

## ARE211, Fall 2009

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### CONTENTS

4. Univariate and Multivariate Differentiation	1
4.1. Univariate calculus: the derivative	1
4.2. The fundamental idea: linear approximations to nonlinear functions	2
4.3. Univariate Calculus: the differential	3
4.4. Multivariate calculus: functions from $\mathbb{R}^n$ to $\mathbb{R}$	5
4.4.1. Partial Derivative	5
4.4.2. The Gradient	6
4.4.3. Crosspartial Derivative	6
4.4.4. The differential for functions from $\mathbb{R}^n$ to $\mathbb{R}$	6

#### 4. UNIVARIATE AND MULTIVARIATE DIFFERENTIATION

##### 4.1. Univariate calculus: the derivative

Assume you all know how to calculate the derivative of a single variable function, i.e., given  $f$ , calculate  $\frac{df(\cdot)}{dx}$ , denoted also  $f'(\cdot)$ . Important to know the difference between  $f'(\cdot)$ , which is a function and  $f'(x)$ , which is a number, the function evaluated at a point.

I'll try to be careful to use this notation from now on:  $g(\cdot)$  is a RULE, represents a function.

Since  $f'(\cdot)$  is a function, like any other, it may have a derivative; if it does, call it  $f''(\cdot)$ . Do example  $f(x) = x^2$ .

Lots of standard kinds of functions you have to be able to differentiate in your sleep. Equivalent of being able to spell. Brainless activity.

#### 4.2. The fundamental idea: linear approximations to nonlinear functions

The most important thing to keep in mind about calculus is:

(Calculus Mantra) When you do calculus, you are, ALWAYS, approximating a small change in a differentiable function by evaluating THE (unique) appropriate LINEAR function at the magnitude of the change. That is, for sufficiently small  $dx$ ,  $f(x + dx) - f(x) \approx f'(x)dx$ .

$df^x(\cdot) = f'(x)(\cdot)$  is the linear function that approximates the difference between  $f(x + \cdot)$  and  $f(x)$ .

Draw picture of the comparison: concave example.

- graph of  $f(\cdot)$  with points  $x^*$  and  $x^* + dx^*$ .
- look at difference in the value of the function at the two points.
- look at the graph of the linear function  $df = f'(x^*)dx$ :
- note that the difference between  $(f(x^* + dx^*) - f(x^*))$  and  $f'(x^*)dx^*$  will be arbitrarily small provided that  $dx^*$  is sufficiently small.
- Explain the enormous practical importance of this.

When  $dx$  is bigger, don't do so well at approximation. Could do better if you threw in the second derivative, i.e.,

$$f(x + dx) - f(x) \approx \text{even better} \quad f'(x)dx + \frac{1}{2}f''(x)dx^2.$$

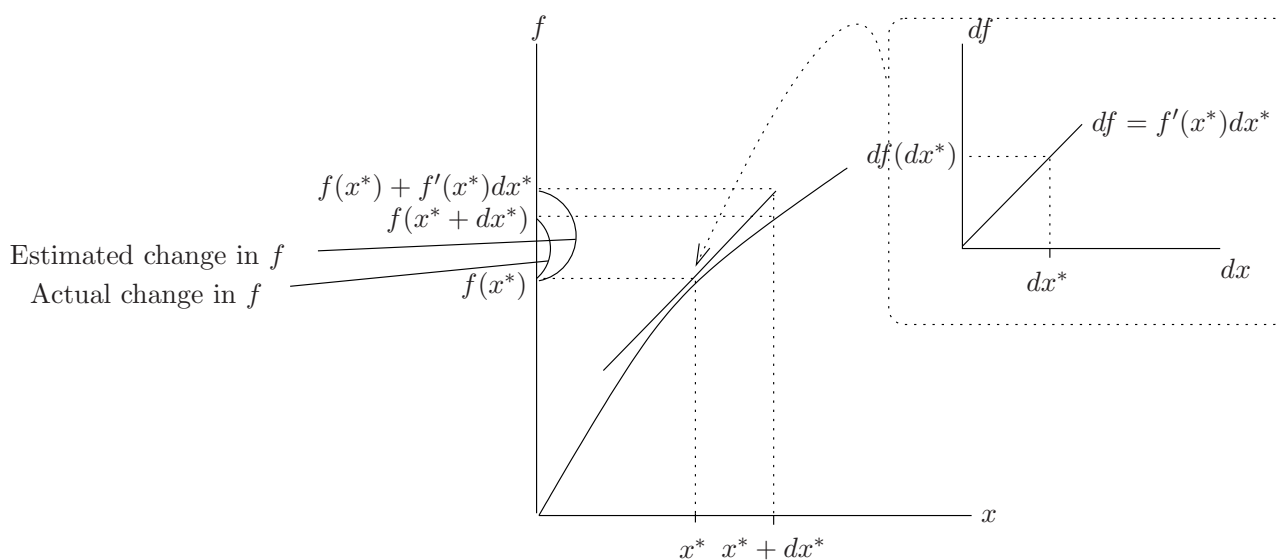


FIGURE 1. Linear Approximations of the change in a nonlinear function

Note that in the above figure,  $f''(x^*) < 0$ . Note also that the linear approximation gives an overestimate of the change, so that adding the second term helps.

