Numerical methods

Session 1: Principles of numerical mathematics

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Consider the following expression:

$$F(x,d) = 0 (1)$$

in which we call x the unknown, d data and F is the relation between x and d.

- If F and d are known, finding x will be called the "direct problem".
- If F and x are known, finding d will be called the "inverse problem".
- If x and d are known, finding F will be called the "identification problem".

In this course we will study the direct problem.



Definition: We say that a problem is well-posed (or stable) if it admits a unique solution x which depends with continuity from the data.

Definition: We say that a problem is ill-posed if it is not well-posed.

Definition: We say that x depends with continuity from the data if a little change δd in the data produces a small change in the solution δx . Mathematically:

If $F(d + \delta d, x + \delta x) = 0$ then:

$$\forall \eta > 0, \exists K(\eta, d) : \|\delta d\| < \eta \Rightarrow \|\delta x\| \le K(\eta, d) \|\delta d\| \qquad (2)$$

where K is a constant that depends on η and d.



Example: Find the number of roots of the polynomial $p(x) = x^4 - (2a - 1)x^2 + a(a - 1)$ (a is the data of the problem). Is easy to check that we have four real roots if $a \ge 1$, two is $a \in [0,1)$ and no real roots if a < 0. This is an ill posed problem because the solution does not depend continuously from the data.

Most problems are not so clearly ill posed. To quantify the well/ill posedness of a problem we define:

Definition: Relative condition number

$$K(d) = \sup_{\delta d \in D} \frac{\|\delta x\|/\|x\|}{\|\delta d\|/\|d\|}$$
(3)

Definition: Absolute condition number

$$K_{abs}(d) = \sup_{\delta d \in D} \frac{\|\delta x\|}{\|\delta d\|}$$
 (4)

D is a neighborhood of the origin that denotes the admissible perturbations of the data.



Note: You can use any norm you want.

Definition: We say a problem is "ill-conditioned" if K is "big" where the definition of big depends on the problem.

It is important to understand that the conditioning of a problem does not depend on the algorithm used to solve it. You can develop stable and unstable algorithms for well-posed problems. The concept of stability for algorithms will be defined later on. Having a "big" or even infinite condition number does not imply that the problem is ill-posed. Some ill-posed problems can be reformulated as an equivalent problem (that is, one that has the same solution) which are well-posed.

If a problem admits a unique solution, then there exist a mapping G, called the **resolvent**, between the data and the solutions sets such that:

$$x = G(d), \text{ that is, } F(G(d), d) = 0$$
 (5)

According to this, and assuming G is differentiable in d (G'(d) exist), the Taylor expansion of G is

$$G(d + \delta d) - G(d) = G'(d)\delta d + o(\|\delta d\|)$$
 for $\delta d \to 0$

This let us redefine the condition numbers in terms of the resolvent *G*:

$$K(D) pprox \|G'(d)\| rac{\|d\|}{\|G(d)\|}$$
 and $K_{abs} pprox \|G'(d)\|$



Example of ill-conditioning: Algebraic second degree equation:

We want to calculate the solutions of $x^2 - 2px + 1$ with p > 1.

Obviously
$$x_{\pm} = p \pm \sqrt{p^2 - 1}$$
.

We can formulate this problem as $F(x, p) = x^2 - 2px + 1$ where p is the data and $x_{\pm} = (x_+, x_-)$ the solution. The resolvent

$$G(p) = (p + \sqrt{p^2 - 1}, p - \sqrt{p^2 - 1})$$
 and its derivative $G'(p) = (1 + 1/\sqrt{p^2 - 1}, 1 - 1/\sqrt{p^2 - 1}).$

$$G'(p) = (1 + 1/\sqrt{p^2 - 1}, 1 - 1/\sqrt{p^2 - 1})$$

Then:

$$egin{align} \mathcal{K}(d) &pprox \| \mathcal{G}'(d) \| rac{\| d \|}{\| \mathcal{G}(d) \|} = rac{(1
ho^2/(
ho^2-1)^{1/2})}{(2(
ho^2-1))^{1/2}} \|
ho \| = rac{p}{
ho^2-1} |
ho | \ & \ \mathcal{K}_{abs}(d) pprox \| \mathcal{G}'(d) \| = \sqrt{2} rac{p}{\sqrt{
ho^2-1}} \end{aligned}$$

If p>>1 then the problem is well-conditioned (two distinct roots). If p=1 (one double root), then G is not differentiable but in the limit $p\to 1^+$ the problem is ill conditioned as $\lim_{p\to 1^+}\|G'(p)\|=\infty$.

