

Chapter 9: Partial Derivatives

Learning Objectives:

1. Describe functions of several variables.
2. Define partial derivatives.
3. Use Python to evaluate partial derivatives.
4. Apply partial derivatives in gradient descent to find the minimum of a function.

9.1 Partial Derivatives

In Chapter 6, you have been introduced to the notion of a derivative which measures the rate of change of $f(x)$ with respect to the independent variable x . In this chapter, we would extend it to finding the derivatives of function of two or more variables.

The following are examples of functions of two or more variables.

Volume of a cylinder, $V = \pi r^2 h$

Ideal gas law, $PV = nRT$

Ohms law, $V = IR$

Cobb-Douglas production function, $Q = AL^\alpha K^\beta$

Let $f(x, y)$ be a function of the two variables x and y . To find the rate of change of $f(x, y)$ w.r.t. both x and y , the technique called **partial differentiation** will be involved. Since $f(x, y)$ is dependent on two variables, we have to, first of all, determine how $f(x, y)$ changes with x while keeping y constant, and how $f(x, y)$ changes with y while keeping x constant. Summing up the effects, the rate of change of $f(x, y)$ w.r.t. both x and y can be evaluated.

Notation for partial derivatives:

The *partial derivative of $f(x, y)$ with respect to x* is written as $\frac{\partial f}{\partial x}$.

$\frac{\partial f}{\partial x}$ is the derivative of $f(x, y)$, where y is treated as the constant and $f(x, y)$ is treated as a function of x alone.

The *partial derivative of $f(x, y)$ with respect to y* is written as $\frac{\partial f}{\partial y}$.

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Example 1.

Compute $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$ of the following.

(a) $f(x, y) = 5x^3y^2$

(b) $f(x, y) = (4x + 3y - 5)^8$

(c) $f(x, y) = \sin\left(\frac{x}{1+y}\right)$

[Ans: (a) $\frac{\partial f}{\partial x} = 15x^2y^2$, $\frac{\partial f}{\partial y} = 10x^3y$ (b) $\frac{\partial f}{\partial x} = 32(4x + 3y - 5)^7$, $\frac{\partial f}{\partial y} = 24(4x + 3y - 5)^7$

(c) $\frac{\partial f}{\partial x} = \frac{1}{1+y} \cos\left(\frac{x}{1+y}\right)$, $\frac{\partial f}{\partial y} = -\frac{x}{(1+y)^2} \cos\left(\frac{x}{1+y}\right)$]

Example 2.

Given that $f(a,b) = \frac{a-b}{a+b}$. Evaluate $\frac{\partial f}{\partial a}$ and $\frac{\partial f}{\partial b}$ when $a = 1$ and $b = 1$.

$$[\text{Ans: } \left. \frac{\partial f}{\partial a} \right|_{a=1,b=1} = \frac{1}{2}, \left. \frac{\partial f}{\partial b} \right|_{a=1,b=1} = -\frac{1}{2}]$$

9.2 Using SymPy for Partial Derivatives

In Chapter 6, we have learnt to use the SymPy library to obtain the derivative, $\frac{dy}{dx}$, of a function, $y = f(x)$. Partial derivatives can also be obtained using the SymPy library. Similar as before, the symbols of the variables need to be declared first.

```
1 import sympy as sp
2
3 # Define the symbols
4 x = sp.Symbol('x')
5 y = sp.Symbol('y')
```

Figure 9.1 Python code for declaring symbols for variables

We then use **diff(func,var)**, where **func** is the expression of the function to be differentiated and **var** is the variable we are differentiating with respect to. Since there are more than one variable in the function, thus it is important to indicate **var** correctly.

