

# ECN312: Intermediate Microeconomic Theory

## MATH REVIEW

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These notes cover some mathematical prerequisites of this class. In the first three sections, I provide a quick review of what you should have learned in your calculus class. In [Section 4](#) I briefly introduce some simple optimization techniques which are used intensively in the remainder of this class. I sacrifice some rigorousness for the sake of accessibility as well as expositional convenience.

## 1 Functions

When we talk about a function, we mean a rule that “transforms” the objects in a given set to those of another. A **function** from  $X$  to  $Y$  is a rule that assigns *each* object in  $X$  *one and only one* object in  $Y$ . In this case we write  $f : X \rightarrow Y$ ; call  $X$  the **domain** of  $f$  and  $Y$  is the **codomain**. Check [Figure 1](#) to make sure that you understand the definition of a function.

### 1.1 Invertible Functions and Inverse

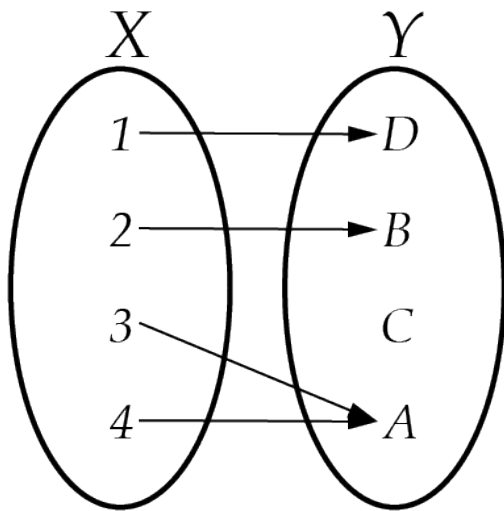
Given a function  $y = f(x)$ , can we always express  $x$  as a function of  $y$ , say  $h(y)$ ? Not necessarily. If this is possible for a function  $f$ , we say that  $f$  is **invertible**; and  $h$  is the **inverse** of  $f$ . For a function  $f$  to be invertible, it has to be that for distinct objects in the domain,  $f$  assigns different objects in the codomain. To be more formal,  $x \neq x'$  implies that  $f(x) \neq f(x')$ . As a first example, the functions shown in the upper left and the upper right panels of [Figure 1](#) are not invertible.

More examples are provided in [Figure 2](#).  $g(x) = x^2/2$  is not invertible because  $g(-2) = g(2) = 2$ : if the inverse of  $g$  exists, “input” 2 corresponds to two “outputs”, namely 2 and  $-2$ , which is not

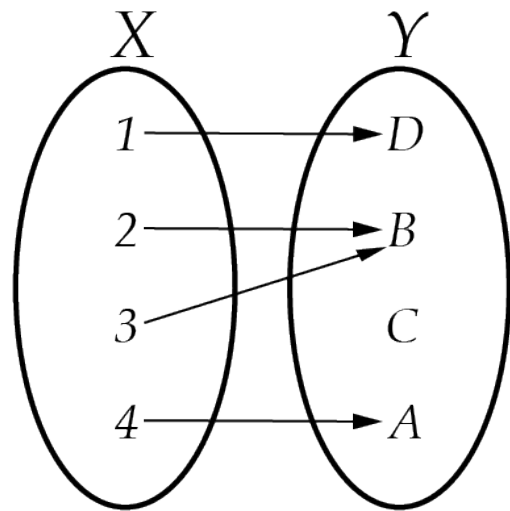
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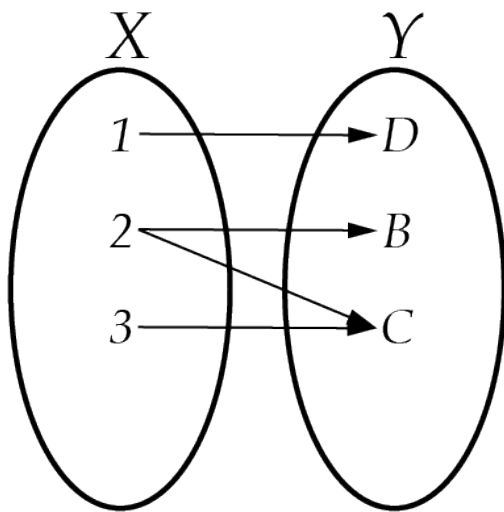
Some material in these notes are taken from the videos by Fernando Leiva Bertran, whom I thank. I am also grateful to Marco Escobar for helpful suggestions.