However, the problem is not ill-posed. We can reformulate it as $F(x,t)=x^2-((1+t^2)/t)x+1$ with $t=p+\sqrt{p^2-1}$. In this case $x_+=t$ and $x_-=1/t$ are the same for t=1, and $K(t)\approx 1 \ \forall t\in \mathbb{R}$



Let's assume the the problem F(x,d)=0 is well-posed. Then, a numerical method to approximate its solution will consist, in general, of a sequence of approximate problems

$$F_n(x_n, d_n) = 0 \quad n \geq 1$$

We would expect that $x_n \underset{n \to \infty}{\to} x$. For that it is necessary that $d_n \to d$ and that F_n approximates F when $n \to \infty$.

Definition: We say that $F_n(x_n, d_n) = 0$ is consistent if

$$F_n(x,d) = F_n(x,d) - F(x,d) \underset{n \to \infty}{\rightarrow} 0$$

where x is the solution of F(x, d) = 0 for the datum d.

Definition: We say that a method is strongly consistent if $F_n(x, d) = 0 \quad \forall n$.

In some cases when iterative methods are used, we can write them as

$$F(x_n,x_{n-1},\cdots,x_{n-q},d_n)=0$$

where $x_n, x_{n-1}, \dots, x_{n-1}$ are given. In this case the property of strong consistency becomes $F_n(x, x, \dots, x, d) = 0 \ \forall n \geq q$.



Examples:

- **1** Newton's method: $x_n = x_{n-1} \frac{f(x_{n-1})}{f'(x_{n-1})}$ is strongly consistent.
- ② Composite midpoint rule: If $x = \int_a^b f(t)dt$, $x_n = H \sum_{k=1}^n f(\frac{t_k + t_{k+1}}{2})$ $n \ge 1$ with H = (b-a)/n and $t_k = a + (k-1)H$. This method to calculate the integral is consistent, but only strongly consistent if f is a piecewise linear polynomial.

In general, numerical methods obtained from the mathematical problem by truncation of limit operations (like integrals, derivatives, series,...) are not strongly consistent.

Definition: We say that a numerical method $F_n(x_n, d_n) = 0$ is well-posed (or stable) if for any fixed n there exists a unique solution x_n corresponding to the datum d_n , that the computation of x_n as a function of d_n is unique, and that x_n depends continuously on the data, i.e:

$$\forall \eta > 0, \exists K_n(\eta, d_d) : \|\delta d_n\| < \eta \Rightarrow \|\delta x - n\| \le K_n(\eta, d_n) \|\delta d_n\|$$
 (6)

We can also define:

$$K_n(d_n) = \sup_{\delta d_n \in D_n} \frac{\|\delta x_n\|/\|x_n\|}{\|\delta d_n\|/\|d_n\|} \qquad K_{abs,n}(d_n) = \sup_{\delta d_n \in D_n} \frac{\|\delta x_n\|}{\|\delta d_n\|} \quad (7)$$

and from these:

$$K^{num}(d_n) = \lim_{n \to \infty} \sup_{n \ge k} K_n(d_n)$$
 (8)

$$K_{abs}^{num}(d_n) = \lim_{n \to \infty} \sup_{n \ge k} K_{abs,n}(d_n)$$
 (9)

 K_{num} is the relative asymptotic condition number and K_{abs}^{num} is the absolute asymptotic condition number of the numerical method corresponding to the datum d_n .

The numerical method is said to be well-conditioned if the condition number K^{num} is "small" for any admissible datum d_n and ill-conditioned otherwise.

We can also define the resolvent G_n for the numerical method:

$$x_n = G(d_n)$$
, that is $F(G_n(d_n), d_n) = 0$

Assuming it is differentiable:

$$K_n(d_n) pprox \|G_n'(d_n)\| rac{\|d_n\|}{\|G_n(d_n)\|} \qquad ext{and} \qquad K_{abs} pprox \|G_n'(d_n)\|$$

Examples:

Sum and subtraction. The sum defined as

$$f: \mathbb{R}^2 \to \mathbb{R}$$
 $(a,b) \to a+b$

has derivative $f'(a,b)=(1,1)^T$, and thus, its condition number $K((a,b))\approx \frac{|a|+|b|}{|a+b|}\approx 1$ The subtraction defined as

$$f: \mathbb{R}^2 \to \mathbb{R}_{a-b}$$

has derivative $f'(a,b) = (1,-1)^T$, and thus, its condition number $K((a,b)) \approx \frac{|a|+|b|}{|a-b|}$ which can be very big if $a \approx b$.



