

## Approximation, Taylor Polynomials, and Derivatives

Derivatives for functions  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  will be central to much of Econ 501A, 501B, and 520 — and also to most of what you'll do as professional economists. The derivative of a function  $f$  is simply a linearization, or linear (or affine) approximation of  $f$ . For *real* functions,  $f : \mathbb{R} \rightarrow \mathbb{R}$ , this is pretty straightforward, and it's something you already know. So we'll start there, and then generalize to functions  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ .

Suppose, then, that we want to approximate the values of  $f(x) = x^2$ . This is as simple as it gets: all we have to do is multiply  $x$  times  $x$  and we get  $f(x)$  *exactly*, not merely an approximation. But this example will actually be instructive, as we'll see.

Here's a second example: We wish to evaluate, or approximate, the values of  $f(x) = e^x$  — let's say we want to approximate  $e^x$  at  $x = 1$ . So we're actually approximating the value of  $e$ . This one is not as obvious as  $f(x) = x^2$ .

Let's first use the simple example of  $f(x) = x^2$  to develop our ideas and some useful notation. Suppose we want to approximate the value of  $f(x)$  for values of  $x$  near  $\bar{x} = 1$ , as in Figure 1, because we know that  $f(\bar{x}) = 1$ . Let's use  $\bar{y}$  to denote  $f(\bar{x})$  — *i.e.*,  $\bar{y} = f(\bar{x})$ . For any  $x \in \mathbb{R}$ , let's write

$$\begin{aligned}\Delta x &= x - \bar{x}, & \text{i.e., } x &= \bar{x} + \Delta x; \\ \Delta y &= y - \bar{y} = f(x) - f(\bar{x}) = f(\bar{x} + \Delta x) - f(\bar{x}) = F(\Delta x); \end{aligned}$$

we're defining  $F$  to be  $F(\Delta x) := f(\bar{x} + \Delta x) - f(\bar{x})$ , so that  $\Delta y = F(\Delta x)$ . Notice that  $\Delta y$  is the *exact* change in  $y$  that takes place, given by  $\Delta y = F(\Delta x)$ , as in Figure 2, and that the graph of  $F$  is the same as the graph of  $f$  but with the coordinates shifted.

We want to find a function, say  $G(\Delta x)$ , that gives a *best approximation* of  $\Delta y = F(\Delta x)$  — we want  $G$  to be a best approximation of the *exact* function  $F(\Delta x)$ . Equivalently, we want a function  $g(x) = f(\bar{x}) + G(\Delta x)$  that approximates  $f(x)$ .

What we want is a *simple* function  $G$  that will be a good approximation of  $F$ . So let's say we want to find the best *linear* function  $G(\Delta x) = a\Delta x$  to approximate  $F(\Delta x)$ . In other words, we want to know what the coefficient  $a$  should be in order to make the function  $G(\Delta x) = a\Delta x$  the best linear approximation of the nonlinear function  $F(\Delta x)$ . We even say that this best linear approximating function is the *linearization* of  $F$  near  $\bar{x}$ . (Note that  $G(0) = 0$ : at  $\Delta x = 0$ ,  $G$  coincides with  $F$ .)

Intuition about the diagram in Figure 3 suggests that the best linear approximation to  $F$ , near  $\bar{x} = 1$ , is the tangent to the graph of  $F$  (which is also the graph of  $f$ ) at  $\bar{x} = 1$ . If that's the case, then the best coefficient  $a$  is the slope of the tangent —  $a$  should be the derivative  $f'(\bar{x})$ , the slope of the tangent to the graph of  $f$  at  $\bar{x}$ . Moreover, if  $a$  is any other number, such as  $\tilde{a}$  in Figure 4, then the approximation, at least near  $\bar{x}$ , will not be as good.

We make this intuition precise by saying that a best approximation  $G(\Delta x)$  is one that satisfies the equation

$$\lim_{\Delta x \rightarrow 0} \frac{1}{\Delta x} [F(\Delta x) - G(\Delta x)] = 0, \quad (1)$$

*i.e.*, as  $\Delta x$  grows small the “error” of the approximation,  $F(\Delta x) - G(\Delta x)$  grows small a lot faster.

