Mathematics for Informatics

Numerical Mathematics: Algorithms
(lecture 10 of 12)

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Recap: Errors

Definition

Let a number α be an approximate value of a number a.

- *The **absolute error** is the value $|\alpha - a|$.*
- *For $a \neq 0$, the **relative error** is $\dfrac{|\alpha - a|}{|a|}$.*

System of linear equations

We want to solve a system of n linear equations. We write the system in matrix representation

$$Ax = b,$$

where $A \in \mathbb{R}^{n,n}$ is regular and $b \in \mathbb{R}^{n,1}$.

This is often a partial subproblem of a larger problem.

Example: system of linear equations (1/2)

Consider two systems of linear equations with 2 unknowns:

$$\begin{pmatrix} 1 & 1/2 \\ 1/2 & 1/3 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 3/2 \\ 1 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} 1 & 1/5 \\ 1/5 & -1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 3/2 \\ 1 \end{pmatrix}.$$

The solutions are

$$(x, y)^T = (0, 3)^T \quad \text{and} \quad (x, y)^T = (85/52, -35/52)^T \approx (1.6346, -0.67308)^T.$$

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Let us try to simulate an error on the input, or during a calculation, by changing the right side to $\begin{pmatrix} 3/2 \\ 5/6 \end{pmatrix}$.

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The solutions change to

$$(x, y)^T = (1, 1)^T \quad \text{and} \quad (x, y)^T = (125/78, -20/39)^T \approx (1.6026, -0.51282)^T.$$

Example: system of linear equations (2/2)

The change in the right side was

$$\begin{pmatrix} 3/2 \\ 1 \end{pmatrix} - \begin{pmatrix} 3/2 \\ 5/6 \end{pmatrix} = \begin{pmatrix} 0 \\ 1/6 \end{pmatrix},$$

a vector of Euclidean length $1/6$ (the relative error is 0.09).

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The change in the solution of **the first equation** was

$$\begin{pmatrix} 0 \\ 3 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} -1 \\ 2 \end{pmatrix}$$

(the relative error is 0.75) and the one in the solution of **the second equation**

$$\begin{pmatrix} 85/52 \\ -35/52 \end{pmatrix} - \begin{pmatrix} 125/78 \\ -20/39 \end{pmatrix} = \begin{pmatrix} 5/156 \\ -25/156 \end{pmatrix}$$

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Why is it that the first system is more sensitive to this change? Why are the two relative errors so different?

Norm - reminder

A **norm** on a vector space V is a mapping $\|\cdot\| : V \mapsto \mathbb{R}_0^+$ which satisfies

1. $\|x\| = 0 \quad \Rightarrow \quad x = 0$,
2. $\|\alpha x\| = |\alpha| \cdot \|x\|$,
3. $\|x + y\| \leq \|x\| + \|y\|$ (triangle inequality),

for all $x, y \in V$ and all scalars α.

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On $\mathbb{R}^n$ (or $\mathbb{C}^n$) the most used norm is probably the **Euclidean norm**:

$$\|x\| = \left(\sum_{i=1}^{n} x_i^2 \right)^{\frac{1}{2}},$$

where $x = (x_1, x_2 \ldots, x_n) \in \mathbb{R}^n$.

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Other commonly used norms include

- $\|x\|_\infty = \max \{ |x_i| : i \in \{1, \ldots, n\} \}$ maximum norm,
- $\|x\|_1 = \sum_{i=1}^{n} |x_i|$ taxicab or L_1 norm.

Matrix norm

Given a vector norm $\|\cdot\|$, we define the **induced matrix norm** of the matrix $A \in \mathbb{R}^{n,n}$ (or for $A \in \mathbb{C}^{n,n}$) as follows

$$\|A\| = \sup\left\{\|Ax\| : x \in \mathbb{R}^{n,1} \text{ and } \|x\| = 1\right\}.$$

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Such norm satisfies

- $\|I\| = 1$,
- $\|Ax\| \leq \|A\| \cdot \|x\|$ (norm consistency),
- $\|AB\| \leq \|A\| \cdot \|B\|$.

Forward and backward error

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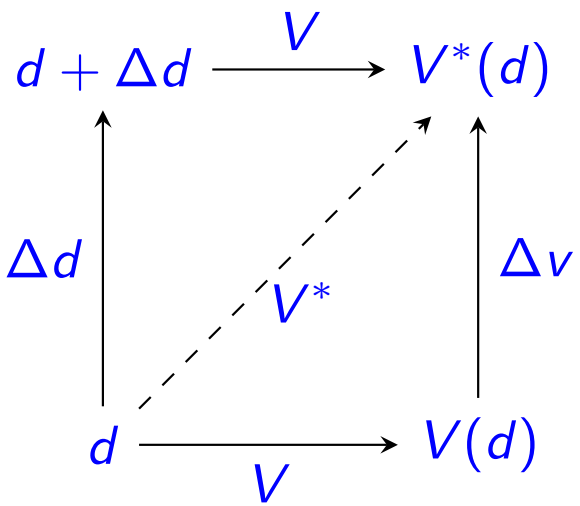

