

# Optimization and Multivariate Calculus

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These notes are to accompany Mathematics for Economists by Simon and Blume.

## 1 Multivariate Calculus

### 1.1 Chain Rule

Let  $w = f(x, y)$  where  $f$  is a differentiable function of  $x$  and  $y$ . Let  $x = g(t)$  and  $y = h(t)$  where  $g$  and  $h$  are differentiable functions of  $t$ . Then by the chain rule:

$$\frac{dw}{dt} = \frac{\partial w}{\partial x} \frac{dx}{dt} + \frac{\partial w}{\partial y} \frac{dy}{dt}$$

#### Example

Let  $w = x^3y^2 - x^2$  and  $x = e^t$  and  $y = \cos(t)$ .

$$\begin{aligned} \frac{dw}{dt} &= \frac{\partial w}{\partial x} \frac{dx}{dt} + \frac{\partial w}{\partial y} \frac{dy}{dt} \\ &= (3x^2y^2 - 2x) (e^t) + (2x^3y) (-\sin(t)) \\ &= (3e^{2t} \cos^2(t) - 2e^t) (e^t) - (2e^{3t} \cos(t)) (\sin(t)) \end{aligned}$$

### 1.2 Total Differential

Recall that when we take a partial derivative, we measure a variable's direct effect on a function (as we keep all other variables constant). If we also want to take into account a variable's indirect effect on a function (i.e. the effect that it has on other variables, which in turn affect the function), then we need to take a total differential.

Consider  $z = f(x, y)$ . The total differential of  $z$  is given by:

$$dz = \frac{\partial z}{\partial x} dx + \frac{\partial z}{\partial y} dy$$

#### Example

Find the total differential for:  $z = 2x \sin(y) - 3x^2y^2$ .

$$\begin{aligned} dz &= \frac{\partial z}{\partial x} dx + \frac{\partial z}{\partial y} dy \\ &= (2 \sin(y) - 6x^2y) dx + (2x \cos(y) - 6x^2y) dy \end{aligned}$$

### 1.3 Implicit Differentiation

Consider the equation  $F(x, y) = 0$  where  $y$  is defined implicitly as a differentiable function of  $x$ . Then,

$$\frac{dy}{dx} = -\frac{\frac{\partial F}{\partial x}}{\frac{\partial F}{\partial y}}$$

#### Example

Consider  $xy^2 + x^3y + 5y - 4 = 0$ . Find  $\frac{dy}{dx}$ :

$$\begin{aligned}\frac{dy}{dx} &= -\frac{\frac{\partial F}{\partial x}}{\frac{\partial F}{\partial y}} \\ &= -\frac{y^2 + 3x^2y}{2xy + x^3 + 5} \\ &= \frac{-y^2 - 3x^2y}{2xy + x^3 + 5}\end{aligned}$$

#### Practice

Use the chain rule to derive the implicit differentiation problem above.

### 1.4 Taylor Series/Polynomial

If  $f$  is differentiable of order  $n + 1$  on interval  $I$ , then there exists  $z$  between points  $x$  and  $c$ , which are on in the interval  $I$ , such that:

$$f(x) = f(c) + f'(c)(x - c) + \frac{f''(c)}{2!}(x - c)^2 + \frac{f'''(c)}{3!}(x - c)^3 + \dots + \frac{f^n(c)}{n!}(x - c)^n + R_n(c)$$

where  $R_n(c) = \frac{f^{n+1}(z)}{(n+1)!}(x - c)^{n+1}$ .

$R_n(c)$  is commonly referred to as the remainder or error. There are many uses of the Taylor polynomial. One use is to approximate the value of a function at a certain point,  $x$ , given that you know the value of the function at a close point,  $c$ . The higher the degree of polynomial we use, the closer we will get the the actual value of  $f(x)$ . You will notice that in each equation below, I have left out the remainder term, thus, we get an approximate value for  $f(x)$

First order Taylor polynomial:  $f(x) \approx f(c) + f'(c)(x - c)$

Second order Taylor polynomial:  $f(x) \approx f(c) + f'(c)(x - c) + \frac{f''(c)}{2!}(x - c)^2$

Third order Taylor polynomial:  $f(x) \approx f(c) + f'(c)(x - c) + \frac{f''(c)}{2!}(x - c)^2 + \frac{f'''(c)}{3!}(x - c)^3$

#### Practice

Given a function is strictly concave, and  $x > c$  (i.e. we are given  $f(c)$  and approximating  $f(x)$ ), show that the approximate value for  $f(x)$  using a first order Taylor polynomial is greater than the actual value of  $f(x)$ .