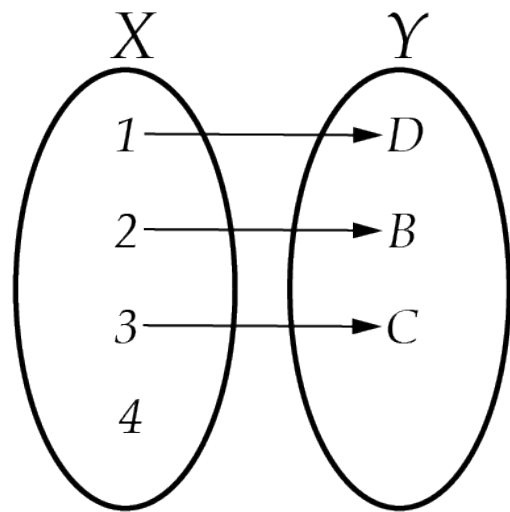
A function



A function



Not a function



Not a function

Figure 1: An illustration of the property of a function

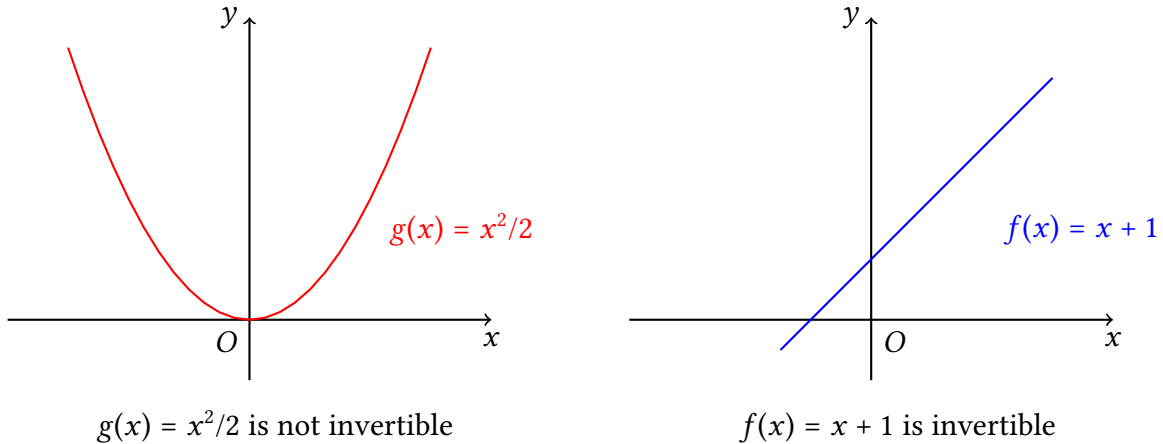


Figure 2: Further examples on functions that are invertible or not invertible.

compatible with the definition of a function.  $f(x) = x + 1$  is invertible: if  $y = x + 1$ , then  $x = y - 1$ ; and hence  $h(y) = y - 1$  is the inverse of  $f$ .

Now consider  $j(x) = x^2/2$ , but with  $x > 0$ . Interestingly,  $j(x)$  is invertible: for  $x, x' > 0$ , if  $x \neq x'$ , then  $x^2/2 \neq (x')^2/2$ . Letting  $y = x^2/2$  for  $x > 0$ , we can find  $x = \sqrt{2y}$ . Thus, the inverse of  $j(x)$  is  $k(y) = \sqrt{2y}$ .

## 1.2 Exponentiation and Logarithm

The functions in which the variable  $x$  appears as an exponent are called **exponential functions**. We are only interested in a particular exponential function,  $f(x) = e^x$ , where  $e$  is a constant approximately equal to 2.71828, known as Euler's number. We abuse notation and call  $f(x) = e^x$  *the* exponential function. It satisfies the following identities:

- (1)  $e^{x+y} = e^x e^y$ ,
- (2)  $(e^x)^y = e^{xy}$ ,
- (3)  $e^{-x} = 1/e^x$ ,
- (4)  $e^0 = 1$ .

The inverse of the exponential function is called a **logarithm function**, denoted by  $l(x) = \log x$ .<sup>1</sup> The logarithm function has the following properties:

- (1)  $\log(xy) = \log x + \log y$ ,
- (2)  $\log(x/y) = \log x - \log y$ ,

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<sup>1</sup>For those who know more about logarithm functions, some author write this function as  $\log_e x$  or  $\ln x$ .

