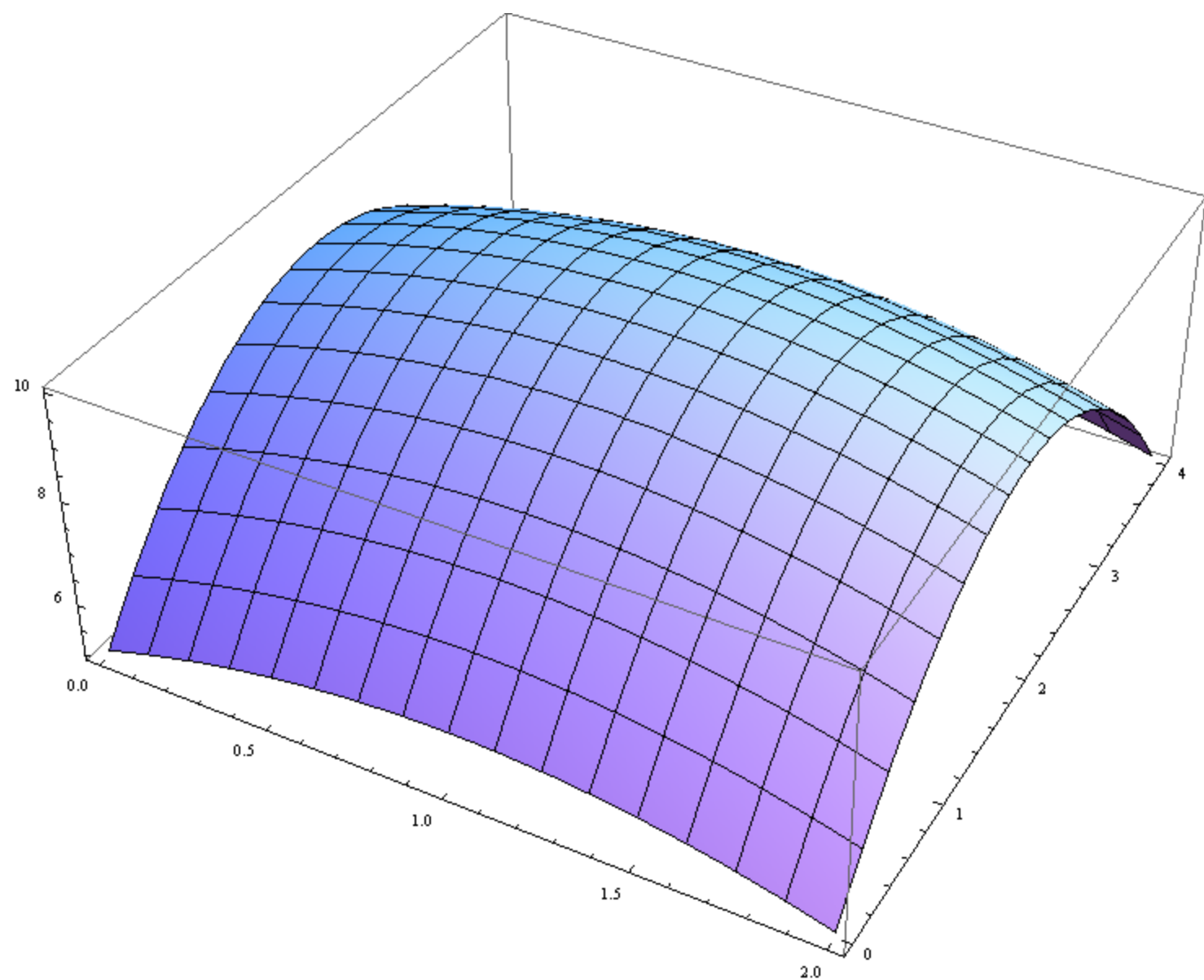
# Total Differential

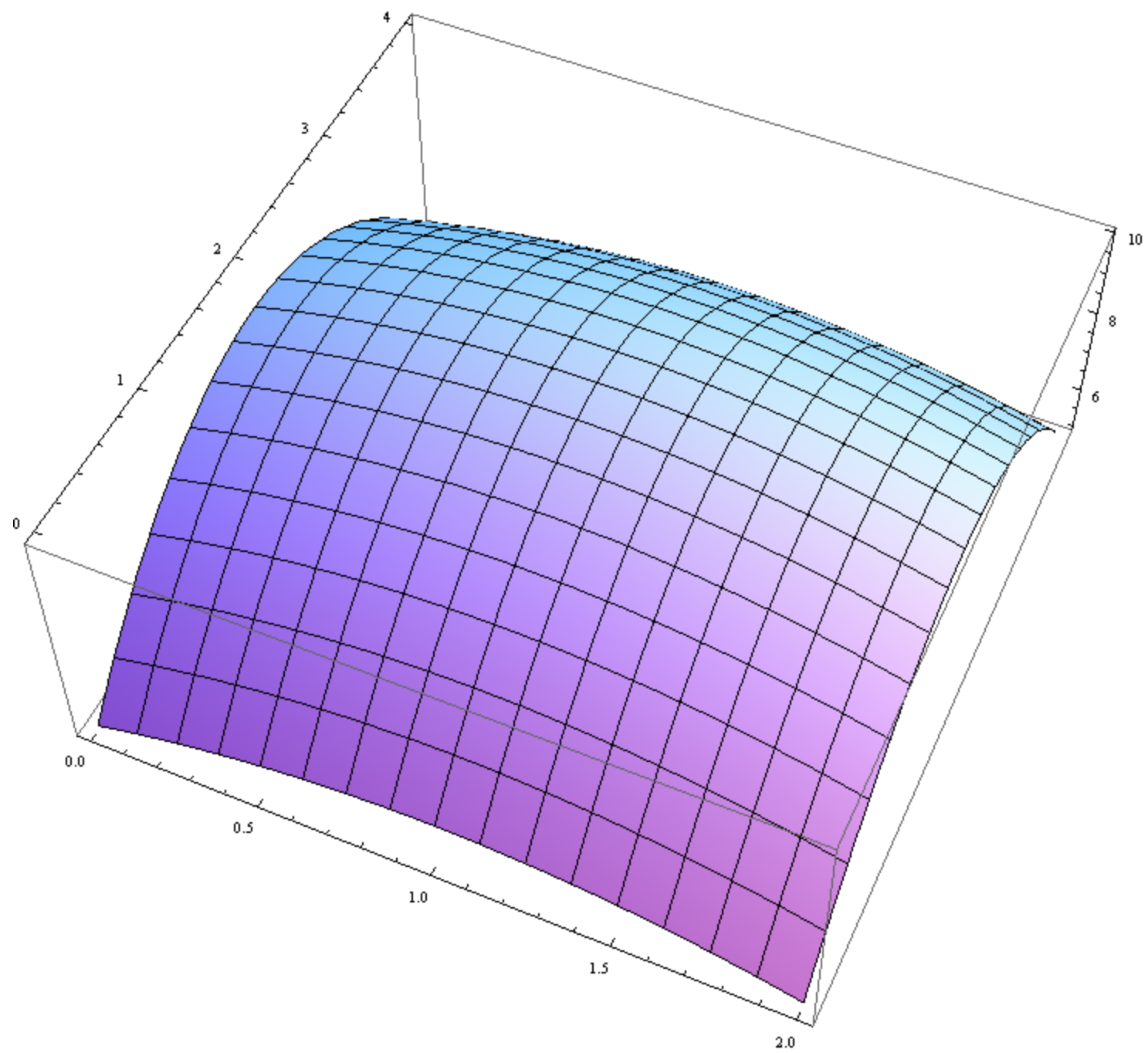
- Suppose that  $y = f(x_1, x_2, \dots, x_n)$
- If all  $x$ 's are varied by a small amount, the total effect on  $y$  will be

