

## ADDITIONAL NOTES ON DIFFERENTIATION

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### 1. THE $o$ NOTATION

It is very convenient to use the notation  $o(h)$  for any function that, after been divided by  $h$ , tends to zero as  $h$  tends to zero. More precisely, if a function  $f(h)$ , which is defined in some interval around 0 has the property

$$\lim_{h \rightarrow 0} \frac{f(h)}{h} = 0$$

we may write briefly

$$f(h) = o(h) \text{ as } h \rightarrow 0.$$

Here  $h$  can be any expression.

Intuitively, this means that  $f(h)$  tends to zero faster than  $h$  itself. E.g.  $f(h) = h^2 = o(h)$  because  $\frac{f(h)}{h} = \frac{h^2}{h} = h$  tends to zero as  $h$  tends to zero. Other examples are  $f(x) = x \sin x = o(x)$ ,  $f(x) = x^2 \ln x = o(x)$ . On the other hand  $f(x) = \sqrt{x} \neq o(x)$ .

We will use the  $o$  notation when the particular form of the function does not matter and we are only interested in the particular limit behaviour of the function.

The  $o$  arithmetic is rather simple as the following examples show:

$$o(h) + o(h) = o(h)$$

This means that sums of  $o$ 's can be combined into one  $o$  which reflects the fact that

$$\lim_{h \rightarrow 0} \frac{f(h)}{h} = 0 \text{ and } \lim_{h \rightarrow 0} \frac{g(h)}{h} = 0 \text{ implies } \lim_{h \rightarrow 0} \frac{f(h) + g(h)}{h} = 0.$$

Another rule is

$$g(h) o(h) = o(h) \text{ if } g(h) \text{ is a bounded function.}$$

Using the  $o$  notation we can express the fact that  $A = f'(a)$  is the derivative of  $f$  at  $a$  by

$$f(x) = f(a) + A(x - a) + o(x - a).$$

Indeed,

$$f(x) - f(a) - A(x - a) = o(x - a)$$

means

$$\lim_{x \rightarrow a} \frac{f(x) - f(a)}{x - a} - A = 0,$$

i.e.

$$\lim_{x \rightarrow a} \frac{f(x) - f(a)}{x - a} = A.$$

## 2. DIFFERENTIATION IN SEVERAL VARIABLES

The formula

$$\Delta f = f(x) - f(a) = A\Delta x + o(\Delta x)$$

means that the increment of the function  $\Delta f$  at some point  $a$  is approximated by the linear function  $A\Delta x = A(x - a)$  up to some error term  $o(\Delta x)$  which tends to zero faster than  $\Delta x$ , i.e. is very small when  $x$  is close enough to  $a$ .

Approximation of non-linear functions by linear ones is the whole point of differential calculus and can be easily generalised to many variables. Let  $f$  be a  $\mathbb{R}^k$ -valued function defined on some ball around a point  $a$  in  $\mathbb{R}^n$ . Then

$$f(x) = f(a) + A(x - a) + o(\|x - a\|)$$

can be read as follows: the vector-valued increment of the function  $\Delta f = f(x) - f(a)$  is equal to a linear mapping

$$A(x - a) = A\Delta x$$

up to a (vector-valued) function that tends to zero faster than  $\|\Delta x\|$  as  $\Delta x \rightarrow 0$ . The linear mapping  $A$  takes arguments in  $\mathbb{R}^n$  (namely  $\Delta x$ ) and values in  $\mathbb{R}^k$ , hence it can be expressed as multiplication of a  $k \times n$  matrix  $A$  with the  $n \times 1$  column  $\Delta x$ .

It is important to understand that the multivariable analog of the derivative for a mapping from  $\mathbb{R}^n$  to  $\mathbb{R}^k$  is a  $k \times n$  matrix. The matrix  $A$  is called *Jacobi matrix* and consists of the partial derivatives

$$A = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \vdots & \vdots \\ \frac{\partial f_k}{\partial x_1} & \dots & \frac{\partial f_k}{\partial x_n} \end{pmatrix}.$$

The linear mapping  $\Delta x \mapsto A\Delta x$  is called the differential of  $f$  at  $a$ . We write

$$df = A\Delta x \text{ or } df = A dx.$$

(We have used  $\Delta x = dx$ .)

