

# Mathematics for Informatics

## Multivariate optimization (lecture 6 of 12)

Francesco DOLCE

`dolcefra@fit.cvut.cz`

Czech Technical University in Prague

Winter 2025/2026

created: October 28, 2025, 19:03

# What shall we do today?

- Multivariate optimization:
  - Gradient
  - Tangent plane
  - Critical points on two or more variables
  - Hessian (matrix)

# Gradient of a function

The **gradient** of a function  $f(x_1, x_2, \dots, x_n)$  at the ( $n$ -dimensional) point  $b \in \mathbb{R}^n$  is the  $n$ -dimensional vector function  $\nabla f(b)$  defined by

$$\nabla f(b) = \left( \frac{\partial f}{\partial x_1}(b), \frac{\partial f}{\partial x_2}(b), \dots, \frac{\partial f}{\partial x_n}(b) \right).$$

# Gradient of a function

The **gradient** of a function  $f(x_1, x_2, \dots, x_n)$  at the ( $n$ -dimensional) point  $b \in \mathbb{R}^n$  is the  $n$ -dimensional vector function  $\nabla f(b)$  defined by

$$\nabla f(b) = \left( \frac{\partial f}{\partial x_1}(b), \frac{\partial f}{\partial x_2}(b), \dots, \frac{\partial f}{\partial x_n}(b) \right).$$

## Example

*Find the gradient of the function  $f(x, y) = x^2 + xy + y^2$  at the point  $(1, 1)$ .*

# Gradient of a function

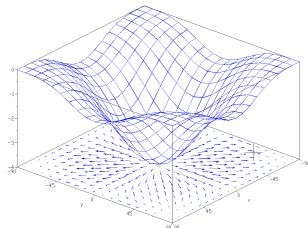
The **gradient** of a function  $f(x_1, x_2, \dots, x_n)$  at the ( $n$ -dimensional) point  $b \in \mathbb{R}^n$  is the  $n$ -dimensional vector function  $\nabla f(b)$  defined by

$$\nabla f(b) = \left( \frac{\partial f}{\partial x_1}(b), \frac{\partial f}{\partial x_2}(b), \dots, \frac{\partial f}{\partial x_n}(b) \right).$$

## Example

Find the gradient of the function  $f(x, y) = x^2 + xy + y^2$  at the point  $(1, 1)$ .

**Geometrical meaning:** the gradient points in the direction of the greatest rate of increase of the function. Its magnitude equals the rate of increase.



# Gradient and the directional derivative

We saw that the partial derivative with respect to  $x$  at the point  $a$  is equal to the slope of tangent line at this point in direction parallel to the  $x$ -axis.

# Gradient and the directional derivative

We saw that the partial derivative with respect to  $x$  at the point  $a$  is equal to the slope of tangent line at this point in direction parallel to the  $x$ -axis.

## Example

*If we are on the graph of the function  $f(x, y) = x^2 + xy + y^2$  at the point  $(1, 1)$  and we start moving in the direction parallel to the  $x$ -axis, i.e., in the direction of the vector  $(1, 0)$ , we will go “uphill” under the angle  $\arctan 3$  since*

$$\frac{\partial f}{\partial x}(1, 1) = 2 + 1 = 3.$$

# Gradient and the directional derivative

We saw that the partial derivative with respect to  $x$  at the point  $a$  is equal to the slope of tangent line at this point in direction parallel to the  $x$ -axis.

## Example

*If we are on the graph of the function  $f(x, y) = x^2 + xy + y^2$  at the point  $(1, 1)$  and we start moving in the direction parallel to the  $x$ -axis, i.e., in the direction of the vector  $(1, 0)$ , we will go “uphill” under the angle  $\arctan 3$  since*

$$\frac{\partial f}{\partial x}(1, 1) = 2 + 1 = 3.$$

What will be the slope if we move in the direction of a general vector  $\vec{v}$ ?



# Gradient and the directional derivative

We saw that the partial derivative with respect to  $x$  at the point  $a$  is equal to the slope of tangent line at this point in direction parallel to the  $x$ -axis.

## Example

If we are on the graph of the function  $f(x, y) = x^2 + xy + y^2$  at the point  $(1, 1)$  and we start moving in the direction parallel to the  $x$ -axis, i.e., in the direction of the vector  $(1, 0)$ , we will go “uphill” under the angle  $\arctan 3$  since

$$\frac{\partial f}{\partial x}(1, 1) = 2 + 1 = 3.$$

What will be the slope if we move in the direction of a general vector  $\vec{v}$ ?