The following code gives the partial derivatives $\frac{\partial z}{\partial x}$ and $\frac{\partial z}{\partial y}$ for $z = x^2y + e^{3xy}$:

```
1 partial_x = sp.diff(x**2*y+sp.exp(3*x*y),x)
2 partial_y = sp.diff(x**2*y+sp.exp(3*x*y),y)
3 print("with respect to x: "+str(partial_x))
4 print("with respect to y: "+str(partial_y))

with respect to x: 2*x*y + 3*y*exp(3*x*y)
with respect to y: x**2 + 3*x*exp(3*x*y)
```

Figure 9.2 Python code and output for partial differentiation

From the output, $\frac{\partial z}{\partial x} = 2xy + 3ye^{3xy}$ and $\frac{\partial z}{\partial y} = x^2 + 3xe^{3xy}$.

Example 3.

Find the partial derivatives of the following functions using SymPy.

(a) $f(x, y) = x^2 y^3 + 2 \sin x + 4y$

(b) $f(x, y) = x e^{xy}$

(c) $f(x, y) = (2x + 3y)(5x - 4y)$

(d) $f(x, y) = \frac{e^{x^2}}{4xy^2}$

[Ans: (a) $f_x(x, y) = 2xy^3 + 2 \cos x$, $f_y(x, y) = 3x^2 y^2 + 4$ (b) $f_x(x, y) = xye^{xy} + e^{xy}$, $f_y(x, y) = x^2 e^{xy}$
 (c) $f_x(x, y) = 20x + 7y$, $f_y(x, y) = 7x - 24y$ (d) $f_x(x, y) = \frac{e^{x^2}}{2y^2} - \frac{e^{x^2}}{4x^2 y^2}$, $f_y(x, y) = -\frac{e^{x^2}}{2xy^3}$]

9.3 An Application of Partial Derivatives – Gradient Descent

Recall in Chapter 8 that you have learnt univariate gradient descent to find the local minimum of a function, $y = f(x)$, of a single variable. In this section, we are going to extend the method to find the local minimum of a function, $z = f(x, y)$, of two variables.

To find the minimum point of a function $z = f(x, y)$, the gradient descent algorithm works in this way:

Algorithm

Step 0. Set a learning rate $\alpha > 0$ and an initial point $x = x_0$, $y = y_0$, and compute $f(x_0, y_0)$.

Step 1. At n -th point $x = x_n$, $y = y_n$, compute $f_x(x_n, y_n)$ and $f_y(x_n, y_n)$.

Step 2. Update to the $(n+1)$ -th point using $x_{n+1} = x_n - \alpha f_x(x_n, y_n)$, $y_{n+1} = y_n - \alpha f_y(x_n, y_n)$ and compute $f(x_{n+1}, y_{n+1})$.

Step 3. Repeat steps 1 and 2 until a stopping criterion is reached.

Each or a combination of the following can be the stopping criterion:

1. The **maximum number of iterations** is reached.
2. The **value of** $f_x^2(x_n, y_n) + f_y^2(x_n, y_n)$ is smaller than a fixed constant.
3. **Convergence**, which, in simple terms, means that the update to the current point does not differ much from the previous point. It can refer to little difference from $x = x_n$, $y = y_n$ to $x = x_{n+1}$, $y = y_{n+1}$ or little reduction in $f(x_n, y_n)$ to $f(x_{n+1}, y_{n+1})$ (the difference is smaller than a fixed constant).

Example 4.

To find the minimum point of $f(x, y) = x^2 + 3y^2$, show the first 3 iterations of the gradient descent algorithm, with an initial point of $x = 4, y = 5$ and step size $\alpha = 0.1$.