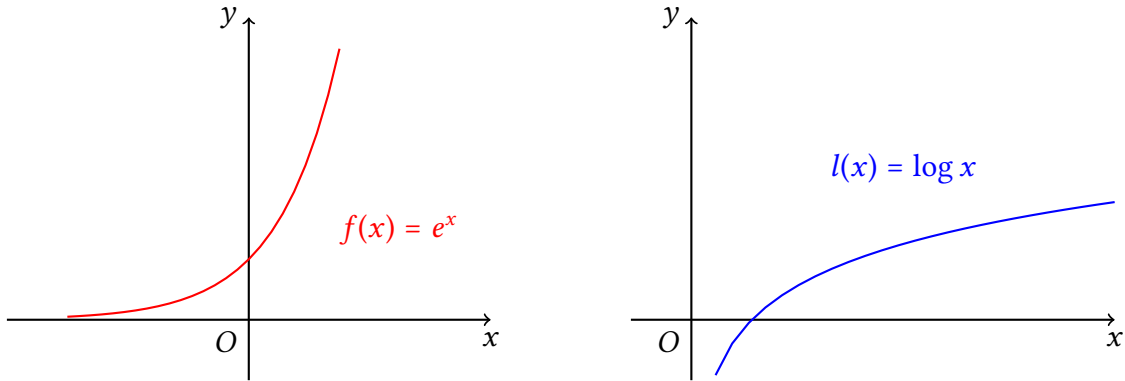


Figure 3: Graphs of the exponential function (left panel) and the logarithm function (right panel).

$$(3) \log(x^y) = y \log x,$$

$$(4) \log 1 = 0.$$

The exponential function and logarithm function are plotted in [Figure 3](#). Note that since  $f(x) = e^x > 0$  for all  $x$ ,  $\log x$ , which is the inverse of  $f(x)$ , is only defined for  $x > 0$ .

## 2 Univariate Functions

### 2.1 From Slopes to Derivatives

We know from high school or pre-calculus that

$$\text{slope} = \frac{\text{rise}}{\text{run}}.$$

More formally, for a univariate function  $f$ , and two points  $x_0$  and  $x_1$ , the slope between  $x_0$  and  $x_1$  is given by

$$\frac{f(x_1) - f(x_0)}{x_1 - x_0}.$$

The slope between  $x_0$  and  $x_1$  measures the “rate of change” between these two points.

Say that  $f$  is **differentiable** at  $x_0$  if

$$\lim_{h \rightarrow 0} \frac{f(x_0 + \Delta x) - f(x_0)}{\Delta x}$$

exists. The **derivative** of  $f$  at  $x_0$ , denoted  $f'(x_0)$ , or  $\frac{df}{dx}(x_0)$ , is this limit. We see that the derivative of  $f$  at  $x_0$  is the limit of the slope between  $x_0$  and  $x_1$ , or the rate of change, as  $x_1 = x_0 + \Delta x$

approaches  $x_0$ ;<sup>2</sup> this is illustrated in Figure 4. And geometrically, the derivative of  $f$  at  $x_0$  is the slope of the line that tangent to the graph of  $f$  at  $x_0$ .

The function  $f$  is said to be **differentiable** if it is differentiable at all points. In this case the **derivative** of  $f$  is defined as the function  $f'(x)$  that assigns each  $x$  the derivative of  $f$  at  $x$ .

In this class, if you do not know how to determine whether a function is differentiable formally, it is not that big a deal. Nonetheless, you should at least know that if a function has a jump or a kink, then it is *not* differentiable at the jump or the kink; see Figure 5 for two examples.

## 2.2 Rules of Taking Derivatives

For some complicated functions, computing derivatives using definition could be a tricky and daunting task. The following few results provide some “shortcuts” for it. Using the definition, we can calculate the following formulas for the derivative of specific functions, where  $a$ ,  $n$ , and  $k$  are constants.

$f(x)$	$f'(x)$
$k$	$0$
$kx^n$	$knx^{n-1}$
$\log x$	$1/x$
$e^x$	$e^x$
$a^x$	$a^x \log a$
$\cos x$	$-\sin x$
$\sin x$	$\cos x$

We do not attempt to prove all of the derivatives in the table above; instead, we find the derivative of  $f = x^3$  as an example to fix ideas. By definition, for any  $x$ , we have

$$\begin{aligned} \lim_{\Delta x \rightarrow 0} \frac{(x + \Delta x)^3 - x^3}{\Delta x} &= \lim_{\Delta x \rightarrow 0} \frac{x^3 + 3x^2(\Delta x) + 3x(\Delta x)^2 - x^3}{\Delta x} = \lim_{\Delta x \rightarrow 0} \frac{3x^2(\Delta x) + 3x(\Delta x)^2}{\Delta x} \\ &= \lim_{\Delta x \rightarrow 0} (3x^2 + 3x(\Delta x)) = 3x^2, \end{aligned}$$

where the first equality holds because

$$(x + \Delta x)^3 = (x + \Delta x)(x + \Delta x)^2 = (x + \Delta x)(x^2 + 2x(\Delta x) + (\Delta x)^2) = x^3 + 3x^2(\Delta x) + 3x(\Delta x)^2 + (\Delta x)^3.$$

Because  $x$  is arbitrary, we have  $f'(x) = 3x^2$  for all  $x$ .

