

# **Unconstrained Optimization**

# UNCONSTRAINED OPTIMIZATION

We generalize the results for a single variable to the case of many variables

Consider the problem:

$$\max_x f(x) \text{ subject to } x \in S$$

where  $x$  is a vector

## Proposition

Let  $f$  be a differentiable function of  $n$  variables defined on the set  $S$ . If the point  $x$  in the interior of  $S$  is a local or global maximizer or minimizer of  $f$  then

$$f'_i(x) = 0 \text{ for } i = 1, \dots, n.$$

Then the condition that all partial derivatives are equal to zero is a necessary condition for an interior optimum (and therefore for an optimum in an unconstrained optimization where each element of  $x$  could be any of the real numbers).

## Conditions under which a stationary point is a local optimum

Let  $f$  be a function of  $n$  variables with continuous partial derivatives of first and second order, defined on the set  $S$ .

Suppose that  $x^*$  is a stationary point of  $f$  in the interior of  $S$  (so that  $f'_i(x^*) = 0$  for all  $i$ ).

If  $H(x^*)$  is negative definite then  $x^*$  is a local maximizer.

If  $x^*$  is a local maximizer then  $H(x^*)$  is negative semidefinite.

If  $H(x^*)$  is positive definite then  $x^*$  is a local minimizer.

If  $x^*$  is a local minimizer then  $H(x^*)$  is positive semidefinite.

where  $H(x)$  denotes the Hessian of  $f$  at  $x$ .

## Conditions under which a stationary point is a global optimum

Suppose that the function  $f$  has continuous partial derivatives in a convex set  $S$  and  $x^*$  is a stationary point of  $f$  in the interior of  $S$  (so that  $f'_i(x^*) = 0$  for all  $i$ ).

1. if  $f$  is concave then  $x^*$  is a global maximizer of  $f$  in  $S$  if and only if it is a stationary point of  $f$
2. if  $f$  is convex then  $x^*$  is a global minimizer of  $f$  in  $S$  if and only if it is a stationary point of  $f$ .

$H(z)$  is negative semidefinite for all  $z \in S \Rightarrow [x$  is a global maximizer of  $f$  in  $S$  if and only if  $x$  is a stationary point of  $f]$

$H(z)$  is positive semidefinite for all  $z \in S \Rightarrow [x$  is a global minimizer of  $f$  in  $S$  if and only if  $x$  is a stationary point of  $f]$ ,

where  $H(x)$  denotes the Hessian of  $f$  at  $x$ .

## Example 1: Unconstrained Maximization with two variables

For example Utility =  $U(x, y)$  or Output =  $F(K, L)$

Now try to find the values of  $x$  and  $y$  which maximise a function  $f(x, y)$

Three steps:

1. Set **both** 1<sup>st</sup> order conditions equal to zero  $f_x = 0$  and  $f_y = 0$   
(the slope of the function with respect to both variables must be simultaneously zero)
2. Solve the equations simultaneously for  $x$  and  $y$

However this is a necessary but not sufficient condition  
(saddle points, points of inflection)

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3. Second order conditions (for maximization)

$$H = \begin{pmatrix} f_{xx} & f_{xy} \\ f_{xy} & f_{yy} \end{pmatrix}$$

$$f_{xx} \leq 0, \quad f_{yy} \leq 0 \quad \text{and} \quad f_{xx}f_{yy} - f_{xy}^2 \geq 0$$

Note: Second order conditions (for minimization) are

$$f_{xx} \geq 0, \quad f_{yy} \geq 0 \quad \text{and} \quad f_{xx}f_{yy} - f_{xy}^2 \geq 0$$

$$f(x,y) = 4x - 2x^2 + 2xy - y^2$$

1. (i).  $f_x = 4 - 4x + 2y = 0$

(ii).  $f_y = 2x - 2y = 0$

2. Solve: from (ii) we have  $x = y$

insert into (i) to get  $4 - 4x + 2x = 0$  or

$$4 = 2x \text{ or } x = 2$$

$$\text{so } y = x = 2$$

3.  $H = \begin{pmatrix} f_{xx} & f_{xy} \\ f_{xy} & f_{yy} \end{pmatrix} = \begin{pmatrix} -4 & 2 \\ 2 & -2 \end{pmatrix}$