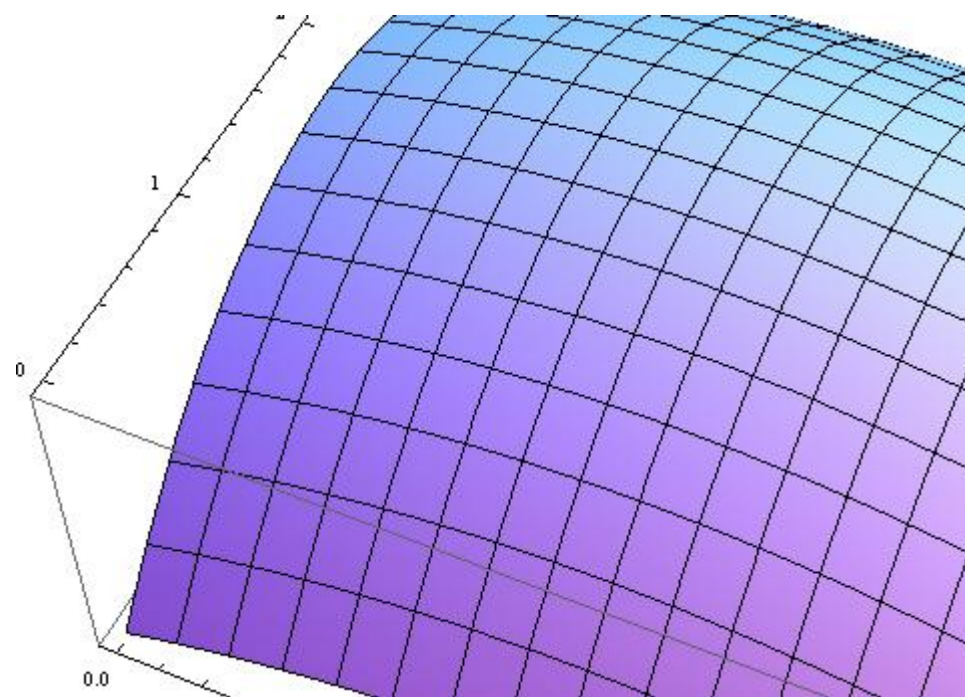
$$dy = \frac{\partial f}{\partial x_1} dx_1 + \frac{\partial f}{\partial x_2} dx_2 + \dots + \frac{\partial f}{\partial x_n} dx_n$$