Next we introduce some more general rules of finding derivatives.

**Result 1.** *Let  $f$  and  $g$  be differentiable univariate functions. Then*

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<sup>2</sup>Loosely, we can say that it is the rate of change at  $x_0$ .

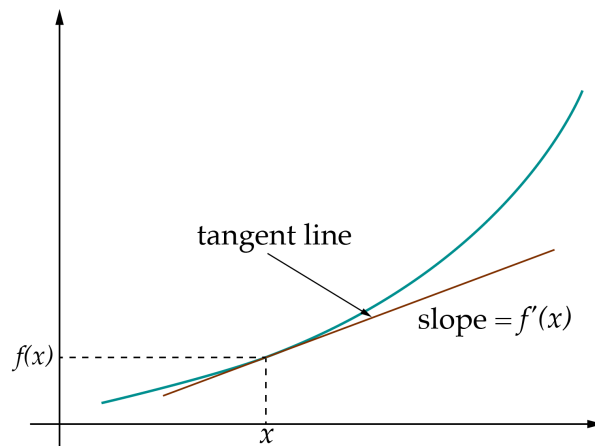
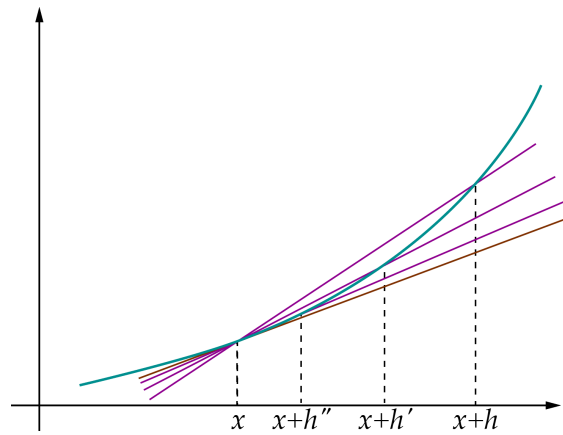
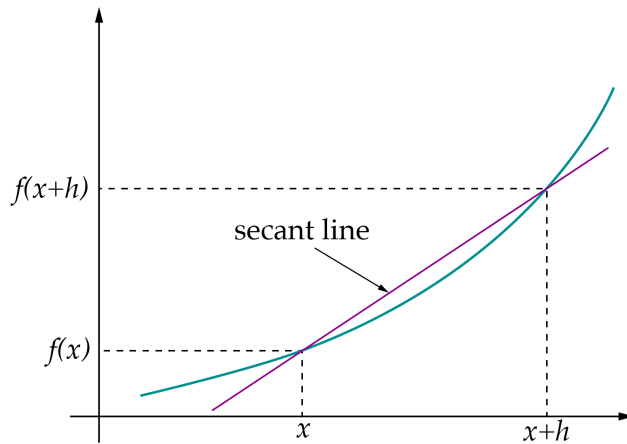


Figure 4: The derivative of a function at a point  $x$  is the limit (as  $\Delta x$  approaches 0) of secants to curve  $y = f(x)$  determined by points  $(x, f(x))$  and  $(x + \Delta x, f(x + \Delta x))$ ; equivalently, it is the slope of the tangent line at  $(x, f(x))$ .

