

# MATH50003 Numerical Analysis

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# Contents

<b>I</b>	<b>Calculus on a Computer</b>	<b>5</b>
I.1	Rectangular rule . . . . .	6
I.2	Divided Differences . . . . .	8
I.3	Dual Numbers . . . . .	9
I.3.1	Differentiating polynomials . . . . .	9
I.3.2	Differentiating other functions . . . . .	10
I.4	Newton's method . . . . .	11
<b>II</b>	<b>Representing Numbers</b>	<b>13</b>
II.1	Integers . . . . .	14
II.1.1	Unsigned Integers . . . . .	14
II.1.2	Signed integer . . . . .	15
II.1.3	Hexadecimal format . . . . .	16
II.2	Reals . . . . .	17
II.2.1	Real numbers in binary . . . . .	17
II.2.2	Floating-point numbers . . . . .	18
II.2.3	IEEE floating-point numbers . . . . .	19
II.2.4	Sub-normal and special numbers . . . . .	19
II.3	Floating Point Arithmetic . . . . .	20
II.3.1	Bounding errors in floating point arithmetic . . . . .	21
II.3.2	Idealised floating point . . . . .	23
II.3.3	Divided differences floating point error bound . . . . .	24
II.4	Interval Arithmetic . . . . .	25
<b>III</b>	<b>Numerical Linear Algebra</b>	<b>29</b>
III.1	Structured Matrices . . . . .	29
III.1.1	Dense matrices . . . . .	30
III.1.2	Triangular matrices . . . . .	31

III.1.3 Banded matrices . . . . .	32
III.2 Differential Equations via Finite Differences . . . . .	33
III.2.1 Indefinite integration . . . . .	34
III.2.2 Forward Euler . . . . .	35
III.2.3 Poisson equation . . . . .	36
III.3 LU and Cholesky factorisations . . . . .	37
III.3.1 Outer products . . . . .	38
III.3.2 LU factorisation . . . . .	38
III.3.3 PLU factorisation . . . . .	39
III.3.4 Cholesky factorisation . . . . .	40
III.4 Polynomial Interpolation and Regression . . . . .	42
III.4.1 Polynomial interpolation . . . . .	42
III.4.2 Polynomial regression . . . . .	44
<b>A Asymptotics and Computational Cost</b>	<b>47</b>
A.1 Asymptotics as $n \rightarrow \infty$ . . . . .	47
A.2 Asymptotics as $x \rightarrow x_0$ . . . . .	48
A.3 Computational cost . . . . .	49
<b>B Permutation Matrices</b>	<b>51</b>

# Chapter I

## Calculus on a Computer

In this first chapter we explore the basics of mathematical computing and numerical analysis. In particular we investigate the following mathematical problems which can not in general be solved exactly:

1. Integration. General integrals have no closed form expressions. Can we use a computer to approximate the values of definite integrals?
2. Differentiation. Differentiating a formula as in calculus is usually algorithmic, however, it is often needed to compute derivatives without access to an underlying formula, eg, a function defined only in code. Can we use a computer to approximate derivatives? A very important application is in Machine Learning, where there is a need to compute gradients to determine the “right” weights in a neural network.
3. Root finding. There is no general formula for finding roots (zeros) of arbitrary functions, or even polynomials that are of degree 5 (quintics) or higher. Can we compute roots of general functions using a computer?

In this chapter we discuss:

1. I.1 Rectangular rule: we review the rectangular rule for integration and deduce the *converge rate* of the approximation. In the lab/problem sheet we investigate its implementation as well as extensions to the Trapezium rule.
2. I.2 Divided differences: we investigate approximating derivatives by a divided difference and again deduce the convergence rates. In the lab/problem sheet we extend the approach to the central differences formula and computing second derivatives. We also observe a mystery: the approximations may have significant errors in practice, and there is a limit to the accuracy.
3. I.3 Dual numbers: we introduce the algebraic notion of a *dual number* which allows the implementation of *forward-mode automatic differentiation*, a high accuracy alternative to divided differences for computing derivatives.
4. I.4 Newton’s method: Newton’s method is a basic approach for computing roots/zeros of a function. We use dual numbers to implement this algorithm.

## I.1 Rectangular rule

One possible definition for an integral is the limit of a Riemann sum, for example:

$$\int_a^b f(x)dx = \lim_{n \rightarrow \infty} h \sum_{j=1}^n f(x_j)$$

where  $x_j = a + jh$  are evenly spaced points dividing up the interval  $[a, b]$ , that is with the *step size*  $h = (b - a)/n$ . This suggests an algorithm known as the (*right-sided*) *rectangular rule* for approximating an integral: choose  $n$  large so that

$$\int_a^b f(x)dx \approx h \sum_{j=1}^n f(x_j).$$

In the lab we explore practical implementation of this approximation, and observe that the error in approximation is bounded by  $C/n$  for some constant  $C$ . This can be expressed using “Big-O” notation:

$$\int_a^b f(x)dx = h \sum_{j=1}^n f(x_j) + O(1/n).$$

In these notes we consider the “Analysis” part of “Numerical Analysis”: we want to *prove* the convergence rate of the approximation, including finding an explicit expression for the constant  $C$ .

To tackle this question we consider the error incurred on a single panel  $(x_{j-1}, x_j)$ , then sum up the errors on rectangles.

Now for a secret. There are only so many tools available in analysis (especially at this stage of your career), and one can make a safe bet that the right tool in any analysis proof is either (1) integration-by-parts, (2) geometric series or (3) Taylor series. In this case we use (1):

**Lemma 1** ((Right-sided) Rectangular Rule error on one panel). *Assuming  $f$  is differentiable we have*

$$\int_a^b f(x)dx = (b - a)f(b) + \delta$$

where  $|\delta| \leq M(b - a)^2$  for  $M = \sup_{a \leq x \leq b} |f'(x)|$ .

**Proof** We write

$$\begin{aligned} \int_a^b f(x)dx &= \int_a^b (x - a)' f(x)dx = [(x - a)f(x)]_a^b - \int_a^b (x - a)f'(x)dx \\ &= (b - a)f(b) + \underbrace{\left( - \int_a^b (x - a)f'(x)dx \right)}_{\delta}. \end{aligned}$$

Recall that we can bound the absolute value of an integral by the supremum of the integrand times the width of the integration interval:

$$\left| \int_a^b g(x)dx \right| \leq (b - a) \sup_{a \leq x \leq b} |g(x)|.$$

The lemma thus follows since

$$\begin{aligned} \left| \int_a^b (x-a)f'(x)dx \right| &\leq (b-a) \sup_{a \leq x \leq b} |(x-a)f'(x)| \\ &\leq (b-a) \sup_{a \leq x \leq b} |x-a| \sup_{a \leq x \leq b} |f'(x)| \\ &\leq M(b-a)^2. \end{aligned}$$

■

Now summing up the errors in each panel gives us the error of using the Rectangular rule:

**Theorem 1** (Rectangular Rule error). *Assuming  $f$  is differentiable we have*

$$\int_a^b f(x)dx = h \sum_{j=1}^n f(x_j) + \delta$$

where  $|\delta| \leq M(b-a)h$  for  $M = \sup_{a \leq x \leq b} |f'(x)|$ ,  $h = (b-a)/n$  and  $x_j = a + jh$ .

**Proof** We split the integral into a sum of smaller integrals:

$$\int_a^b f(x)dx = \sum_{j=1}^n \int_{x_{j-1}}^{x_j} f(x)dx = \sum_{j=1}^n [(x_j - x_{j-1})f(x_j) + \delta_j] = h \sum_{j=1}^n f(x_j) + \underbrace{\sum_{j=1}^n \delta_j}_{\delta}$$

where  $\delta_j$ , the error on each panel as in the preceding lemma, satisfies

$$|\delta_j| \leq (x_j - x_{j-1})^2 \sup_{x_{j-1} \leq x \leq x_j} |f'(x)| \leq Mh^2.$$

Thus using the triangular inequality we have

$$|\delta| = \left| \sum_{j=1}^n \delta_j \right| \leq \sum_{j=1}^n |\delta_j| \leq Mnh^2 = M(b-a)h.$$

■

Note a consequence of this lemma is that the approximation converges as  $n \rightarrow \infty$  (i.e.  $h \rightarrow 0$ ). In the labs and problem sheets we will consider the left-sided rule:

$$\int_a^b f(x)dx \approx h \sum_{j=0}^{n-1} f(x_j).$$

We also consider the *Trapezium rule*. Here we approximate an integral by an affine function:

$$\int_a^b f(x)dx \approx \int_a^b \frac{(b-x)f(a) + (x-a)f(b)}{b-a} dx = \frac{b-a}{2} [f(a) + f(b)].$$

Subdividing an interval  $a = x_0 < x_1 < \dots < x_n = b$  and applying this approximation separately on each subinterval  $[x_{j-1}, x_j]$ , where  $h = (b-a)/n$  and  $x_j = a + jh$ , leads to the approximation

$$\int_a^b f(x)dx \approx \frac{h}{2} f(a) + h \sum_{j=1}^{n-1} f(x_j) + \frac{h}{2} f(b)$$

We shall see both experimentally and provably that this approximation converges faster than the rectangular rule.

## I.2 Divided Differences

Given a function, how can we approximate its derivative at a point? We consider an intuitive approach to this problem using *(Right-sided) Divided Differences*:

$$f'(x) \approx \frac{f(x+h) - f(x)}{h}$$

Note by the definition of the derivative we know that this approximation will converge to the true derivative as  $h \rightarrow 0$ . But in numerical approximations we also need to consider the rate of convergence.

Now in the previous section I mentioned there are three basic tools in analysis: (1) integration-by-parts, (2) geometric series or (3) Taylor series. In this case we use (3):

**Proposition 1** (divided differences error). *Suppose that  $f$  is twice-differentiable on the interval  $[x, x+h]$ . The error in approximating the derivative using divided differences is*

$$f'(x) = \frac{f(x+h) - f(x)}{h} + \delta$$

where  $|\delta| \leq Mh/2$  for  $M = \sup_{x \leq t \leq x+h} |f''(t)|$ .

**Proof** Follows immediately from Taylor's theorem:

$$f(x+h) = f(x) + f'(x)h + \underbrace{\frac{f''(t)}{2}h^2}_{h\delta}$$

for some  $x \leq t \leq x+h$ , by bounding:

$$|\delta| \leq \left| \frac{f''(t)}{2}h \right| \leq \frac{Mh}{2}.$$

■

Unlike the rectangular rule, the computational cost of computing the divided difference is independent of  $h$ ! We only need to evaluate a function  $f$  twice and do a single division. Here we are assuming that the computational cost of evaluating  $f$  is independent of the point of evaluation. Later we will investigate the details of how computers work with numbers via floating point, and confirm that this is a sensible assumption.

So why not just set  $h$  ridiculously small? In the lab we explore this question and observe that there are significant errors introduced in the numerical realisation of this algorithm. We will return to the question of understanding these errors after learning floating point numbers.

There are alternative versions of divided differences. Left-side divided differences evaluates to the left of the point where we wish to know the derivative:

$$f'(x) \approx \frac{f(x) - f(x-h)}{h}$$

and central differences:

$$f'(x) \approx \frac{f(x+h) - f(x-h)}{2h}$$



We can further arrive at an approximation to the second derivative by composing a left- and right-sided finite difference:

$$f''(x) \approx \frac{f'(x+h) - f'(x)}{h} \approx \frac{\frac{f(x+h)-f(x)}{h} - \frac{f(x)-f(x-h)}{h}}{h} = \frac{f(x+h) - 2f(x) + f(x-h)}{h^2}$$

In the lab we investigate the convergence rate of these approximations (in particular, that central differences is more accurate than standard divided differences) and observe that they too suffer from unexplained (for now) loss of accuracy as  $h \rightarrow 0$ . In the problem sheet we prove the theoretical converge rate, which is never realised because of these errors.

## I.3 Dual Numbers

In this section we introduce a mathematically beautiful alternative to divided differences for computing derivatives: *dual numbers*. These are a commutative ring that *exactly* compute derivatives, which when implemented on a computer gives very high-accuracy approximations to derivatives. They underpin forward-mode [automatic differentiation](#). Automatic differentiation is a basic tool in Machine Learning for computing gradients necessary for training neural networks.

**Definition 1** (Dual numbers). Dual numbers  $\mathbb{D}$  are a commutative ring (over  $\mathbb{R}$ ) generated by 1 and  $\epsilon$  such that  $\epsilon^2 = 0$ . Dual numbers are typically written as  $a + b\epsilon$  where  $a$  and  $b$  are real.

This is very much analogous to complex numbers, which are a field generated by 1 and  $i$  such that  $i^2 = -1$ . Compare multiplication of each number type:

$$\begin{aligned}(a + bi)(c + di) &= ac + (bc + ad)i + bdi^2 = ac - bd + (bc + ad)i \\(a + b\epsilon)(c + d\epsilon) &= ac + (bc + ad)\epsilon + bd\epsilon^2 = ac + (bc + ad)\epsilon\end{aligned}$$

And just as we view  $\mathbb{R} \subset \mathbb{C}$  by equating  $a \in \mathbb{R}$  with  $a + 0i \in \mathbb{C}$ , we can view  $\mathbb{R} \subset \mathbb{D}$  by equating  $a \in \mathbb{R}$  with  $a + 0\epsilon \in \mathbb{D}$ .

### I.3.1 Differentiating polynomials

Polynomials evaluated on dual numbers are well-defined as they depend only on the operations  $+$  and  $*$ . From the formula for multiplication of dual numbers we deduce that evaluating a polynomial at a dual number  $a + b\epsilon$  tells us the derivative of the polynomial at  $a$ :

**Theorem 2** (polynomials on dual numbers). *Suppose  $p$  is a polynomial. Then*

$$p(a + b\epsilon) = p(a) + bp'(a)\epsilon$$

#### Proof

First consider  $p(x) = x^n$  for  $n \geq 0$ . The cases  $n = 0$  and  $n = 1$  are immediate. For  $n > 1$  we have by induction:

$$(a + b\epsilon)^n = (a + b\epsilon)(a + b\epsilon)^{n-1} = (a + b\epsilon)(a^{n-1} + (n-1)ba^{n-2}\epsilon) = a^n + bna^{n-1}\epsilon.$$

For a more general polynomial

$$p(x) = \sum_{k=0}^n c_k x^k$$

the result follows from linearity:

$$p(a+b\epsilon) = \sum_{k=0}^n c_k (a+b\epsilon)^k = c_0 + \sum_{k=1}^n c_k (a^k + kba^{k-1}\epsilon) = \sum_{k=0}^n c_k a^k + b \sum_{k=1}^n c_k k a^{k-1} \epsilon = p(a) + bp'(a)\epsilon.$$

■

**Example 1** (differentiating polynomial). Consider computing  $p'(2)$  where

$$p(x) = (x-1)(x-2) + x^2.$$

We can use dual numbers to differentiate, avoiding expanding in monomials or applying rules of differentiating:

$$p(2+\epsilon) = (1+\epsilon)\epsilon + (2+\epsilon)^2 = \epsilon + 4 + 4\epsilon = 4 + \underbrace{5}_{p'(2)}\epsilon$$

### I.3.2 Differentiating other functions

We can extend real-valued differentiable functions to dual numbers in a similar manner. First, consider a standard function with a Taylor series (e.g.  $\cos$ ,  $\sin$ ,  $\exp$ , etc.)

$$f(x) = \sum_{k=0}^{\infty} f_k x^k$$

so that  $a$  is inside the radius of convergence. This leads naturally to a definition on dual numbers:

$$\begin{aligned} f(a+b\epsilon) &= \sum_{k=0}^{\infty} f_k (a+b\epsilon)^k = f_0 + \sum_{k=1}^{\infty} f_k (a^k + ka^{k-1}b\epsilon) = \sum_{k=0}^{\infty} f_k a^k + \sum_{k=1}^{\infty} f_k k a^{k-1} b \epsilon \\ &= f(a) + bf'(a)\epsilon \end{aligned}$$

More generally, given a differentiable function we can extend it to dual numbers:

**Definition 2** (dual extension). Suppose a real-valued function  $f$  is differentiable at  $a$ . If

$$f(a+b\epsilon) = f(a) + bf'(a)\epsilon$$

then we say that it is a *dual extension* at  $a$ .