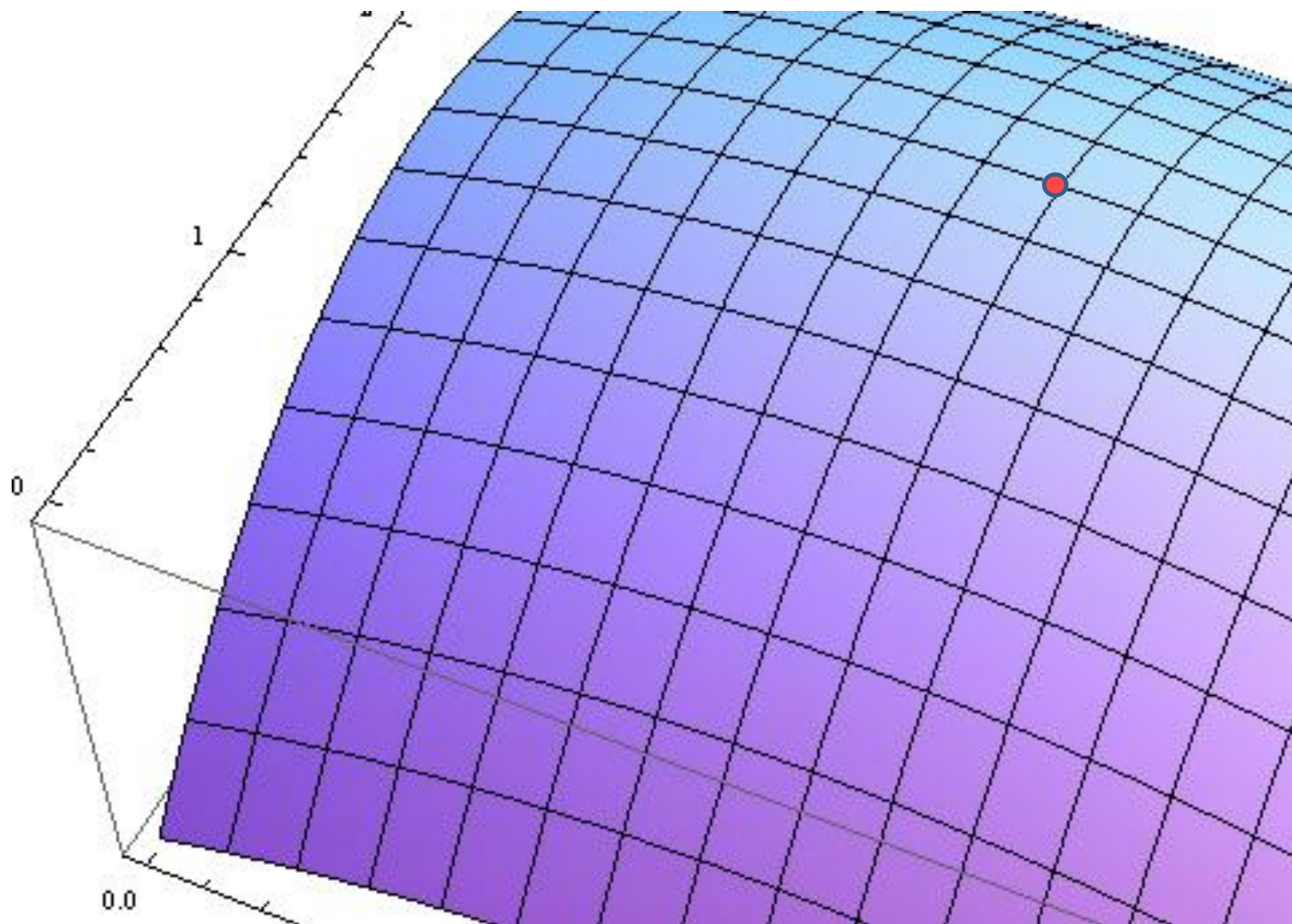
$$dy = f_1 dx_1 + f_2 dx_2 + \dots + f_n dx_n$$

