

# MA2104 - Multivariable Calculus

Liew Zhao Wei

Semester 1, 2023-2024

---

## 1 Vectors

Multivariable calculus is the study of *scalar fields* and *vector fields*.

### Definition 1.1 (Scalar Field)

A *scalar field* is a map  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ . It is also called a *scalar-valued* function.

### Definition 1.2 (Vector Field)

A *vector field* is a map  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ . It is also called a *vector-valued* function.

## 2 Coordinate Systems

Cylindrical and spherical coordinates are both natural extensions of the polar coordinates in  $\mathbb{R}^2$ , but in slightly different ways – cylindrical coordinates tack on a  $z$ -coordinate, while spherical coordinates tack on an angle  $\rho$  from the positive  $z$ -axis.

### 2.1 Cylindrical Coordinates

*Cylindrical coordinates* are useful for describing objects with an axis of symmetry.

#### Definition 2.1 (Cylindrical Coordinate Conversions)

We can convert between cylindrical and cartesian coordinates like so:

$$\text{Cylindrical to Cartesian: } \begin{cases} x = r \cos \theta \\ y = r \sin \theta \\ z = z \end{cases} \quad \text{Cartesian to Cylindrical: } \begin{cases} r^2 = x^2 + y^2 \\ \tan \theta = y/x \\ z = z \end{cases}$$

We typically impose the constraints  $r \geq 0$  and  $0 \leq \theta < 2\pi$  to ensure that all points on  $\mathbb{R}^3$ , except those on the  $z$ -axis, are uniquely represented.

### 2.2 Spherical Coordinates

*Spherical coordinates* are useful for describing objects with a centre of symmetry.

#### Definition 2.2 (Spherical Coordinate Conversions)

We can convert between spherical and cartesian coordinates like so:

$$\text{Spherical to Cartesian: } \begin{cases} x = \rho \sin \varphi \cos \theta \\ y = \rho \sin \varphi \sin \theta \\ z = \rho \cos \varphi \end{cases} \quad \text{Cartesian to Spherical: } \begin{cases} \rho^2 = x^2 + y^2 + z^2 \\ \tan \theta = y/x \\ \cos \varphi = \sqrt{x^2 + y^2}/\rho \end{cases}$$

We typically impose the constraints  $\rho \geq 0$ ,  $0 \leq \theta < 2\pi$  and  $0 \leq \varphi \leq \pi$  to ensure that all points on  $\mathbb{R}^3$ , except the origin, are uniquely represented.

## 2.3 Hyperspherical Coordinates

We can even generalize spherical coordinates to higher dimensions in the form of *hyperspherical coordinates*. The idea is to tack on more angles to the spherical coordinates, so that we can describe objects with more axes of symmetry.

### Definition 2.3 (Hyperspherical Coordinate Conversions)

$$\text{Spherical to Cartesian: } \begin{cases} x_1 = \rho \sin \varphi_1 \cdots \sin \varphi_{n-2} \cos \varphi_{n-1} \\ x_2 = \rho \sin \varphi_1 \cdots \sin \varphi_{n-2} \sin \varphi_{n-1} \\ x_3 = \rho \sin \varphi_1 \cdots \sin \varphi_{n-3} \cos \varphi_{n-2} \\ x_4 = \rho \sin \varphi_1 \cdots \sin \varphi_{n-4} \cos \varphi_{n-3} \\ \vdots \\ x_n = \rho \cos \varphi_1 \end{cases}$$

Notice the similarity with spherical coordinates.

Just like for spherical coordinates, we typically impose the constraints

$$\begin{aligned} 0 &\leq \rho \\ 0 &\leq \varphi_i \leq \pi && \text{for } i = 1, \dots, n-2 \\ 0 &\leq \varphi_{n-1} < 2\pi \end{aligned}$$

to ensure that all points on  $\mathbb{R}^n$ , except the origin, are uniquely represented.

## 3 Basic Topology

We begin with some basic topological definitions and results that we'll use later on.

### Definition 3.1 (Neighbourhood)

A *neighbourhood* of a point  $p$  is a set  $N_r(p)$  consisting of all points  $q$  such that  $\|q - p\| < r$  for some  $r > 0$ .

An *open ball* with center  $p \in \mathbb{R}^n$  and radius  $r$  is a neighbourhood  $N_r(p)$  in  $\mathbb{R}^n$ . A *closed ball* is similarly defined, but with  $\|q - p\| \leq r$  instead.

### Definition 3.2 (Limit point)

A point  $p$  is a *limit point* of a set  $S$  if every neighbourhood of  $p$  contains a point  $q \in S$  such that  $q \neq p$ . Such a point is also called an *accumulation point*.