Thus, for basic functions we have natural extensions:

$$\begin{aligned} \exp(a+b\epsilon) &:= \exp(a) + b\exp(a)\epsilon \\ \sin(a+b\epsilon) &:= \sin(a) + b\cos(a)\epsilon \\ \cos(a+b\epsilon) &:= \cos(a) - b\sin(a)\epsilon \\ \log(a+b\epsilon) &:= \log(a) + \frac{b}{a}\epsilon \\ \sqrt{a+b\epsilon} &:= \sqrt{a} + \frac{b}{2\sqrt{a}}\epsilon \\ |a+b\epsilon| &:= |a| + b\operatorname{sign} a \epsilon \end{aligned}$$

provided the function is differentiable at  $a$ . Note the last example does not have a convergent Taylor series (at 0) but we can still extend it where it is differentiable.

Going further, we can add, multiply, and compose such functions:

**Lemma 2** (product and chain rule). *If  $f$  is a dual extension at  $g(a)$  and  $g$  is a dual extension at  $a$ , then  $q(x) := f(g(x))$  is a dual extension at  $a$ . If  $f$  and  $g$  are dual extensions at  $a$  then  $r(x) := f(x)g(x)$  is also dual extensions at  $a$ . In other words:*

$$\begin{aligned} q(a + b\epsilon) &= q(a) + bq'(a)\epsilon \\ r(a + b\epsilon) &= r(a) + br'(a)\epsilon \end{aligned}$$

**Proof** For  $q$  it follows immediately:

$$\begin{aligned} q(a + b\epsilon) &= f(g(a + b\epsilon)) = f(g(a) + bg'(a)\epsilon) \\ &= f(g(a)) + bg'(a)f'(g(a))\epsilon = q(a) + bq'(a)\epsilon. \end{aligned}$$

For  $r$  we have

$$\begin{aligned} r(a + b\epsilon) &= f(a + b\epsilon)g(a + b\epsilon) = (f(a) + bf'(a)\epsilon)(g(a) + bg'(a)\epsilon) \\ &= f(a)g(a) + b(f'(a)g(a) + f(a)g'(a))\epsilon = r(a) + br'(a)\epsilon. \end{aligned}$$

A simple corollary is that any function defined in terms of addition, multiplication, composition, etc. of functions that are dual with differentiation will be differentiable via dual numbers.

**Example 2** (differentiating non-polynomial). Consider differentiating  $f(x) = \exp(x^2 + e^x)$  at the point  $a = 1$  by evaluating on the duals:

$$f(1 + \epsilon) = \exp(1 + 2\epsilon + e + e\epsilon) = \exp(1 + e) + \exp(1 + e)(2 + e)\epsilon.$$

Therefore we deduce that

$$f'(1) = \exp(1 + e)(2 + e).$$

## I.4 Newton's method

In school you may recall learning Newton's method: a way of approximating zeros/roots to a function by using a local approximation by an affine function. That is, approximate a function  $f(x)$  locally around an initial guess  $x_0$  by its first order Taylor series:

$$f(x) \approx f(x_0) + f'(x_0)(x - x_0)$$

and then find the root of the right-hand side which is

$$f(x_0) + f'(x_0)(x - x_0) = 0 \Leftrightarrow x = x_0 - \frac{f(x_0)}{f'(x_0)}.$$

We can then repeat using this root as the new initial guess. In other words we have a sequence of *hopefully* more accurate approximations:

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}.$$

The convergence theory of Newton's method is rich and beautiful but outside the scope of this module. But provided  $f$  is smooth, if  $x_0$  is sufficiently close to a root this iteration will converge.

Thus *if* we can compute derivatives, we can (sometimes) compute roots. The lab will explore using dual numbers to accomplish this task. This is in some sense a baby version of how Machine Learning algorithms train neural networks.

# Chapter II

## Representing Numbers

In this chapter we aim to answer the question: when can we rely on computations done on a computer? Why are some computations (differentiation via divided differences), extremely inaccurate whilst others (integration via rectangular rule) accurate up to about 16 digits? In order to address these questions we need to dig deeper and understand at a basic level what a computer is actually doing when manipulating numbers.

Before we begin it is important to have a basic model of how a computer works. Our simplified model of a computer will consist of a **Central Processing Unit (CPU)**—the brains of the computer—and **Memory**—where data is stored. Inside the CPU there are **registers**, where data is temporarily stored after being loaded from memory, manipulated by the CPU, then stored back to memory. Memory is a sequence of bits: 1s and 0s, essentially “on/off” switches, and memory is *finite*. Finally, if one has a  $p$ -bit CPU (eg a 32-bit or 64-bit CPU), each register consists of exactly  $p$ -bits. Most likely  $p = 64$  on your machine.

Thus representing numbers on a computer must overcome three fundamental limitations:

1. CPUs can only manipulate data  $p$ -bits at a time.
2. Memory is finite (in particular at most  $2^p$  bytes).
3. There is no such thing as an “error”: if anything goes wrong in the computation we must use some of the  $p$ -bits to indicate this.

This is clearly problematic: there are an infinite number of integers and an uncountable number of reals! Each of which we need to store in precisely  $p$ -bits. Moreover, some operations are simply undefined, like division by 0. This chapter discusses the solution used to this problem, alongside the mathematical analysis that is needed to understand the implications, in particular, that computations have *error*.

In particular we discuss:

1. II.1 Integers: unsigned (non-negative) and signed integers are representable using exactly  $p$ -bits by using modular arithmetic in all operations.
2. II.2 Reals: real numbers are approximated by floating point numbers, which are a computers version of scientific notation.

3. II.3 Floating Point Arithmetic: arithmetic with floating point numbers is exact up-to-rounding, which introduces small-but-understandable errors in the computations. We explain how these errors can be analysed mathematically to get rigorous bounds.
4. II.4 Interval Arithmetic: rounding can be controlled in order to implement *interval arithmetic*, a way to compute rigorous bounds for computations. In the lab, we use this to compute up to 15 digits of  $e \equiv \exp 1$  rigorously with precise bounds on the error.

## II.1 Integers

In this section we discuss the following:

1. Unsigned integers: how computers represent non-negative integers using only  $p$ -bits, via [modular arithmetic](#).
2. Signed integers: how negative integers are handled using the [Two's-complement](#) format.

Mathematically, CPUs only act on  $p$ -bits at a time, with  $2^p$  possible sequences. That is, essentially all functions  $f$  are either of the form  $f : \mathbb{Z}_{2^p} \rightarrow \mathbb{Z}_{2^p}$  or  $f : \mathbb{Z}_{2^p} \times \mathbb{Z}_{2^p} \rightarrow \mathbb{Z}_{2^p}$ , where we use the following notation:

**Definition 3** (finite integers). Denote the set of the first  $m$  non-negative integers as  $\mathbb{Z}_m := \{0, 1, \dots, m-1\}$ .

To translate between integers and bits we will need to write integers in binary format. That is, as sequence of 0s and 1s:

**Definition 4** (binary format). For  $B_0, \dots, B_p \in \{0, 1\}$  denote an integer in *binary format* by:

$$\pm(B_p \dots B_1 B_0)_2 := \pm \sum_{k=0}^p B_k 2^k$$

**Example 3** (integers in binary). A simple integer example is  $5 = 2^2 + 2^0 = (101)_2$ . On the other hand, we write  $-5 = -(101)_2$ . Another example is  $258 = 2^8 + 2 = (100000010)_2$ .

### II.1.1 Unsigned Integers

Computers represent integers by a finite number of  $p$ -bits, with  $2^p$  possible combinations of 0s and 1s. Denote these  $p$ -bits as  $B_{p-1} \dots B_1 B_0$  where  $B_k \in \{0, 1\}$ . For *unsigned integers* (non-negative integers) these bits dictate the first  $p$  binary digits:  $(B_{p-1} \dots B_1 B_0)_2$ . Integers represented with  $p$ -bits on a computer are interpreted as representing elements of  $\mathbb{Z}_{2^p}$  and integer arithmetic on a computer is equivalent to arithmetic modulo  $2^p$ . We denote modular arithmetic with  $m = 2^p$  as follows:

$$\begin{aligned} x \oplus_m y &:= (x + y) \pmod{m} \\ x \ominus_m y &:= (x - y) \pmod{m} \\ x \otimes_m y &:= (x * y) \pmod{m} \end{aligned}$$

When  $m$  is implied by context we just write  $\oplus, \ominus, \otimes$ . Note that the  $(\text{mod } m)$  function simply drops all bits except for the first  $p$ -bits when writing a number in binary.

**Example 4** (arithmetic with 8-bit unsigned integers). If the result of an operation lies between 0 and  $m = 2^8 = 256$  then arithmetic works exactly like standard integer arithmetic. For example,

$$17 \oplus_{256} 3 = 20 \pmod{256} = 20$$

$$17 \ominus_{256} 3 = 14 \pmod{256} = 14$$

**Example 5** (overflow with 8-bit unsigned integers). If we go beyond the range the result “wraps around”. For example, with true integers we have

$$255 + 1 = (11111111)_2 + (00000001)_2 = (100000000)_2 = 256$$

However, the result is impossible to store in just 8-bits! So as mentioned instead it treats the integers as elements of  $\mathbb{Z}_{256}$  by dropping any extra digits:

$$255 \oplus_{256} 1 = 255 + 1 \pmod{256} = (100000000)_2 \pmod{256} = 0.$$

On the other hand, if we go below 0 we wrap around from above:

$$3 \ominus_{256} 5 = -2 \pmod{256} = 254 = (11111110)_2$$

**Example 6** (multiplication of 8-bit unsigned integers). Multiplication works similarly: for example,

$$254 \otimes_{256} 2 = 254 * 2 \pmod{256} = (11111110)_2 * 2 \pmod{256} = (111111100)_2 \pmod{256} = 252.$$

Note that multiplication by 2 is the same as shifting the binary digits left by one, just as multiplication by 10 shifts base-10 digits left by 1.

## II.1.2 Signed integer

Signed integers use the [Two's complement](#) convention. The convention is if the first bit is 1 then the number is negative: in this case if the bits had represented the unsigned integer  $2^p - y$  then they represent the signed integer  $-y$ . Thus for  $p = 8$  we are interpreting  $2^7$  through  $2^8 - 1$  as negative numbers. More precisely:

**Definition 5** (signed integers). Denote the finite signed integers as

$$\mathbb{Z}_{2^p}^s := \{-2^{p-1}, \dots, -1, 0, 1, \dots, 2^{p-1} - 1\}.$$

**Definition 6** (Shifted mod). Define for  $y = x \pmod{2^p}$

$$x \pmod^s{2^p} := \begin{cases} y & 0 \leq y \leq 2^{p-1} - 1 \\ y - 2^p & 2^{p-1} \leq y \leq 2^p - 1 \end{cases}$$

Note that if  $R_p(x) = x \pmod^s{2^p}$  then it can be viewed as a map  $R_p : \mathbb{Z} \rightarrow \mathbb{Z}_{2^p}^s$  or a one-to-one map  $R_p : \mathbb{Z}_{2^p} \rightarrow \mathbb{Z}_{2^p}^s$  whose inverse is  $R_p^{-1}(x) = x \pmod{2^p}$ . It can also be viewed as the identity map on signed integers  $R_p : \mathbb{Z}_{2^p}^s \rightarrow \mathbb{Z}_{2^p}^s$ , that is,  $R_p(x) = x$  if  $x \in \mathbb{Z}_{2^p}^s$ .

Arithmetic works precisely the same for signed and unsigned integers up to the mapping  $R_p$ , e.g. we have for  $m = 2^p$

$$x \oplus_m^s y := (x + y) \pmod^s m$$

$$x \ominus_m^s y := (x - y) \pmod^s m$$

$$x \otimes_m^s y := (x * y) \pmod^s m$$

**Example 7** (addition of 8-bit signed integers). Consider  $(-1) + 1$  in 8-bit arithmetic:

$$-1 \oplus_{256}^s 1 = -1 + 1 \pmod{256} = 0$$

On the bit level this computation is exactly the same as unsigned integers. We represent the number  $-1$  using the same bits as the unsigned integer  $2^8 - 1 = 255$ , that is using the bits  $11111111$  (i.e., we store it equivalently to  $(11111111)_2 = 255$ ) and the number  $1$  is stored using the bits  $00000001$ . When we add this with true integer arithmetic we have

$$\begin{aligned} &(01111111)_2 + \\ &(00000001)_2 = \\ &(10000000)_2 \end{aligned}$$

Modular arithmetic drops the leading 1 and we are left with all zeros.

**Example 8** (signed overflow with 8-bit signed integers). If we go above  $2^{p-1} - 1 = 2^7 - 1 = 127$  we have perhaps unexpected results:

$$127 \oplus_{256}^s 1 = 128 \pmod{256} = 128 - 256 = -128.$$

Again on the bit level this computation is exactly the same as unsigned integers. We represent the number  $127$  using the bits  $01111111$  and the number  $1$  is stored using the bits  $00000001$ . When we add this with true integer arithmetic we have

$$\begin{aligned} &(01111111)_2 + \\ &(00000001)_2 = \\ &(10000000)_2 \end{aligned}$$

Because the first bit is 1 we interpret this as a negative number using the formula:

$$(10000000)_2 \pmod{256} = 128 \pmod{256} = -128.$$

**Example 9** (multiplication of 8-bit signed integers). Consider computation of  $(-2) * 2$ :

$$(-2) \otimes_{2^p}^s 2 = -4 \pmod{2^p} = -4$$

On the bit level, the bits of  $-2$  (which is one less than  $-1$ ) are  $11111110$ . Multiplying by 2 is like multiplying by 10 in base-10, that is, we shift the bits. Hence in true arithmetic we have

$$\begin{aligned} &(01111110)_2 * 2 = \\ &(11111100)_2 \end{aligned}$$

We drop the leading 1 due to modular arithmetic. We still have a leading 1 hence the number is viewed as negative. In particular we have

$$\begin{aligned} (11111100)_2 \pmod{256} &= (11111100)_2 \pmod{256} = 2^7 + 2^6 + 2^5 + 2^4 + 2^3 + 2^2 \pmod{256} \\ &= 252 \pmod{256} = -4. \end{aligned}$$

### II.1.3 Hexadecimal format

In coding it is often convenient to use base-16 as it is a power of 2 but uses less characters than binary. The digits used are 0 through 9 followed by  $a = 10$ ,  $b = 11$ ,  $c = 12$ ,  $d = 13$ ,  $e = 14$ , and  $f = 15$ .