## Theorem

Given a function  $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ , a point  $a \in \mathbb{R}^n$  and a **unit** vector  $\vec{v} \in \mathbb{R}^n$ , the *derivative in the direction of the vector  $\vec{v}$*  is the dot product of the gradient and  $\vec{v}$ , i.e.,  $\nabla f(a_1, a_2, \dots, a_n) \cdot \vec{v}$ .

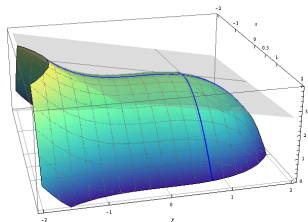
# Tangent plane

The **tangent plane** to a function  $f(x, y)$  at the point  $(x_0, y_0)$  is a 2-dimensional plane that “touches” the graph of the function at  $(x_0, y_0)$ .

# Tangent plane

The **tangent plane** to a function  $f(x, y)$  at the point  $(x_0, y_0)$  is a 2-dimensional plane that “touches” the graph of the function at  $(x_0, y_0)$ . Its equation is

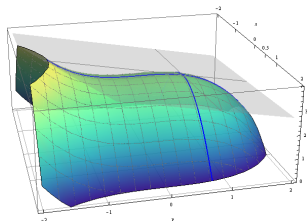
$$z = \frac{\partial f}{\partial x}(x_0, y_0) \cdot (x - x_0) + \frac{\partial f}{\partial y}(x_0, y_0) \cdot (y - y_0) + f(x_0, y_0).$$



# Tangent plane

The **tangent plane** to a function  $f(x, y)$  at the point  $(x_0, y_0)$  is a 2-dimensional plane that “touches” the graph of the function at  $(x_0, y_0)$ . Its equation is

$$z = \frac{\partial f}{\partial x}(x_0, y_0) \cdot (x - x_0) + \frac{\partial f}{\partial y}(x_0, y_0) \cdot (y - y_0) + f(x_0, y_0).$$



## Example

Find the tangent plane to  $f(x, y) = x^2 + xy + y^2$  at  $(1, 1)$ .

# Critical points – two variables

- In the one dimensional case the critical points are those points where the tangent line is parallel to the  $x$ -axis, i.e., points where  $f'(x) = 0$ , or where the derivative does not exist.

# Critical points – two variables

- In the one dimensional case the critical points are those points where the tangent line is parallel to the  $x$ -axis, i.e., points where  $f'(x) = 0$ , or where the derivative does not exist.
- The **critical points** of a two variable function are those points where the tangent plane is parallel to the plane given by the  $x$ -axis and the  $y$ -axis or where the gradient does not exist.

# Critical points – two variables

- In the one dimensional case the critical points are those points where the tangent line is parallel to the  $x$ -axis, i.e., points where  $f'(x) = 0$ , or where the derivative does not exist.
- The **critical points** of a two variable function are those points where the tangent plane is parallel to the plane given by the  $x$ -axis and the  $y$ -axis or where the gradient does not exist.

The first class of these points can be found as a solution of

$$\nabla f(x, y) = (0, 0)$$

which leads to the system of two equations for two variables

$$\begin{cases} \frac{\partial f}{\partial x}(x, y) = 0 \\ \frac{\partial f}{\partial y}(x, y) = 0 \end{cases} .$$

# Critical points – more variables

For an  $n$ -variable function  $f(x_1, x_2, \dots, x_n)$  the situation is analogous:  
The **critical points** of  $f(x_1, x_2, \dots, x_n)$  are points satisfying the equation

$$\nabla f(x_1, x_2, \dots, x_n) = 0$$

i.e., points satisfying the system of  $n$  equations for  $n$  variables

$$\left\{ \begin{array}{lcl} \frac{\partial f}{\partial x_1}(x_1, x_2, \dots, x_n) & = & 0 \\ \frac{\partial f}{\partial x_2}(x_1, x_2, \dots, x_n) & = & 0 \\ & \vdots & \\ \frac{\partial f}{\partial x_n}(x_1, x_2, \dots, x_n) & = & 0 \end{array} \right. ,$$

or where the gradient does not exist.