The equation (1) can also be written as

$$\lim_{\Delta x \rightarrow 0} \frac{[f(\bar{x} + \Delta x) - f(\bar{x})] - a\Delta x}{\Delta x} = 0, \quad (2)$$

or as

$$\lim_{\Delta x \rightarrow 0} \frac{[f(\bar{x} + \Delta x) - f(\bar{x})]}{\Delta x} = a. \quad (3)$$

We have to tie up one loose end here: the left-hand side of the equation (3), and also of (1) and (2), is the limit of a function of  $\Delta x$ . We need to know the limit exists, and that it’s unique, in order to say that the coefficient  $a$  that we’re looking for is this limit. In general, of course, the limit might or might not exist. So we say that a best linear approximation to the function  $F$  is the function  $G(\Delta x) = a\Delta x$ , where  $a$  is given by (3), *if the limit exists*. And if it does, we know it’s unique, because we know that’s a property of the limit of a function.

This motivates the definition of the derivative of a real function:

**Definition:** Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  and let  $\bar{x} \in \mathbb{R}$ . The **derivative** of  $f$  at  $\bar{x}$ , denoted  $f'(\bar{x})$ , is the number  $a \in \mathbb{R}$  for which the function  $G(\Delta x) = a\Delta x$  is a **best linear approximation (BLA)** of  $F(\Delta x) := f(\bar{x} + \Delta x) - f(\bar{x})$  — *i.e.*,

$$f'(\bar{x}) := \lim_{\Delta x \rightarrow 0} \frac{[f(\bar{x} + \Delta x) - f(\bar{x})]}{\Delta x} \quad (4)$$

if this limit exists, in which case we say that  $f$  is **differentiable** at  $\bar{x}$ .

So far, we’ve just been reviewing things you already know. Before we move ahead, let’s go back to our example of  $f(x) = x^2$  and see how all this works for that function.

**Example 1:** Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be the function defined by  $f(x) = x^2$ .

**Example 2:** Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be the function defined by  $f(x) = e^x$ .

I haven’t typed up the examples yet.

There are two directions in which we need to generalize what we've done so far: (i) we need to study 2nd-order (quadratic) and higher-order approximations, and (ii) we need to do the same things for functions whose domain is  $\mathbb{R}^n$  as we've done for functions with domain  $\mathbb{R}$ . We'll do the higher-order approximations first.

## Taylor Polynomials

In the example in the previous section we suggested that in addition to a best linear approximation we could also define a best quadratic approximation to a function  $f$ , or to the function  $F(\Delta x) = f(\bar{x} + \Delta x) - f(\bar{x})$ . Here we're actually going to go farther and define a best approximation of order  $n$ , the best  $n$ -th degree polynomial approximation of  $F$ , for any  $n \in \mathbb{N}$ . As we did in the linear-approximation case, where  $n = 1$ , we start with the fact that  $F(0) = 0$  — *i.e.*,  $f(\bar{x} + \Delta x) = f(\bar{x})$  when  $\Delta x = 0$ . We're looking for the best  $n$ -th degree polynomial to approximate  $F$ , so we're looking for the best function

$$G_n(\Delta x) = a_1 \Delta x + a_2 (\Delta x)^2 + a_3 (\Delta x)^3 + \cdots + a_n (\Delta x)^n. \quad (5)$$

Let's use the notation  $G_n^{(k)}$ ,  $F^{(k)}$ , and  $f^{(k)}$  to denote the  $k$ -th derivatives of the functions  $G_n$ ,  $F$ , and  $f$ ; and note that  $F^{(k)}(\Delta x) = f^{(k)}(\bar{x} + \Delta x)$  — in particular,  $F^{(k)}(0) = f^{(k)}(\bar{x})$ .

By analogy with the case  $n = 1$  we'll guess that for every  $n$  the best approximation of order  $n$  satisfies the condition that

$$G_n^{(n)}(\Delta x) = F^{(n)}(\Delta x) \text{ at } \Delta x = 0, \quad (6)$$

— *i.e.*, not only does the value of  $G$  equal the value of  $F$  at  $\Delta x = 0$ , but the first derivative (the slope) of the linear approximation  $G_1(\cdot)$  has the same value as  $F'$  at  $\Delta x = 0$  (*i.e.*, at  $\bar{x}$ ); the second derivative (the curvature) of  $G_2(\cdot)$  has the same value as  $F''(\cdot)$  at  $\Delta x = 0$ ; and so on, with  $G_n^{(n)}(0) = F^{(n)}(0)$  for every  $n$ .