**Example 10** (Hexadecimal number). We can interpret a number in format as follows:

$$(a5f2)_{16} = a * 16^3 + 5 * 16^2 + f * 16 + 2 = 10 * 16^3 + 5 * 16^2 + 15 * 16 + 2 = 42,482$$

We will see in the labs that unsigned integers are displayed in base-16.



## II.2 Reals

In this chapter, we introduce the [IEEE Standard for Floating-Point Arithmetic](#). There are multiple ways of representing real numbers on a computer, as well as the precise behaviour of operations such as addition, multiplication, etc. One can use

1. [Fixed-point arithmetic](#): essentially representing a real number as an integer where a decimal point is inserted at a fixed position. This turns out to be impractical in most applications, e.g., due to loss of relative accuracy for small numbers.
2. [Floating-point arithmetic](#): essentially scientific notation where an exponent is stored alongside a fixed number of digits. This is what is used in practice.
3. [Level-index arithmetic](#): stores numbers as iterated exponents. This is the most beautiful mathematically but unfortunately is not as useful for most applications and is not implemented in hardware.

Before the 1980s each processor had potentially a different representation for floating-point numbers, as well as different behaviour for operations. IEEE introduced in 1985 was a means to standardise this across processors so that algorithms would produce consistent and reliable results.

This chapter may seem very low level for a mathematics course but there are two important reasons to understand the behaviour of floating-point numbers in details:

1. Floating-point arithmetic is very precisely defined, and can even be used in rigorous computations as we shall see in the labs. But it is not exact and its important to understand how errors in computations can accumulate.
2. Failure to understand floating-point arithmetic can cause catastrophic issues in practice, with the extreme example being the [explosion of the Ariane 5 rocket](#).

### II.2.1 Real numbers in binary

Reals can also be presented in binary format, that is, a sequence of 0s and 1s alongside a decimal point:

**Definition 7** (real binary format). For  $b_1, b_2, \dots \in \{0, 1\}$ , Denote a non-negative real number in *binary format* by:

$$(B_p \dots B_0.b_1b_2b_3\dots)_2 := (B_p \dots B_0)_2 + \sum_{k=1}^{\infty} \frac{b_k}{2^k}.$$

**Example 11** (rational in binary). Consider the number  $1/3$ . In decimal recall that:

$$1/3 = 0.3333\dots = \sum_{k=1}^{\infty} \frac{3}{10^k}$$

We will see that in binary

$$1/3 = (0.010101\dots)_2 = \sum_{k=1}^{\infty} \frac{1}{2^{2k}}$$

Both results can be proven using the geometric series:

$$\sum_{k=0}^{\infty} z^k = \frac{1}{1-z}$$

provided  $|z| < 1$ . That is, with  $z = \frac{1}{4}$  we verify the binary expansion:

$$\sum_{k=1}^{\infty} \frac{1}{4^k} = \frac{1}{1-1/4} - 1 = \frac{1}{3}$$

A similar argument with  $z = 1/10$  shows the decimal case.

## II.2.2 Floating-point numbers

Floating-point numbers are a subset of real numbers that are representable using a fixed number of bits.

**Definition 8** (floating-point numbers). Given integers  $\sigma$  (the *exponential shift*),  $Q$  (the number of *exponent bits*) and  $S$  (the *precision*), define the set of *Floating-point numbers* by dividing into *normal*, *sub-normal*, and *special number* subsets:

$$F_{\sigma,Q,S} := F_{\sigma,Q,S}^{\text{normal}} \cup F_{\sigma,Q,S}^{\text{sub}} \cup F^{\text{special}}.$$

The *normal numbers*  $F_{\sigma,Q,S}^{\text{normal}} \subset \mathbb{R}$  are

$$F_{\sigma,Q,S}^{\text{normal}} := \{\pm 2^{q-\sigma} \times (1.b_1b_2b_3 \dots b_S)_2 : 1 \leq q < 2^Q - 1\}.$$

The *sub-normal numbers*  $F_{\sigma,Q,S}^{\text{sub}} \subset \mathbb{R}$  are

$$F_{\sigma,Q,S}^{\text{sub}} := \{\pm 2^{1-\sigma} \times (0.b_1b_2b_3 \dots b_S)_2\}.$$

The *special numbers*  $F^{\text{special}} \not\subset \mathbb{R}$  are

$$F^{\text{special}} := \{\infty, -\infty, \text{NaN}\}$$

where NaN is a special symbol representing “not a number”, essentially an error flag.

Note this set of real numbers has no nice *algebraic structure*: it is not closed under addition, subtraction, etc. On the other hand, we can control errors effectively hence it is extremely useful for analysis.

Floating-point numbers are stored in  $1 + Q + S$  total number of bits, in the format

$$\textcolor{red}{s} \textcolor{teal}{q}_{Q-1} \dots \textcolor{teal}{q}_0 \textcolor{blue}{b}_1 \dots \textcolor{blue}{b}_S$$

The first bit ( $s$ ) is the *sign bit*: 0 means positive and 1 means negative. The bits  $q_{Q-1} \dots q_0$  are the *exponent bits*: they are the binary digits of the unsigned integer  $q$ :

$$q = (\textcolor{teal}{q}_{Q-1} \dots \textcolor{teal}{q}_0)_2.$$

Finally, the bits  $b_1 \dots b_S$  are the *significand bits*. If  $1 \leq q < 2^Q - 1$  then the bits represent the normal number

$$x = \pm 2^{q-\sigma} \times (1.\textcolor{blue}{b}_1\textcolor{blue}{b}_2\textcolor{blue}{b}_3 \dots \textcolor{blue}{b}_S)_2.$$

If  $q = 0$  (i.e. all bits are 0) then the bits represent the sub-normal number

$$x = \pm 2^{1-\sigma} \times (0.\textcolor{blue}{b}_1\textcolor{blue}{b}_2\textcolor{blue}{b}_3 \dots \textcolor{blue}{b}_S)_2.$$

If  $q = 2^Q - 1$  (i.e. all bits are 1) then the bits represent a special number, discussed later.

### II.2.3 IEEE floating-point numbers

**Definition 9** (IEEE floating-point numbers). IEEE has 3 standard floating-point formats: 16-bit (half precision), 32-bit (single precision) and 64-bit (double precision) defined by (you *do not* need to memorise these):

$$\begin{aligned} F_{16} &:= F_{15,5,10} \\ F_{32} &:= F_{127,8,23} \\ F_{64} &:= F_{1023,11,52} \end{aligned}$$

**Example 12** (interpreting 16-bits as a float). Consider the number with bits

0 10000 1010000000

assuming it is a half-precision float ( $F_{16}$ ). Since the sign bit is 0 it is positive. The exponent is  $2^4 - \sigma = 16 - 15 = 1$ . Hence this number is:

$$2^1(1.1010000000)_2 = 2(1 + 1/2 + 1/8) = 3 + 1/4 = 3.25.$$

**Example 13** (rational to 16-bits). How is the number  $1/3$  stored in  $F_{16}$ ? Recall that

$$1/3 = (0.010101\dots)_2 = 2^{-2}(1.0101\dots)_2 = 2^{13-15}(1.0101\dots)_2$$

and since  $13 = (1101)_2$  the exponent bits are 01101. For the significand we round the last bit to the nearest element of  $F_{16}$ , (the exact rule for rounding is explained in detail later), so we have

$$1.0101010101010101010101\dots \approx 1.0101010101 \in F_{16}$$

and the significand bits are 0101010101. Thus the stored bits for  $1/3$  are:

0 01101 0101010101

### II.2.4 Sub-normal and special numbers

For sub-normal numbers, the simplest example is zero, which has  $q = 0$  and all significand bits zero: 0 00000 0000000000. Unlike integers, we also have a negative zero, which has bits: 1 00000 0000000000. This is treated as identical to positive 0 (except for degenerate operations as explained in the lab).

**Example 14** (subnormal in 16-bits). Consider the number with bits

1 00000 1100000000

assuming it is a half-precision float ( $F_{16}$ ). Since all exponent bits are zero it is sub-normal. Since the sign bit is 1 it is negative. Hence this number is:

$$-2^{1-\sigma}(0.1100000000)_2 = -2^{-14}(2^{-1} + 2^{-2}) = -3 \times 2^{-16}$$

The special numbers extend the real line by adding  $\pm\infty$  but also a notion of “not-a-number” NaN. Whenever the bits of  $q$  of a floating-point number are all 1 then they represent an element of  $F^{\text{special}}$ . If all  $b_k = 0$ , then the number represents either  $\pm\infty$ . All other special floating-point numbers represent NaN.

**Example 15** (special in 16-bits). The number with bits

1 11111 0000000000

has all exponent bits equal to 1, and significand bits 0 and sign bit 1, hence represents  $-\infty$ . On the other hand, the number with bits

1 11111 0000000001

has all exponent bits equal to 1 but does not have all significand bits equal to 0, hence is one of many representations for NaN.

## II.3 Floating Point Arithmetic

Arithmetic operations on floating-point numbers are *exact up to rounding*. There are three basic rounding strategies: round up/down/nearest. Mathematically we introduce a function to capture the notion of rounding:

**Definition 10** (rounding).  $\text{fl}_{\sigma,Q,S}^{\text{up}} : \mathbb{R} \rightarrow F_{\sigma,Q,S}$  denotes the function that rounds a real number up to the nearest floating-point number that is greater or equal.  $\text{fl}_{\sigma,Q,S}^{\text{down}} : \mathbb{R} \rightarrow F_{\sigma,Q,S}$  denotes the function that rounds a real number down to the nearest floating-point number that is greater or equal.  $\text{fl}_{\sigma,Q,S}^{\text{nearest}} : \mathbb{R} \rightarrow F_{\sigma,Q,S}$  denotes the function that rounds a real number to the nearest floating-point number. In case of a tie, it returns the floating-point number whose least significant bit is equal to zero. We use the notation  $\text{fl}$  when  $\sigma, Q, S$  and the rounding mode are implied by context, with  $\text{fl}^{\text{nearest}}$  being the default rounding mode.

In more detail on the behaviour of nearest mode, if a positive number  $x$  is between two normal floats  $x_- \leq x \leq x_+$  we can write its expansion as

$$x = 2^{q-\sigma}(1.b_1b_2 \dots b_S b_{S+1} \dots)_2$$

where

$$\begin{aligned} x_- &:= \text{fl}^{\text{down}}(x) = 2^{q-\sigma}(1.b_1b_2 \dots b_S)_2 \\ x_+ &:= \text{fl}^{\text{up}}(x) = x_- + 2^{q-S} \end{aligned}$$

Write the half-way point as:

$$x_h := \frac{x_+ + x_-}{2} = x_- + 2^{q-S-1} = 2^{q-\sigma}(1.b_1b_2 \dots b_S 1)_2$$

If  $x_- \leq x < x_h$  then  $\text{fl}(x) = x_-$  and if  $x_h < x \leq x_+$  then  $\text{fl}(x) = x_+$ . If  $x = x_h$  then it is exactly half-way between  $x_-$  and  $x_+$ . The rule is if  $b_S = 0$  then  $\text{fl}(x) = x_-$  and otherwise  $\text{fl}(x) = x_+$ .

In IEEE arithmetic, the arithmetic operations  $+$ ,  $-$ ,  $*$ ,  $/$  are defined by the property that they are exact up to rounding. Mathematically we denote these operations as  $\oplus, \ominus, \otimes, \oslash : F_{\sigma,Q,S} \otimes F_{\sigma,Q,S} \rightarrow F_{\sigma,Q,S}$  as follows:

$$\begin{aligned} x \oplus y &:= \text{fl}(x + y) \\ x \ominus y &:= \text{fl}(x - y) \\ x \otimes y &:= \text{fl}(x * y) \\ x \oslash y &:= \text{fl}(x / y) \end{aligned}$$

Note also that  $\wedge$  and `sqrt` are similarly exact up to rounding. Also, note that when we convert a Julia command with constants specified by decimal expansions we first round the constants to floats, e.g., `1.1 + 0.1` is actually reduced to

$$\text{fl}(1.1) \oplus \text{fl}(0.1)$$

This includes the case where the constants are integers (which are normally exactly floats but may be rounded if extremely large).

**Example 16** (decimal is not exact). On a computer `1.1+0.1` is close to but not exactly the same thing as `1.2`. This is because  $\text{fl}(1.1) \neq 1 + 1/10$  and  $\text{fl}(0.1) \neq 1/10$  since their expansion in *binary* is not finite. For  $F_{16}$  we have:

$$\begin{aligned}\text{fl}(1.1) &= \text{fl}((1.00011001100\mathbf{011}\dots)_2) = (1.0001100110)_2 \\ \text{fl}(0.1) &= \text{fl}(2^{-4}(1.10011001100\mathbf{011}\dots)_2) = 2^{-4} * (1.1001100110)_2 = (0.00011001100110)_2\end{aligned}$$

Thus when we add them we get

$$\text{fl}(1.1) + \text{fl}(0.1) = (1.0011001100\mathbf{011})_2$$

where the red digits indicate those beyond the 10 significant digits representable in  $F_{16}$ . In this case we round down and get

$$\text{fl}(1.1) \oplus \text{fl}(0.1) = (1.0011001100)_2$$

On the other hand,

$$\text{fl}(1.2) = \text{fl}((1.0011001100\mathbf{11001100}\dots)_2) = (1.0011001101)_2$$

which differs by 1 bit.

**WARNING (non-associative)** These operations are not associative! E.g.  $(x \oplus y) \oplus z$  is not necessarily equal to  $x \oplus (y \oplus z)$ . Commutativity is preserved, at least.

### II.3.1 Bounding errors in floating point arithmetic

When dealing with normal numbers there are some important constants that we will use to bound errors.