# Critical points – more variables

For an  $n$ -variable function  $f(x_1, x_2, \dots, x_n)$  the situation is analogous:  
The **critical points** of  $f(x_1, x_2, \dots, x_n)$  are points satisfying the equation

$$\nabla f(x_1, x_2, \dots, x_n) = 0$$

i.e., points satisfying the system of  $n$  equations for  $n$  variables

$$\left\{ \begin{array}{lcl} \frac{\partial f}{\partial x_1}(x_1, x_2, \dots, x_n) & = & 0 \\ \frac{\partial f}{\partial x_2}(x_1, x_2, \dots, x_n) & = & 0 \\ & \vdots & \\ \frac{\partial f}{\partial x_n}(x_1, x_2, \dots, x_n) & = & 0 \end{array} \right. ,$$

or where the gradient does not exist.

(Instead of a tangent plane, we have a **tangent hyperplane**.)

# Critical points – example

## Example

*Find all critical points of*

$$f(x_1, x_2, x_3) = x_1x_3 + x_1^2 - x_2 + x_2x_3 + x_2^2 + 3x_3^2,$$

# Critical points – example

## Example

*Find all critical points of*

$$f(x_1, x_2, x_3) = x_1x_3 + x_1^2 - x_2 + x_2x_3 + x_2^2 + 3x_3^2,$$

We get

$$\nabla f(x_1, x_2, x_3) = (x_3 + 2x_1, -1 + x_3 + 2x_2, x_1 + x_2 + 6x_3)$$

which always exists.

# Critical points – example

## Example

Find all critical points of

$$f(x_1, x_2, x_3) = x_1x_3 + x_1^2 - x_2 + x_2x_3 + x_2^2 + 3x_3^2,$$

We get

$$\nabla f(x_1, x_2, x_3) = (x_3 + 2x_1, -1 + x_3 + 2x_2, x_1 + x_2 + 6x_3)$$

which always exists. Thus the critical points are the solution of the system

$$\begin{cases} x_3 + 2x_1 &= 0 \\ -1 + x_3 + 2x_2 &= 0 \\ x_1 + x_2 + 6x_3 &= 0 \end{cases},$$

which, using the standard procedure for a system of linear equations, gives us the only solution  $\left(\frac{1}{20}, \frac{11}{20}, \frac{-1}{10}\right)$ .

# Type of a critical point (1 of 4)

In the one dimensional case, we can use the second derivative to decide the type of the critical point.

## Theorem

Let  $x_0$  be a critical point of a function  $f(x)$  such that  $f'(x_0) = 0$  and  $f''(x_0)$  exists.

- If  $f''(x_0) > 0$ , then the function is **convex** at  $x_0$ , and  $x_0$  is a point of a minimum.
- If  $f''(x_0) < 0$ , then the function is **concave** at  $x_0$ , and  $x_0$  is a point of a maximum.
- If  $f''(x_0) = 0$ , then  $x_0$  may be a minimum, maximum, inflection point, ...

# Type of a critical point (1 of 4)

In the one dimensional case, we can use the second derivative to decide the type of the critical point.

## Theorem

Let  $x_0$  be a critical point of a function  $f(x)$  such that  $f'(x_0) = 0$  and  $f''(x_0)$  exists.

- If  $f''(x_0) > 0$ , then the function is **convex** at  $x_0$ , and  $x_0$  is a point of a minimum.
- If  $f''(x_0) < 0$ , then the function is **concave** at  $x_0$ , and  $x_0$  is a point of a maximum.
- If  $f''(x_0) = 0$ , then  $x_0$  may be a minimum, maximum, inflection point, ...

Do we have something similar for more variables? What is the second derivative?

# Type of a critical point (2 of 4)

The analogue of the second derivative is the following.

## Definition

For a function  $f(x_1, x_2, \dots, x_n)$  we define the *Hessian matrix* as

$$\nabla^2 f(x_1, x_2, \dots, x_n) = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2}(x_1, \dots, x_n) & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n}(x_1, \dots, x_n) \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1}(x_1, \dots, x_n) & \cdots & \frac{\partial^2 f}{\partial x_n^2}(x_1, \dots, x_n) \end{pmatrix}$$

*assuming that all the derivatives exist.*

# Type of a critical point (3 of 4)

We would like to construct rules like “If  $f''(x_0) > 0$ , then the critical point  $x_0$  is the point of minimum”.

But to say that the matrix is “positive” is problematic . . . Let us use a different notion.