$$\Delta y = f_1 \Delta x_1 + f_2 \Delta x_2 + \dots + f_n \Delta x_n$$

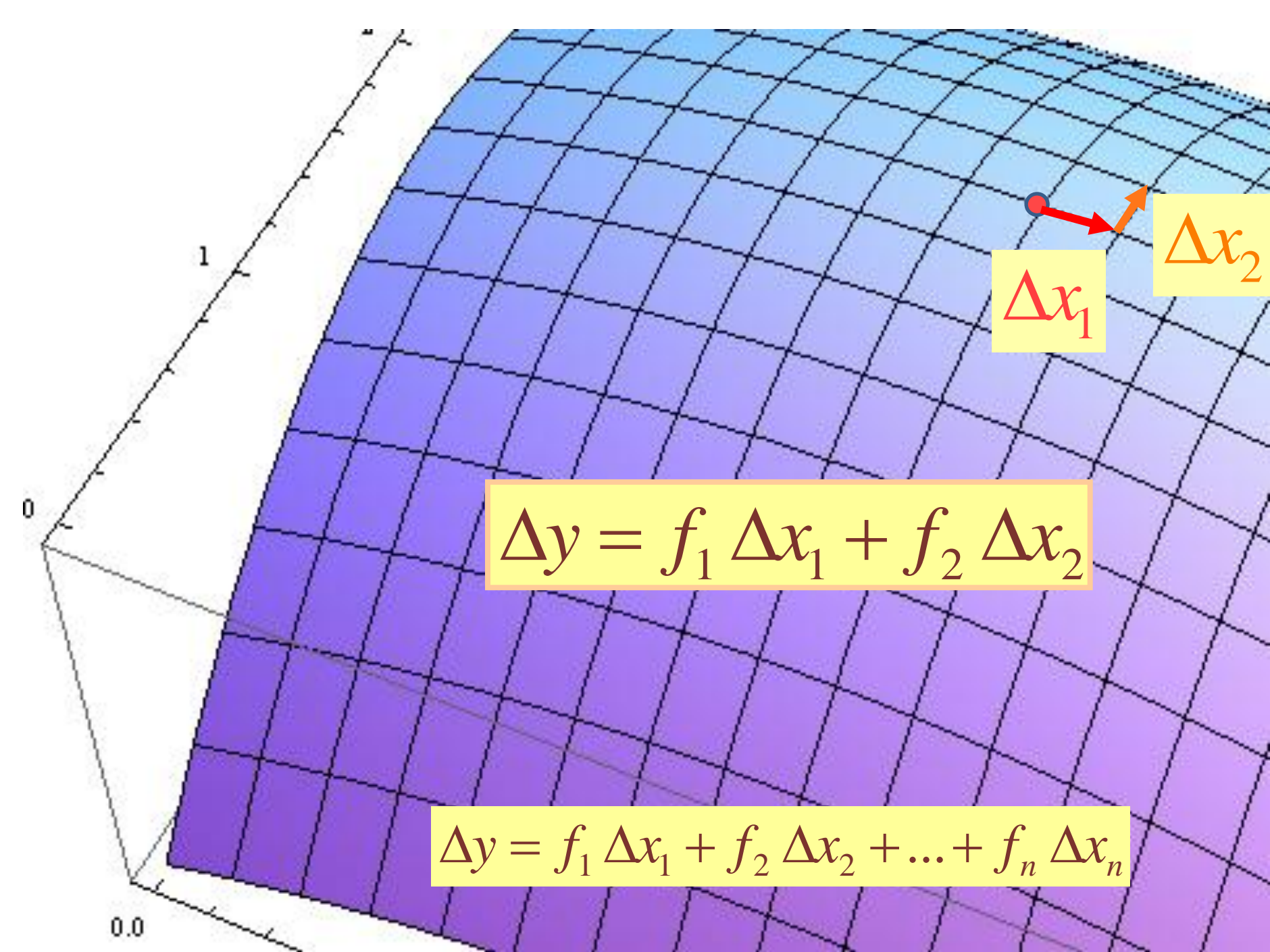












$$\Delta y = f_1 \Delta x_1 + f_2 \Delta x_2$$

$$\Delta y = f_1 \Delta x_1 + f_2 \Delta x_2 + \dots + f_n \Delta x_n$$



$$\Delta y = f_1 \Delta x_1 + f_2 \Delta x_2 + \dots + f_n \Delta x_n$$

# First-Order Condition for a Maximum

- A necessary condition for a maximum of the function  $f(x_1, x_2, \dots, x_n)$  is that  $dy = 0$  for **any** combination of small changes in the  $x$ 's
  - this can only be true if

$$f_1 = f_2 = \dots = f_n = 0$$

- A point where this condition holds is called a critical point

# Second-Order Conditions

- This condition is not sufficient to ensure a maximum
  - we need to examine the second-order partial derivatives of the function  $f$
  - conditions that will make  $f$  concave would be sufficient for a maximum

# Finding a Maximum

- Suppose that  $y$  is a function of  $x_1$  and  $x_2$

$$y = - (x_1 - 1)^2 - (x_2 - 2)^2 + 10$$

$$y = -x_1^2 + 2x_1 - x_2^2 + 4x_2 + 5$$

- First-order conditions imply that

$$\frac{\partial y}{\partial x_1} = -2x_1 + 2 = 0$$

OR

$$x_1^* = 1$$

$$\frac{\partial y}{\partial x_2} = -2x_2 + 4 = 0$$

$$x_2^* = 2$$

# Implicit Functions

- An “explicit” function which is shown with a dependent variable ( $y$ ) as a function of one or more independent variables ( $x$ ) such as

$$y = mx + b$$

can be written as an “implicit” function

$$y - mx - b = 0$$

$$f(x, y, m, b) = 0$$

# Derivatives from Implicit Functions

- It will sometimes be helpful to compute derivatives directly from implicit functions without solving for one of the variables directly