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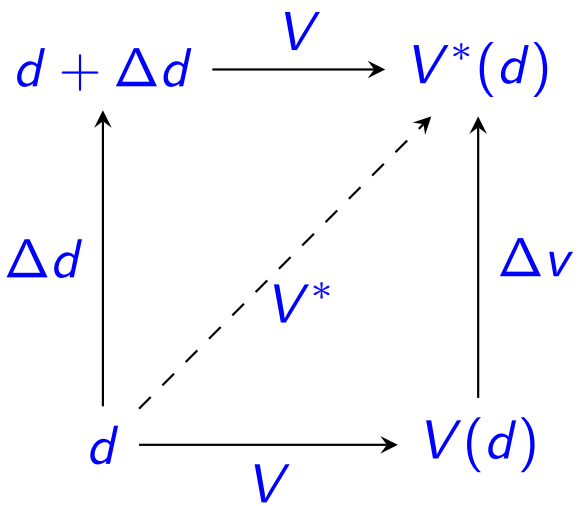

If for every input d the backward error is relatively small, we say that the algorithm is **backward stable**. ("Small" depends on the context.)

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The **relative condition number** of a problem is

$$C_r = \lim_{\varepsilon \to 0^+} \sup_{\substack{d+\delta d \in D \\ \|\delta d\| \leq \varepsilon}} \frac{\frac{\|V(d+\delta d) - V(d)\|}{\|V(d)\|}}{\frac{\|\delta d\|}{\|d\|}},$$

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where D is the domain of V.

If $C_r \approx 1$, then we say that the problem is **well-conditioned**.
If it is large, we say the problem is **ill-conditioned**.

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Finally,

$$\frac{\|\delta x\|}{\|x\|} \leq \|A\| \cdot \|A^{-1}\| \frac{\|\delta b\|}{\|b\|},$$

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Of course, the condition number depends on the chosen norm.

Example of two sets of linear equations revisited

Let us revisit the example we saw earlier:

$$A_1 = \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1/3 \end{pmatrix} \quad \text{and} \quad A_2 = \begin{pmatrix} 1 & 1/5 \\ 1/5 & -1 \end{pmatrix},$$

The inverses are

$$A_1^{-1} = \begin{pmatrix} 4 & -6 \\ -6 & 12 \end{pmatrix} \quad \text{and} \quad A_2^{-1} \approx \begin{pmatrix} 0.961538 & 0.192308 \\ 0.192308 & -0.961538 \end{pmatrix},$$

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To calculate the condition number $\kappa(A) = \|A\| \cdot \|A^{-1}\|$ we use the norm $\|A\|_\infty$:

$$\kappa(A_1) = \frac{3}{2} \cdot 18 = 27 \quad \text{and} \quad \kappa(A_2) = \frac{18}{13} \approx 1.3846056.$$

The problem with the matrix A_1 is significantly more **ill-conditioned** than with the matrix A_2. This is in accordance with our previous observations.

Direct methods

A **direct method** calculates a solution of a problem in finitely many steps such that in absolute theoretical precision in gives the exact solution.

Idea of iterative methods

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Every following (approximate) solution is derived from the previous:

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for $k > 0$ and some mapping T.

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If T is the same for all k, the method is called **stationary**.

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The idea: choose the matrix Q so that the sequence (x_k) converges to some x^*.
Then,

$$Qx^* = (Q - A)x^* + b$$

and thus

$$Ax^* = b.$$

Convergence - choice of Q

We use the equality $x_k = Q^{-1}\big((Q - A)x_{k-1} + b\big)$ in

$$\begin{aligned} x_k - x &= Q^{-1}\big((Q - A)x_{k-1} + b\big) - x \\ &= (I - Q^{-1}A)x_{k-1} - x + Q^{-1}b \\ &= (I - Q^{-1}A)x_{k-1} - (I - Q^{-1}A)x \\ &= (I - Q^{-1}A)(x_{k-1} - x), \end{aligned}$$

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The vector e_k will be "smaller" than e_{k-1} if W is "small".
("Small" can be determined using norms.)

Since $e_k = W^k e_0$, to lower the error at each step we need to have $\lim_{k\to+\infty} W^k = 0$.

Convergence vs. spectral radius

The **Spectral radius** of a matrix M is the number $\rho(M)$ defined as the greatest eigenvalues (in absolute value), i.e.,

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Theorem

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Thus, in our case, the method converges **if and only if**

$$\rho(W) < 1,$$

i.e., all the eigenvalues of the matrix $W = I - Q^{-1}A$ are in absolute value less than 1.

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The condition of convergence $\rho(W) < 1$ does not imply anything on the speed from the previous estimate.

However, the estimate on the right side is strictly decreasing if $\|W\| < 1$.

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This is impractical since we do not have the exact solution.

In the step k we can calculate the so-called **residue** $Ax_k - b$ and the **convergence criterion** can be set to

$$\|Ax_k - b\| < \varepsilon.$$

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where, supposing $\|W\| < 1$, the last inequality gives

$$\|e_k\| < \frac{\varepsilon}{1 - \|W\|}.$$

Thus, this criterion can be effectively used if $\|W\| < 1$, but not too close to 1.