#### Note

A Maclaurin series is a special case of a Taylor series or polynomial. In a Maclaurin series,  $c = 0$ .

## 2 Unconstrained Optimization

### 2.1 Optima

Let  $f : X \rightarrow \mathbb{R}$  where  $X \subseteq \mathbb{R}^n$ :

Global Optima

- $x^* \in X$  is a **global max** of  $F$  on  $X$  if  $F(x^*) \geq F(x)$  for all  $x \in X$
- $x^* \in X$  is a **global min** of  $F$  on  $X$  if  $F(x^*) \leq F(x)$  for all  $x \in X$

Strict Global Optima

- $x^* \in X$  is a **strict global max** of  $F$  on  $X$  if  $F(x^*) > F(x)$  for all  $x \in X$
- $x^* \in X$  is a **strict global min** of  $F$  on  $X$  if  $F(x^*) < F(x)$  for all  $x \in X$

Local Optima

- $x^* \in X$  is a **local max** of  $F$  if there is a epsilon-ball  $B_\varepsilon(x^*)$  around  $x^*$  such that  $F(x^*) \geq F(x)$  for all  $x \in X$
- $x^* \in X$  is a **local min** of  $F$  if there is a epsilon-ball  $B_\varepsilon(x^*)$  around  $x^*$  such that  $F(x^*) \leq F(x)$  for all  $x \in X$

Strict Local Optima

- $x^* \in X$  is a **strict local max** of  $F$  if there is a epsilon-ball  $B_\varepsilon(x^*)$  around  $x^*$  such that  $F(x^*) > F(x)$  for all  $x \in X$
- $x^* \in X$  is a **strict local min** of  $F$  if there is a epsilon-ball  $B_\varepsilon(x^*)$  around  $x^*$  such that  $F(x^*) < F(x)$  for all  $x \in X$

### 2.2 First Order Conditions

Before we talk about first order conditions, we need to define what the interior of a set is. Consider the set  $X \subseteq \mathbb{R}^n$ .  $X^\circ$  is the interior of set  $X$ , where  $X^\circ$  is defined as:

$$X^\circ = \{x \in X : \exists B_\varepsilon(x) \subseteq X\}$$

Each element of  $X^\circ$  is an interior point of  $X$ .

**Theorem:** Let  $F : X \rightarrow \mathbb{R}$  be a  $C^1$  function where  $X \subseteq \mathbb{R}^n$ . If  $x^*$  is a local max or min of  $F$  on  $X$  and  $x^*$  is an interior point of  $X$  then:

$$DF_{x^*} = \mathbf{0}$$

#### Example

Let  $F(x, y) = x^3 - y^3 + 9xy$ . We can find the "critical points" by setting the first order partial derivatives equal to 0:

$$\begin{aligned}\frac{\partial F}{\partial x} &: 3x^2 + 9y = 0 \\ \frac{\partial F}{\partial y} &: -3y^2 + 9x = 0\end{aligned}$$

From the first equation, we find that  $y = -\frac{1}{3}x^2$ . Substitute this into the second equation:

$$\begin{aligned}0 &= -3\left(-\frac{1}{3}x^2\right)^2 + 9x \\ &= -\frac{1}{3}x^4 + 9x \\ &\Rightarrow x = 0 \text{ or } x = 3\end{aligned}$$

Plugging these values into either equation gives us the critical points:  $(0, 0)$  and  $(3, -3)$ .

Notice that from the theorem above, in order for  $x^*$  to be an optimum, it is a necessary condition for all first order partials at  $x^*$  to be equal to 0. That being said, having all first order partials equal to 0 does not mean that that point is an optimum. That point is known as a **critical point** and could be either a local max, a local min, or a saddle point. We have to check second order conditions to determine what kind of critical point  $x^*$  is.

## 2.3 Second Order Conditions

**Theorem:** Let  $F : X \rightarrow \mathbb{R}$  be a  $C^2$  function where  $X \subseteq \mathbb{R}^n$  and  $X$  is an open set. Further suppose that  $x^*$  is a critical point of  $F$ .

- $x^*$  is a strict local max of  $F$  if the Hessian,  $D^2F_{x^*}$  is negative definite.
- $x^*$  is a strict local min of  $F$  if the Hessian,  $D^2F_{x^*}$  is positive definite.
- $x^*$  is a saddle point of  $F$  (neither a local min or local max) if the Hessian,  $D^2F_{x^*}$  is indefinite.

