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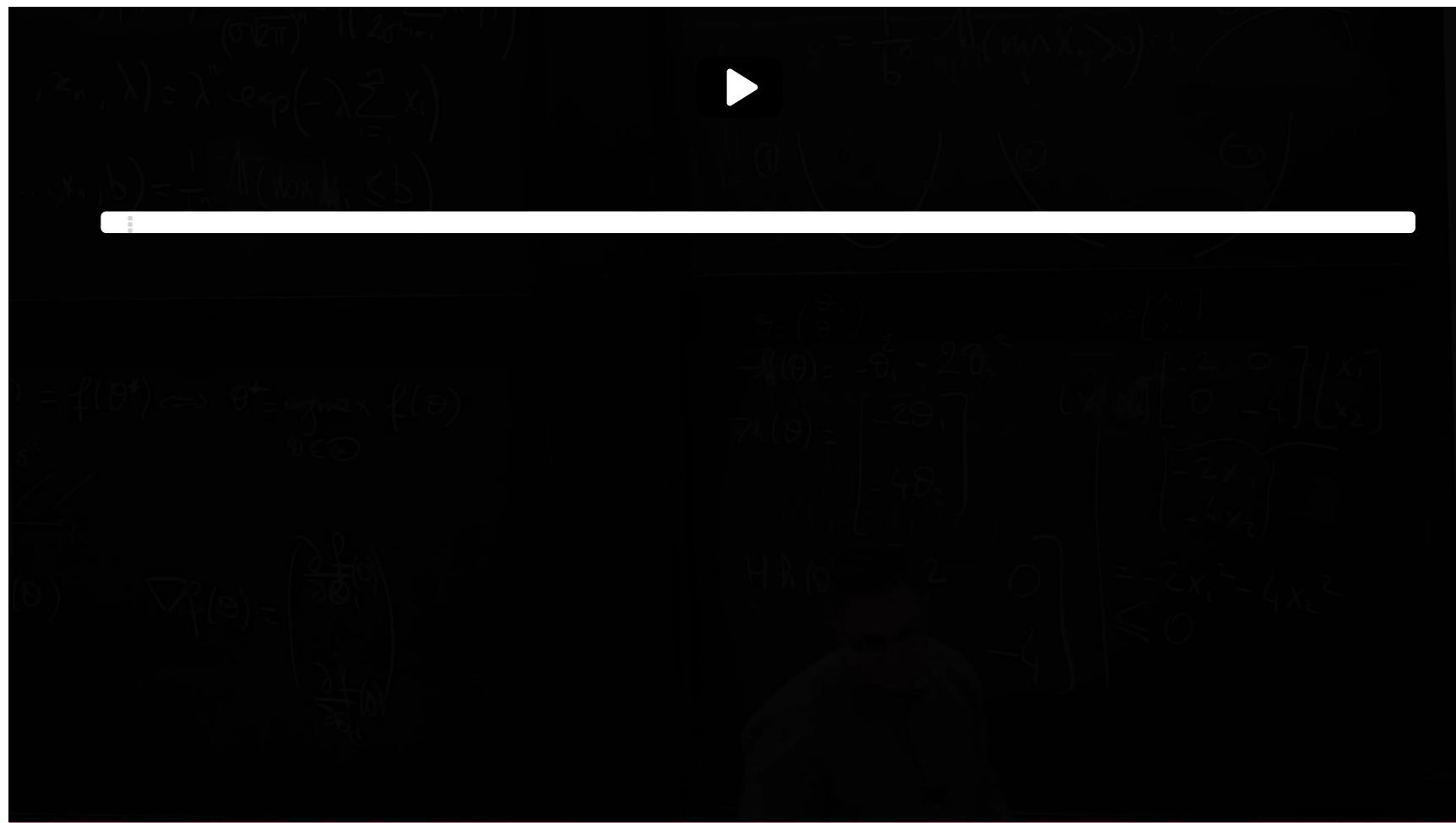


[Course](#) > [Unit 3 Methods of Estimation](#) > [Likelihood Estimation](#) > [Lecture 9: Introduction to Maximum Likelihood Estimation](#) > 8. Review: Gradients and Hessians; Concavity in Higher dimensions

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## 8. Review: Gradients and Hessians; Concavity in Higher dimensions