• Finding the roots of $x^2-2px+1=0$ is well-conditioned, but we can develop an unstable algorithm: $x_-=p-\sqrt{p^2-1}$ because this formula is subject to errors due to numerical cancellation of digits in the subtraction. The Newton's method could be a stable algorithm to solve this problem:

$$x_n = x_{n-1} - \frac{x_{n-1}^2 - 2px_{n-1} + 1}{2x_{n-1} - 2p}$$

The method's condition number is $K_n(p) = \frac{|p|}{|x_n-p|}$. To compute $K_n^{num}(p)$ we notice that if the algorithm converges, then $x_n \to x_+$ or x_- , therefore, $|x_n-p| \to \sqrt{p^2-1}$ and $k_n(p) \to K_n^{num}(p) \approx \frac{|p|}{\sqrt{p^2-1}}$ which is similar to the condition number of the exact problem. Then, if $p \approx 1$ the problem is ill-conditioned.

Definition: We say that the numerical method $F_n(x_n, d_n) = 0$ is convergent if and only if

$$\forall \epsilon > 0 \ \exists n_0(\epsilon), \exists \delta(n_0, \epsilon) : \forall n > n_0, \forall \|\delta d_n\| < \delta(n_0, \epsilon) \Rightarrow$$

$$||x(d)-x_n(d+\delta d_n)||<\epsilon$$

where d is an admissible datum, x(d) the corresponding solution, and $x(d + \delta d_n)$ is the solution of the numerical problem $(F_n(x_n, d_n))$ with datum $d + \delta d_n$.

Definition: Absolute and relative errors:

$$E(x_n) = |x - x_n|$$
 $E_{rel}(x_n) = \frac{|x - x_n|}{|x|}$ $(x \neq 0)$

Definition: Error by component:

$$E_{rel}^{c}(x_n) = \max_{i,j} \frac{|(x - x_n)_{i,j}|}{|x_{i,j}|} \quad (x_{i,j} \neq 0)$$

Relations between stability and convergence

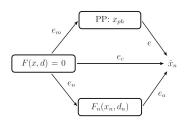
The concepts of stability and convergence are strongly connected. If a (numerical) problem is well-posed, stability is a necessary condition for convergence. Moreover, if the numerical problem is consistent, stability is a sufficient condition for convergence. This is known as "equivalence" or "Lax-Richtmyer" theorem: For a consistent numerical method, stability is equivalent to convergence.

Sources of errors in computational models

Whenever the numerical problem (NP) is an approximation of a mathematical problem (MP) and this latter is in turn a model of a physical problem (PP), we say that NP $(F_n(x_n, d_n) = 0)$ is a computational model for PP.

The global error $e = |x_{ph} - x_n|$ can be interpreted as the sum of the MP error $e_m = x - x_{ph}$ and the computational problem error $e_c = \hat{x} - x$ ($e = e_m + e_c$).

 e_a : Error induced by the numerical algorithm and the rounding errors.



In general, we can enumerate the following sources of error:

- Errors due to the model, that can be reduced by using a proper model.
- Errors due to data, that can be reduced improving the measurement's accuracy.
- Truncation errors, arising from the approximation (truncation) of limit operations (integrals, derivatives,...).
- Rounding errors.

Type 3 and 4 errors give rise to the computational error. A numerical method will be convergent if this error can be made arbitrarily small increasing the computational effort. Although convergence is the primary goal of a numerical method, there are also the accuracy, the reliability and the efficiency.

Accuracy means that the errors are small with respect to a fixed tolerance. It is usually quantified by the infinitesimal order of the error e_n with respect to the discretization characteristic parameter (for example the largest grid spacing).

Note: Machine precision does not limit, theoretically, the accuracy. Reliability means that it is very likely that the global error is below a certain tolerance.

Efficiency mean that the computational (effort) complexity needed to control the error (number of operation and memory) is as small as possible.

Definition: Algorithm is a directive that indicates, through elementary operations, all the passages needed to solve a problem. It should finish after a finite number of steps, and as a consequence the executor (man or machine) must find within the algorithm itself all the instructions to completely solve the problem. Complexity of an algorithm is a measure of its executing time. Complexity of a problem is the complexity of the algorithm with smallest complexity capable of solving the problem.