Solution

We first work out the partial derivatives of $f(x, y)$:

$$f_x(x, y) =$$

$$f_y(x, y) =$$

Iteration 1: Initial point $x_0 = 4, y_0 = 5 \Rightarrow f(x_0, y_0) = f(4, 5) =$

$$\begin{aligned} f_x(x_0, y_0) &= f_x(4, 5) \\ &= \end{aligned}$$

$$\begin{aligned} f_y(x_0, y_0) &= f_y(4, 5) \\ &= \end{aligned}$$

$$\begin{aligned} x_1 &= x_0 - \alpha f_x(x_0, y_0) \\ &= \end{aligned}$$

$$\begin{aligned} y_1 &= y_0 - \alpha f_y(x_0, y_0) \\ &= \end{aligned}$$

$$f(x_1, y_1) =$$

Iteration 2: $x_1 =$, $y_1 =$

$$\begin{aligned} f_x(x_1, y_1) &= \\ &= \end{aligned}$$

$$\begin{aligned} f_y(x_1, y_1) &= \\ &= \end{aligned}$$

$$\begin{aligned} x_2 &= x_1 - \alpha f_x(x_1, y_1) \\ &= \end{aligned}$$

$$\begin{aligned} y_2 &= y_1 - \alpha f_y(x_1, y_1) \\ &= \end{aligned}$$

$$f(x_2, y_2) =$$

Iteration 3: $x_2 =$, $y_2 =$,

$$\begin{aligned} f_x(x_2, y_2) &= \\ &= \end{aligned}$$

$$\begin{aligned} f_y(x_2, y_2) &= \\ &= \end{aligned}$$

$$\begin{aligned} x_3 &= x_2 - \alpha f_x(x_2, y_2) \\ &= \end{aligned}$$

$$\begin{aligned} y_3 &= y_2 - \alpha f_y(x_2, y_2) \\ &= \end{aligned}$$

$$f(x_3, y_3) =$$

The minimum point of the function $f(x, y) = x^2 + 3y^2$ is at $x = 0, y = 0$. You can observe that with each iteration, we become nearer to the minimum point.

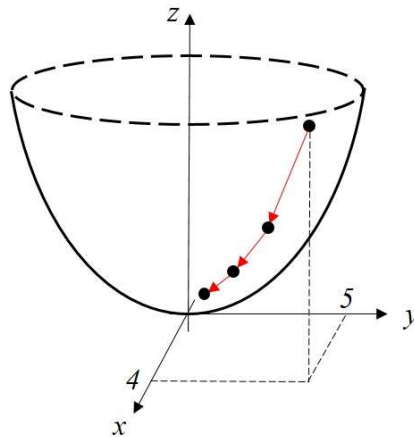


Figure 9.3

[Ans: Iteration 1: $x_1 = 3.2, y_1 = 2, f(x_1, y_1) = 22.24$
 Iteration 2: $x_2 = 2.56, y_2 = 0.8, f(x_2, y_2) = 8.4736$
 Iteration 3: $x_3 = 2.048, y_3 = 0.32, f(x_3, y_3) = 4.5015$]

Using the function in Example 4, gradient descent can be implemented in Python as follows:

```

1  import numpy as np
2
3  next_x = 4 # Initial point
4  next_y = 5 # Initial point
5  alpha = 0.1 # Learning rate
6  epsilon = 0.001 # Stopping criterion constant
7  max_iters = 500 # Maximum number of iterations
8
9  # Partial derivatives and function
10 partialf_x = lambda x,y: 2*x
11 partialf_y = lambda x,y: 6*y
12 func = lambda x,y: x**2+3*y**2
13
14 next_func = func(next_x,next_y) # Initial value of function
15
16 for n in range(max_iters):
17     current_x = next_x
18     current_y = next_y
19     current_func = next_func
20     next_x = current_x-alpha*partialf_x(current_x,current_y) # update of x
21     next_y = current_y-alpha*partialf_y(current_x,current_y) # update of y
22     next_func = func(next_x,next_y)
23     change_func = abs(next_func-current_func) # stopping criterion: values of function converge
24     print("Iteration",n+1," : x = ",next_x," , y = ",next_y," , f(x,y) = ",next_func)
25     if change_func<epsilon:
26         break