– the total differential of  $g(x,y) = 0$  is

$$0 = g_x dx + g_y dy$$

– this means that

$$\frac{dy}{dx} = -\frac{g_x}{g_y}$$

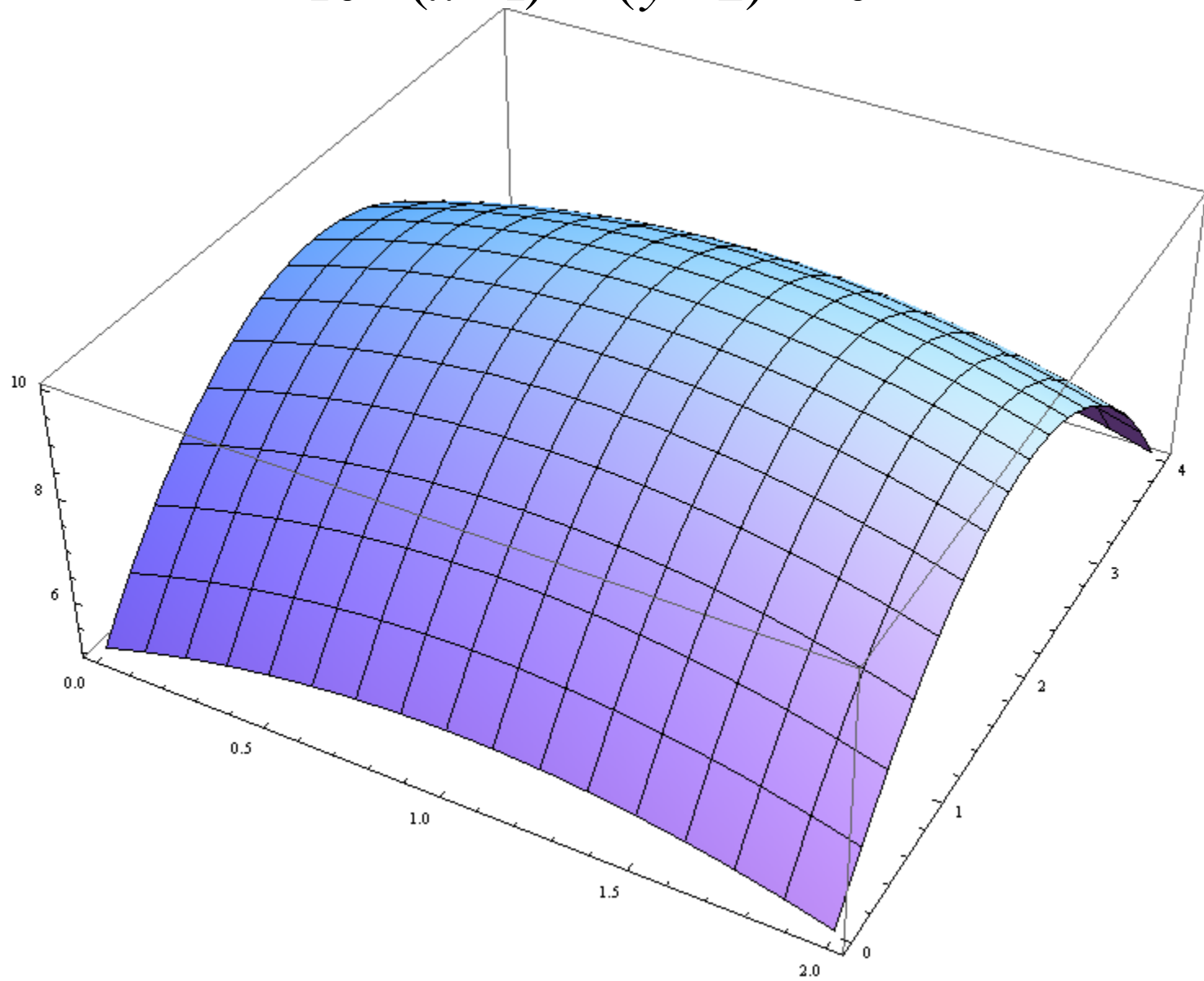
# Implicit Function Theorem

- It may not always be possible to locally solve implicit functions of the form  $g(x,y)=0$  for unique explicit functions of the form  $y = f(x)$

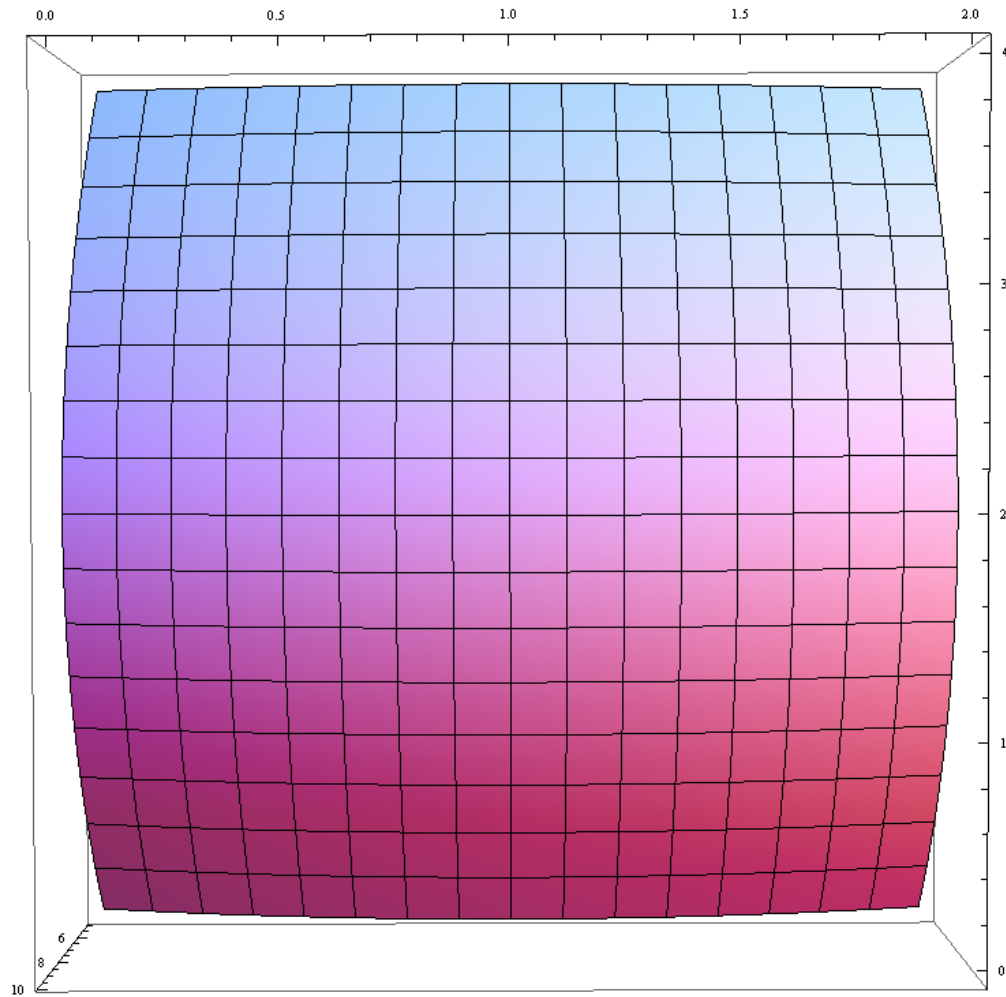
Sufficient condition for  $y = f(x)$  to exist :