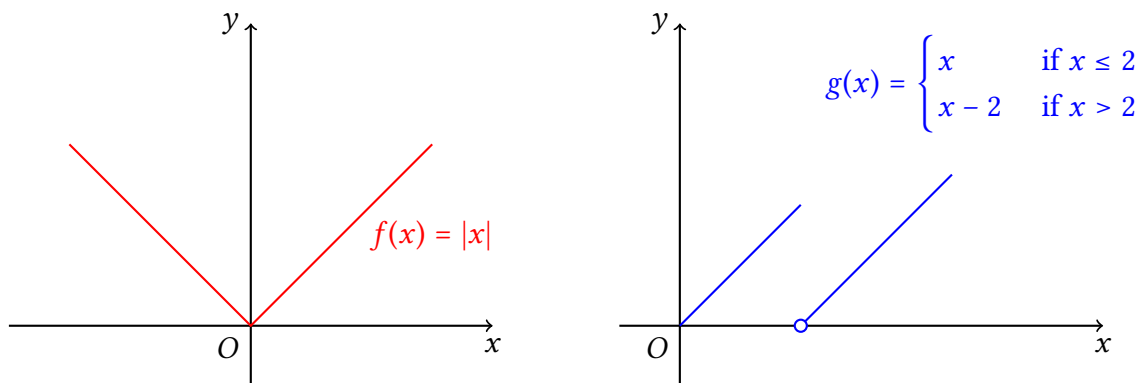


Figure 5: Examples of non-differentiable functions.  $f(x)$  displayed in the left panel is not differentiable at  $x = 0$  because it has a kink there;  $g(x)$  plotted in the right panel is not differentiable at  $x = 2$  because there is a jump.

(1)  $[f(x) + g(x)]' = f'(x) + g'(x)$ ;

(2)  $[f(x)g(x)]' = f'(x)g(x) + f(x)g'(x)$ ; and

(3) if  $g(x) \neq 0$ ,

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

**Example 1.** Consider  $f(x) = x^2(\log x + 1)$ . Its derivative is given by

$$f'(x) = 2x(\log x + 1) + x^2(1/x) = 2x \log x + 3x.$$

Consider  $g(x) = 1/x$ . Its derivative is given by

$$g'(x) = \frac{0 \cdot x - 1 \cdot 1}{x^2} = -\frac{1}{x^2}.$$

**Result 2** (Chain rule). Let  $f$  and  $u$  be univariate differentiable functions. If  $f(x)$  can be written as  $f(u(x))$ , then

$$f'(x) = f'(u)u'(x).$$

**Example 2.** Consider  $f(x) = e^{2x^2}$ . To use the chain rule, let  $u = 2x^2$ . Then

$$f'(x) = f'(u)u'(x) = e^u(4x) = 4xe^{2x^2}.$$

Now consider  $g(x) = \log(x^2 + 5)$ . Again, let  $v = x^2 + 5$ . Then

$$g'(x) = g'(v)v'(x) = \left( \frac{1}{v} \right) 2x = \frac{2x}{x^2 + 5}.$$

### 3 Multivariate functions

Let  $f$  be a multivariate function; for expositional ease, assume that it is a function of three variables,  $x$ ,  $y$ , and  $z$ . The **partial derivative** of  $f$  with respect to its  $x$ , at  $(x^0, y^0, z^0)$ , is

$$\lim_{\Delta x \rightarrow 0} \frac{f(x^0 + \Delta x, y^0, z^0) - f(x^0, y^0, z^0)}{\Delta x},$$

provided that the above limit exists. The partial derivative of  $f$  with respect to  $y$  and  $z$  are analogously defined.

When the partial derivative of  $f$  with respect to  $x$  exists, it is the derivative of  $f$  with respect to  $x$  *holding all other variables fixed*; it is denoted  $\frac{\partial f}{\partial x}$ . Consequently, to calculate partial derivatives, we just need to take all other variables as constants, and apply the rules we introduced in [Section 2.2](#) to  $x_j$ .

**Example 3.** Let  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$  be defined as

$$f(x, y) = x^2 + xy + y + 1,$$

then

$$\frac{\partial f}{\partial x} = 2x + y, \quad \text{and} \quad \frac{\partial f}{\partial y} = x + 1.$$

Let  $g : \mathbb{R}_{++}^2 \rightarrow \mathbb{R}$  be defined as

$$g(x, y) = e^{xy} + y \log x + 3,$$

then

$$\frac{\partial g}{\partial x} = ye^{xy} + \frac{y}{x}, \quad \text{and} \quad \frac{\partial g}{\partial y} = xe^{xy} + \log x.$$

**Result 3** (Chain rule for partial derivatives). *Let  $f$  and  $u$  be multivariate differentiable functions; for expositional ease, assume that they are functions of three variables. If  $f(x, y, z)$  can be written as  $f(u(x, y, z))$ , then*

$$\frac{\partial f}{\partial x} = f'(u) \frac{\partial u}{\partial x}, \quad \frac{\partial f}{\partial y} = f'(u) \frac{\partial u}{\partial y}, \quad \text{and} \quad \frac{\partial f}{\partial z} = f'(u) \frac{\partial u}{\partial z}.$$