```

Figure 9.4 Gradient descent code

The convergence criterion used in this code is the difference in the **values of the function**. The output of the code is as follows:

```
Iteration 1 : x = 3.2 , y = 2.0 , f(x,y) = 22.240000000000002
Iteration 2 : x = 2.56 , y = 0.7999999999999998 , f(x,y) = 8.4736
Iteration 3 : x = 2.048 , y = 0.3199999999999999 , f(x,y) = 4.501504
Iteration 4 : x = 1.6384 , y = 0.12799999999999995 , f(x,y) = 2.73350656
Iteration 5 : x = 1.31072 , y = 0.05119999999999997 , f(x,y) = 1.7258512384000002
Iteration 6 : x = 1.0485760000000002 , y = 0.020479999999999984 , f(x,y) = 1.1007699189760005
Iteration 7 : x = 0.8388608000000002 , y = 0.008191999999999993 , f(x,y) = 0.7038887683686403
Iteration 8 : x = 0.6710886400000001 , y = 0.0032767999999999964 , f(x,y) = 0.45039217499176976
Iteration 9 : x = 0.5368709120000001 , y = 0.0013107199999999983 , f(x,y) = 0.28823553011246705
Iteration 10 : x = 0.4294967296000001 , y = 0.0005242879999999992 , f(x,y) = 0.18446826537081645
Iteration 11 : x = 0.3435973836800001 , y = 0.0002097151999999996 , f(x,y) = 0.11805929401313653
Iteration 12 : x = 0.27487790694400005 , y = 8.3886079999999985e-05 , f(x,y) = 0.0755578848365376
Iteration 13 : x = 0.21990232555520003 , y = 3.3554431999999993e-05 , f(x,y) = 0.0483570361622849
Iteration 14 : x = 0.17592186044416003 , y = 1.3421772799999973e-05 , f(x,y) = 0.030948501522566473
Iteration 15 : x = 0.140737488355328 , y = 5.368709119999989e-06 , f(x,y) = 0.0198070407150352
Iteration 16 : x = 0.1125899068426241 , y = 2.147483647999996e-06 , f(x,y) = 0.012676506016117355
Iteration 17 : x = 0.09007199254740993 , y = 8.589934591999983e-07 , f(x,y) = 0.008112963843674279
Iteration 18 : x = 0.07205759403792794 , y = 3.4359738367999934e-07 , f(x,y) = 0.00519229685889006
Iteration 19 : x = 0.057646075230342354 , y = 1.374389534719997e-07 , f(x,y) = 0.0033230699895189586
Iteration 20 : x = 0.04611686018427388 , y = 5.4975581388799866e-08 , f(x,y) = 0.0021267647932649326
Iteration 21 : x = 0.03689348814741911 , y = 2.199023255519943e-08 , f(x,y) = 0.0013611294676852048
```

Figure 9.5 Output of the gradient descent code

It can be seen that from Iteration 20 to Iteration 21, the reduction in the value of $f(x, y)$ is: $0.00213 - 0.00136 = 0.00077$, which is less than epsilon. Hence, the algorithm converges and the output shows that the minimum point is at $x = 0$, $y = 0$ and $f(x, y) = 0$.

Example 5.

Repeat the example above to find the minimum of $f(x, y) = x^2 + 3y^2$ with learning rates $\alpha = 0.05$ and $\alpha = 0.5$. Use the difference in values of $f(x, y)$ less than epsilon as the convergence criterion. Set the initial point to be at $x_0 = 4$, $y_0 = 5$, epsilon = 0.001 and maximum number of iterations to be 500. Compare all results with the above (Example 4) where $\alpha = 0.1$.

Example 6.

Find the minimum point of the function $f(x, y) = x^2 + y^4 + 3y^3 - y^2 - 3y$ using the gradient descent algorithm with the following settings:

(a) Initial point = (1, 1), learning rate = 0.05, epsilon = 0.0001, maximum iteration = 500

(b) Initial point = (0, -3), learning rate = 0.05, epsilon = 0.0001, maximum iteration = 500

Compare and comment on your results.