$$g_y \neq 0$$

$$10 - (x-1)^2 - (y-2)^2 = 0$$



$$10 - (x-1)^2 - (y-2)^2 = 0$$





# Implicit Function Theorem

- It may not always be possible to locally solve implicit functions of the form  $g(x,y)=0$  for unique explicit functions of the form  $y = f(x)$

Sufficient condition for  $y = f(x)$  to exist :

$$g_y \neq 0$$

# The Envelope Theorem

- The envelope theorem concerns how the optimal value for a function changes when a parameter of the function changes
  - this is easiest to see by using an example

# The Envelope Theorem

- Suppose that  $y$  (ice cream seller's profit) is a function of  $x$  (ice cream output)

$$y = -x^2 + ax$$

- If  $a$  (temperature) is assigned a specific value, then  $y$  becomes a function of  $x$  only and the value of  $x$  that maximizes  $y$  can be calculated



# How does the profit depend on temperature?

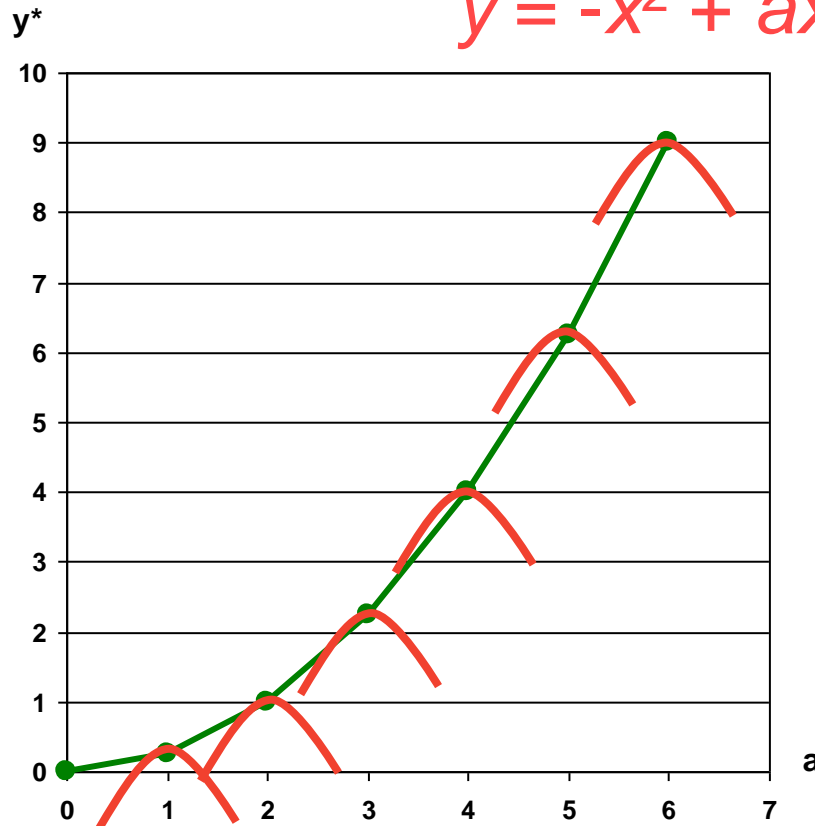
## Use the Envelope Theorem

Optimal Values of  $x$  and  $y$  for Alternative Values of  $a$

<u>Value of <math>a</math></u>	<u>Value of <math>x^*</math></u>	<u>Value of <math>y^*</math> (Profit)</u>
0	0	0
1	$1/2$	$1/4$
2	1	1
3	$3/2$	$9/4$
4	2	4
5	$5/2$	$25/4$
6	3	9