**Definition 11** (machine epsilon/smallest positive normal number/largest normal number). *Machine epsilon* is denoted

$$\epsilon_{m,S} := 2^{-S}.$$

When  $S$  is implied by context we use the notation  $\epsilon_m$ . The *smallest positive normal number* is  $q = 1$  and  $b_k$  all zero:

$$\min |F_{\sigma,Q,S}^{\text{normal}}| = 2^{1-\sigma}$$

where  $|A| := \{|x| : x \in A\}$ . The *largest (positive) normal number* is

$$\max F_{\sigma,Q,S}^{\text{normal}} = 2^{2^Q-2-\sigma}(1.11\dots)_2 = 2^{2^Q-2-\sigma}(2 - \epsilon_m)$$

We can bound the error of basic arithmetic operations in terms of machine epsilon, provided a real number is close to a normal number:

**Definition 12** (normalised range). The *normalised range*  $\mathcal{N}_{\sigma,Q,S} \subset \mathbb{R}$  is the subset of real numbers that lies between the smallest and largest normal floating-point number:

$$\mathcal{N}_{\sigma,Q,S} := \{x : \min |F_{\sigma,Q,S}^{\text{normal}}| \leq |x| \leq \max F_{\sigma,Q,S}^{\text{normal}}\}$$

When  $\sigma, Q, S$  are implied by context we use the notation  $\mathcal{N}$ .

We can use machine epsilon to determine bounds on rounding:

**Proposition 2** (round bound). *If  $x \in \mathcal{N}$  then*

$$\text{fl}^{\text{mode}}(x) = x(1 + \delta_x^{\text{mode}})$$

where the relative error is bounded by:

$$\begin{aligned} |\delta_x^{\text{nearest}}| &\leq \frac{\epsilon_m}{2} \\ |\delta_x^{\text{up/down}}| &< \epsilon_m. \end{aligned}$$

### Proof

We will show this result for the nearest rounding mode. Note first that

$$\text{fl}(-x) = -\text{fl}(x)$$

and hence it suffices to prove the result for positive  $x$ . Write

$$x = 2^{q-\sigma}(1.b_1b_2\dots b_S\textcolor{red}{b}_{S+1}\dots)_2.$$

Define

$$\begin{aligned} x_- &:= \text{fl}^{\text{down}}(x) = 2^{q-\sigma}(1.b_1b_2\dots b_S)_2 \\ x_+ &:= \text{fl}^{\text{up}}(x) = x_- + 2^{q-\sigma-S} \\ x_h &:= \frac{x_+ + x_-}{2} = x_- + 2^{q-\sigma-S-1} = 2^{q-\sigma}(1.b_1b_2\dots b_S\textcolor{red}{1})_2 \end{aligned}$$

so that  $x_- \leq x \leq x_+$ . We consider two cases separately.

**(Round Down)** First consider the case where  $x$  is such that we round down:  $\text{fl}(x) = x_-$ . Since  $2^{q-\sigma} \leq x_- \leq x \leq x_h$  we have

$$|\delta_x| = \frac{x - x_-}{x} \leq \frac{x_h - x_-}{x_-} = \frac{2^{q-\sigma-S-1}}{2^{q-\sigma}} = 2^{-S-1} = \frac{\epsilon_m}{2}.$$

**(Round Up)** If  $\text{fl}(x) = x_+$  then  $2^{q-\sigma} \leq x_- < x_h \leq x \leq x_+$  and hence

$$|\delta_x| = \frac{x_+ - x}{x} \leq \frac{x_+ - x_h}{x_-} = \frac{2^{q-\sigma-S-1}}{2^{q-\sigma}} = 2^{-S-1} = \frac{\epsilon_m}{2}.$$

■

This immediately implies relative error bounds on all IEEE arithmetic operations, e.g., if  $x + y \in \mathcal{N}$  then we have

$$x \oplus y = (x + y)(1 + \delta_1)$$

where (assuming the default nearest rounding)  $|\delta_1| \leq \frac{\epsilon_m}{2}$ .

### II.3.2 Idealised floating point

With a complicated formula it is mathematically inelegant to work with normalised ranges: one cannot guarantee apriori that a computation always results in a normal float. Extending the bounds to subnormal numbers is tedious, rarely relevant, and beyond the scope of this module. Thus to avoid this issue we will work with an alternative mathematical model:

**Definition 13** (idealised floating point). An idealised mathematical model of floating point numbers for which the only subnormal number is zero can be defined as:

$$F_{\infty,S} := \{\pm 2^q \times (1.b_1b_2b_3 \dots b_S)_2 : q \in \mathbb{Z}\} \cup \{0\}$$

Note that  $F_{\sigma,Q,S}^{\text{normal}} \subset F_{\infty,S}$  for all  $\sigma, Q \in \mathbb{N}$ . The definition of rounding  $\text{fl}_{\infty,S}^{\text{mode}} : \mathbb{R} \rightarrow F_{\infty,S}$  naturally extend to  $F_{\infty,S}$  and hence we can consider bounds for floating point operations such as  $\oplus$ ,  $\ominus$ , etc. And in this model the round bound is valid for all real numbers (including  $x = 0$ ).

**Example 17** (bounding a simple computation). We show how to bound the error in computing  $(1.1 + 1.2) * 1.3 = 2.99$  and we may assume idealised floating-point arithmetic  $F_{\infty,S}$ . First note that  $1.1$  on a computer is in fact  $\text{fl}(1.1)$ , and we will always assume nearest rounding unless otherwise stated. Thus this computation becomes

$$(\text{fl}(1.1) \oplus \text{fl}(1.2)) \otimes \text{fl}(1.3)$$

We will show the *absolute error* is given by

$$(\text{fl}(1.1) \oplus \text{fl}(1.2)) \otimes \text{fl}(1.3) = 2.99 + \delta$$

where  $|\delta| \leq 28\epsilon_m$ . First we find

$$\begin{aligned} \text{fl}(1.1) \oplus \text{fl}(1.2) &= (1.1(1 + \delta_1) + 1.2(1 + \delta_2))(1 + \delta_3) \\ &= 2.3 + \underbrace{1.1\delta_1 + 1.2\delta_2 + 2.3\delta_3 + 1.1\delta_1\delta_3 + 1.2\delta_2\delta_3}_{\delta_4}. \end{aligned}$$

While  $\delta_1\delta_3$  and  $\delta_2\delta_3$  are absolutely tiny in practice we will bound them rather naïvely by eg.

$$|\delta_1\delta_3| \leq \epsilon_m^2/4 \leq \epsilon_m/4.$$

Further we round up constants to integers in the bounds for simplicity. We thus have the bound

$$|\delta_4| \leq (2 + 2 + 3 + 1 + 1) \frac{\epsilon_m}{2} \leq 5\epsilon_m.$$

Writing  $\text{fl}(1.3) = 1.3(1 + \delta_5)$  and also incorporating an error from the rounding in  $\otimes$  we arrive at

$$\begin{aligned} (\text{fl}(1.1) \oplus \text{fl}(1.2)) \otimes \text{fl}(1.3) &= (2.3 + \delta_4)1.3(1 + \delta_5)(1 + \delta_6) \\ &= 2.99 + \underbrace{1.3(\delta_4 + 2.3\delta_5 + 2.3\delta_6 + \delta_4\delta_5 + \delta_4\delta_6 + 2.3\delta_5\delta_6 + \delta_4\delta_5\delta_6)}_{\delta} \end{aligned}$$

We use the bounds

$$\begin{aligned} |\delta_4\delta_5|, |\delta_4\delta_6| &\leq 5\epsilon_m^2/2 \leq 5\epsilon_m/2, \\ |\delta_5\delta_6| &\leq \epsilon_m^2/4 \leq \epsilon_m/4 \\ |\delta_4\delta_5\delta_6| &\leq 5\epsilon_m^3/4 \leq \epsilon_m. \end{aligned}$$

Thus the *absolute error* is bounded (bounding 1.3 by 2) by

$$|\delta| \leq 2(5 + 3/2 + 3/2 + 5/4 + 5/2 + 3/4 + 5/4)\epsilon_m \leq 28\epsilon_m$$

### II.3.3 Divided differences floating point error bound

We can use the bound on floating point arithmetic to deduce a bound on divided differences that captures the phenomena we observed where the error of divided differences became large as  $h \rightarrow 0$ . We assume that the function we are attempting to differentiate is computed using floating point arithmetic in a way that has a small absolute error.

**Theorem 3** (divided difference error bound). *Assume we are working in idealised floating-point arithmetic  $F_{\infty,S}$ . Let  $f$  be twice-differentiable in a neighbourhood of  $x \in F_{\infty,S}$  and assume that*

$$f(x) = f^{\text{FP}}(x) + \delta_x^f$$

where  $f^{\text{FP}} : F_{S,\infty} \rightarrow F_{S,\infty}$  has uniform absolute accuracy in that neighbourhood, that is:

$$|\delta_x^f| \leq c\epsilon_m$$

for a fixed constant  $c \geq 0$ . The divided difference approximation partially implemented with floating point satisfies

$$\frac{f^{\text{FP}}(x+h) \ominus f^{\text{FP}}(x)}{h} = f'(x) + \delta_{x,h}^{\text{FD}}$$

where

$$|\delta_{x,h}^{\text{FD}}| \leq \frac{|f'(x)|}{2}\epsilon_m + Mh + \frac{4c\epsilon_m}{h}$$

for  $M = \sup_{x \leq t \leq x+h} |f''(t)|$ .

#### Proof

We have

$$\begin{aligned} (f^{\text{FP}}(x+h) \ominus f^{\text{FP}}(x))/h &= \frac{f(x+h) - \delta_{x+h}^f - f(x) + \delta_x^f}{h}(1 + \delta_1) \\ &= \frac{f(x+h) - f(x)}{h}(1 + \delta_1) + \frac{\delta_x^f - \delta_{x+h}^f}{h}(1 + \delta_1) \end{aligned}$$

where  $|\delta_1| \leq \epsilon_m/2$ . Applying Taylor's theorem we get

$$(f^{\text{FP}}(x+h) \ominus f^{\text{FP}}(x))/h = f'(x) + \underbrace{f'(x)\delta_1 + \frac{f''(t)}{2}h(1 + \delta_1) + \frac{\delta_x^f - \delta_{x+h}^f}{h}(1 + \delta_1)}_{\delta_{x,h}^{\text{FD}}}$$

The bound then follows, using the very pessimistic bound  $|1 + \delta_1| \leq 2$ .

■

The previous theorem neglected some errors due to rounding, which was done for simplicity. This is justified under fairly general restrictions:

**Corollary 1** (divided differences in practice). *We have*

$$(f^{\text{FP}}(x \oplus h) \ominus f^{\text{FP}}(x)) \oslash h = \frac{f^{\text{FP}}(x+h) \ominus f^{\text{FP}}(x)}{h}$$

whenever  $h = 2^{j-n}$  for  $0 \leq n \leq S$  and the last binary place of  $x \in F_{\infty,S}$  is zero, that is  $x = \pm 2^j(1.b_1 \dots b_{S-1}0)_2$ .



**Proof**

When  $h = 2^{-n}$  we have for any normal float  $y = \pm 2^j(1.b_1 \dots b_S)_2 \in F_{\infty, S}$  that

$$y/h = \pm 2^{j-n}(1.b_1 \dots b_S)_2 \in F_{\infty, S} \Rightarrow y/h = y \odot h.$$

If  $b_S = 0$  the worst possible case is that we increase the exponent by one as we are just adding 1 to one of the digits  $b_1, \dots, b_S$ . This would cause us to lose the last digit. But if that is zero no error is incurred when we round.

■

The three-terms of this bound tell us a story: the first term is a fixed (small) error, the second term tends to zero as  $h \rightarrow 0$ , while the last term grows like  $\epsilon_m/h$  as  $h \rightarrow 0$ . Thus we observe convergence while the second term dominates, until the last term takes over. Of course, a bad upper bound is not the same as a proof that something grows, but it is a good indication of what happens *in general* and suffices to choose  $h$  so that these errors are balanced (and thus minimised). Since in general we do not have access to the constants  $c$  and  $M$  we employ the following heuristic to balance the two sources of errors:

**Heuristic (divided difference with floating-point step)** Choose  $h$  proportional to  $\sqrt{\epsilon_m}$  in divided differences so that  $Mh$  and  $\frac{4c\epsilon_m}{h}$  are (roughly) the same magnitude.

In the case of double precision  $\sqrt{\epsilon_m} \approx 1.5 \times 10^{-8}$ , which is close to when the observed error begins to increase in the examples we saw before.

**Remark** While divided differences is of debatable utility for computing derivatives, it is extremely effective in building methods for solving differential equations, as we shall see later. It is also very useful as a “sanity check” if one wants something to compare with other numerical methods for differentiation.

**Remark** It is also possible to deduce an error bound for the rectangular rule showing that the error caused by round-off is on the order of  $n\epsilon_m$ , that is it does in fact grow but the error without round-off which was bounded by  $M/n$  will be substantially greater for all reasonable values of  $n$ .

## II.4 Interval Arithmetic

It is possible to use rounding modes (up/down) to do rigorous computation to compute bounds on the error in, for example, the digits of  $e$ . To do this we will use set/interval arithmetic. For sets  $X, Y \subseteq \mathbb{R}$ , the set arithmetic operations are defined as

$$\begin{aligned} X + Y &:= \{x + y : x \in X, y \in Y\}, \\ XY &:= \{xy : x \in X, y \in Y\}, \\ X/Y &:= \{x/y : x \in X, y \in Y\} \end{aligned}$$

We will use floating point arithmetic to construct approximate set operations  $\oplus, \otimes$  so that

$$\begin{aligned} X + Y &\subseteq X \oplus Y, \\ XY &\subseteq X \otimes Y, \\ X/Y &\subseteq X \odot Y \end{aligned}$$

thereby a complicated algorithm can be run on sets and the true result is guaranteed to be a subset of the output.

When our sets are intervals we can deduce simple formulas for basic arithmetic operations. For simplicity we only consider the case where all values are positive.

**Proposition 3** (interval bounds). *For intervals  $X = [a, b]$  and  $Y = [c, d]$  satisfying  $0 < a \leq b$  and  $0 < c \leq d$ , and  $n > 0$ , we have:*

$$\begin{aligned} X + Y &= [a + c, b + d] \\ X/n &= [a/n, b/n] \\ XY &= [ac, bd] \end{aligned}$$

**Proof** We first show  $X + Y \subseteq [a + c, b + d]$ . If  $z \in X + Y$  then  $z = x + y$  such that  $a \leq x \leq b$  and  $c \leq y \leq d$  and therefore  $a + c \leq z \leq b + d$  and  $z \in [a + c, b + d]$ . Equality follows from convexity. First note that  $a + c, b + d \in X + Y$ . Any point  $z \in [a + c, b + d]$  can be written as a convex combination of the two endpoints: there exists  $0 \leq t \leq 1$  such that

$$z = (1 - t)(a + c) + t(b + d) = \underbrace{(1 - t)a + tb}_x + \underbrace{(1 - t)c + td}_y$$

Because intervals are convex we have  $x \in X$  and  $y \in Y$  and hence  $z \in X + Y$ .

The remaining two proofs are left for the problem sheet.