### Definition 3.3 (Isolated point)

An *isolated point* of a set  $S$  is a point  $p \in S$  such that  $p$  is not a limit point of  $S$ . That is, there is some neighbourhood of  $p$  that contains no other points of  $S$ .

### Definition 3.4 (Interior point)

An *interior point* of a set  $S$  is a point  $p \in S$  such that there is some neighbourhood of  $p$  that is contained in  $S$ .

**Definition 3.5 (Open set)**

A set  $S$  is *open* if every point of  $S$  is an interior point of  $S$ .

**Definition 3.6 (Closed set)**

A set  $S$  is *closed* if it contains all of its limit points.

**Theorem 3.7 (Complement of open set is closed)**

A set is open if and only if its complement is closed.

## 4 Limits and Continuity

We begin by extending the definitions of limits and continuity to vector fields.

### 4.1 Limits

**Definition 4.1 (Limit)**

Consider a function  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ . We write

$$\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x}) = \mathbf{L} \quad (1)$$

to mean that given any  $\epsilon > 0$ , there is a  $\delta > 0$  such that if  $0 < \|\mathbf{x} - \mathbf{a}\| < \delta$ , then  $\|\mathbf{f}(\mathbf{x}) - \mathbf{L}\| < \epsilon$ .

Intuitively, this means that  $\mathbf{f}(\mathbf{x})$  can be made arbitrarily close to  $\mathbf{L}$  by taking  $\mathbf{x}$  sufficiently close to  $\mathbf{a}$ . The geometric interpretation is that given an open ball  $B_\epsilon$  centred at  $\mathbf{L}$ , there is an open ball  $B_\delta$  centred at  $\mathbf{a}$  such that  $\mathbf{f}(\mathbf{x})$  is contained in  $B_\epsilon$  whenever  $\mathbf{x}$  is contained in  $B_\delta$ .

The usual theorems concerning limits of sums, products, and quotients hold for scalar fields. For vector fields, we have natural extensions of these theorems, but without quotients.

**Theorem 4.2 (Algebraic Properties of Limits)**

Suppose that  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x}) = \mathbf{L}$  and  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{g}(\mathbf{x}) = \mathbf{M}$ . Then

1.  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x}) = \mathbf{L} + \mathbf{M}$
2.  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} c\mathbf{f}(\mathbf{x}) = c\mathbf{L}$  for any scalar  $c$
3.  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x}) \cdot \mathbf{g}(\mathbf{x}) = \mathbf{L} \cdot \mathbf{M}$
4.  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \|\mathbf{f}(\mathbf{x})\| = \|\mathbf{L}\|$

(3) is proved by rewriting

$$\mathbf{f}(\mathbf{x}) \cdot \mathbf{g}(\mathbf{x}) - \mathbf{L} \cdot \mathbf{M} = (\mathbf{f}(\mathbf{x}) - \mathbf{L}) \cdot (\mathbf{g}(\mathbf{x}) - \mathbf{M}) + \mathbf{L} \cdot (\mathbf{g}(\mathbf{x}) - \mathbf{M}) + \mathbf{M} \cdot (\mathbf{f}(\mathbf{x}) - \mathbf{L})$$

(4) is proved by using (3) and the fact that  $\|\mathbf{v}\| = \sqrt{\mathbf{v} \cdot \mathbf{v}}$ .

**Theorem 4.3 (Uniqueness of Limits)**

If  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x})$  exists, then it is unique.

**Theorem 4.4 (Limit Exists Iff Limit of Components Exist)**

Consider a function  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ . Then  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x})$  exists if and only if  $\lim_{\mathbf{x} \rightarrow \mathbf{a}} f_i(\mathbf{x})$  exists for each  $i = 1, \dots, m$ . In this case,

$$\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x}) = \left( \lim_{\mathbf{x} \rightarrow \mathbf{a}} f_1(\mathbf{x}), \dots, \lim_{\mathbf{x} \rightarrow \mathbf{a}} f_m(\mathbf{x}) \right) \quad (2)$$

This is proved by observing that  $f_i = \mathbf{f} \cdot \mathbf{e}_i$ , and applying the algebraic properties of limits.

## 4.2 Continuity

**Definition 4.5 (Continuity)**

Consider a function  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$  and let  $\mathbf{a} \in X$ .  $\mathbf{f}$  is *continuous at  $\mathbf{a}$*  if either  $\mathbf{a}$  is an isolated point of  $X$  or if

$$\lim_{\mathbf{x} \rightarrow \mathbf{a}} \mathbf{f}(\mathbf{x}) = \mathbf{f}(\mathbf{a}) \quad (3)$$

If  $\mathbf{f}$  is continuous at every point of  $X$ , then we simply say that  $\mathbf{f}$  is *continuous*.