Finite precision calculations

All ideas so far were made in the **theoretical absolute precision**.
In **finite precision** the method may not converge even if $\|W\| < 1$ due to rounding errors.

However, an advantage of iterative methods in a finite precision arithmetic is that at each step the rounding errors from the previous step are "forgotten". We start the new iteration with a better approximate solution.

Finite precision calculations

All ideas so far were made in the **theoretical absolute precision**.
In **finite precision** the method may not converge even if $\|W\| < 1$ due to rounding errors.

However, an advantage of iterative methods in a finite precision arithmetic is that at each step the rounding errors from the previous step are "forgotten". We start the new iteration with a better approximate solution.

In finite arithmetic the method can diverge even if the problem is not ill-conditioned.

Thus, in practice, we need another parameter of the method - a maximum number of iterations. If we reach this number of iterations without satisfying a convergence criterion, then the method outputs failure.

Choices of Q

Denote by $a_{i,j}$ the entries of the matrix A and denote

$$L = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ a_{2,1} & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n-1} & 0 \end{pmatrix} \text{ and } D = \begin{pmatrix} a_{1,1} & 0 & \cdots & 0 \\ 0 & a_{2,2} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & a_{n,n} \end{pmatrix}.$$

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We will mention the following choices of Q:

- Richardson method $Q = I$,
- Jacobi method $Q = D$,
- successive overrelaxation / SOR method $Q = \frac{1}{\omega} D + L$.

Richardson method

Set $Q = I$.

The recurrence relation is given by

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The convergence is for a narrow class of matrices: A must be close to I so that

$$\|I - A\| < 1.$$

Jacobi method

Set $Q = D$.

The recurrence relation is given by

$$Dx_k = (D - A)x_{k-1} + b = -(L + U)x_{k-1} + b.$$

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Proposition

If the matrix A is diagonally dominant, then the Jacobi method converges for any choice of x_0.

A matrix is diagonally dominant if, for each row, the sum of the absolute values of all the entries except the one on the diagonal is less than the absolute value of the entry on the diagonal.

SOR method

Set $Q = \frac{1}{\omega} D + L$, where $\omega \in \mathbb{R} \setminus \{0\}$.

The recurrence relation is given by

$$\left(\frac{1}{\omega} D + L\right) x_k = \left(\frac{1}{\omega} D + L - A\right) x_{k-1} + b = \left(\left(-1 + \frac{1}{\omega}\right) D - U\right) x_{k-1} + b.$$

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Proposition

For $0 < \omega < 2$ the SOR method converges if A is symmetric, positive definite and has positive diagonal entries.

The parameter ω is used to speed up the convergence.
The choice $\omega = 1$ is the *Gauss-Seidel* method.

Algorithm

Inputs: matrices A, Q, vector b, precision ε, maximum number of iterations K.

1. choose $\widehat{x}_0$ at random
2. for k from 1 to K do
   - 2.1 $\widehat{x}_{k+1} = Q^{-1}(Q - A)\widehat{x}_k + Q^{-1}b$
   - 2.2 if $\|A\widehat{x}_k - b\| < \varepsilon$, **return** $\widehat{x}_k$ (or in general if any convergence criterion is satisfied)
3. **return** "no solution found after K steps".

Demonstration - Jacobi method (1/2)

Let $A = \begin{pmatrix} 2 & 1 \\ 1 & 4 \end{pmatrix}$. $\quad \left\| I - D^{-1}A \right\| = \frac{1}{2}$.

We use the Jacobi method to calculate a solution for $b = (3,5)^T$.
The exact solution is $(1,1)^T$.

The convergence criterion used is $\|A\widehat{x}_k - b\| < 10^{-2}$.

k	$\widehat{x}_k$	$\|A\widehat{x}_k - b\|$
0	$(0.5, 1.5)$	1.58113883008
1	$(0.75, 1.125)$	0.450693909433
2	$(0.9375, 1.0625)$	0.197642353761
3	$(0.96875, 1.015625)$	0.0563367386791
4	$(0.9921875, 1.0078125)$	0.0247052942201
5	$(0.99609375, 1.001953125)$	0.00704209233489

Demonstration - Jacobi method (2/2)

...the same problem but with a different $\widehat{x}_0$, which is further from the exact solution.

k	$\widehat{x}_k$	$\|A\widehat{x}_k - b\|$
0	$(-10, 10)$	28.1780056072
1	$(-3.5, 3.75)$	9.01734439844
2	$(-0.375, 2.125)$	3.5222507009
3	$(0.4375, 1.34375)$	1.1271680498
4	$(0.828125, 1.140625)$	0.440281337613
5	$(0.9296875, 1.04296875)$	0.140896006226
6	$(0.978515625, 1.017578125)$	0.0550351672016
7	$(0.9912109375, 1.00537109375)$	0.0176120007782
8	$(0.997314453125, 1.002197265625)$	0.0068793959002