The first order leading principal minor is  $f_{xx} = -4 < 0$

The second order leading principal minor is

$$f_{xx}f_{yy} - f_{xy}^2 = (-4)(-2) - (2)^2 = 4 > 0$$

Then the matrix  $H$  is negative definite

$f$  is (strictly) concave, so we have a maximum point where  $x = 2$   
and  $y = 2$



## Example 2

Maximize  $f(x) = -x_1^2 - 2x_2^2$

The first order conditions are:

$$\begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{pmatrix} = \begin{pmatrix} -2x_1 \\ -4x_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

Is this a maximum? – it will be if function is concave

1. H is,

$$H = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{pmatrix} = \begin{pmatrix} -2 & 0 \\ 0 & -4 \end{pmatrix}$$

From H find the leading principal matrices by eliminating:

1. The last  $n-1$  rows and columns – written as  $D_1 = (-2)$
2. The last  $n-2$  rows and columns – written as  $D_2 = H$

Compute the determinants of these leading principal matrices.

1.  $|D_1| = -2$

2.  $|H| = 8$

Then the matrix H is negative definite

f is (strictly) concave

the values of x which satisfy FOC (0 and 0) give a maximum.

### Example 3

$$\text{Total revenue } R = 12q_1 + 18q_2$$

$$\text{Total Cost} = 2q_1^2 + q_1q_2 + 2q_2^2$$

Find the values of  $q_1$  and  $q_2$  that maximise profit

$$\text{Profit} = \text{revenue} - \text{cost} = 12q_1 + 18q_2 - (2q_1^2 + q_1q_2 + 2q_2^2)$$

The first order conditions are:

$$\begin{pmatrix} \frac{\partial \pi}{\partial q_1} \\ \frac{\partial \pi}{\partial q_2} \end{pmatrix} = \begin{pmatrix} 12 - 4q_1 - q_2 \\ 18 - q_1 - 4q_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

Solving for  $q_1$  and  $q_2$  gives  $q_1 = 2$  and  $q_2 = 4$

Is this a maximum? –it will be if function is concave

The Hessian is

$$H = \begin{pmatrix} \frac{\partial^2 \pi}{\partial q_1^2} & \frac{\partial^2 \pi}{\partial q_1 \partial q_2} \\ \frac{\partial^2 \pi}{\partial q_2 \partial q_1} & \frac{\partial^2 \pi}{\partial q_2^2} \end{pmatrix} = \begin{pmatrix} -4 & -1 \\ -1 & -4 \end{pmatrix}$$

From H find the leading principal matrices by eliminating:

1. The last  $n-1$  rows and columns – written as  $D_1 = (-4)$
2. The last  $n-2$  rows and columns – written as  $D_2 = H$

Compute the determinants of these leading principal matrices.

1.  $|D_1| = -4$
2.  $|H| = (-4) * (-4) - 1 = 15$

So H is negative definite, then  $f$  is (strictly) concave and the values for  $q_1$  and  $q_2$  maximise profits

## Example with three variables

$$\text{Maximize } f(x) = -x_1^2 - 2x_2^2 - x_3^2$$

The first order conditions are:

$$\begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \frac{\partial f}{\partial x_3} \end{pmatrix} = \begin{pmatrix} -2x_1 \\ -4x_2 \\ -2x_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

The Hessian is:

$$H = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \frac{\partial^2 f}{\partial x_1 \partial x_3} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \frac{\partial^2 f}{\partial x_2 \partial x_3} \\ \frac{\partial^2 f}{\partial x_3 \partial x_1} & \frac{\partial^2 f}{\partial x_3 \partial x_2} & \frac{\partial^2 f}{\partial x_3^2} \end{pmatrix} = \begin{pmatrix} -2 & 0 & 0 \\ 0 & -4 & 0 \\ 0 & 0 & -2 \end{pmatrix}$$