Tutorial 9

1. Evaluate $f(x, y, z) = x^2 + 2y + z$ when $x = 3$, $y = 4$ and $z = 1$.
2. The volume V of a right circular cylinder is given by the formula $V = \pi r^2 h$, where r is the radius and h is the height.
 - (a) Find the formula for the instantaneous rate of change of V with respect to r if r changes and h remains constant.
 - (b) Find the formula for the instantaneous rate of change of V with respect to h if h changes and r remains constant.
 - (c) Suppose that h has a constant value of 4 cm. but r varies. Find the rate of change of V with respect to r at the point where $r = 6$ cm.
 - (d) Suppose that r has a constant value of 8 cm but h varies. Find the instantaneous rate of change of V with respect to h at the point where $h = 10$ cm.
3. Find the partial derivatives of the given function.

(a) $f(x, y) = x^5 + x^3 y^2 + 3xy^4$	(b) $f(r, s) = r \cdot \ln(r^2 + s^2)$
(c) $u = te^{w/t}$	(d) $z = (1 + x^2 y)e^{3y}$
(e) $z = \ln(xy)$	(f) $f(x, y) = x^2 \sin(xy) - 3y^3$
(g) $g(x, y, z) = xyz + y^2 z^3 - 4xz^2$	(h) $f(x, y, z) = x \cos yz + 2x^2 e^z$
4. Evaluate the indicated partial derivatives.

(a) $f(x, y) = \sqrt{x^2 + y^2}$, $f_x(3, 4)$	(b) $f(x, y, z) = \frac{x}{y+z}$, $f_z(3, 2, 1)$
--	---
5. To find the minimum point of $f(x, y) = e^{2x^2 + (y-1)^2}$, show the first 2 iterations of the gradient descent algorithm with an initial point of $x = 1$, $y = 2$ and learning rate $\alpha = 0.01$. Using epsilon = 0.001, find the minimum point of $f(x, y)$.
(Use the difference in values of $f(x, y)$ less than epsilon as the convergence criterion.)
6. To find a minimum point of $f(x, y) = \cos(x^2) + y^2$, show the first 3 iterations of the gradient descent algorithm with an initial point of $x = -1$, $y = 2$ and learning rate $\alpha = 0.1$. Find the minimum point of $f(x, y)$. Using epsilon = 0.0001, find the minimum point of $f(x, y)$.
(Use the difference in values of $f(x, y)$ less than epsilon as the convergence criterion.)

7. To find the minimum point of $f(x, y) = (6 - x - 3y)^2 + (2 - x - y)^2$, show the first 3 iterations of the gradient descent algorithm with an initial point of $x = 0, y = 0$ and learning rate $\alpha = 0.05$. Using $\text{epsilon} = 0.00001$, find the minimum point of $f(x, y)$. (Use the difference in values of $f(x, y)$ less than epsilon as the convergence criterion.)
- 8.* Use the gradient descent algorithm to find the **maximum** point of $f(x, y) = e^{-x^2+2x} - y^2$. Set the initial point at $x = 2, y = 1$, learning rate $\alpha = 0.05$ and $\text{epsilon} = 0.00001$. Use the difference in values of $f(x, y)$ less than epsilon as the convergence criterion.
(Hint: Find the minimum point of $g(x, y) = -f(x, y)$.)
9. Use the gradient descent algorithm to find the minimum point of $f(x, y) = \cos 0.125x^3 - \sin y$ with the following settings:
- (a) Initial point: $x = 2.5, y = 1$, learning rate $\alpha = 0.1$
 - (b) Initial point: $x = -2, y = -4$, learning rate $\alpha = 0.1$
 - (c) Initial point: $x = -2, y = -4$, learning rate $\alpha = 0.01$
 - (d) Initial point: $x = -2, y = -4$, learning rate $\alpha = 0.5$

Set $\text{epsilon} = 0.0001$ for all three cases and 500 as maximum number of iterations. Use the difference in values of $f(x, y)$ less than epsilon as the convergence criterion. Compare and comment on your results.