This is the germ of a crucial theorem called Taylor's theorem, that we'll see more of later.

### 4.3. Univariate Calculus: the differential

You've probably seen the expression  $dy = f'(x)dx$ , known as the *differential*, before. What sort of object is this? What's the relationship between the differential and the derivative? Answer is ridiculously simple. Recall from last time about linear functions from  $\mathbb{R}^1$  to  $\mathbb{R}^1$  and scalars; every such function is uniquely defined by a single scalar. E.g., I talked about the *function*  $p$ , when I

really meant the rule  $f(\cdot)$  defined by  $f(x) = px$ . Well... The differential is to the derivative as the linear function is to the scalar/vector that defines it.

The relationship between the differential and the derivative is the same as the relationship between any linear function and the scalar/vector/matrix that defines it.

Defn: the differential of  $f$  at  $x$  is the linear function defined by the scalar  $f'(x)$ . In other words, the differential of  $f$  at  $x$  is the unique linear function whose coefficient (slope) is equal to the derivative of  $f$  at  $x$ .

Restate: The most important thing to keep in mind about calculus is: when you do calculus on  $f$  at  $x$ , you are, ALWAYS, approximating a small change in  $f$ , starting from  $x$ , by evaluating *the differential of  $f$  at  $x$*  at the magnitude of the change. This is the idea that underlies *all* of comparative statics.

That is,  $dy = f'(x)dx$  is the value of the approximation to the change in  $f$  when you shift from  $x$  to  $x + dx$ .

Economic example: have  $\pi(p)$ , i.e., profits are a function of prices (assuming optimal input choices for prices  $p$ .) If  $p$  change is small enough,  $d\pi \approx \pi'(p)dp$ .

It is the ability to make computations like this—we call them comparative statics—that distinguish economists from art historians and sociologists. Example:

- Let  $f(x) = x^3 + 2x^2$
- set  $x^* = 1$ ,  $dx^* = 0.1$
- then  $f(x^*) = 3$ ,  $f'(x^*) = 3x^{*2} + 4x^* = 7$ ,  $f(x^* + dx^*) = 1.1^3 + 2 * 1.21 = 3.751$ .
- The true difference  $f(x^* + dx^*) - f(x^*)$  is .751.
- the estimated difference is  $f'(x^*)dx^* = 0.70$ , not bad.

#### 4.4. Multivariate calculus: functions from $\mathbb{R}^n$ to $\mathbb{R}$

4.4.1. *Partial Derivative.* . Cookbook approach: If  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ , then  $f_i(\cdot) \equiv \frac{\partial f(\cdot)}{\partial x_i}$  is the (usual) derivative of the single variable function you get by treating all other variables as constant.

Example:

$$\begin{aligned} f(\mathbf{x}) &= x_1^2 + 2x_1x_2 + x_2^2 \\ &= x_1^2 + 2x_1\alpha + \beta \end{aligned}$$

$$\begin{aligned} f_1(\mathbf{x}) &= 2x_1 + 2\alpha + 0 \\ &= 2x_1 + 2x_2 \end{aligned}$$

A more graphical view of partial derivatives. Take a cross-section of the graph of the function along the  $i$ 'th axis, and look at the slope of the single-dimensional function you obtain in this way. This slope is the  $i$ 'th partial derivative.

Similarly, you could take a diagonal cross-section, and get a different one-dimensional slope. Generally, you get what is called a *directional derivative*. Partial derivatives are just special kinds of directional derivatives: in particular, they tell you the slopes you obtain when you take cross-sections along the various axes.

4.4.2. *The Gradient.* Given a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ , the gradient of  $f$  is just the function from  $\mathbb{R}^n$  to  $\mathbb{R}^n$  that maps each  $\mathbf{x} \in \mathbb{R}^n$  to the vector of partial derivatives of  $f$  at  $\mathbf{x}$ . That is,

$$\nabla f(\cdot) = \begin{bmatrix} f_1(\cdot) \\ \vdots \\ f_i(\cdot) \\ \vdots \\ f_n(\cdot) \end{bmatrix}$$

Emphasize that  $\nabla f(\cdot)$  is the exact analog for  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ . as  $f'(\cdot)$  is for  $f : \mathbb{R} \rightarrow \mathbb{R}$ . In fact the words “slope of  $f$ ,” “gradient of  $f$ ” and “derivative of  $f$ ” are synonymous.