Observe that many of the properties of limits also hold for continuity.

**Theorem 4.6 (Continuity of Composite Functions)**

If  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$  is continuous at  $\mathbf{a}$  and  $\mathbf{g}: Y \subseteq \mathbb{R}^m \rightarrow \mathbb{R}^p$  is continuous at  $\mathbf{f}(\mathbf{a})$ , then  $\mathbf{g} \circ \mathbf{f}$  is continuous at  $\mathbf{a}$ .

## 5 Derivatives

Now, we extend the definition of derivatives to vector fields.

### 5.1 Partial Derivatives

**Definition 5.1 (Directional Derivative)**

Consider a scalar field  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  and let  $\mathbf{a} \in X$ . If  $\mathbf{v}$  is a unit vector, then the *directional derivative of  $f$  at  $\mathbf{a}$  in the direction of  $\mathbf{v}$*  is

$$D_{\mathbf{v}}f(\mathbf{a}) = \lim_{h \rightarrow 0} \frac{f(\mathbf{a} + h\mathbf{v}) - f(\mathbf{a})}{h} \quad (4)$$

if the limit exists.

**Definition 5.2 (Partial Derivative)**

Consider a scalar field  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  and let  $\mathbf{a} \in X$ . The *partial derivative of  $f$  with respect to  $x_i$  at  $\mathbf{a}$*  is the directional derivative of  $f$  at  $\mathbf{a}$  in the direction of  $\mathbf{e}_i$  and is denoted by  $\frac{\partial f}{\partial x_i}$ ,  $f_{x_i}(\mathbf{a})$ , or  $D_{x_i}f(\mathbf{a})$ .

**Definition 5.3 (Smoothness of a Function)**

Let  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be a scalar field whose partial derivatives up to order  $k$  exist and are continuous. Then,  $f$  is said to be of class  $C^k$ . If  $f$  is of class  $C^k$  for all  $k \geq 1$ , then  $f$  is said to be of class  $C^\infty$  or *smooth*.

**Theorem 5.4 (Order of Continuous Partial Derivatives Does not Matter)**

Let  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be a scalar field of class  $C^k$ . Then the order in which we compute any  $k$ th-order partial derivative does not matter. That is, for any  $i_1, \dots, i_k \in \{1, \dots, n\}$ , we have

$$\frac{\partial^k f}{\partial x_{i_1} \cdots \partial x_{i_k}} = \frac{\partial^k f}{\partial x_{\sigma(i_1)} \cdots \partial x_{\sigma(i_k)}} \quad (5)$$

**5.2 Total derivatives**

The definitions of differentiability for scalar fields generalize naturally to vector fields, so I will simply state the ones for vector fields.

**Definition 5.5 (Jacobian Matrix)**

Consider a vector field  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ . Define  $D\mathbf{f}$  to be

$$D\mathbf{f} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} \quad (6)$$

$D\mathbf{f}$  is called the *Jacobian matrix* of  $\mathbf{f}$ . The  $i$ th row of  $D\mathbf{f}$  is the gradient vector  $\nabla f_i$ .

Observe that  $D\mathbf{f}$  is a linear map from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ . We will see that if a derivative exists at  $\mathbf{a}$ , then it must be equal to  $D\mathbf{f}(\mathbf{a})$ .

**Definition 5.6 (Differentiability)**

Consider a vector field  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$  and let  $\mathbf{a} \in X$ .  $\mathbf{f}$  is *differentiable at  $\mathbf{a}$*  if the linear map  $D\mathbf{f}(\mathbf{a})$  exists and

$$\lim_{\mathbf{x} \rightarrow \mathbf{a}} \frac{\|\mathbf{f}(\mathbf{x}) - (\mathbf{f}(\mathbf{a}) + D\mathbf{f}(\mathbf{a})(\mathbf{x} - \mathbf{a}))\|}{\|\mathbf{x} - \mathbf{a}\|} = 0 \quad (7)$$

$\mathbf{f}$  is also said to be *differentiable at  $\mathbf{a}$* .

If  $\mathbf{f}$  is differentiable at  $\mathbf{a}$ , then the function  $\mathbf{h}(\mathbf{x}) = \mathbf{f}(\mathbf{a}) + D\mathbf{f}(\mathbf{a})(\mathbf{x} - \mathbf{a})$  is the *tangent hyperplane* of  $\mathbf{f}$  at  $\mathbf{a}$  and is a good linear approximation of  $\mathbf{f}$  near  $\mathbf{a}$ .

