

# Computational Mathematics

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September 3, 2023

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## **Part I**

# **Numerical analysis**

## **Chapter 1**

# **Ordinary differential equations**

**1.1 Polynomial interpolations**

**1.2 Differentiation and integration**

**1.3 Runge-Kutta methods**

**1.4 Multi-step methods**

## **Chapter 2**

# **Numerical linear algebra**

## Chapter 3

# Finite difference methods

### 3.1 Elliptic equations

3.1 (1D Poisson equation). Consider the following boundary value problem:

$$\begin{cases} -u''(x) = f(x), & \text{in } (0, 1), \\ u(0) = u(1) = 0. \end{cases}$$

We discretize it by  $(u_j)_{j=0}^N$  such that  $hN = 1$  and

$$\begin{cases} -\frac{u_{j+1} - 2u_j + u_{j-1}}{h^2} = f_j, & \text{for } j = 1, \dots, N-1, \\ u_0 = u_N = 0. \end{cases}$$

$$\frac{1}{h^2} \begin{pmatrix} 2 & -1 & & 0 \\ -1 & 2 & \ddots & \\ & \ddots & \ddots & -1 \\ 0 & & -1 & 2 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_{N-1} \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_{N-1} \end{pmatrix}$$

eigenvalue problems

### 3.2 Parabolic equations

### 3.3 Hyperbolic equations

CFD

# Chapter 4

## Finite element methods

### 4.0.1 Approximation of Banach spaces

We follow closely Temam for the abstract error analysis. The word “approximation” in here can be replaced into “discretization”.

**Definition 4.0.1** (Approximation). Let  $X$  be a Banach space. An *approximation* of  $X$  is an indexed family  $X_h$  of finite-dimensional normed spaces, with a *prolongation operator*  $p_h \in B(X_h, X)$  and a *restriction operator*  $r_h : X \rightarrow X_h$ . The operator  $p_h r_h : X \rightarrow X$  is called the *truncation operator*.

$$\begin{array}{c} X \\ \downarrow r_h \quad \uparrow p_h \\ X_h \end{array}$$

**Definition 4.0.2** (Errors). Let  $X_h$  be an approximation of a Banach space  $X$ . For  $x \in X$  and  $x_h \in X_h$ , the quantities  $E(x_h, x) := \|p_h x_h - x\|$  and  $DE(x_h, x) := \|x_h - r_h x\|$  are called the *error* and the *discrete error* between  $x$  and  $x_h$ . The quantity  $TE(x) := \|x - p_h r_h x\|$  is called the *truncation error*.

**Definition 4.0.3** (Stable and convergent approximations). We say an approximation  $X_h$  is

- (a) *stable* if  $\|p_h\| + \|r_h\| \lesssim 1$ ,
- (b) *convergent* if  $\|p_h r_h x - x\| \rightarrow 0$  for each  $x \in X$ .

**Lemma 4.0.4.** Let  $X_h$  be an approximation of a Banach space  $X$ . If  $X_h$  is stable and convergent, then for each net  $x_h \in X_h$  the discrete convergence implies the strong convergence.

*Proof.* We have for each  $x \in X$  that

$$DE = \|r_h\| \cdot E \quad \text{and} \quad E = \|p_h\| \cdot DE + TE. \quad \square$$

**Lemma 4.0.5.** Let  $X_h$  be an approximation of a Banach space  $X$ . If  $\|p_h x\| \sim \|x\|$ , then the stability of  $X_h$  follows from the convergence of  $X_h$ .

*Proof.* It is by the uniform boundedness principle:

$$\|r_h x\| \lesssim \|p_h r_h x - x\| + \|x\|. \quad \square$$

In most cases we have  $\|p_h x\| = \|x\|$ , so for an approximation it is enough to verify the truncation error converges to zero.



### 4.0.2 Approximation of problems

A *well-posed problem* is an operator  $L : \mathcal{X} \rightarrow \mathcal{Y}$  such that there is a continuous operator  $L^{-1} : Y \rightarrow X$  satisfying  $LL^{-1} = \text{id}_Y$ , where  $X \subset \mathcal{X}$  and  $Y \subset \mathcal{Y}$  are embeddings. Say, consider the spaces  $\mathcal{X}$  and  $\mathcal{Y}$  as space of distributions. We will always assume  $L : X \rightarrow Y$  is a right invertible (i.e. well-posed) linear operator between Banach spaces.

**Definition 4.0.6** (Approximation). Let  $L$  be a well-posed linear problem. An *approximation* of  $L$  is an indexed family  $L_h \in L(X_h, Y_h)$  of invertible linear operators, where  $X_h$  and  $Y_h$  are stable and convergent approximations of  $X$  and  $Y$ .