Emphasize the important distinction between the “gradient of  $f$ ” which is a *function*, written  $\nabla f$  or  $\nabla f(\cdot)$  and the “gradient of  $f$  at  $\mathbf{x}$ ,” which is a vector.

4.4.3. *Crosspartial Derivative.* A cross-partial derivative is just an entry in the matrix which is the derivative of the derivative. That is, take a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ . The  $i$ 'th partial derivative of this function  $f_i(\cdot)$  is a function, like any other, and if the function is differentiable, it has derivatives:

$$f_{ij}(\cdot) \equiv \frac{\partial^2 f}{\partial x_i \partial x_j}(\cdot) \text{ is the } j\text{'th partial derivative of the function } f_i(\cdot) \equiv \frac{\partial f}{\partial x_i}(\cdot).$$

Thus, the Hessian of  $f$  just consists of the matrix of crosspartials of  $f$ .

4.4.4. *The differential for functions from  $\mathbb{R}^n$  to  $\mathbb{R}$ .* Recall from earlier: the most important thing to keep in mind about calculus is that when you do calculus on  $f$  at  $x$ , you are, ALWAYS, approximating a small change in  $f$ , starting from  $x$ , by evaluating *the differential of  $f$  at  $x$*  at the magnitude of the change. We'll look at two numerical examples, then look at the picture.

Numerical Example 1: Use the example above:  $f(x, y) = x^2 + y^2$ ;  $\nabla f(\cdot) = (2x, 2y)$ ; Consider  $(dx, dy) = (0.1, 0.1)$ , set  $(x^0, y^0) = (100, 100)$  and approximate  $f(x^0 + dx, y^0 + dy) - f(x^0, y^0)$  by  $\nabla f(x^0, y^0) * (0.1, 0.1) = (200, 200) * (0.1, 0.1) = 40$ . Note that this approximation is virtually the same as the one you get when you use the directional derivative! Now evaluate at  $f$  at both  $(x^0, y^0) = (100, 100)$  and  $(x^0 + dx, y^0 + dy) = (100.1, 100.1)$ , and compare:  $f(x^0, y^0) = 20,000$   $f(x^0 + dx, y^0 + dy) = 20040.02$  Actual difference is 40.02.

Numerical Example 2:  $y = f(\ell, k)$ ;  $\nabla f(\cdot) = (f_\ell(\cdot), f_k(\cdot))$ . Fix  $(\bar{\ell}, \bar{k})$ . Evaluate the difference  $f(\bar{\ell}, \bar{k}) - f(\ell, k)$  by the value of the differential, evaluated at  $(\bar{\ell}, \bar{k}) - (\ell, k)$ :

$$f(\bar{\ell}, \bar{k}) - f(\ell, k) = dy = f_\ell(\bar{\ell}, \bar{k})d\ell + f_k(\bar{\ell}, \bar{k})dk$$

Now for the picture:

Exactly the same thing for functions from  $\mathbb{R}^n$  to  $\mathbb{R}$ . Evaluate the difference  $f(\mathbf{x} + \mathbf{dx}) - f(\mathbf{x})$ , where here  $\mathbf{dx}$  and  $\mathbf{x}$ 's are both vectors, by the value of the differential, evaluated at the difference,  $\mathbf{dx}$ .

What's the differential, in terms that we've used before? Recall that it is a linear function from  $\mathbb{R}^n$  to  $\mathbb{R}$ ; so it is characterized by a vector of coefficients. What is the vector? Answer: the gradient, evaluated at  $x$ .

Thus:  $df = \nabla f(\mathbf{x}) \cdot \mathbf{dx}$ . See Fig. 2 below. As the figure indicates, the differential here plays exactly the same role as it played for functions from  $\mathbb{R}$  to  $\mathbb{R}$ . In Fig. 2, the tangent plane lies below the function, at least a neighborhood of  $\mathbf{x}$ . Then, as we move from  $\mathbf{x}$  to  $\mathbf{x} + \mathbf{dx}$ , the value of the function declines; but the height of the tangent plane declines even further. Applying the calculus mantra, we approximate the change in  $f$ , i.e.,  $f(\mathbf{x} + \mathbf{dx}) - f(\mathbf{x})$ , by translating the tangent plane so that  $\mathbf{x}$  becomes the new origin, then approximate the change in  $f$  when you move from  $\mathbf{x}$  to  $\mathbf{x} + \mathbf{dx}$  by evaluating the height of this translated plane at the point  $\mathbf{dx}$ . Notice from the top panel that the absolute value of  $df^{\mathbf{x}}(\mathbf{dx})$  over-estimates the absolute magnitude of the change in the function.