The results for scalar fields generalize naturally to vector fields too.

**Theorem 5.7 (Differentiability Implies Continuity)**

If  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$  is differentiable at  $\mathbf{a}$ , then it is also continuous at  $\mathbf{a}$ .

**Theorem 5.8 (Continuity and Existence of Partial Derivatives Imply Differentiability)**

If  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$  is continuous at  $\mathbf{a}$  and if all the partial derivatives of  $\mathbf{f}$  exist in some neighbourhood of  $\mathbf{a}$ , then  $\mathbf{f}$  is differentiable at  $\mathbf{a}$ .

**Theorem 5.9 (Differentiable Iff Components are Differentiable)**

Consider a vector field  $\mathbf{f}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ .  $\mathbf{f}$  is differentiable at  $\mathbf{a}$  if and only if each component function  $f_i$  is differentiable at  $\mathbf{a}$ .

Some familiar algebraic properties of derivatives also hold for vector fields.

**Theorem 5.10 (Linearity of Differentiation)**

If  $\mathbf{f}, \mathbf{g}: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$  are differentiable at  $\mathbf{a}$  and  $c$  is a scalar, then

1.  $D(c\mathbf{f})(\mathbf{a}) = cD\mathbf{f}(\mathbf{a})$
2.  $D(\mathbf{f} + \mathbf{g})(\mathbf{a}) = D\mathbf{f}(\mathbf{a}) + D\mathbf{g}(\mathbf{a})$

For scalar-valued functions, product and quotient properties hold too.

**Theorem 5.11 (Product and Quotient of Derivatives)**

If  $f, g: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  are differentiable at  $\mathbf{a}$ , then

1.  $D(fg)(\mathbf{a}) = g(\mathbf{a})Df(\mathbf{a}) + f(\mathbf{a})Dg(\mathbf{a})$
2.  $D\left(\frac{f}{g}\right)(\mathbf{a}) = \frac{g(\mathbf{a})Df(\mathbf{a}) - f(\mathbf{a})Dg(\mathbf{a})}{g(\mathbf{a})^2}$

### 5.3 Chain Rule

We use the chain rule so much that it deserves its own section.

**Theorem 5.12 (Chain Rule)**

Consider the vector fields  $\mathbf{f}: X \subseteq \mathbb{R}^m \rightarrow \mathbb{R}^p$  and  $\mathbf{g}: Y \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ . If  $\mathbf{g}$  is differentiable at  $\mathbf{x} \in Y$  and  $\mathbf{f}$  is differentiable at  $\mathbf{g}(\mathbf{x})$ , then  $\mathbf{f} \circ \mathbf{g}$  is differentiable at  $\mathbf{x}$  and

$$D(\mathbf{f} \circ \mathbf{g})(\mathbf{x}) = D\mathbf{f}(\mathbf{g}(\mathbf{x}))D\mathbf{g}(\mathbf{x}) \quad (8)$$

The chain rule is also used in implicit differentiation under a condition stipulated by the following theorem.

**Theorem 5.13 (Implicit Function Theorem)**

Consider the scalar field  $F: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  of class  $C^1$ . Let  $\mathbf{a}$  be a point of the level set  $S = \{\mathbf{x} \in \mathbb{R}^n \mid f(\mathbf{x}) = c\}$ . If  $F_{x_n}(\mathbf{a}) \neq 0$ , then there is a neighbourhood  $U$  of  $(a_1, \dots, a_{n-1}) \in \mathbb{R}^{n-1}$ , a neighbourhood  $V$  of  $a_n \in \mathbb{R}$ , and a function  $f: U \subseteq \mathbb{R}^{n-1} \rightarrow V$  of class  $C^1$  such that if  $(x_1, \dots, x_{n-1}) \in U$  and  $x_n \in V$  satisfy  $F(x_1, \dots, x_{n-1}, x_n) = c$ , then  $x_n = f(x_1, \dots, x_{n-1})$ .

## 6 Maxima, Minima, and Saddle Points

Calculus is largely useful in solving optimization problems involving the extrema of scalar fields.

**Definition 6.1 (Stationary Point)**

A point  $\mathbf{a}$  is a *stationary point* of a differentiable scalar field  $f$  if  $\nabla f(\mathbf{a}) = \mathbf{0}$ .

**Definition 6.2 (Critical Point)**

A point  $\mathbf{a}$  is a *critical point* of a differentiable scalar field  $f$  if it is stationary or if  $\nabla f(\mathbf{a})$  does not exist.