**Example 4** (harder). Consider

$$f(x, y) = \sqrt{3xy + \log(x+1)}.$$



Then let  $u(x, y) = 3xy + \log(x + 1)$ , so  $f(u) = \sqrt{u}$ ; consequently,<sup>3</sup>

$$\frac{\partial f}{\partial x} = f'(u) \frac{\partial u}{\partial x} = \left( \frac{1}{2\sqrt{u}} \right) \left( 3y + \frac{1}{x+1} \right) = \frac{3y + \frac{1}{x+1}}{2\sqrt{3xy + \log(x+1)}};$$

and

$$\frac{\partial f}{\partial y} = f'(u) \frac{\partial u}{\partial y} = \frac{3x}{2\sqrt{3xy + \log(x+1)}}.$$

## 4 Optimization

### 4.1 Unconstrained Optimization

Consider a function of one variable, denote it by  $f(x)$ . Sometimes we are interested in finding the points at which  $f(x)$  attains its maximum; write the maximization problem as  $\max f(x)$ . If  $f(x)$  attains its maximum at  $x^*$ , we say that  $x^*$  **solves** the maximization problem  $\max f(x)$ , or  $x^*$  **maximizes**  $f(x)$ . And  $f(x)$  is called the **objective function** of this maximization problem.

The following celebrated result, often called “the first-order condition”, says that if a differentiable function  $f(x)$  attains its maximum at  $x^*$ , then the derivative of  $f$  at  $x^*$  is 0. This is illustrated in [Figure 6](#).

**Result 4** (First-order condition, one variable). *Let  $f(x)$  be a differentiable function. If  $x^*$  maximizes  $f(x)$ , then  $f'(x^*) = 0$ .*

Importantly, [Result 4](#) states that *if  $x^*$  maximizes  $f(x)$ , then the derivative of  $f$  at  $x^*$  is 0*. Not the other way around! In fact, as shown in [Figure 7](#), we can easily find points such that the first-order condition hold but they do not solve the maximization problem. *In this class, however; so long as  $f$  is differentiable, unless otherwise specified, you can solve the maximization problem by just taking the first-order condition.*

[Result 4](#) can be generalized to functions with many variables; to ease exposition, we only state the result for two variables. It says that, if a differentiable function  $f(x, y)$  attains its maximum at  $(x^*, y^*)$ , then *all* partial derivatives of  $f$  at  $(x^*, y^*)$  is 0.

**Result 5** (First-order condition, two variables). *Let  $f(x, y)$  be a differentiable function. If  $(x^*, y^*)$  maximizes  $f(x, y)$ , then*

$$\frac{\partial f}{\partial x}(x^*, y^*) = \frac{\partial f}{\partial y}(x^*, y^*) = 0.$$

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<sup>3</sup>Note that  $f(u) = \sqrt{u} = u^{1/2}$ ; and hence  $f'(u) = (1/2)u^{(1/2)-1} = (1/2)u^{-1/2} = (1/2)(1/\sqrt{u}) = 1/(2\sqrt{u})$ .

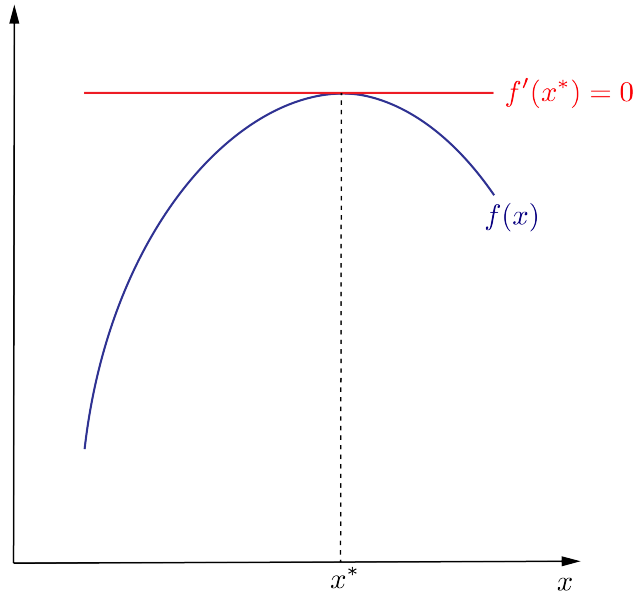


Figure 6: An illustration of the first-order condition.