Sometimes economists refer to the differential as the *total differential*. It is important to recognize that the total derivative of a function and the total differential are completely different things. The

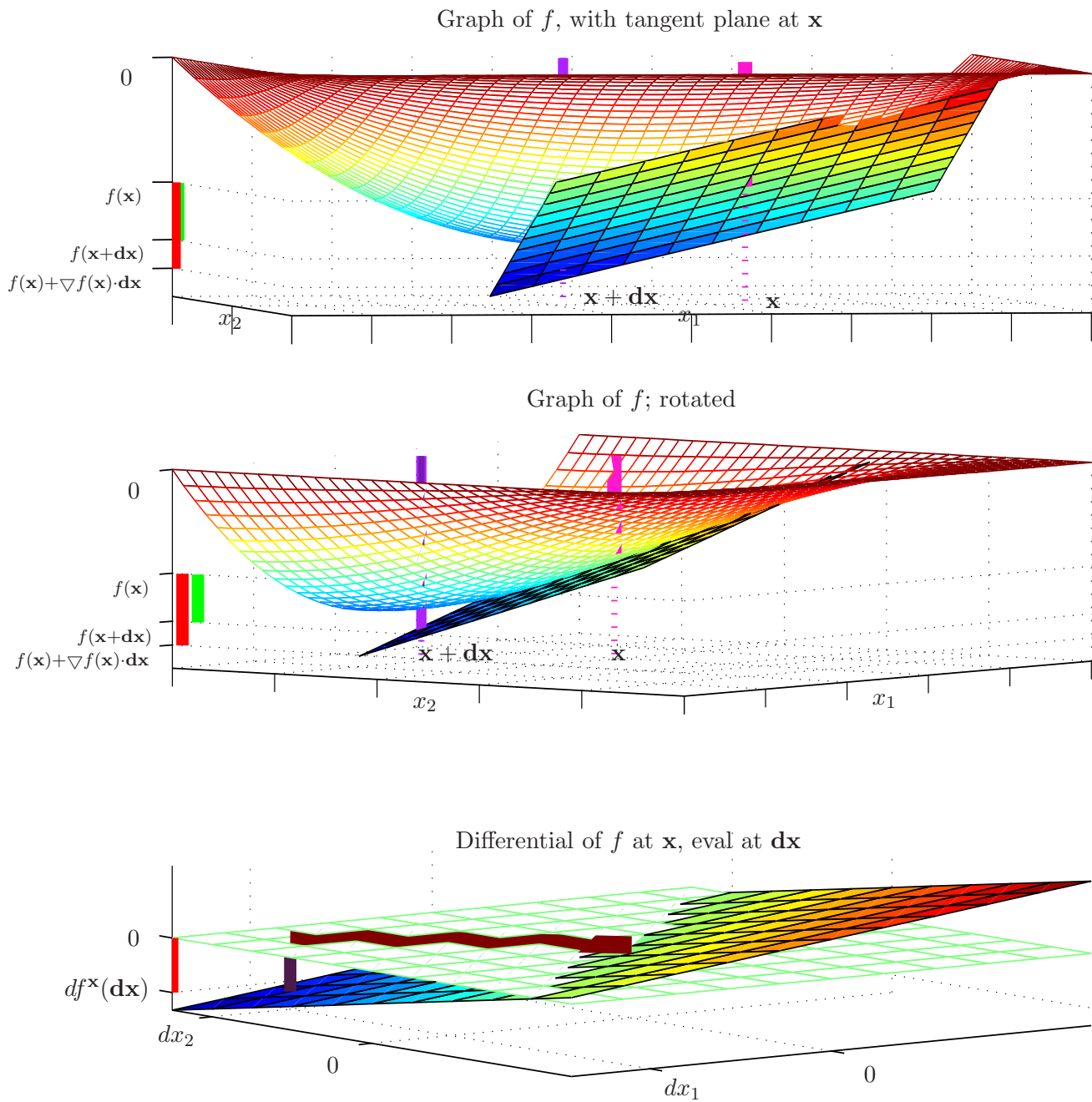


FIGURE 2. Linear Approximation of the change in a nonlinear multivariate function  
total derivative is related to (but not the same as) a directional derivative (i.e., you take the cross section of the function in a certain direction). The total differential is the name of a linear function.