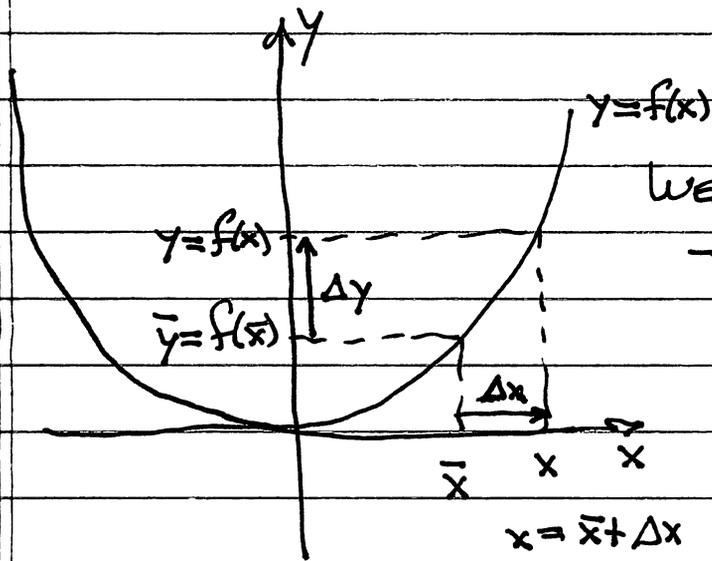
Combining (5) and (6) for each  $n$ , we have

$$a_1 = f'(\bar{x}), \quad a_2 = \frac{1}{2} f''(\bar{x}), \quad a_3 = \frac{1}{3} \left(\frac{1}{2}\right) f'''(\bar{x}), \quad \cdots, \quad a_k = \frac{1}{k!} f^{(k)}(\bar{x}), \quad \cdots, \quad a_n = \frac{1}{n!} f^{(n)}(\bar{x}). \quad (7)$$

**Exercise:** Verify that (7) is correct — *i.e.*, that  $a_k = \frac{1}{k!} f^{(k)}(\bar{x})$  for each  $k = 1, \dots, n$  in the function  $G_n(\cdot)$  in (5).

The function  $G_n$  in Equation (5), with the coefficients as in (7), is called the homogeneous  $n$ -th degree **Taylor polynomial** of  $f$ , which approximates the increment  $\Delta y$ . The non-homogeneous form of the Taylor polynomial, which approximates the value of  $f$  at  $x = \bar{x} + \Delta x$ , is

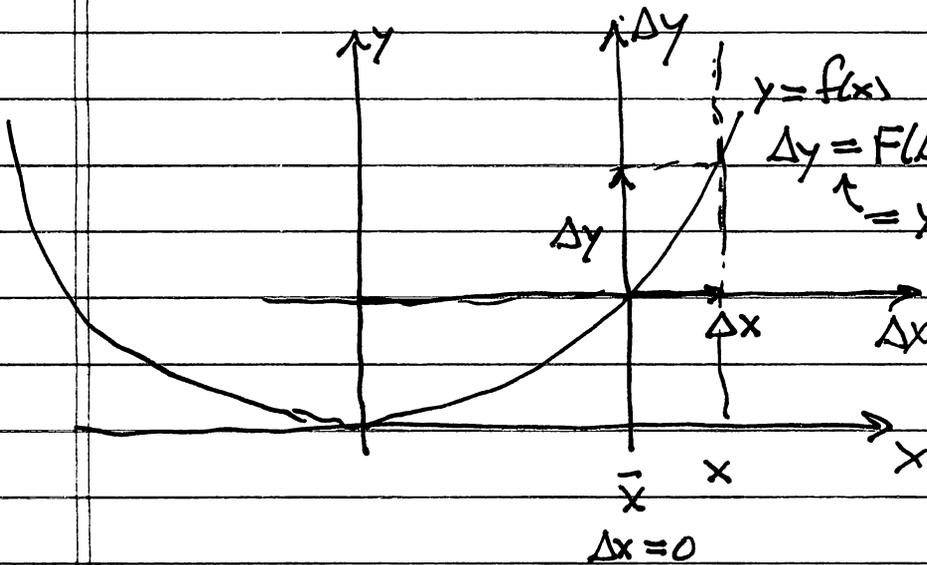
$$\begin{aligned} P_n(x) &= f(\bar{x}) + G_n(\Delta x) \\ &= f(\bar{x}) + f'(\bar{x})\Delta x + \frac{1}{2} f''(\bar{x})(\Delta x)^2 + \frac{1}{6} f'''(\bar{x})(\Delta x)^3 + \cdots + \frac{1}{n!} f^{(n)}(\bar{x})(\Delta x)^n. \end{aligned}$$



WE WANT TO APPROXIMATE  $f(x)$

- i.e., APPROXIMATE  $\Delta y$  IF WE KNOW  $f(x)$ .