# The Envelope Theorem

$$y = -x^2 + ax$$



As  $a$  increases,  
the maximal value  
for  $y$  increases

The relationship  
between  $a$  and  $y$   
is quadratic

$$\frac{dy^*}{da} = ?$$

# The Envelope Theorem

- Suppose we are interested in how  $y^*$  changes as  $a$  changes

$$\frac{dy^*}{da} = ?$$

- There are two ways we can do this
  - calculate the slope of  $y^*$  directly
  - apply envelope theorem

# The Direct Approach

- To calculate the slope of the function, we must solve for the optimal value of  $x$  for any value of  $a$

$$dy/dx = -2x + a = 0$$

$$x^* = a/2$$

- Substituting, we get

$$y^* = -(x^*)^2 + a(x^*) = -(a/2)^2 + a(a/2)$$

$$y^* = -a^2/4 + a^2/2 = a^2/4$$

# The Direct Approach

- Therefore,

$$dy^*/da = 2a/4 = a/2$$

- We can save time by using the envelope theorem ( $x^*$  may not also be explicit)
  - for small changes in  $a$ ,  $dy^*/da$  can be computed by holding  $x$  at  $x^*$  and calculating  $\partial y/\partial a$  directly from  $y$



# The Envelope Theorem Way

$$\partial y / \partial a = x$$

- Holding  $x = x^*$

$$\partial y / \partial a = x^* = a/2$$

- This is the same result found earlier

# The Envelope Theorem

- The change in the optimal value of a function with respect to a parameter of that function can be found by partially differentiating the objective function while holding  $x$  (or several  $x$ 's) at its optimal value

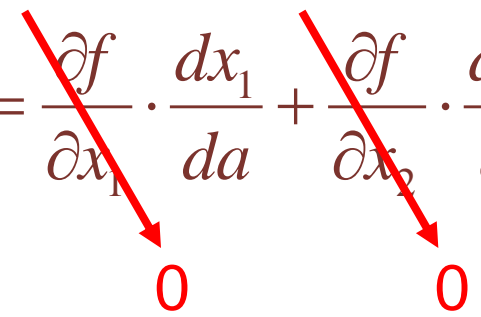
$$\frac{dy^*}{da} = \left. \frac{\partial y}{\partial a} \right|_{x=x^*(a)}$$

# The Math of Envelope Theorem

- How did the formula come about? We have from maximizing  $y = f[x_1, x_2, a]$  with respect to  $x_1$  and  $x_2$

$$y^* = f(x_1^*(a), x_2^*(a), a)$$

- Taking derivative w.r.t.  $a$

$$\frac{dy^*}{da} = \frac{\partial f}{\partial x_1} \cdot \frac{dx_1}{da} + \frac{\partial f}{\partial x_2} \cdot \frac{dx_2}{da} + \frac{\partial f}{\partial a}$$


The diagram shows two red diagonal lines crossing out the first two terms of the equation. Below each crossed-out term is a red '0', indicating that these terms are zero.

# The Envelope Theorem: Extension

- This can be extended to the case where  $y$  is a function of several variables

$$y = f(x_1, \dots, x_n, a)$$

- Finding an optimal value for  $y$  would consist of solving  $n$  first-order equations

$$\partial y / \partial x_i = 0 \quad (i = 1, \dots, n)$$

# The Envelope Theorem

- Optimal values for these  $x$ 's would be a function of  $a$

$$x_1^* = x_1^*(a)$$

$$x_2^* = x_2^*(a)$$

•

•

•

$$x_n^* = x_n^*(a)$$

# The Envelope Theorem

- Substituting into the original objective function gives us the optimal value of  $y$  ( $y^*$ )

$$y^* = f[x_1^*(a), x_2^*(a), \dots, x_n^*(a), a]$$

- Differentiating yields

$$\frac{dy^*}{da} = \frac{\partial f}{\partial x_1} \cdot \frac{dx_1}{da} + \frac{\partial f}{\partial x_2} \cdot \frac{dx_2}{da} + \dots + \frac{\partial f}{\partial x_n} \cdot \frac{dx_n}{da} + \frac{\partial f}{\partial a}$$

# The Envelope Theorem

- Because of first-order conditions, all terms except  $\partial f / \partial a$  are equal to zero if the  $x$ 's are at their optimal values
- Therefore,

$$\frac{dy^*}{da} = \frac{\partial f}{\partial a}$$

# Constrained Maximization

- Suppose that we wish to find the values of  $x_1, x_2, \dots, x_n$  that maximize

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

subject to a constraint

$$g(x_1, x_2, \dots, x_n) = 0$$



# Lagrangian Multiplier Method

- The Lagrangian multiplier method starts with setting up the expression

$$\mathcal{L} = f(x_1, x_2, \dots, x_n) + \lambda g(x_1, x_2, \dots, x_n)$$

–  $\lambda$  is called a Lagrangian multiplier

$$\mathcal{L} = f(x_1, x_2, \dots, x_n) + \lambda g(x_1, x_2, \dots, x_n)$$

# Lagrangian Multiplier Method

- First-Order Conditions

$$\partial \mathcal{L} / \partial x_1 = f_1 + \lambda g_1 = 0$$

$$\partial \mathcal{L} / \partial x_2 = f_2 + \lambda g_2 = 0$$

⋮

$$\partial \mathcal{L} / \partial x_n = f_n + \lambda g_n = 0$$

$$\partial \mathcal{L} / \partial \lambda = g(x_1, x_2, \dots, x_n) = 0$$

# Interpretation of Lagrangian Multiplier

- Rate at which the maximum increases as the constraint is relaxed – shadow price for the constraint