# Type of a critical point (3 of 4)

We would like to construct rules like “If  $f''(x_0) > 0$ , then the critical point  $x_0$  is the point of minimum”.

But to say that the matrix is “positive” is problematic ... Let us use a different notion.

## Definition

A matrix  $A \in \mathbb{R}^{n,n}$  is

- ① *positively definite* if for all non-zero vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T > 0$ ;

# Type of a critical point (3 of 4)

We would like to construct rules like “If  $f''(x_0) > 0$ , then the critical point  $x_0$  is the point of minimum”.

But to say that the matrix is “positive” is problematic . . . Let us use a different notion.

## Definition

A matrix  $A \in \mathbb{R}^{n,n}$  is

- Ⓐ *positively definite* if for all non-zero vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T > 0$ ;
- Ⓑ *positively semidefinite* if for all vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T \geq 0$  and the equality is true for at least one non-zero vector  $b \in \mathbb{R}^n$ ;

# Type of a critical point (3 of 4)

We would like to construct rules like “If  $f''(x_0) > 0$ , then the critical point  $x_0$  is the point of minimum”.

But to say that the matrix is “positive” is problematic ... Let us use a different notion.

## Definition

A matrix  $A \in \mathbb{R}^{n,n}$  is

- (i) *positively definite* if for all non-zero vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T > 0$ ;
- (ii) *positively semidefinite* if for all vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T \geq 0$  and the equality is true for at least one non-zero vector  $b \in \mathbb{R}^n$ ;
- (iii) *negatively definite* if for all non-zero vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T < 0$ ;
- (iv) *negatively semidefinite* if for all vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T \leq 0$  and the equality is true for at least one non-zero vector  $b \in \mathbb{R}^n$ ;

# Type of a critical point (3 of 4)

We would like to construct rules like “If  $f''(x_0) > 0$ , then the critical point  $x_0$  is the point of minimum”.

But to say that the matrix is “positive” is problematic ... Let us use a different notion.

## Definition

A matrix  $A \in \mathbb{R}^{n,n}$  is

- (i) *positively definite* if for all non-zero vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T > 0$ ;
- (ii) *positively semidefinite* if for all vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T \geq 0$  and the equality is true for at least one non-zero vector  $b \in \mathbb{R}^n$ ;
- (iii) *negatively definite* if for all non-zero vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T < 0$ ;
- (iv) *negatively semidefinite* if for all vectors  $a \in \mathbb{R}^n$  it holds that  $aAa^T \leq 0$  and the equality is true for at least one non-zero vector  $b \in \mathbb{R}^n$ ;
- (v) *indefinite* otherwise.

# Type of a critical point (4 of 4)

## Theorem

If  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  has all second partial derivative continuous at a critical point  $b \in \mathbb{R}^n$ , then

- (i) if  $\nabla^2 f(b)$  is positively definite, then  $b$  is a point of local minimum;
- (ii) if  $\nabla^2 f(b)$  is negatively definite, then  $b$  is a point of local maximum;
- (iii) if  $\nabla^2 f(b)$  is indefinite, then  $b$  is a saddle point.

# Sylvester's criterion on definiteness

For an  $n \times n$  dimensional **symmetric** matrix  $A$  we define the **principal minors**:

- $M_1$  is the upper left 1-by-1 corner of  $A$ ,
- $M_2$  is the upper left 2-by-2 corner of  $A$ ,
- ...
- $M_n$  is the upper left  $n$ -by- $n$  corner of  $A$ .

## Theorem

Let  $A \in \mathbb{R}^{n,n}$  be a symmetric matrix.

- $A$  is positively definite if and only if the determinants of all principal minors are positive.
- $A$  is negatively definite if and only if the determinant of  $M_i$  is negative for odd  $i$  and positive for even  $i$ .

# Example

## Example

*Find all minima and maxima of the function*

$$f(x, y) = \frac{3x^4 - 4x^3 - 12x^2 + 18}{12(1 + 4y^2)}.$$

# Example

## Example

*Find all minima and maxima of the function*

$$f(x, y) = \frac{3x^4 - 4x^3 - 12x^2 + 18}{12(1 + 4y^2)}.$$

**Solution:** The critical points are  $(-1, 0)$ ,  $(0, 0)$  and  $(2, 0)$ ; they are a saddle point, a point of maximum and a point of minimum, respectively.