FIGURE 1



$$\Delta y = F(\Delta x) = f(\bar{x} + \Delta x) - f(\bar{x})$$

$$\uparrow = y - \bar{y}$$

↑  
THE EXACT  $\Delta y$ ,  
NOT AN  
APPROXIMATION

FIGURE 2

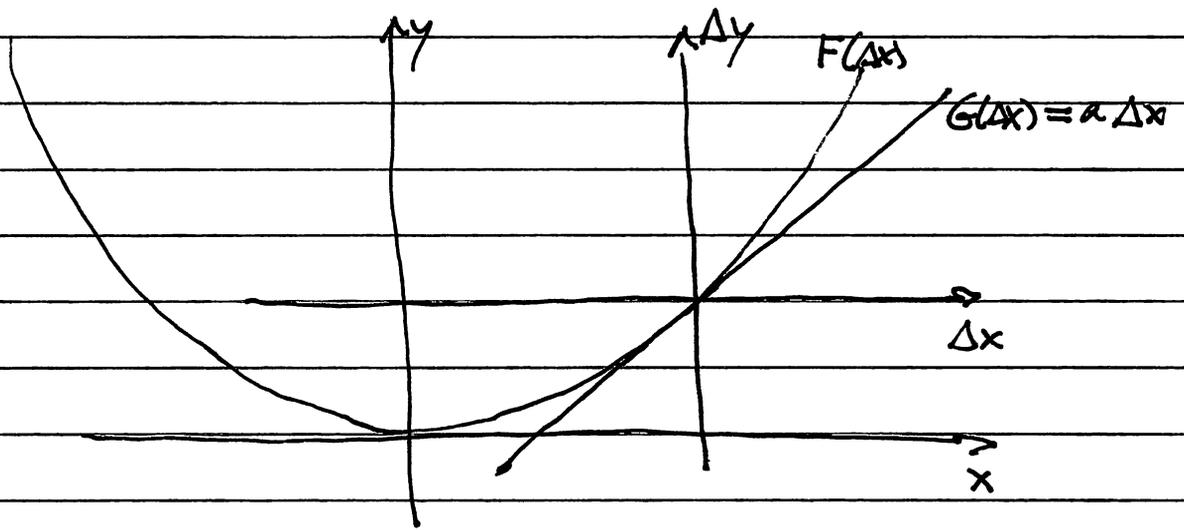


FIGURE 3

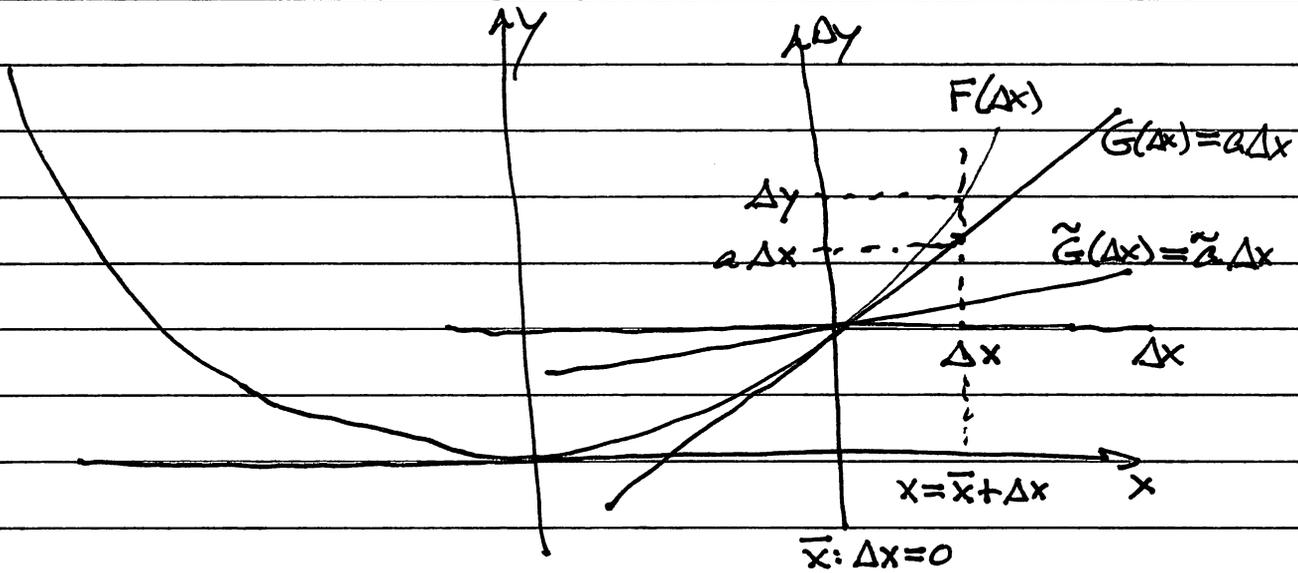


FIGURE 4