From  $H$  find the leading principal matrices by eliminating:

1. The last  $n-1$  rows and columns –  $D_1 = (-2)$

2. The last  $n-2$  rows and columns –  $D_2 = \begin{pmatrix} -2 & 0 \\ 0 & -4 \end{pmatrix}$

3. The last 0 rows and columns –  $D_3 = H$

1. Compute the determinants of these leading principal matrices.

1.  $|D_1| = -2,$

2.  $|D_2| = 8$

3.  $|H| = -16$

$H$  is negative definite, then  $f$  is (strictly) concave

## Summing up – two variable maximization

1. Differentiate  $f(x)$  and solve the first order conditions are:

$$\begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

2. Check concavity of  $f$  to see if the conditions represent a maximum.

a. We compute the Hessian

b. We check if it is negative definite

c. i.e. check if, for all  $x_1$  and  $x_2$ ,

$$\frac{\partial^2 f}{\partial x_1^2} < 0 \quad \text{and} \quad \begin{vmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{vmatrix} \quad \text{or} \quad \begin{vmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{vmatrix} = f_{11}f_{22} - f_{21}f_{12} > 0$$

3. If these conditions hold, H is negative definite, f is strictly concave and the stationary point is a maximum

4. If these conditions are violated by equality, i.e. are equal to zero, check the conditions for semi definiteness

$$\frac{\partial^2 f}{\partial x_1^2} \leq 0 \quad \frac{\partial^2 f}{\partial x_2^2} \leq 0 \quad \begin{vmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{vmatrix} = f_{11}f_{22} - f_{21}f_{12} \geq 0$$

5. If these conditions hold, H is negative semidefinite, f is concave and the stationary point is a maximum

6. If these conditions are violated, we need further investigation



## Summing up – 3 variable maximization

1. Differentiate  $f(x)$  and solve the the first order conditions are:

$$\begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \frac{\partial f}{\partial x_3} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

2. Check concavity of  $f$  to see if the conditions represent a maximum.

a. We compute the Hessian

b. We check if it is negative definite

b. We check if it is negative definite

$$\frac{\partial^2 f}{\partial x_1^2} < 0 \quad \left| \begin{array}{cc} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{array} \right| \text{ or } \left| \begin{array}{cc} f_{11} & f_{12} \\ f_{21} & f_{22} \end{array} \right| = f_{11}f_{22} - f_{21}f_{12} > 0$$

$$\left| \begin{array}{ccc} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{array} \right| = f_{11} \left| \begin{array}{cc} f_{22} & f_{23} \\ f_{32} & f_{33} \end{array} \right| - f_{12} \left| \begin{array}{cc} f_{21} & f_{23} \\ f_{31} & f_{33} \end{array} \right| + f_{13} \left| \begin{array}{cc} f_{21} & f_{22} \\ f_{31} & f_{32} \end{array} \right| < 0$$

3. If these conditions hold, H is negative definite, f is strictly concave and the stationary point is a maximum

4. If these conditions are violated by equality, i.e. are equal to zero, check the conditions for semi definiteness

$$f_{11} \leq 0, f_{22} \leq 0, f_{33} \leq 0$$

$$\begin{vmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{vmatrix} \geq 0 \quad \begin{vmatrix} f_{11} & f_{13} \\ f_{31} & f_{33} \end{vmatrix} \geq 0 \quad \begin{vmatrix} f_{22} & f_{23} \\ f_{32} & f_{33} \end{vmatrix} \geq 0$$

$$\begin{vmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{vmatrix} \leq 0$$

5. If these conditions hold, H is negative semidefinite, f is concave and the stationary point is a maximum

6. If these conditions are violated, we need further investigation

## Important properties

Consider the problem

$$\max_x f(x) \text{ subject to } x \in S$$

and let  $x^*$  be its solution

1)  $x^*$  is the solution of the following problem:

$$\max_x g(f(x)) \text{ subject to } x \in S$$

where  $g(\cdot)$  is a non decreasing function

2) The following problem is equivalent

$$\min_x -f(x) \text{ subject to } x \in S$$