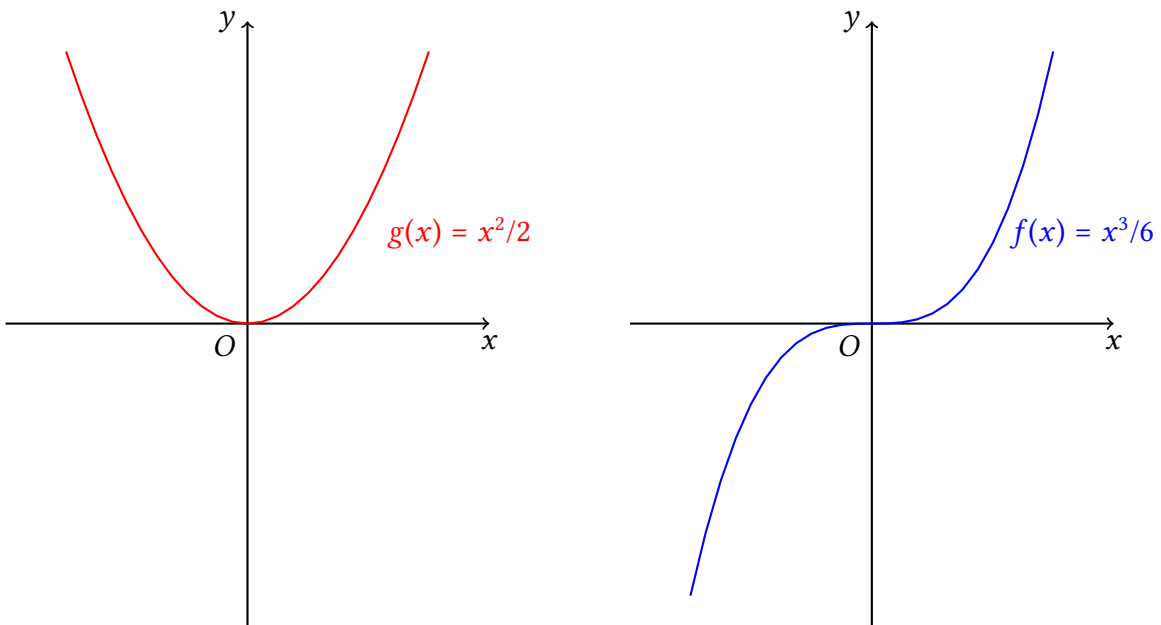


Figure 7: Points that satisfies the first-order condition may not maximize a function. The eft panel plots  $g(x) = x^2/2$ ;  $g'(0) = 0$ , but clearly  $x = 0$  minimizes  $g$ . In the right panel,  $f(x) = x^3/6$ ;  $f'(0) = 0$  but  $x = 0$  neither maximizes nor minimizes  $f$ .

**Example 5.** Consider the unconstrained optimization problem

$$\max_{x,y} 12x + 12y - 2x^2 - y^2 + 2xy.$$

The first-order conditions are

$$\begin{aligned}\frac{\partial f}{\partial x}(x^*, y^*) &= 12 - 4x^* + 2y^* = 0; \\ \frac{\partial f}{\partial y}(x^*, y^*) &= 12 - 2y^* + 2x^* = 0.\end{aligned}$$

Add up the two equalities above, we get  $x^* = 12$ . Plug this into one of the equalities above, we have  $y^* = 18$ . Thus,  $(x^*, y^*) = (12, 18)$  solves this problem.

## 4.2 Constrained Optimization

Often in optimization problems, we face some constraints: Anne might want to buy the fastest car in the world, but she doesn't make that much of money; and Bob might want to go to the summit of every mountain, but for safety reasons he has to stay on the hiking trail. A constrained optimization problem can be written as

$$\begin{aligned}\max_{x,y} \quad & f(x, y) \\ \text{subject to} \quad & g(x, y) = c\end{aligned}\tag{1}$$

where  $c$  is a number.

Naturally, to deal with constrained optimization problems, we would like to transform them to unconstrained ones. One way of doing that is usually called the “substitution method”: we use  $g(x, y) = c$  to express  $y$  as a function of  $x$ , say  $y = h(x)$ , and then plug  $y = h(x)$  into the objective function  $f(x, y)$ . To understand how it works, let us look at an example.

**Example 6.** Consider the constrained optimization problem

$$\begin{aligned}\max_{x,y} \quad & 12x + 12y - x^2 - y^2 + 2xy; \\ \text{subject to} \quad & x + y = 4.\end{aligned}$$

The constraint can be written as  $y = 4 - x$ ; plugging into the objective function, we get

$$\max_x 12x + 12(4 - x) - x^2 - (4 - x)^2 + 2x(4 - x).$$

The first-order condition is

$$12 - 12 - 2x^* - 2(4 - x^*)(-1) + 8 - 4x^* = 0;$$

simplify, we get

$$8x^* = 16,$$

and hence  $x^* = 2$ . Consequently,  $y^* = 4 - x^* = 2$ . Therefore, the solution of the optimization problem is  $(x^*, y^*) = (2, 2)$ .