**Definition 6.3 (Extrema)**

Let  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be a differentiable scalar field. A point  $\mathbf{a}$  is a *local/relative minimum* of  $f$  if there is some neighbourhood  $N$  of  $\mathbf{a}$  such that  $f(\mathbf{a}) \leq f(\mathbf{x})$  for all  $\mathbf{x} \in N$ . Similarly,  $\mathbf{a}$  is a *local/relative maximum* of  $f$  if there is some neighbourhood  $N$  of  $\mathbf{a}$  such that  $f(\mathbf{a}) \geq f(\mathbf{x})$  for all  $\mathbf{x} \in N$ . If  $\mathbf{a}$  is either a local minimum or a local maximum, then it is an *extremum* of  $f$ .

**Theorem 6.4 (Extremum Implies Stationary)**

Let  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be a differentiable scalar field. If  $\mathbf{a} \in X$  is a local extremum of  $f$ , then it is stationary. That is,  $\nabla f(\mathbf{a}) = \mathbf{0}$ .

Note that the converse is not true, which is the case for saddle points.

**Definition 6.5 (Saddle Point)**

Let  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be a differentiable scalar field. A stationary point  $\mathbf{a}$  is a *saddle point* if  $\mathbf{a}$  is not a local extremum of  $f$ . That is, every neighbourhood of  $\mathbf{a}$  contains points  $\mathbf{x}$  such that  $f(\mathbf{x}) < f(\mathbf{a})$  and others such that  $f(\mathbf{x}) > f(\mathbf{a})$ .

**6.1 Second Derivative Test**

To determine the nature of a critical point, we can use the *second partial derivative test*.

**Definition 6.6 (Hessian Matrix)**

Consider a differentiable scalar field  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ . The *Hessian matrix* of  $f$  is

$$Hf = \begin{bmatrix} f_{x_1 x_1} & \cdots & f_{x_1 x_n} \\ \vdots & \ddots & \vdots \\ f_{x_n x_1} & \cdots & f_{x_n x_n} \end{bmatrix} \quad (9)$$

**Theorem 6.7 (Second Partial Derivative Test)**

Let  $f: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be a differentiable scalar field. Given a stationary point  $\mathbf{a} \in X$  of  $f$ , consider the sequence of leading principal minors  $d_k$  of the Hessian matrix  $Hf(\mathbf{a})$  where

$$d_k = \begin{vmatrix} f_{x_1 x_1}(\mathbf{a}) & \cdots & f_{x_1 x_k}(\mathbf{a}) \\ \vdots & \ddots & \vdots \\ f_{x_k x_1}(\mathbf{a}) & \cdots & f_{x_k x_k}(\mathbf{a}) \end{vmatrix} \quad (10)$$

for all  $1 \leq k \leq n$ . Then, the following cases hold:

1. If  $d_k > 0$  for all  $k$ , then  $\mathbf{a}$  is a local minimum of  $f$ .
2. If  $d_k > 0$  for even  $k$  and  $d_k < 0$  for odd  $k$ , then  $\mathbf{a}$  is a local maximum of  $f$ .
3. Otherwise,  $\mathbf{a}$  is a saddle point of  $f$ .

If  $\det Hf(\mathbf{a}) = 0$ , we say that  $\mathbf{a}$  is *degenerate*.

The cases above can also be expressed in terms of the eigenvalues of  $Hf(\mathbf{a})$ :

1. If all eigenvalues are positive (equivalently, the Hessian is positive definite), then  $\mathbf{a}$  is a local minimum of  $f$ .
2. If all eigenvalues are negative (equivalently, the Hessian is negative definite), then  $\mathbf{a}$  is a local maximum of  $f$ .
3. Otherwise, if  $\det Hf(\mathbf{a}) \neq 0$ , then  $\mathbf{a}$  is a saddle point of  $f$ .

**6.2 Lagrange's Multipliers**

Lagrange's Multipliers come in handy when solving extremum problems with constraints. The method stems from the following theorem.

**Theorem 6.8** (Lagrange's Multipliers)

Let  $f, g: X \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$  be scalar fields of class  $C^1$ . Let  $S = \{x \in X \mid g(\mathbf{x}) = c\}$  denote the level set of  $g$  at height  $c$ . Then if  $f$  restricted to  $S$  has an extremum at point  $\mathbf{a} \in S$  such that  $\nabla g(\mathbf{a}) \neq \mathbf{0}$ , then

$$\nabla f(\mathbf{a}) = \lambda \nabla g(\mathbf{a}) \tag{11}$$

for some scalar  $\lambda$ .