Now most of the statements and proofs carry over from one-variable calculus to multivariable calculus. In particular, the multivariable chain rule becomes very simple: Let  $f$  be a  $\mathbb{R}^k$ -valued function defined in some ball in  $\mathbb{R}^m$  around  $b$  and  $g$  be a  $\mathbb{R}^m$ -valued function defined in some ball in  $\mathbb{R}^n$  around  $a$  such that  $g(a) = b$  and  $g$  is differentiable at  $a$  and  $f$  is differentiable at  $b$ , i.e.

$$\begin{aligned} f(y) &= f(b) + B(y - b) + o(\|y - b\|) \\ g(x) &= g(a) + A(x - a) + o(\|x - a\|). \end{aligned}$$

Then  $f(g(x))$  is differentiable at  $a$  and

$$f(g(x)) = f(g(a)) + BA(x - a) + o(\|x - a\|),$$

where  $BA$  is the matrix product of  $B$  and  $A$ . Thus, the chain rule reduces to multiplying matrices. The proof is similar to the proof for one-variable functions.

### 3. THE IMPLICIT MAPPING THEOREM

One of the most important tasks in calculus is to solve systems of non-linear equations

$$(1) \quad \begin{aligned} f_1(x_1, \dots, x_n) &= 0 \\ &\vdots \\ f_k(x_1, \dots, x_n) &= 0 \end{aligned}$$

where  $f_1, \dots, f_k$  are functions of  $x_1, \dots, x_n$ . To solve such a system usually means to express  $k$  of the  $x$  variables (e.g. the first  $k$  variables  $x_1, \dots, x_k$ ) as functions of the remaining  $n - k$  variables

$$(2) \quad \begin{aligned} x_1 &= g_1(x_{k+1}, \dots, x_n) \\ &\vdots \\ x_k &= g_k(x_{k+1}, \dots, x_n) \end{aligned}$$

in such a way that inserting  $g_1, \dots, g_k$  instead of  $x_1, \dots, x_k$  turns the system (1) into an identity, i.e.

$$\begin{aligned} f_1(g_1(x_{k+1}, \dots, x_n), \dots, g_k(x_{k+1}, \dots, x_n), x_{k+1}, x_n) &\equiv 0 \\ &\vdots \\ f_k(g_1(x_{k+1}, \dots, x_n), \dots, g_k(x_{k+1}, \dots, x_n), x_{k+1}, x_n) &\equiv 0 \end{aligned}$$

If (1) was a system of linear equations

$$(3) \quad \begin{aligned} f_1(x_1, \dots, x_n) &= a_{11}x_1 + \dots + a_{1n}x_n = 0 \\ &\vdots \\ f_k(x_1, \dots, x_n) &= a_{k1}x_1 + \dots + a_{kn}x_n = 0 \end{aligned}$$

we could solve by using the Gaussian algorithm and we would find a solution as desired if the determinant of the matrix of the first  $k$  columns of coefficients

$$\det \begin{pmatrix} a_{11} & \dots & a_{1k} \\ \vdots & \vdots & \vdots \\ a_{k1} & \dots & a_{kk} \end{pmatrix} \neq 0.$$

The implicit mapping theorem states

**Theorem 1.** *If  $f$  is a  $\mathbb{R}^k$ -valued mapping defined on some ball around  $a \in \mathbb{R}^n$  such that  $f(a) = 0$  and all partial derivatives  $\frac{\partial f_i}{\partial x_j}$  are defined and continuous and the determinant*

$$\det \begin{pmatrix} \frac{\partial f_1}{\partial x_1}(a) & \dots & \frac{\partial f_1}{\partial x_k}(a) \\ \vdots & \vdots & \vdots \\ \frac{\partial f_k}{\partial x_1}(a) & \dots & \frac{\partial f_k}{\partial x_k}(a) \end{pmatrix} \neq 0$$

then the system  $f(x) = 0$  has a solution of the form (2).

The following inverse mapping theorem is a consequence of Theorem 1.

**Theorem 2.** *If  $f$  is a  $\mathbb{R}^n$ -valued mapping defined on some ball around  $a \in \mathbb{R}^n$  such that  $f(a) = b$  and all partial derivatives  $\frac{\partial f_i}{\partial x_j}$  are defined and continuous and the determinant*

$$\det \begin{pmatrix} \frac{\partial f_1}{\partial x_1}(a) & \dots & \frac{\partial f_1}{\partial x_n}(a) \\ \vdots & & \vdots \\ \frac{\partial f_n}{\partial x_1}(a) & \dots & \frac{\partial f_n}{\partial x_n}(a) \end{pmatrix} \neq 0$$

*then the mapping  $f(x)$  has an inverse  $g(y)$  defined on some ball around  $b$ , i.e.  $g(f(x)) \equiv x$  and  $f(g(y)) \equiv y$ .*

To prove this we apply the implicit mapping theorem to the  $\mathbb{R}^n$ -valued mapping  $f(x) - y$  on  $\mathbb{R}^{2n}$ .