### Example

Using the same example as before,  $F(x, y) = x^3 - y^3 + 9xy$ . The critical points are  $(0, 0)$  and  $(3, -3)$ . The Hessian of  $F$  is:

$$\begin{pmatrix} 6x & 9 \\ 9 & -6y \end{pmatrix}$$

At the critical point  $(0, 0)$ , the Hessian is:

$$\begin{pmatrix} 0 & 9 \\ 9 & 0 \end{pmatrix}$$

Notice that the first order leading principal minor is:  $|0| = 0$ , and the second order leading principal minor is  $\begin{vmatrix} 0 & 9 \\ 9 & 0 \end{vmatrix} = -81$ . Notice that the Hessian at  $(0, 0)$  is indefinite, thus  $(0, 0)$  is a saddle point.

At the critical point  $(3, -3)$ , the Hessian is:

$$\begin{pmatrix} 18 & 9 \\ 9 & 18 \end{pmatrix}$$

Notice that the first order leading principal minor is:  $|18| = 18$ , and the second order leading principal minor is  $\begin{vmatrix} 18 & 9 \\ 9 & 18 \end{vmatrix} = 243$ . Notice that the Hessian at  $(3, -3)$  is positive definite, thus  $(3, -3)$  is a strict local min.

**Theorem:** Let  $F : X \rightarrow \mathbb{R}$  be a  $C^2$  function where  $X \subseteq \mathbb{R}^n$ . Suppose that  $x^*$  is an interior point of  $X$  and  $x^*$  is a local max (respectively min) of  $F$ . Then:

1.  $DF_{x^*} = \mathbf{0}$
2.  $D^2F_{x^*}$  is negative semi-definite (respectively, positive semi-definite)

**Theorem:** Let  $F : X \rightarrow \mathbb{R}$  be a  $C^2$  function where  $X \subseteq \mathbb{R}^n$  and  $X$  is an open, convex set. The following conditions are equivalent (meaning if one condition is true, the other conditions are true):

1.  $F$  is a concave function on  $X$
2.  $F(y) - F(x) \leq DF_x(y - x) \quad \forall x, y \in X$
3.  $D^2F_{x^*}$  is negative semi-definite  $\forall x, y \in X$

### Practice

Let  $F : X \rightarrow \mathbb{R}$  be a  $C^2$  function where  $X \subseteq \mathbb{R}^n$  and  $X$  is an open, convex set. Show that  $F$  is a concave function on  $X \Rightarrow F(y) - F(x) \leq DF_x(y - x) \quad \forall x, y \in X$

The following conditions are equivalent:

1.  $F$  is a convex function on  $X$
2.  $F(y) - F(x) \geq DF_x(y - x) \quad \forall x, y \in X$
3.  $D^2F_{x^*}$  is positive semi-definite  $\forall x, y \in X$

Now, assume that  $F$  is a concave function on  $X$ , then we know that  $F(y) - F(x) \leq DF_x(y - x) \quad \forall x, y \in X$ . Notice that if  $x^*$  is a local max or min and in the interior of  $X$ , then it follows that  $DF_{x^*} = \mathbf{0}$ . Thus  $F(y) - F(x^*) \leq 0 \Rightarrow F(x^*) \geq F(y) \quad \forall y \in X$ . Thus, the following follows:

**Theorem:** If  $F$  is a concave function on  $X$  and  $DF_{x^*} = \mathbf{0}$  for some  $x^* \in X$ , then  $x^*$  is a global max of  $F$  on  $X$

**Theorem:** If  $F$  is a convex function on  $X$  and  $DF_{x^*} = \mathbf{0}$  for some  $x^* \in X$ , then  $x^*$  is a global min of  $F$  on  $X$

## Exercises

1. Consider the function  $f(x) = \ln(1 + x)$ .

(a) Calculate  $f(.5)$ .

(b) Using a first order Taylor polynomial, approximate  $f(.5)$  using  $x_0 = 0$ .

(c) Using a second order Taylor polynomial, approximate  $f(.5)$  using  $x_0 = 0$ .

(d) Using a third order Taylor polynomial, approximate  $f(.5)$  using  $x_0 = 0$ .

2. Differentiate implicitly to find  $\frac{dy}{dx}$ :

$$x^2 - 3xy + y^2 - 2x + y - 5 = 0$$

3. Find the critical points and classify these as local max, local min, saddle point, or "can't tell":

$$f(x, y, z) = (x^2 + 2y^2 + 3z^2) e^{-(x^2 + y^2 + z^2)}$$