We also do not need to assume in fact the stability of  $r_h$ . The approximation  $X_h$  of  $X$  is where we should take subtly, and the art of numerical analysis begins with the choice of  $X_h$ . The following diagram does not commute, but *approximately* commute.

$$\begin{array}{ccc} X & \xrightarrow{L} & Y \\ r_h \downarrow & \nearrow p_h & \downarrow r_h \\ X_h & \xrightarrow{L_h} & Y_h \end{array}$$

**Definition 4.0.7.** Let  $L_h$  be an approximation of a well-posed linear problem  $L$ . We say  $L_h$  is

- (a) *consistent* if  $CE = \|r_h Lx - L_h r_h x\| \rightarrow 0$  for each  $x$ ,
- (b) *stable* if  $\|L_h^{-1}\| \lesssim 1$ ,
- (c) *convergent* if  $DE = \|L_h^{-1} r_h Lx - r_h x\| \rightarrow 0$  for each  $x$ .

**Theorem 4.0.8** (Lax equivalence). *Let  $L_h$  be an approximation of a well-posed linear problem  $L$ . If  $L_h$  is consistent, then it is stable if and only if it is convergent.*

*Proof.* ( $\Rightarrow$ ) It is clear from

$$DE = \|x_h - r_h x\| \leq \|L_h^{-1}\| \|r_h Lx - L_h r_h x\| = \|L_h^{-1}\| \cdot CE.$$

( $\Leftarrow$ ) If we show for the net of operators  $p_h L_h^{-1} r_h : Y \rightarrow X$  that  $p_h L_h^{-1} r_h y$  is bounded in  $X$  for each  $y \in Y$ , then by the uniform boundedness principle the operators  $p_h L_h^{-1} r_h$  is uniformly bounded, and we obtain the stability from

$$\|L_h^{-1}\| = \|r_h p_h L_h^{-1} r_h p_h\| \leq \|r_h\| \|p_h L_h^{-1} r_h\| \|p_h\|.$$

Since  $L$  is surjective by the well-posedness, there is  $x \in X$  such that  $Lx = y$ . With this  $x$  we have

$$\|p_h L_h^{-1} r_h y - x\| \leq \|p_h\| \cdot DE + TE \rightarrow 0,$$

so we are done. □

### 4.0.3 Numerical analyses

For a numerical approximation, we can consider three analyses:

1. Consistency analysis,
2. Stability analysis,
3. Error analysis.

Note that we have  $DE \leq \|L_h^{-1}\| \cdot CE$ . If we have the estimate for the rate of the consistency error from the consistency analysis, and also if we have the bound of  $\|L_h^{-1}\|$  in the stability analysis, we can easily obtain an *error estimate*. In this regard, the main difficulty is the former two.

### Consistency analysis

Usually the Taylor's theorem is used in finite difference schemes.

### Stability analysis

For the bound of  $\|L_h^{-1}\|$ , we have to make a *stability estimate*

$$\|x_h\| \lesssim \|L_h x_h\|.$$

We have some notes about uniqueness and existence: the injectivity of  $L_h^{-1}$  clearly follows from the above estimate, and the surjectivity is deduced thanks to the finite-dimensional nature of  $X_h$  and  $Y_h$  when their dimensions coincide.

### Error analysis

In the Ritz-Galerkin approximation the discrete solution operator  $p_h L_h^{-1} r_h L$  can be directly shown to be an orthogonal projection called the *Ritz projection*, which deduces an *a priori* convergence result before justifying proving consistency and stability.

#### 4.0.4 Applications

**Example 4.0.9.** Consider

$$\begin{cases} u'(x) - u(x) = f(x) & \text{in } x \in (0, 1), \\ u(0) = c. \end{cases}$$

Let  $X := C^1([0, 1])$ ,  $Y := C([0, 1]) \times \mathbb{R}$ , and  $Au(x) := (u'(x) - u(x), u(0))$ . Then it is well-posed since there is  $E : Y \rightarrow X$  defined by

$$E(f, c)(x) := c + \int_0^x e^{-y} f(y) dy$$

satisfies

**Example 4.0.10.** Consider

$$\begin{cases} -\Delta u(x) = f(x) & \text{in } x \in (0, 1)^2, \\ u(x) = 0 & \text{on } x \in \partial(0, 1)^2. \end{cases}$$

Let  $X =, Y =, Au$

**Example 4.0.11.** Consider

$$\begin{cases} \partial u(t, x) = \Delta u(t, x) & \text{in } (t, x) \in (0, \infty) \times (0, 1), \\ u(0, x) = f(x) & \text{on } x \in [0, 1], \\ u(t, 0) = 0 & \text{on } t \in [0, \infty), \\ u(t, 1) = 0 & \text{on } t \in [0, \infty), \end{cases}$$

Let  $X =, Y =, Au$

$$u_j^n, t = t_0 + nk, x = x_0 + jh$$

## **Chapter 5**

# **Optimization**

### **5.1 Convex optimization**

### **5.2 Optimal control**

### **5.3 Operations research**

theory of decision making

### **5.4 Mathematical programming**

## Chapter 6

# Monte Carlo method

stochastic

## **Part II**

# **Information theory**

## **Chapter 7**

# **Communication theory**

shannon's theory

## **Chapter 8**

# **Coding theory**

## **Chapter 9**

# **Cryptography**



## **Part III**

# **Mathematical statistics**

## **Chapter 10**

# **Statistical models**

# Chapter 11

## Statistical inference

estimation, testing hypothesis, ranking, selection

### 11.1 Parametric inference

### 11.2 Non-parametric inference

## Chapter 12