■

We want to implement floating point variants of these operations that are guaranteed to contain the true set arithmetic operations. We do so as follows:

**Definition 14** (floating point interval arithmetic). For intervals  $A = [a, b]$  and  $B = [c, d]$  satisfying  $0 < a \leq b$  and  $0 < c \leq d$ , and  $n > 0$ , define:

$$\begin{aligned} [a, b] \oplus [c, d] &:= [\text{fl}^{\text{down}}(a + c), \text{fl}^{\text{up}}(b + d)] \\ [a, b] \ominus [c, d] &:= [\text{fl}^{\text{down}}(a - d), \text{fl}^{\text{up}}(b - c)] \\ [a, b] \oslash n &:= [\text{fl}^{\text{down}}(a/n), \text{fl}^{\text{up}}(b/n)] \\ [a, b] \otimes [c, d] &:= [\text{fl}^{\text{down}}(ac), \text{fl}^{\text{up}}(bd)] \end{aligned}$$

**Example 18** (small sum). consider evaluating the first few terms in the Taylor series of the exponential at  $x = 1$  using interval arithmetic with half-precision  $F_{16}$  arithmetic. The first three terms are exact since all numbers involved are exactly floats, in particular if we evaluate  $1 + x + x^2/2$  with  $x = 1$  we get

$$1 + 1 + 1/2 \in 1 \oplus [1, 1] \oplus ([1, 1] \otimes [1, 1]) \oslash 2 = [5/2, 5/2]$$

Noting that

$$1/6 = (1/3)/2 = 2^{-3}(1.01010101\dots)_2$$

we can extend the computation to another term:

$$\begin{aligned} 1 + 1 + 1/2 + 1/6 &\in [5/2, 5/2] \oplus ([1, 1] \oslash 6) \\ &= [2(1.01)_2, 2(1.01)_2] \oplus 2^{-3}[(1.0101010101)_2, (1.0101010110)_2] \\ &= [\text{fl}^{\text{down}}(2(1.0101010101\textcolor{red}{0101})_2), \text{fl}^{\text{up}}(2(1.0101010101\textcolor{red}{011})_2)] \\ &= [2(1.0101010101)_2, 2(1.0101010110)_2] \\ &= [2.666015625, 2.66796875] \end{aligned}$$

**Example 19** (exponential with intervals). Consider computing  $\exp(x)$  for  $0 \leq x \leq 1$  from the Taylor series approximation:

$$\exp(x) = \sum_{k=0}^n \frac{x^k}{k!} + \underbrace{\exp(t) \frac{x^{n+1}}{(n+1)!}}_{\delta_{x,n}}$$

where we can bound the error by (using the fact that  $e = 2.718\dots \leq 3$ )

$$|\delta_{x,n}| \leq \frac{\exp(1)}{(n+1)!} \leq \frac{3}{(n+1)!}.$$

Put another way:  $\delta_{x,n} \in \left[-\frac{3}{(n+1)!}, \frac{3}{(n+1)!}\right]$ . We can use this to adjust the bounds derived from interval arithmetic for the interval arithmetic expression:

$$\exp(X) \subseteq \left(\bigoplus_{k=0}^n X \oslash k \oslash k!\right) \oplus \left[\text{fl}^{\text{down}}\left(-\frac{3}{(n+1)!}\right), \text{fl}^{\text{up}}\left(\frac{3}{(n+1)!}\right)\right]$$

For example, with  $n = 3$  we have  $|\delta_{1,2}| \leq 3/4! = 1/2^3$ . Thus we can prove that:

$$\begin{aligned} e &= 1 + 1 + 1/2 + 1/6 + \delta_x \in [2(1.0101010101)_2, 2(1.0101010110)_2] \oplus [-1/2^3, 1/2^3] \\ &= [2(1.0100010101)_2, 2(1.0110010110)_2] = [2.541015625, 2.79296875] \end{aligned}$$

In the lab we get many more digits by using a computer to compute the bounds.



# Chapter III

## Numerical Linear Algebra

Many problems in mathematics are linear: for example, polynomial regression and differential equations. Numerical methods for such applications invariably result in (finite-dimensional) linear systems that must be solved numerically on a computer: the dimensions of the problems are often in the 1000s, millions, or even billions. One would certainly not want to tackle that with Gaussian elimination by hand! In this chapter we discuss algorithms, and in particular matrix factorisations, that are computed using floating point operations. We also introduce some basic applications.

In particular we discuss:

1. III.1 Structured Matrices: we discuss special structured matrices such as triangular and tridiagonal.
2. III.2 Differential Equations: using divided differences we can reduce differential equations to linear systems. This motivates the investigation of numerical algorithms for solving linear systems.
3. III.3 LU and Cholesky Factorisations: we look at computing a factorisation of a square matrix as a product of a lower and upper triangular matrix, including the special case where the matrix is symmetric positive definite. Hidden in this is an algorithm to prove positive definiteness.
4. III.4 Polynomial Regression: often in data science one needs to approximate data by a polynomial. We discuss how to reduce this problem to solving a rectangular least squares problem.
5. III.5 Orthogonal Matrices: we discuss different types of orthogonal matrices, which will be used to simplify rectangular least squares problems.
6. III.6 QR Factorisation: we introduce an algorithm to compute a factorisation of a rectangular matrix as a product of an orthogonal and upper triangular matrix, thereby solving least squares problems.

### III.1 Structured Matrices

We have seen how algebraic operations ( $+$ ,  $-$ ,  $*$ ,  $/$ ) are defined exactly in terms of rounding ( $\oplus$ ,  $\ominus$ ,  $\otimes$ ,  $\oslash$ ) for floating point numbers. Now we see how this allows us to do (approximate)

linear algebra operations on matrices.

A matrix can be stored in different formats, in particular it is important for large scale simulations that we take advantage of *sparsity*: if we know a matrix has entries that are guaranteed to be zero we can implement faster algorithms. We shall see that this comes up naturally in numerical methods for solving differential equations.

In particular, we will discuss some basic types of structure in matrices:

1. *Dense*: This can be considered unstructured, where we need to store all entries in a vector or matrix. Matrix-vector multiplication reduces directly to standard algebraic operations. Solving linear systems with dense matrices will be discussed later.
2. *Triangular*: If a matrix is upper or lower triangular, multiplication requires roughly half the number of operations. Crucially, we can apply the inverse of a triangular matrix using forward-elimination or back-substitution.
3. *Banded*: If a matrix is zero apart from entries a fixed distance from the diagonal it is called banded and matrix-vector multiplication has a lower *complexity*: the number of operations scales linearly with the dimension (instead of quadratically). We discuss three cases: diagonal, tridiagonal and bidiagonal matrices.

**Remark** For those who took the first half of the module, there was an important emphasis on working with *linear operators* rather than *matrices*. That is, there was an emphasis on basis-independent mathematical techniques, which is critical for extension of results to infinite-dimensional spaces (which might not have a complete basis). However, in terms of practical computation we need to work with some representation of an operator and the most natural is a matrix. And indeed we will see in the next section how infinite-dimensional differential equations can be solved by reduction to finite-dimensional matrices. (Restricting attention to matrices is also important as some of the students have not taken the first half of the module.)

### III.1.1 Dense matrices

A basic operation is matrix-vector multiplication. For a field  $\mathbb{F}$  (typically  $\mathbb{R}$  or  $\mathbb{C}$ , or this can be relaxed to be a ring), consider a matrix and vector whose entries are in  $\mathbb{F}$ :

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} = [\mathbf{a}_1 | \cdots | \mathbf{a}_n] \in \mathbb{F}^{m \times n}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{F}^n.$$

where  $\mathbf{a}_j = A\mathbf{e}_j \in \mathbb{F}^m$  are the columns of  $A$ . Recall the usual definition of matrix multiplication:

$$A\mathbf{x} := \begin{bmatrix} \sum_{j=1}^n a_{1j}x_j \\ \vdots \\ \sum_{j=1}^n a_{mj}x_j \end{bmatrix}.$$

When we are working with floating point numbers  $A \in F^{m \times n}$  we obtain an approximation:

$$A\mathbf{x} \approx \begin{bmatrix} \oplus_{j=1}^n (a_{1j} \otimes x_j) \\ \vdots \\ \oplus_{j=1}^n (a_{mj} \otimes x_j) \end{bmatrix}.$$

This actually encodes an algorithm for computing the entries.

This algorithm uses  $O(mn)$  floating point operations (see the appendix if you are unaware of Big-O notation, here our complexities are implicitly taken to be when  $m$  or  $n$  tends to  $\infty$ ): each of the  $m$  entry consists of  $n$  multiplications and  $n - 1$  additions, hence we have a total of  $2n - 1 = O(n)$  operations per row for a total of  $m(2n - 1) = O(mn)$  operations. For a square matrix this is  $O(n^2)$  operations which we call *quadratic complexity*. In the problem sheet we see how the floating point error can be bounded in terms of norms, thus reducing the problem to a purely mathematical concept.

Sometimes there are multiple ways of implementing numerical algorithms. We have an alternative formula where we multiply by columns:

$$A\mathbf{x} = x_1\mathbf{a}_1 + \cdots + x_n\mathbf{a}_n.$$

The floating point formula for this is exactly the same as the previous algorithm and the number of operations is the same. Just the order of operations has changed. Surprisingly, this latter version is significantly faster.

**Remark** Floating point operations are sometimes called FLOPs, which are a standard measurement of speed of CPUs. However, FLOP sometimes uses an alternative definitions that combines an addition and multiplication as a single FLOP. In the lab we give an example showing that counting the precise number of operations is somewhat of a fools errand: algorithms such as the two approaches for matrix multiplication with the exact same number of operations can have wildly different speeds. We will therefore only be concerned with *complexity*; the asymptotic growth (Big-O) of operations as  $n \rightarrow \infty$ , in which case the difference between FLOPs and operations is immaterial.

### III.1.2 Triangular matrices

The simplest sparsity case is being triangular: where all entries above or below the diagonal are zero. We consider upper and lower triangular matrices:

$$U = \begin{bmatrix} u_{11} & \cdots & u_{1n} \\ & \ddots & \vdots \\ & & u_{nn} \end{bmatrix}, \quad L = \begin{bmatrix} \ell_{11} & & \\ \vdots & \ddots & \\ \ell_{n1} & \cdots & \ell_{nn} \end{bmatrix}.$$

Matrix multiplication can be modified to take advantage of the zero pattern of the matrix. Eg., if  $L \in \mathbb{F}^{n \times n}$  is lower triangular we have:

$$L\mathbf{x} = \begin{bmatrix} \ell_{1,1}x_1 \\ \sum_{j=1}^2 \ell_{2j}x_j \\ \vdots \\ \sum_{j=1}^n \ell_{nj}x_j \end{bmatrix}.$$

When implemented in floating point this uses roughly half the number of multiplications:  $1 + 2 + \cdots + n = n(n + 1)/2$  multiplications. (It is also about twice as fast in practice.) The complexity is still quadratic:  $O(n^2)$  operations.

Triangularity allows us to also invert systems using forward- or back-substitution. In particular if  $\mathbf{x}$  solves  $L\mathbf{x} = \mathbf{b}$  then we have:

$$x_k = \frac{b_k - \sum_{j=1}^{k-1} \ell_{kj}x_j}{\ell_{kk}}$$

Thus we can compute  $x_1, x_2, \dots, x_n$  in sequence.

### III.1.3 Banded matrices

A *banded matrix* is zero off a prescribed number of diagonals. We call the number of (potentially) non-zero diagonals the *bandwidths*:

**Definition 15** (bandwidths). A matrix  $A$  has *lower-bandwidth*  $l$  if  $a_{kj} = 0$  for all  $k - j > l$  and *upper-bandwidth*  $u$  if  $a_{kj} = 0$  for all  $j - k > u$ . We say that it has *strictly lower-bandwidth*  $l$  if it has lower-bandwidth  $l$  and there exists a  $j$  such that  $a_{j+l,j} \neq 0$ . We say that it has *strictly upper-bandwidth*  $u$  if it has upper-bandwidth  $u$  and there exists a  $k$  such that  $a_{k,k+u} \neq 0$ .

A square banded matrix has the sparsity pattern:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1,u+1} & & & \\ \vdots & a_{22} & \ddots & a_{2,u+2} & & \\ a_{1+l,1} & \ddots & \ddots & \ddots & \ddots & \\ & a_{2+l,2} & \ddots & \ddots & \ddots & a_{n-u,n} \\ & & \ddots & \ddots & \ddots & \vdots \\ & & & a_{n,n-l} & \cdots & a_{nn} \end{bmatrix}$$

A banded matrix has better complexity for matrix multiplication and solving linear systems: we can multiply square banded matrices in linear complexity:  $O(n)$  operations. We consider two cases in particular (in addition to diagonal): bidiagonal and tridiagonal.

**Definition 16** (Bidiagonal). If a square matrix has bandwidths  $(l, u) = (1, 0)$  it is *lower-bidiagonal* and if it has bandwidths  $(l, u) = (0, 1)$  it is *upper-bidiagonal*.

For example, if

$$L = \begin{bmatrix} \ell_{11} & & & & \\ \ell_{21} & \ell_{22} & & & \\ & \ddots & \ddots & & \\ & & \ell_{n,n-1} & \ell_{nn} & \end{bmatrix}$$

then lower-bidiagonal multiplication becomes

$$L\mathbf{x} = \begin{bmatrix} \ell_{1,1}x_1 \\ \ell_{21}x_1 + \ell_{22}x_2 \\ \vdots \\ \ell_{n,n-1}x_{n-1} + \ell_{nn}x_n \end{bmatrix}.$$

This requires  $O(1)$  operations per row (at most 2 multiplications and 1 addition) and hence the total is only  $O(n)$  operations. A bidiagonal matrix is always triangular and we can also invert in  $O(n)$  operations: if  $L\mathbf{x} = \mathbf{b}$  then  $x_1 = b_1/\ell_{11}$  and for  $k = 2, \dots, n$  we can compute

$$x_k = \frac{b_k - \ell_{k-1,k}x_{k-1}}{\ell_{kk}}.$$

**Definition 17** (Tridiagonal). If a square matrix has bandwidths  $l = u = 1$  it is *tridiagonal*.

For example,

$$A = \begin{bmatrix} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{nn} \end{bmatrix}$$



is tridiagonal. Matrix multiplication is clearly  $O(n)$  operations: each row has  $O(1)$  non-zeros and there are  $n$  rows. But so is solving linear systems, which we shall see later.

## III.2 Differential Equations via Finite Differences

Linear algebra is a powerful tool for solving linear equations, including  $\infty$ -dimensional ones like differential equations. In this section we discuss *finite differences*: an algorithmic way of reducing ODEs to linear systems by replacing derivatives with divided difference approximations.