### Concavity in Higher Dimensions: Gradients, Hessians, Semi-Definiteness



▶ 11:46 / 11:46

▶ 1.50x

**Video**[Download video file](#)**Transcripts**[Download SubRip \(.srt\) file](#)[Download Text \(.txt\) file](#)**Multivariable Calculus Review: Compute the Gradient**

1/1 point (graded)

Let

$$f: \mathbb{R}^d \rightarrow \mathbb{R}$$

$$\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_d \end{pmatrix} \mapsto f(\theta).$$

denote a **differentiable** function. The **gradient** of  $f$  is the vector-valued function

$$\nabla f: \mathbb{R}^d \rightarrow \mathbb{R}^d$$

$$\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_d \end{pmatrix} \mapsto \begin{pmatrix} \frac{\partial f}{\partial \theta_1} \\ \frac{\partial f}{\partial \theta_2} \\ \vdots \\ \frac{\partial f}{\partial \theta_d} \end{pmatrix} \bigg|_{\theta}.$$

Consider  $f(\theta) = -c_1\theta_1^2 - c_2\theta_2^2 - c_3\theta_3^2$  where  $c_1, c_2, c_3 > 0$  are positive real numbers.

Compute the gradient  $\nabla f$ .

(Enter your answer as a vector, e.g., type **[3,2,x]** for the vector  $\begin{pmatrix} 3 \\ 2 \\ x \end{pmatrix}$ . Note the square brackets, and commas as separators. Enter **c\_i** for  $c_i$ , **theta\_i** for  $\theta_i$ .)

$\nabla f =$   **✓ Answer:** [-2\*c\_1\*theta\_1,-2\*c\_2\*theta\_2,-2\*c\_3\*theta\_3]

STANDARD NOTATION

**Solution:**

$$f(\theta) = -c_1\theta_1^2 - c_2\theta_2^2 - c_3\theta_3^2$$

$$\nabla f(\theta) = \left( \begin{array}{c} \frac{\partial f}{\partial \theta_1} \\ \frac{\partial f}{\partial \theta_2} \\ \frac{\partial f}{\partial \theta_3} \end{array} \right) \bigg|_{\theta} = \begin{pmatrix} -2c_1\theta_1 \\ -2c_2\theta_2 \\ -2c_3\theta_3 \end{pmatrix}.$$

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You have used 1 of 3 attempts

**i** Answers are displayed within the problem

## Multivariable Calculus Review: Compute the Hessian Matrix

1/1 point (graded)

As above, let

$$f: \mathbb{R}^d \rightarrow \mathbb{R} \quad \theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_d \end{pmatrix} \mapsto f(\theta).$$

denote a **twice-differentiable** function.The **Hessian** of  $f$  is the matrix

$$\mathbf{H}f: \mathbb{R}^d \rightarrow \mathbb{R}^{d \times d}$$

whose entry in the  $i$ -th row and  $j$ -th column is defined by

$$(\mathbf{H}f)_{ij} := \frac{\partial^2}{\partial \theta_i \partial \theta_j} f, \quad 1 \leq i, j \leq d.$$

The Hessian matrix of  $f$  in this context is also denoted by  $\nabla^2 f$ , the **second derivative** of  $f$ . This is not to be confused with the "Laplacian" of  $f$ , which is also denoted the same way.

Consider the same function  $f(\theta) = -c_1\theta_1^2 - c_2\theta_2^2 - c_3\theta_3^2$  where  $c_1, c_2, c_3 > 0$  as in the previous problem. Compute the Hessian matrix  $\mathbf{H}f$ .

(Enter your answer as a matrix, e.g. by typing `[[1,2],[5*x,y-1]]` for the matrix  $\begin{pmatrix} 1 & 2 \\ 5x & y-1 \end{pmatrix}$ . Note the square brackets, and commas as separators.)

$\mathbf{H}f =$

`[-2*c_1,0,0],[0,-2*c_2,0],[0,0,-2*c_3]`



Answer: `[-2*c_1,0,0],[0,-2*c_2,0],[0,0,-2*c_3]`

STANDARD NOTATION

### Solution:

Recall from the previous problem:

$$f(\theta) = -c_1\theta_1^2 - c_2\theta_2^2 - c_3\theta_3^2$$

$$\nabla f(\theta) = \left( \begin{array}{c} \frac{\partial f}{\partial \theta_1} \\ \frac{\partial f}{\partial \theta_2} \\ \frac{\partial f}{\partial \theta_3} \end{array} \right) \bigg|_{\theta} = \begin{pmatrix} -2c_1\theta_1 \\ -2c_2\theta_2 \\ -2c_3\theta_3 \end{pmatrix}.$$