We will come back to this in just a bit for a good understanding

# Constrained Maximization

- Suppose a farmer had a certain length of fence ( $P$ ) and wished to enclose the largest possible rectangular area
  - let  $x$  and  $y$  be the lengths of the sides
- Problem: choose  $x$  and  $y$  to maximize the area ( $A = x \cdot y$ ) subject to the constraint that the perimeter is fixed at  $P = 2x + 2y$

# Constrained Maximization

- Setting up the Lagrangian multiplier:

$$\mathcal{L} = x \cdot y + \lambda(P - 2x - 2y)$$

- The first-order conditions for a maximum are

$$\partial \mathcal{L} / \partial x = y - 2\lambda = 0$$

$$\partial \mathcal{L} / \partial y = x - 2\lambda = 0$$

$$\partial \mathcal{L} / \partial \lambda = P - 2x - 2y = 0$$

# Constrained Maximization

- Since  $y/2 = x/2 = \lambda$ ,  $x$  must be equal to  $y$ 
  - the field should be square
- Since  $x = y$  and  $y = 2\lambda$ , we can use the constraint to show that

$$x = y = P/4$$

$$\lambda = P/8$$

# Constrained Maximization

- Interpretation of the Lagrangian multiplier
  - $\lambda$  suggests that an extra yard of fencing would add  $P/8$  to the area
  - The Lagrangian multiplier provides information about the implicit value of the constraint

# Constrained Maximization & Envelope Theorem

- Suppose that we want to maximize

$$y = f(x_1, \dots, x_n; a)$$

subject to the constraint

$$g(x_1, \dots, x_n; a) = 0$$

- Solve by setting partial derivatives of Lagrangian equal to 0



# Constrained Maximization & Envelope Theorem

- It can be shown that

$$dy^*/da = \partial \mathcal{L} / \partial a \text{ at } (x_1^*, \dots, x_n^*; a)$$

- the change in the maximal value of  $y$  from a change in  $a$  can be found by partially differentiating  $\mathcal{L}$  and evaluating the partial derivative at the optimal point

# Inequality Constraints (Not in the textbook)

- In some economic problems the constraints need not hold exactly
- Suppose we seek to maximize  $y = f(x_1, x_2)$  subject to

$$g_1(x_1, x_2) \geq 0,$$

$$g_2(x_1, x_2) \geq 0$$

# Lagrangian

- We define
- $\mathcal{L} = f(x_1, x_2) + \lambda_1 g_1(x_1, x_2) + \lambda_2 g_2(x_1, x_2)$
- Now we write down the first order conditions for this Lagrangian
- In this case the multipliers have specific signs:  $\lambda_1, \lambda_2 \geq 0$
- Complementary slackness: at least one of  $g_i(x_1, x_2)$  or  $\lambda_i$  must be zero at solution

# Kuhn-Tucker Conditions

- Sometimes we have a standard constrained optimization problem with equality constraints that the right hand side is negative.
- In that case we can convert the non-negativity constraints to equality constraints and work with the Lagrangian the standard way

# Second Order Conditions - Functions of One Variable

- Let  $y = f(x)$
- A necessary condition for a maximum is that

$$dy/dx = f'(x) = 0$$

- to ensure that the point is a maximum,  $y$  must be decreasing for movements away from it

# Second Order Conditions – Sufficiency Condition

$$\frac{d^2 y}{dx^2} = f''(x) < 0$$

- This means that the function  $f$  must have a concave shape at the critical point

# Second Order Conditions - Functions of Two Variables

- Suppose that  $y = f(x_1, x_2)$
- First order conditions for a maximum are

$$\partial y / \partial x_1 = f_1 = 0$$

$$\partial y / \partial x_2 = f_2 = 0$$

- to ensure that the point is a maximum,  $y$  must diminish for movements in any direction away from the critical point

# Second Order Conditions - Functions of Two Variables

$$f_{11} < 0, f_{11}f_{22} - f_{12}^2 > 0$$

The rest of the sufficiency conditions will be on a need-to-know basis 😊



# Quasi-Concavity

- A function  $U$  is quasi-concave if for each number  $c$  the following set is convex

$$[(x, y) \mid U(x, y) \geq c]$$

# Duality

- Any constrained maximization problem has a dual problem in constrained minimization
  - focuses attention on the constraints in the original problem

To be studied later

# Integration

- Integration is the inverse of differentiation
  - let  $F(x)$  be the integral of  $f(x)$
  - then  $f(x)$  is the derivative of  $F(x)$

$$\frac{dF(x)}{dx} = F'(x) = f(x)$$

# Integration

- We denote an integral as

$$F(x) = \int f(x) dx$$

- If  $f(x) = x$  then

$$F(x) = \int f(x) dx = \int x dx = \frac{x^2}{2} + C$$

- $C$  is an arbitrary constant of integration

# Definite Integrals

- We can also use integration to sum up the area under a function over some defined interval

$$F'(x) = f(x) \Rightarrow \int_{x=a}^{x=b} f(x)dx = F(b) - F(a)$$

$$\int_{x=a}^{x=b} f(x)dx = \text{area under } f(x)$$

# Definite Integrals