We will focus on the following differential equations. Indefinite integration for  $a \leq x \leq b$  can be viewed as solving a very simple first-order linear ODE: given a constant  $c \in \mathbb{F}$  (where as before  $\mathbb{F}$  is usually  $\mathbb{R}$  or  $\mathbb{C}$ ) and a function  $f : [a, b] \rightarrow \mathbb{F}$ , find a differentiable function  $u : [a, b] \rightarrow \mathbb{F}$  such that

$$\begin{aligned} u(a) &= c, \\ u'(x) &= f(x). \end{aligned}$$

We will then allow for more complicated first order linear ODEs with variable coefficients: given a constant  $c$  and functions  $f, \omega : [a, b] \rightarrow \mathbb{F}$  find  $u$  such that

$$\begin{aligned} u(a) &= c, \\ u'(x) - \omega(x)u(x) &= f(x). \end{aligned}$$

For second-order differential equations you may have seen *initial value problems* where the value and derivative at an initial point  $x = a$  are provided. Instead, we will consider *boundary value problems* where the value at the left and right endpoints are imposed. In particular we will consider the Poisson equation with *Dirichlet conditions* (i.e. conditions on the left and right of an interval): given constants  $c, d$  and a function  $f$  find a twice-differentiable function  $u$  such that

$$\begin{aligned} u(a) &= c, \\ u''(x) &= f(x), \\ u(b) &= d \end{aligned}$$

In higher dimensions, the Poisson equation (and other *elliptic* partial differential equations) typically have boundary conditions imposed on the boundary of a complicated geometry and the techniques we discuss for our simple 1D model problem extend to these more challenging settings.

Briefly, the basic idea of finite differences is a systematic way of reducing a differential equation to a linear system. For each problem we will do the following steps:

1. Discretise  $[a, b]$  by a grid of points  $x_0, \dots, x_n$  and write the ODE on each grid point.
2. Replace derivatives of the solution  $u$  with its values on a grid  $u(x_j)$  by using a divided difference formula.
3. In the formula replace unknown values of  $u(x_j)$  at the grid by new unknowns  $u_j$ .

4. Deduce from this a linear system that can be solved to compute  $u_j$  so that (hopefully)  $u_j \approx u(x_j)$ .

**Remark** One can prove convergence of finite difference approximations but this is beyond the scope of this module. In the lab we determine convergence rates experimentally.

### III.2.1 Indefinite integration

We begin with the simplest differential equation on an interval  $[a, b]$ :

$$\begin{aligned} u(a) &= c, \\ u'(x) &= f(x) \end{aligned}$$

As in integration we will use an evenly spaced grid  $a = x_0 < x_1 < \dots < x_n = b$  defined by  $x_j := a + hj$  where  $h := (b - a)/n$ . The solution is of course  $u(x) = c + \int_a^x f(x)dx$  and we could use Rectangular or Trapezium rules to obtain approximations to  $u(x_j)$  for each  $j$ , however, we shall take another approach that will generalise to other differential equations.

Consider a divided difference approximation like right-sided divided differences:

$$u'(x) \approx \frac{u(x+h) - u(x)}{h}.$$

When applied to a grid point  $x_j \in \{x_0, \dots, x_{n-1}\}$  this becomes:

$$u'(x_j) \approx \frac{u(x_j+h) - u(x_j)}{h} = \frac{u(x_{j+1}) - u(x_j)}{h}$$

Note that  $x_n$  is not permitted since that would depend on  $u(x_{n+1})$ , but  $x_{n+1} > b$  and we have only assumed  $f$  is defined on  $[a, b]$ . We use this approximation as follows:

- (1) Write the ODE and initial conditions on the grid. Since right-sided divided differences will depend on  $x_j$  and  $x_{j+1}$  we stop at  $x_{n-1}$  to avoid going past our grid:

$$\begin{bmatrix} u(x_0) \\ u'(x_0) \\ u'(x_1) \\ \vdots \\ u'(x_{n-1}) \end{bmatrix} = \underbrace{\begin{bmatrix} c \\ f(x_0) \\ f(x_1) \\ \vdots \\ f(x_{n-1}) \end{bmatrix}}_{\mathbf{b}}$$

- (2) Replace derivatives with divided differences, changing equality to an approximation:

$$\begin{bmatrix} u(x_0) \\ (u(x_1) - u(x_0))/h \\ (u(x_2) - u(x_1))/h \\ \vdots \\ (u(x_n) - u(x_{n-1}))/h \end{bmatrix} \approx \mathbf{b}$$

(3) We do not know  $u(x_j)$  hence we replace it with other unknowns  $u_j$ , but where the approximation is turned back into an equality: we want to find  $u_0, \dots, u_n$  such that

$$\begin{bmatrix} u_0 \\ (u_1 - u_0)/h \\ (u_2 - u_1)/h \\ \vdots \\ (u_n - u_{n-1})/h \end{bmatrix} = \mathbf{b}$$

(4) This can be rewritten as a lower bidiagonal linear system:

$$\underbrace{\begin{bmatrix} 1 & & & & \\ -1/h & 1/h & & & \\ & \ddots & \ddots & & \\ & & -1/h & 1/h \end{bmatrix}}_L \underbrace{\begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_n \end{bmatrix}}_{\mathbf{u}} = \mathbf{b}$$

We can determine  $\mathbf{u}$  by solving  $L\mathbf{u} = \mathbf{b}$  using forward-substitution.

As mentioned before, it is possible to prove that as  $n \rightarrow \infty$  we have for all  $j$  that  $u_j \rightarrow u(x_j)$  (uniformly). But we will leave this to be shown experimentally in the lab.

### III.2.2 Forward Euler

We can extend this to more general first-order linear differential equations with a variable coefficient:

$$\begin{aligned} u(a) &= c \\ u'(x) - \omega(x)u(x) &= f(x) \end{aligned}$$

The steps proceed very similar to before:

(1) Write the ODE and initial conditions on the grid, avoiding  $x_n$  so that we don't go past the endpoint:

$$\begin{bmatrix} u(x_0) \\ u'(x_0) + \omega(x_0)u(x_0) \\ u'(x_1) + \omega(x_1)u(x_1) \\ \vdots \\ u'(x_{n-1}) + \omega(x_{n-1})u(x_{n-1}) \end{bmatrix} = \underbrace{\begin{bmatrix} c \\ f(x_0) \\ f(x_1) \\ \vdots \\ f(x_{n-1}) \end{bmatrix}}_{\mathbf{b}}$$

(2) Replace derivatives with divided differences:

$$\begin{bmatrix} u(x_0) \\ (u(x_1) - u(x_0))/h + \omega(x_0)u(x_0) \\ (u(x_2) - u(x_1))/h + \omega(x_1)u(x_1) \\ \vdots \\ (u(x_n) - u(x_{n-1}))/h + \omega(x_{n-1})u(x_{n-1}) \end{bmatrix} \approx \mathbf{b}$$

(3) Replace  $u(x_j)$  by its approximation  $u_j$  but now with the system being an equality:

$$\begin{bmatrix} u_0 \\ (u_1 - u_0)/h + \omega(x_0)u_0 \\ (u_2 - u_1)/h + \omega(x_1)u_1 \\ \vdots \\ (u_n - u_{n-1})/h + \omega(x_{n-1})u_{n-1} \end{bmatrix} = \mathbf{b}$$

(4) This is equivalent to the linear system:

$$\underbrace{\begin{bmatrix} 1 & & & & \\ \omega(x_0) - 1/h & 1/h & & & \\ & \ddots & \ddots & & \\ & & \omega(x_{n-1}) - 1/h & 1/h \end{bmatrix}}_L \underbrace{\begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_n \end{bmatrix}}_{\mathbf{u}} = \mathbf{b}$$

We can solve  $L\mathbf{u} = \mathbf{b}$  using forward-substitution so that  $u_j \approx u(x_j)$ .

### III.2.3 Poisson equation

Consider the Poisson equation with Dirichlet conditions (a two-point boundary value problem): given constants  $c, d$  and a function  $f : [a, b] \rightarrow \mathbb{R}$  find a twice differentiable function  $u : [a, b] \rightarrow \mathbb{R}$  satisfying

$$\begin{aligned} u(a) &= c, \\ u''(x) &= f(x), \\ u(b) &= d \end{aligned}$$

We shall adapt the procedure using the second-order divided difference approximation from the first problem sheet:

$$u''(x) \approx \frac{u(x-h) - 2u(x) + u(x+h)}{h^2}$$

When applied to a grid point  $x_1, \dots, x_{n-1}$  this becomes:

$$u''(x_j) \approx \frac{u(x_j-h) - 2u(x_j) + u(x_j+h)}{h^2} = \frac{u(x_{j-1}) - 2u(x_j) + u(x_{j+1}))}{h^2}$$

Note that  $x_0$  and  $x_n$  are not permitted since that would go past the endpoints of the interval. We use this approximation as follows:

(1) Write the ODE and boundary conditions on the grid (putting the left condition on the top and right condition on the bottom):

$$\begin{bmatrix} u(x_0) \\ u''(x_1) \\ u''(x_2) \\ \vdots \\ u''(x_{n-1}) \\ u(x_n) \end{bmatrix} = \underbrace{\begin{bmatrix} c \\ f(x_1) \\ f(x_2) \\ \vdots \\ f(x_{n-1}) \\ d \end{bmatrix}}_{\mathbf{b}}$$

(2) Replace derivatives with divided differences:

$$\begin{bmatrix} u(x_0) \\ \frac{u(x_0)-2u(x_1)+u(x_2)}{h^2} \\ \frac{u(x_1)-2u(x_2)+u(x_3)}{h^2} \\ \vdots \\ \frac{u(x_{n-2})-2u(x_{n-1})+u(x_n)}{h^2} \\ u(x_n) \end{bmatrix} \approx \mathbf{b}$$

(3) Replace  $u(x_j)$  by its approximation  $u_j$ : we want to find  $u_0, \dots, u_n$  so that

$$\begin{bmatrix} u_0 \\ \frac{u_0-2u_1+u_2}{h^2} \\ \frac{u_1-2u_2+u_3}{h^2} \\ \vdots \\ \frac{u_{n-2}-2u_{n-1}+u_n}{h^2} \\ u_n \end{bmatrix} = \mathbf{b}$$

(4) This is equivalent to a tridiagonal linear system:

$$\underbrace{\begin{bmatrix} 1 & & & & & \\ 1/h^2 & -2/h^2 & 1/h & & & \\ & \ddots & \ddots & \ddots & & \\ & & 1/h^2 & -2/h^2 & 1/h & \\ & & & & 1 \end{bmatrix}}_A \underbrace{\begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_n \end{bmatrix}}_{\mathbf{u}} = \mathbf{b}$$

We are left with the question: how do we solve a tridiagonal linear system  $A\mathbf{u} = \mathbf{b}$ ? We will answer this question in the next section.

### III.3 LU and Cholesky factorisations

In this section we consider the following factorisations for square invertible matrices  $A$ :

1. The *LU factorisation*:  $A = LU$  where  $L$  is lower triangular and  $U$  is upper triangular. This is equivalent to Gaussian elimination without pivoting, so may not exist (e.g. if  $a_{11} = 0$ ).
2. The *PLU factorisation*:  $A = P^\top LU$  where  $P$  is a permutation matrix (a matrix when multiplying a vector is equivalent to permuting its rows),  $L$  is lower triangular and  $U$  is upper triangular. This is equivalent to Gaussian elimination with pivoting. It always exists but may be unstable in extremely rare cases. We won't discuss the details of computing the PLU factorisation but will explore practical usage in the lab.
3. For a real square *symmetric positive definite* ( $A \in \mathbb{R}^{n \times n}$  such that  $A^\top = A$  and  $\mathbf{x}^\top A \mathbf{x} > 0$  for all  $\mathbf{x} \in \mathbb{R}^n$ ,  $\mathbf{x} \neq 0$ ) matrix the LU decomposition has a special form called the *Cholesky factorisation*:  $A = LL^\top$ . This provides an algorithmic way to *prove* that a matrix is symmetric positive definite, and is roughly twice as fast as the LU factorisation to compute.

### III.3.1 Outer products

In what follows we will use outer products extensively:

**Definition 18** (outer product). Given  $\mathbf{x} \in \mathbb{F}^m$  and  $\mathbf{y} \in \mathbb{F}^n$  the *outer product* is:

$$\mathbf{xy}^\top := [\mathbf{xy}_1 | \cdots | \mathbf{xy}_n] = \begin{bmatrix} x_1 y_1 & \cdots & x_1 y_n \\ \vdots & \ddots & \vdots \\ x_m y_1 & \cdots & x_m y_n \end{bmatrix}.$$

Note this is equivalent to matrix-matrix multiplication if we view  $\mathbf{x}$  as a  $m \times 1$  matrix and  $\mathbf{y}$  as a  $n \times 1$  matrix.

**Proposition 4** (rank-1). A matrix  $A \in \mathbb{F}^{m \times n}$  has rank 1 if and only if there exists  $\mathbf{x} \in \mathbb{F}^m$  and  $\mathbf{y} \in \mathbb{F}^n$  such that

$$A = \mathbf{xy}^\top.$$

**Proof** This follows immediately as if  $A = \mathbf{xy}^\top$  then all columns are multiples of  $\mathbf{x}$ . On the other hand, if  $A$  has rank-1 there exists a nonzero column  $\mathbf{x} := \mathbf{a}_j$  that all other columns are multiples of. ■

### III.3.2 LU factorisation

Gaussian elimination can be interpreted as an LU factorisation. Write a matrix  $A \in \mathbb{F}^{n \times n}$  as follows:

$$A = \begin{bmatrix} \alpha_1 & \mathbf{w}_1^\top \\ \mathbf{v}_1 & K_1 \end{bmatrix}$$

where  $\alpha_1 = a_{11}$ ,  $\mathbf{v}_1 = A[2 : n, 1]$  and  $\mathbf{w}_1 = A[1, 2 : n]$  (that is,  $\mathbf{v}_1 \in \mathbb{F}^{n-1}$  is a vector whose entries are the 2nd through last row of the first column of  $A$  whilst  $\mathbf{w}_1 \in \mathbb{F}^{n-1}$  is a vector containing the 2nd through last entries in the last column of  $A$ ). Gaussian elimination consists of taking the first row, dividing by  $\alpha$  and subtracting from all other rows. That is equivalent to multiplying by a lower triangular matrix:

$$\begin{bmatrix} 1 & \\ -\mathbf{v}_1/\alpha_1 & I \end{bmatrix} A = \begin{bmatrix} \alpha_1 & \mathbf{w}_1^\top \\ K_1 - \mathbf{v}_1 \mathbf{w}_1^\top / \alpha_1 \end{bmatrix}$$

where  $A_2 := K_1 - \mathbf{v}_1 \mathbf{w}_1^\top / \alpha_1$  happens to be a rank-1 perturbation of  $K$ . We can write this another way:

$$A = \underbrace{\begin{bmatrix} 1 & \\ \mathbf{v}_1/\alpha_1 & I \end{bmatrix}}_{L_1} \begin{bmatrix} \alpha_1 & \mathbf{w}_1^\top \\ A_2 \end{bmatrix}$$

Now assume we continue this process and manage to deduce an LU factorisation  $A_2 = L_2 U_2$ . Then

$$A = L_1 \begin{bmatrix} \alpha_1 & \mathbf{w}_1^\top \\ L_2 U_2 \end{bmatrix} = \underbrace{L_1 \begin{bmatrix} 1 & \\ & L_2 \end{bmatrix}}_L \underbrace{\begin{bmatrix} \alpha_1 & \mathbf{w}_1^\top \\ U_2 \end{bmatrix}}_U$$

Note we can multiply through to find

$$L = \begin{bmatrix} 1 & \\ \mathbf{v}_1/\alpha_1 & L_2 \end{bmatrix}.$$

Noting that if  $A \in \mathbb{F}^{1 \times 1}$  then it has a trivial LU factorisation we can use the above construction to proceed recursively until we arrive at the trivial case.