Note that, however; the substitution method need not work for every constrained optimization problem: in many cases, we might not be able to express  $y$  as a function of  $x$  using the constraint. See [Figure 8](#) for an example.

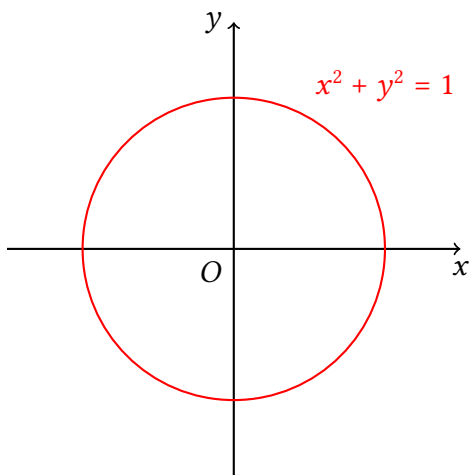


Figure 8: The equation  $x^2 + y^2 = 1$  does not define  $y$  as a function of  $x$ , which makes the substitution method tricky.

The good news is, there is a more systematic way of solving a constrained optimization problem. The idea is that, by introducing an “auxiliary variable”  $\lambda$ , we somehow incorporate the constraint into the objective function.

For an example, consider the constrained optimization problem (1). We introduce a new function, which is called a **Lagrangian**:

$$\mathcal{L}(x, y, \lambda) = f(x, y) + \lambda[c - g(x, y)].$$

Now we solve the unconstrained optimization problem with the objective function being  $\mathcal{L}(x, y, \lambda)$ . The first-order conditions are

$$\frac{\partial \mathcal{L}}{\partial x} = \frac{\partial f}{\partial x} - \lambda \frac{\partial g}{\partial x} = 0; \tag{2}$$

$$\frac{\partial \mathcal{L}}{\partial y} = \frac{\partial f}{\partial y} - \lambda \frac{\partial g}{\partial y} = 0; \tag{3}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = c - g(x, y) = 0. \tag{4}$$

Note that (4) is no more than writing down the constraint once again. Because  $\lambda$  is an auxiliary variable and we do not really need to solve it, so we aim to eliminate it first. To this end, note that (2) and (3) can be written as

$$\begin{aligned}\frac{\partial f/\partial x}{\partial g/\partial x} &= \lambda; \\ \frac{\partial f/\partial y}{\partial g/\partial y} &= \lambda.\end{aligned}$$

Consequently,

$$\frac{\frac{\partial f/\partial x}{\partial g/\partial x}}{\frac{\partial f/\partial y}{\partial g/\partial y}} = \frac{\lambda}{\lambda} = 1,$$

which is equivalent to

$$\frac{\partial f/\partial x}{\partial f/\partial y} = \frac{\partial g/\partial x}{\partial g/\partial y}. \quad (5)$$

Using (5) and (4), now we have two equations and two unknowns, and hence we can solve for  $(x^*, y^*)$ .

For an example, consider the optimization problem in [Example 6](#) again. Write down the Lagrangian,

$$\mathcal{L} = 12x + 12y - x^2 - y^2 + 2xy + \lambda(4 - x - y).$$

The first-order conditions are

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial x}(x^*, y^*) &= 12 - 2x^* + 2y^* - \lambda = 0; \\ \frac{\partial \mathcal{L}}{\partial y}(x^*, y^*) &= 12 - 2y^* + 2x^* - \lambda = 0; \\ \frac{\partial \mathcal{L}}{\partial \lambda}(x^*, y^*) &= 4 - x^* - y^* = 0.\end{aligned}$$

The first two equations can be written as

$$\begin{aligned}12 - 2x^* + 2y^* &= \lambda. \\ 12 - 2y^* + 2x^* &= \lambda;\end{aligned}$$

and hence

$$\frac{12 - 2x^* + 2y^*}{12 - 2y^* + 2x^*} = \frac{\lambda}{\lambda} = 1 \quad \Rightarrow \quad 12 - 2x^* + 2y^* = 12 - 2y^* + 2x^*;$$

simplify, we get  $x^* = y^*$ . Plug this into  $4 - x^* - y^* = 0$ , the solution is  $(x^*, y^*) = (2, 2)$ , which is the same as in [Example 6](#).