One way to compute the Hessian is to start with the  $j$ -th column of the Hessian matrix by the gradient of the  $j$ -th component of  $\nabla f$ . We obtain:

$$f(\theta) = -c_1\theta_1^2 - c_2\theta_2^2 - c_3\theta_3^2$$

$$\mathbf{H}f(\theta) = \begin{pmatrix} \nabla \left( \begin{array}{c} | \\ -2c_1\theta_1 \\ | \end{array} \right) & \nabla \left( \begin{array}{c} | \\ -2c_2\theta_2 \\ | \end{array} \right) & \nabla \left( \begin{array}{c} | \\ -2c_3\theta_3 \\ | \end{array} \right) \end{pmatrix}$$

$$= \begin{pmatrix} -2c_1 & 0 & 0 \\ 0 & -2c_2 & 0 \\ 0 & 0 & -2c_3 \end{pmatrix}.$$

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You have used 1 of 3 attempts

**i** Answers are displayed within the problem

## Semi-Definiteness

3/3 points (graded)

A symmetric (real-valued)  $d \times d$  matrix  $\mathbf{A}$  is **positive semi-definite** if

$$\mathbf{x}^T \mathbf{A} \mathbf{x} \geq 0 \quad \text{for all } \mathbf{x} \in \mathbb{R}^d.$$

If the inequality above is strict, i.e. if  $\mathbf{x}^T \mathbf{A} \mathbf{x} > 0$  for all non-zero vectors  $\mathbf{x} \in \mathbb{R}^d$ , then  $\mathbf{A}$  is **positive definite**.

Analogously, a symmetric (real-valued)  $d \times d$  matrix  $\mathbf{A}$  is **negative semi-definite** (*resp.* **negative definite**) if  $\mathbf{x}^T \mathbf{A} \mathbf{x}$  is **non-positive** (*resp.* **negative**) for all  $\mathbf{x} \in \mathbb{R}^d - \{\mathbf{0}\}$ .

Note that by definition, positive (or negative) definiteness implies positive (or negative) semi-definiteness.

Consider the same function as in the problems above:

$$f(\theta) = -c_1\theta_1^2 - c_2\theta_2^2 - c_3\theta_3^2 \quad \text{where } c_1, c_2, c_3 > 0.$$

Compute  $\mathbf{x}^T (\mathbf{H}f) \mathbf{x}$  where  $\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$ .

$\mathbf{x}^T (\mathbf{H}f) \mathbf{x} =$ 

$$-2 \cdot c_1 \cdot x_1^2 - 2 \cdot c_2 \cdot x_2^2 - 2 \cdot c_3 \cdot x_3^2$$

✓ Answer:  $-2 \cdot c_1 \cdot x_1^2 - 2 \cdot c_2 \cdot x_2^2 - 2 \cdot c_3 \cdot x_3^2$ 

$$-2 \cdot c_1 \cdot x_1^2 - 2 \cdot c_2 \cdot x_2^2 - 2 \cdot c_3 \cdot x_3^2$$

The matrix  $\mathbf{H}f$  is (Choose all that apply.)☐ positive semi-definite☐ positive definite☒ negative semi-definite☒ negative definiteHence, the function  $f$  is  
(Choose all that apply.)☒ concave☒ strictly concave☐ convex☐ strictly convex**Solution:**

Recall from the previous problem that

$$\mathbf{H}f(\theta) = \begin{pmatrix} -2c_1 & 0 & 0 \\ 0 & 2c_2 & 0 \\ 0 & 0 & -2c_3 \end{pmatrix}.$$

Then

$$\begin{aligned} \mathbf{x}^T (\mathbf{H}f) \mathbf{x} &= \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} -2c_1 & 0 & 0 \\ 0 & 2c_2 & 0 \\ 0 & 0 & -2c_3 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ &= -2c_1 x_1^2 - 2c_2 x_2^2 - 2c_3 x_3^2 < 0. \end{aligned}$$

Since  $c_1, c_2, c_3 > 0$ , this means the  $\mathbf{H}f$  is negative definite, (also negative semi-definite), and hence  $f$  is strictly concave (also concave).

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☒ strictly convex and convex

Since last option allows for multiple answer, I want to be sure the understanding is right. Something that is convex, is not necessarily strictly convex.. but if something is "Strict..."

5

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