Answers

1. 18
2. (a) $2\pi rh$ (b) πr^2 (c) 48π (d) 64π
3. (a) $f_x(x, y) = 5x^4 + 3x^2y^2 + 3y^4$; $f_y(x, y) = 2x^3y + 12xy^3$
 (b) $f_r(r, s) = \ln(r^2 + s^2) + \frac{2r^2}{r^2 + s^2}$; $f_s(r, s) = \frac{2rs}{r^2 + s^2}$
 (c) $\frac{\partial u}{\partial t} = e^{\frac{w}{t}} \left(1 - \frac{w}{t}\right)$; $\frac{\partial u}{\partial w} = e^{\frac{w}{t}}$
 (d) $\frac{\partial z}{\partial x} = 2xye^{3y}$; $\frac{\partial z}{\partial y} = x^2e^{3y} + 3e^{3y}(1 + x^2y)$
 (e) $\frac{\partial z}{\partial x} = \frac{1}{x}$; $\frac{\partial z}{\partial y} = \frac{1}{y}$
 (f) $f_x(x, y) = 2x \sin(xy) + x^2y \cos(xy)$; $f_y(x, y) = x^3 \cos(xy) - 9y^2$
 (g) $g_x(x, y, z) = yz - 4z^2$; $g_y(x, y, z) = xz + 2yz^3$; $g_z(x, y, z) = xy + 3y^2z^2 - 8xz$
 (h) $f_x(x, y, z) = \cos yz + 4xe^z$; $f_y(x, y, z) = -xz \sin yz$; $f_z(x, y, z) = -xy \sin yz + 2x^2e^z$
4. (a) $\frac{3}{5}$ (b) $-\frac{1}{3}$
5. Iteration 1: $x_1 = 0.1966, y_1 = 1.5983, f(x_1, y_1) = 1.5453$
 Iteration 2: $x_2 = 0.1844, y_2 = 1.5798, f(x_2, y_2) = 1.4981$
 ... Iteration 61: $x = 0.0119, y = 1.150, f(x, y) = 1.023$
6. Iteration 1: $x_1 = -1.1683, y_1 = 1.6, f(x_1, y_1) = 2.7644$
 Iteration 2: $x_2 = -1.3970, y_2 = 1.28, f(x_2, y_2) = 1.2667$
 Iteration 3: $x_3 = -1.6564, y_3 = 1.024, f(x_3, y_3) = 0.1267$
 ... Iteration 23: $x = -1.772, y = 0.0118, f(x, y) = -1.0$
7. Iteration 1: $x_1 = 0.8, y_1 = 2, f(x_1, y_1) = 1.28$
 Iteration 2: $x_2 = 0.64, y_2 = 1.68, f(x_2, y_2) = 0.2048$
 Iteration 3: $x_3 = 0.64, y_3 = 1.744, f(x_3, y_3) = 0.16384$
 ... Iteration 105: $x = 0.0180, y = 1.993, f(x, y) = 0.000131$
- 8*. Iteration 48: $x = 1.0, y = 0.00636, f(x, y) = 2.718$
9. (a) Iteration 29: $x = 2.929, y = 1.543, f(x, y) = -2.0$
 (b) Iteration 31: $x = -2.929, y = -4.684, f(x, y) = -2.0$
 (c) Iteration 201: $x = -2.929, y = -4.643, f(x, y) = -2.0$
 (d) Did not converge after 500 iterations

Different initial points may lead to different minimum points as evident in (a) and (b). A lower learning rate may result in slower convergence, comparing (b) and (c). Too large a learning rate may result in the algorithm to fail to converge as seen in (d).