**Example 20** (LU by-hand). Consider the matrix

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 2 & 4 & 8 \\ 1 & 4 & 9 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & & \\ 2 & 1 & \\ 1 & & 1 \end{bmatrix}}_{L_1} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 2 & 6 \\ 0 & 3 & 8 \end{bmatrix}$$

In more detail, for  $\alpha_1 := a_{11} = 1$ ,  $\mathbf{v}_1 := A[2 : 3, 1] = [2, 1]^\top$ ,  $\mathbf{w}_1 = A[1, 2 : 3] = [1, 1]^\top$  and

$$K_1 := A[2 : 3, 2 : 3] = \begin{bmatrix} 4 & 8 \\ 4 & 9 \end{bmatrix}$$

we have

$$A_2 := K_1 - \mathbf{v}_1 \mathbf{w}_1^\top / \alpha_1 = \begin{bmatrix} 4 & 8 \\ 4 & 9 \end{bmatrix} - \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 6 \\ 3 & 8 \end{bmatrix}.$$

We then repeat the process and determine (with  $\alpha_2 := A_2[1, 1] = 2$ ,  $\mathbf{v}_2 := A_2[2 : 2, 1] = [3]$ ,  $\mathbf{w}_2 := A_2[1, 2 : 2] = [6]$  and  $K_2 := A_2[2 : 2, 2 : 2] = [8]$ ):

$$A_2 = \begin{bmatrix} 2 & 6 \\ 3 & 8 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & \\ 3/2 & 1 \end{bmatrix}}_{L_2} \begin{bmatrix} 2 & 6 \\ -1 & -1 \end{bmatrix}$$

The last “matrix” is 1 x 1 so we get the trivial decomposition:

$$A_3 := K_2 - \mathbf{v}_2 \mathbf{w}_2^\top / \alpha_2 = [-1] = \underbrace{[1]}_{L_3} [-1]$$

Putting everything together and placing the columns of  $L_k$  inside the columns of  $L$  we have

$$A = \underbrace{\begin{bmatrix} 1 & & \\ 2 & 1 & \\ 1 & 3/2 & 1 \end{bmatrix}}_L \underbrace{\begin{bmatrix} 1 & 1 & 1 \\ 0 & 2 & 6 \\ 0 & 0 & -1 \end{bmatrix}}_U$$

### III.3.3 PLU factorisation

We learned in first year linear algebra that if a diagonal entry is zero when doing Gaussian elimination one has to *row pivot*. For stability, in implementation one may wish to pivot even if the diagonal entry is nonzero: swap the largest in magnitude entry for the entry on the diagonal turns out to be significantly more stable than standard LU.

This is equivalent to a PLU decomposition. Here we use a *permutation matrix*, whose action on a vector permutes its entries, as discussed in the appendix. That is, consider a permutation which we identify with a vector  $\sigma = [\sigma_1, \dots, \sigma_n]$  containing the integers  $1, \dots, n$  exactly once. The permutation operator represents the action of permuting the entries in a vector:

$$P_\sigma(\mathbf{v}) := \mathbf{v}[\sigma] = \begin{bmatrix} v_{\sigma_1} \\ \vdots \\ v_{\sigma_n} \end{bmatrix}$$

This is a linear operator, and hence we can identify it with a *permutation matrix*  $P_\sigma \in \mathbb{R}^{n \times n}$  (more precisely the entries of  $P_\sigma$  are either 1 or 0). Importantly, products of permutation matrices are also permutation matrices and permutation matrices are orthogonal, that is,  $P_\sigma^{-1} = P_\sigma^\top$ .

**Theorem 4 (PLU).** *A matrix  $A \in \mathbb{C}^{n \times n}$  is invertible if and only if it has a PLU decomposition:*

$$A = P^\top LU$$

where the diagonal of  $L$  are all equal to 1 and the diagonal of  $U$  are all non-zero, and  $P$  is a permutation matrix.

### Proof

If we have a PLU decomposition of this form then  $L$  and  $U$  are invertible and hence the inverse is simply  $A^{-1} = U^{-1}L^{-1}P$ . Hence we consider the other direction.

If  $A \in \mathbb{C}^{1 \times 1}$  we trivially have an LU decomposition  $A = [1] * [a_{11}]$  as all  $1 \times 1$  matrices are triangular. We now proceed by induction: assume all invertible matrices of lower dimension have a PLU factorisation. As  $A$  is invertible not all entries in the first column are zero. Therefore there exists a permutation  $P_1$  so that  $\alpha := (P_1 A)[1, 1] \neq 0$ . Hence we write

$$P_1 A = \begin{bmatrix} \alpha & \mathbf{w}^\top \\ \mathbf{v} & K \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & \\ \mathbf{v}/\alpha & I \end{bmatrix}}_{L_1} \begin{bmatrix} \alpha & \mathbf{w}^\top \\ & K - \mathbf{v}\mathbf{w}^\top/\alpha \end{bmatrix}$$

We deduce that  $A_2 := K - \mathbf{v}\mathbf{w}^\top/\alpha$  is invertible because  $A$  and  $L_1$  are invertible (Exercise).

By assumption we can write  $A_2 = P_2^\top L_2 U_2$ . Thus we have:

$$\begin{aligned} \underbrace{\begin{bmatrix} 1 & \\ & P_2 \end{bmatrix}}_P P_1 A &= \begin{bmatrix} 1 & \\ & P_2 \end{bmatrix} \begin{bmatrix} \alpha & \mathbf{w}^\top \\ \mathbf{v} & A_2 \end{bmatrix} = \begin{bmatrix} 1 & \\ & P_2 \end{bmatrix} L_1 \begin{bmatrix} \alpha & \mathbf{w}^\top \\ & P_2^\top L_2 U_2 \end{bmatrix} \\ &= \begin{bmatrix} 1 & \\ P_2 \mathbf{v}/\alpha & P_2 \end{bmatrix} \begin{bmatrix} 1 & \\ & P_2^\top L_2 \end{bmatrix} \begin{bmatrix} \alpha & \mathbf{w}^\top \\ & U_2 \end{bmatrix} \\ &= \underbrace{\begin{bmatrix} 1 & \\ P_2 \mathbf{v}/\alpha & L_2 \end{bmatrix}}_L \underbrace{\begin{bmatrix} \alpha & \mathbf{w}^\top \\ & U_2 \end{bmatrix}}_U. \end{aligned}$$

■

We don't discuss the practical implementation of this factorisation (though an algorithm is hidden in the above proof). We also note that for stability one uses the permutation that always puts the largest in magnitude entry in the top row. In the lab we explore the practical usage of this factorisation.

## III.3.4 Cholesky factorisation

A *Cholesky factorisation* is a form of Gaussian elimination (without pivoting) that exploits symmetry in the problem, resulting in a substantial speedup. It is only applicable for *symmetric positive definite* (SPD) matrices, or rather, the algorithm for computing it succeeds if and only if the matrix is SPD. In other words, it gives an algorithmic way to prove whether or not a matrix is SPD.



**Definition 19** (positive definite). A square matrix  $A \in \mathbb{R}^{n \times n}$  is *positive definite* if for all  $\mathbf{x} \in \mathbb{R}^n, \mathbf{x} \neq 0$  we have

$$\mathbf{x}^\top A \mathbf{x} > 0$$

First we establish some basic properties of positive definite matrices:

**Proposition 5** (conj. pos. def.). If  $A \in \mathbb{R}^{n \times n}$  is positive definite and  $V \in \mathbb{R}^{n \times n}$  is non-singular then

$$V^\top A V$$

is positive definite.

**Proof** See problem sheet. ■

**Proposition 6** (diag positivity). If  $A \in \mathbb{R}^{n \times n}$  is positive definite then its diagonal entries are positive:  $a_{kk} > 0$ .

**Proof** See problem sheet. ■

**Theorem 5** (subslice pos. def.). If  $A \in \mathbb{R}^{n \times n}$  is positive definite and  $\mathbf{k} \in \{1, \dots, n\}^m$  is a vector of  $m$  integers where any integer appears only once, then  $A[\mathbf{k}, \mathbf{k}] \in \mathbb{R}^{m \times m}$  is also positive definite.

**Proof** See problem sheet. ■

Here is the key result:

**Theorem 6** (Cholesky and SPD). A matrix  $A$  is symmetric positive definite if and only if it has a Cholesky factorisation

$$A = LL^\top$$

where the diagonals of  $L$  are positive.

**Proof** If  $A$  has a Cholesky factorisation it is symmetric ( $A^\top = (LL^\top)^\top = A$ ) and for  $\mathbf{x} \neq 0$  we have

$$\mathbf{x}^\top A \mathbf{x} = (L^\top \mathbf{x})^\top L^\top \mathbf{x} = \|L^\top \mathbf{x}\|^2 > 0$$

where we use the fact that  $L$  is non-singular.

For the other direction we will prove it by induction, with the  $1 \times 1$  case being trivial. Assume all lower dimensional symmetric positive definite matrices have Cholesky decompositions. Write

$$A = \begin{bmatrix} \alpha & \mathbf{v}^\top \\ \mathbf{v} & K \end{bmatrix} = \underbrace{\begin{bmatrix} \sqrt{\alpha} & \\ \frac{\mathbf{v}}{\sqrt{\alpha}} & I \end{bmatrix}}_{L_1} \begin{bmatrix} 1 & \\ & K - \frac{\mathbf{v}\mathbf{v}^\top}{\alpha} \end{bmatrix} \underbrace{\begin{bmatrix} \sqrt{\alpha} & \frac{\mathbf{v}^\top}{\sqrt{\alpha}} \\ & I \end{bmatrix}}_{L_1^\top}.$$

Note that  $A_2 := K - \frac{\mathbf{v}\mathbf{v}^\top}{\alpha}$  is a subslice of  $L_1^{-1} A L_1^{-\top}$ , hence by the previous proposition is itself symmetric positive definite. Thus we can write

$$A_2 = K - \frac{\mathbf{v}\mathbf{v}^\top}{\alpha} = L_2 L_2^\top$$

and hence  $A = LL^\top$  for

$$L = L_1 \begin{bmatrix} 1 & \\ & L_2 \end{bmatrix} = \begin{bmatrix} \sqrt{\alpha} & \\ \frac{\mathbf{v}}{\sqrt{\alpha}} & L_2 \end{bmatrix}$$

satisfies  $A = LL^\top$ . ■

**Example 21** (Cholesky by hand). Consider the matrix

$$A = \begin{bmatrix} 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 2 & 1 \\ 1 & 1 & 1 & 2 \end{bmatrix}$$

Then  $\alpha_1 = 2$ ,  $\mathbf{v}_1 = [1, 1, 1]$ , and

$$A_2 = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 2 \end{bmatrix} - \frac{1}{2} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 3 & 1 & 1 \\ 1 & 3 & 1 \\ 1 & 1 & 3 \end{bmatrix}.$$

Continuing, we have  $\alpha_2 = 3/2$ ,  $\mathbf{v}_2 = [1/2, 1/2]$ , and

$$A_3 = \frac{1}{2} \left( \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix} - \frac{1}{3} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \end{bmatrix} \right) = \frac{1}{3} \begin{bmatrix} 4 & 1 \\ 1 & 4 \end{bmatrix}$$

Next,  $\alpha_3 = 4/3$ ,  $\mathbf{v}_3 = [1]$ , and

$$A_4 = [4/3 - 3/4 * (1/3)^2] = [5/4]$$

i.e.  $\alpha_4 = 5/4$ .

Thus we get

$$L = \begin{bmatrix} \sqrt{\alpha_1} & & & \\ \frac{\mathbf{v}_1[1]}{\sqrt{\alpha_1}} & \sqrt{\alpha_2} & & \\ \frac{\mathbf{v}_1[2]}{\sqrt{\alpha_2}} & \frac{\mathbf{v}_2[1]}{\sqrt{\alpha_2}} & \sqrt{\alpha_3} & \\ \frac{\mathbf{v}_1[3]}{\sqrt{\alpha_3}} & \frac{\mathbf{v}_2[2]}{\sqrt{\alpha_3}} & \frac{\mathbf{v}_3[1]}{\sqrt{\alpha_3}} & \sqrt{\alpha_4} \end{bmatrix} = \begin{bmatrix} \sqrt{2} & & & \\ \frac{1}{\sqrt{2}} & \sqrt{\frac{3}{2}} & & \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} & \frac{2}{\sqrt{3}} & \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{12}} & \frac{\sqrt{5}}{2} \end{bmatrix}$$

## III.4 Polynomial Interpolation and Regression

*Polynomial interpolation* is the process of finding a polynomial that equals data at a precise set of points. A more robust scheme is *polynomial regression* where we use more data than the degrees of freedom in the polynomial. We therefore determine the polynomial using *least squares*: find the polynomial whose samples at the points are as close as possible to the data, as measured in the 2-norm. This least squares problem is done numerically will be discussed in the next few sections.

### III.4.1 Polynomial interpolation

Our primary goal is given a set of points  $x_j$  and data  $f_j$ , usually samples of a function  $f_j = f(x_j)$ , find a polynomial that interpolates the data at the points:

**Definition 20** (interpolatory polynomial). Given *distinct* points  $\mathbf{x} = [x_1, \dots, x_n]^\top \in \mathbb{F}^n$  and data  $\mathbf{f} = [f_1, \dots, f_n]^\top \in \mathbb{F}^n$ , a degree  $n - 1$  *interpolatory polynomial*  $p(x)$  satisfies

$$p(x_j) = f_j$$

The easiest way to solve this problem is to invert the Vandermonde system:

**Definition 21** (Vandermonde). The *Vandermonde matrix* associated with  $\mathbf{x} \in \mathbb{F}^m$  is the matrix

$$V_{\mathbf{x},n} := \begin{bmatrix} 1 & x_1 & \cdots & x_1^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & \cdots & x_m^{n-1} \end{bmatrix} \in \mathbb{F}^{m \times n}.$$

When it is clear from context we omit the subscripts  $\mathbf{x}, n$ .

Writing the coefficients of a polynomial

$$p(x) = \sum_{k=0}^{n-1} c_k x^k$$

as a vector  $\mathbf{c} = [c_0, \dots, c_{n-1}]^\top \in \mathbb{F}^n$ , we note that  $V$  encodes the linear map from coefficients to values at a grid, that is,

$$V\mathbf{c} = \begin{bmatrix} c_0 + c_1 x_1 + \cdots + c_{n-1} x_1^{n-1} \\ \vdots \\ c_0 + c_1 x_m + \cdots + c_{n-1} x_m^{n-1} \end{bmatrix} = \begin{bmatrix} p(x_1) \\ \vdots \\ p(x_m) \end{bmatrix}.$$

In the square case (where  $m = n$ ), the coefficients of an interpolatory polynomial are given by  $\mathbf{c} = V^{-1}\mathbf{f}$ , so that

$$\begin{bmatrix} p(x_1) \\ \vdots \\ p(x_n) \end{bmatrix} = V\mathbf{c} = VV^{-1}\mathbf{f}.$$

This inversion is justified by the following:

**Proposition 7** (interpolatory polynomial uniqueness). *Interpolatory polynomials are unique and therefore square Vandermonde matrices are invertible.*

**Proof** Suppose  $p$  and  $\tilde{p}$  are both interpolatory polynomials of the same function. Then  $p(x) - \tilde{p}(x)$  vanishes at  $n$  distinct points  $x_j$ . By the fundamental theorem of algebra it must be zero, i.e.,  $p = \tilde{p}$ .

For the second part, if  $V\mathbf{c} = 0$  for  $\mathbf{c} = [c_0, \dots, c_{n-1}]^\top \in \mathbb{F}^n$  then for  $q(x) = c_0 + \cdots + c_{n-1}x^{n-1}$  we have

$$q(x_j) = \mathbf{e}_j^\top V\mathbf{c} = 0$$

hence  $q$  vanishes at  $n$  distinct points and is therefore 0, i.e.,  $\mathbf{c} = 0$ .

■

We can invert square Vandermonde matrix numerically in  $O(n^3)$  operations using the PLU factorisation. But it turns out we can also construct the interpolatory polynomial directly, and evaluate the polynomial in only  $O(n^2)$  operations. We will use the following polynomials which equal 1 at one grid point and zero at the others:

**Definition 22** (Lagrange basis polynomial). The *Lagrange basis polynomial* is defined as

$$\ell_k(x) := \prod_{j \neq k} \frac{x - x_j}{x_k - x_j} = \frac{(x - x_1) \cdots (x - x_{k-1})(x - x_{k+1}) \cdots (x - x_n)}{(x_k - x_1) \cdots (x_k - x_{k-1})(x_k - x_{k+1}) \cdots (x_k - x_n)}$$

Plugging in the grid points verifies that:  $\ell_k(x_j) = \delta_{kj}$ .

We can use these to construct the interpolatory polynomial:

**Theorem 7** (Lagrange interpolation). *The unique interpolation polynomial is:*

$$p(x) = f_1 \ell_1(x) + \cdots + f_n \ell_n(x)$$

**Proof** Note that

$$p(x_j) = \sum_{k=1}^n f_k \ell_k(x_j) = f_j.$$

■

**Example 22** (interpolating an exponential). We can interpolate  $\exp(x)$  at the points 0, 1, 2. That is, our data is  $\mathbf{f} = [e, e, e^2]^\top$  and the interpolatory polynomial is

$$\begin{aligned} p(x) &= \ell_1(x) + e\ell_2(x) + e^2\ell_3(x) = \frac{(x-1)(x-2)}{(-1)(-2)} + e\frac{x(x-2)}{(-1)} + e^2\frac{x(x-1)}{2} \\ &= (1/2 - e + e^2/2)x^2 + (-3/2 + 2e - e^2/2)x + 1 \end{aligned}$$

**Remark** Interpolating at evenly spaced points is a really *bad* idea: interpolation is inherently ill-conditioned. The labs will explore this issue experimentally. Another serious issue is that monomials are a horrible basis for interpolation. This is intuitive: when  $n$  is large  $x^n$  is basically zero near the origin and hence  $x_j^n$  in numerically lose linear independence. We will discuss alternative bases in Part IV.

### III.4.2 Polynomial regression

Often interpolation is not sufficient. Data is often on an evenly spaced grid in which case (as seen in the labs) interpolation breaks down catastrophically. Or the data is noisy and one ends up over resolving: approximating the noise rather than the signal. A simple solution is *polynomial regression* use more sample points than the degrees of freedom in the polynomial. The special case of an affine polynomial is called *linear regression*.

More precisely, for  $\mathbf{x} \in \mathbb{F}^m$  and for  $n < m$  we want to find a degree  $n - 1$  polynomial

$$p(x) = \sum_{k=0}^{n-1} c_k x^k$$

such that

$$\begin{bmatrix} p(x_1) \\ \vdots \\ p(x_m) \end{bmatrix} \approx \underbrace{\begin{bmatrix} f_1 \\ \vdots \\ f_m \end{bmatrix}}_{\mathbf{f}}.$$

Mapping between coefficients  $\mathbf{c} \in \mathbb{F}^n$  to polynomial values on a grid can be accomplished via rectangular Vandermonde matrices. In particular, our goal is to choose  $\mathbf{c} \in \mathbb{F}^n$  so that

$$V\mathbf{c} = \begin{bmatrix} p(x_1) \\ \vdots \\ p(x_m) \end{bmatrix} \approx \mathbf{f}.$$

We do so by solving the *least squares* system: given  $V \in \mathbb{F}^{m \times n}$  and  $\mathbf{f} \in \mathbb{F}^m$  we want to find  $\mathbf{c} \in \mathbb{F}^n$  such that

$$\|V\mathbf{c} - \mathbf{f}\|$$

is minimal. Note interpolation is a special case where this norm is precisely zero (which is indeed minimal), but in general this norm may be rather large. We will discuss the numerical solution of least squares problems in the next few sections.

**Remark** Using regression instead of interpolation can overcome the issues with evenly spaced grids. However, the monomial basis is still very problematic.



# Appendix A

## Asymptotics and Computational Cost

We introduce Big-O, little-o and asymptotic notation and see how they can be used to describe computational cost.

### A.1 Asymptotics as $n \rightarrow \infty$

Big-O, little-o, and “asymptotic to” are used to describe behaviour of functions at infinity.

**Definition 23** (Big-O).

$$f(n) = O(\phi(n)) \quad (\text{as } n \rightarrow \infty)$$

means  $\left| \frac{f(n)}{\phi(n)} \right|$  is bounded for sufficiently large  $n$ . That is, there exist constants  $C$  and  $N_0$  such that, for all  $n \geq N_0$ ,  $\left| \frac{f(n)}{\phi(n)} \right| \leq C$ .

**Definition 24** (little-O).

$$f(n) = o(\phi(n)) \quad (\text{as } n \rightarrow \infty)$$

means  $\lim_{n \rightarrow \infty} \frac{f(n)}{\phi(n)} = 0$ .

**Definition 25** (asymptotic to).

$$f(n) \sim \phi(n) \quad (\text{as } n \rightarrow \infty)$$

means  $\lim_{n \rightarrow \infty} \frac{f(n)}{\phi(n)} = 1$ .

**Example 23** (asymptotics with  $n$ ). 1.

$$\frac{\cos n}{n^2 - 1} = O(n^{-2})$$

as

$$\left| \frac{\frac{\cos n}{n^2 - 1}}{n^{-2}} \right| \leq \left| \frac{n^2}{n^2 - 1} \right| \leq 2$$

for  $n \geq N_0 = 2$ .

2.

$$\log n = o(n)$$

$$\text{as } \lim_{n \rightarrow \infty} \frac{\log n}{n} = 0.$$

3.

$$n^2 + 1 \sim n^2$$

$$\text{as } \frac{n^2+1}{n^2} \rightarrow 1.$$

Note we sometimes write  $f(O(\phi(n)))$  for a function of the form  $f(g(n))$  such that  $g(n) = O(\phi(n))$ .

We have some simple algebraic rules:

**Proposition 8** (Big-O rules).

$$\begin{aligned} O(\phi(n))O(\psi(n)) &= O(\phi(n)\psi(n)) & (\text{as } n \rightarrow \infty) \\ O(\phi(n)) + O(\psi(n)) &= O(|\phi(n)| + |\psi(n)|) & (\text{as } n \rightarrow \infty). \end{aligned}$$

**Proof** See any standard book on asymptotics, eg [F.W.J. Olver, Asymptotics and Special Functions](#). ■

## A.2 Asymptotics as $x \rightarrow x_0$

We also have Big-O, little-o and "asymptotic to" at a point:

**Definition 26** (Big-O).

$$f(x) = O(\phi(x)) \quad (\text{as } x \rightarrow x_0)$$

means  $|\frac{f(x)}{\phi(x)}|$  is bounded in a neighbourhood of  $x_0$ . That is, there exist constants  $C$  and  $r$  such that, for all  $0 \leq |x - x_0| \leq r$ ,  $|\frac{f(x)}{\phi(x)}| \leq C$ .

**Definition 27** (little-O).

$$f(x) = o(\phi(x)) \quad (\text{as } x \rightarrow x_0)$$

means  $\lim_{x \rightarrow x_0} \frac{f(x)}{\phi(x)} = 0$ .

**Definition 28** (asymptotic to).

$$f(x) \sim \phi(x) \quad (\text{as } x \rightarrow x_0)$$

means  $\lim_{x \rightarrow x_0} \frac{f(x)}{\phi(x)} = 1$ .

**Example 24** (asymptotics with  $x$ ).

$$\exp x = 1 + x + O(x^2) \quad \text{as } x \rightarrow 0$$

since  $\exp x = 1 + x + \frac{\exp t}{2}x^2$  for some  $t \in [0, x]$  and

$$\left| \frac{\frac{\exp t}{2}x^2}{x^2} \right| \leq \frac{3}{2}$$

provided  $x \leq 1$ .



## A.3 Computational cost

We will use Big-O notation to describe the computational cost of algorithms. Consider the following simple sum

$$\sum_{k=1}^n x_k^2$$

which we might implement as:

```
function sumsq(x)
    n = length(x)
    ret = 0.0
    for k = 1:n
        ret = ret + x[k]^2
    end
    ret
end
```

sumsq (generic function with 1 method)

Each step of this algorithm consists of one memory look-up ( $z = x[k]$ ), one multiplication ( $w = z*z$ ) and one addition ( $ret = ret + w$ ). We will ignore the memory look-up in the following discussion. The number of CPU operations per step is therefore 2 (the addition and multiplication). Thus the total number of CPU operations is  $2n$ . But the constant 2 here is misleading: we didn't count the memory look-up, thus it is more sensible to just talk about the asymptotic complexity, that is, the *computational cost* is  $O(n)$ .

Now consider a double sum like:

$$\sum_{k=1}^n \sum_{j=1}^k x_j^2$$

which we might implement as:

```
function sumsq2(x)
    n = length(x)
    ret = 0.0
    for k = 1:n
        for j = 1:k
            ret = ret + x[j]^2
        end
    end
    ret
end
```

sumsq2 (generic function with 1 method)

Now the inner loop is  $O(1)$  operations (we don't try to count the precise number), which we do  $k$  times for  $O(k)$  operations as  $k \rightarrow \infty$ . The outer loop therefore takes

$$\sum_{k=1}^n O(k) = O\left(\sum_{k=1}^n k\right) = O\left(\frac{n(n+1)}{2}\right) = O(n^2)$$

operations.



# Appendix B

## Permutation Matrices

Permutation matrices are matrices that represent the action of permuting the entries of a vector, that is, matrix representations of the symmetric group  $S_n$ , acting on  $\mathbb{R}^n$ . Recall every  $\sigma \in S_n$  is a bijection between  $\{1, 2, \dots, n\}$  and itself. We can write a permutation  $\sigma$  in *Cauchy notation*:

$$\begin{pmatrix} 1 & 2 & 3 & \cdots & n \\ \sigma_1 & \sigma_2 & \sigma_3 & \cdots & \sigma_n \end{pmatrix}$$

where  $\{\sigma_1, \dots, \sigma_n\} = \{1, 2, \dots, n\}$  (that is, each integer appears precisely once). We denote the *inverse permutation* by  $\sigma^{-1}$ , which can be constructed by swapping the rows of the Cauchy notation and reordering.

We can encode a permutation in vector  $\sigma = [\sigma_1, \dots, \sigma_n]$ . This induces an action on a vector (using indexing notation)

$$\mathbf{v}[\sigma] = \begin{bmatrix} v_{\sigma_1} \\ \vdots \\ v_{\sigma_n} \end{bmatrix}$$

**Example 25** (permutation of a vector). Consider the permutation  $\sigma$  given by

$$\begin{pmatrix} 1 & 2 & 3 & 4 & 5 \\ 1 & 4 & 2 & 5 & 3 \end{pmatrix}$$

We can apply it to a vector:

```
using LinearAlgebra
σ = [1, 4, 2, 5, 3]
v = [6, 7, 8, 9, 10]
v[σ] # we permute entries of v

5-element Vector{Int64}:
 6
 9
 7
10
 8
```

Its inverse permutation  $\sigma^{-1}$  has Cauchy notation coming from swapping the rows of the Cauchy notation of  $\sigma$  and sorting:

$$\begin{pmatrix} 1 & 4 & 2 & 5 & 3 \\ 1 & 2 & 3 & 4 & 5 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 2 & 4 & 3 & 5 \\ 1 & 3 & 2 & 5 & 4 \end{pmatrix}$$

Note that the operator

$$P_\sigma(\mathbf{v}) = \mathbf{v}[\sigma]$$

is linear in  $\mathbf{v}$ , therefore, we can identify it with a matrix whose action is:

$$P_\sigma \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} v_{\sigma_1} \\ \vdots \\ v_{\sigma_n} \end{bmatrix}.$$

The entries of this matrix are

$$P_\sigma[k, j] = \mathbf{e}_k^\top P_\sigma \mathbf{e}_j = \mathbf{e}_k^\top \mathbf{e}_{\sigma_j^{-1}} = \delta_{k, \sigma_j^{-1}} = \delta_{\sigma_k, j}$$

where  $\delta_{k,j}$  is the *Kronecker delta*:

$$\delta_{k,j} := \begin{cases} 1 & k = j \\ 0 & \text{otherwise} \end{cases}.$$

This construction motivates the following definition:

**Definition 29** (permutation matrix).  $P \in \mathbb{R}^{n \times n}$  is a permutation matrix if it is equal to the identity matrix with its rows permuted.

**Proposition 9** (permutation matrix inverse). *Let  $P_\sigma$  be a permutation matrix corresponding to the permutation  $\sigma$ . Then*

$$P_\sigma^\top = P_{\sigma^{-1}} = P_\sigma^{-1}$$

*That is,  $P_\sigma$  is orthogonal:*

$$P_\sigma^\top P_\sigma = P_\sigma P_\sigma^\top = I.$$

### Proof

We prove orthogonality via:

$$\mathbf{e}_k^\top P_\sigma^\top P_\sigma \mathbf{e}_j = (P_\sigma \mathbf{e}_k)^\top P_\sigma \mathbf{e}_j = \mathbf{e}_{\sigma_k^{-1}}^\top \mathbf{e}_{\sigma_j^{-1}} = \delta_{k,j}$$

This shows  $P_\sigma^\top P_\sigma = I$  and hence  $P_\sigma^{-1} = P_\sigma^\top$ .

■