

5374 Fall '22

Numerical Linear Algebra

Lecture 5

(cf. Solomon's chapter 4, section on "Sensitivity Analysis")

Condition number

Let's consider

$$Ax = b$$

for some A which is $n \times n$ and invertible.

How does the solution x vary when we vary A or b ? Let us fix a $n \times n$ matrix \dot{A} and a \mathbb{R}^n vector \dot{b} , and set for all small enough ε , the matrix and vector

$$A_\varepsilon = A + \varepsilon \dot{A}, \quad b_\varepsilon = b + \varepsilon \dot{b}$$

$$(\text{so, note } A_0 = A, \quad b_0 = b)$$

Exercise: Using Cramer's rule (namely, $\det(A) \neq 0 \Leftrightarrow A$ is invertible) show there is a $\varepsilon_0 > 0$ depends on A and \dot{A} such that if $|\varepsilon| < \varepsilon_0$ then A_ε is also invertible.

(this means that, when thought of as a subset of \mathbb{R}^{n^2} , the set of invertible matrices is an open set)

Then for those small ε we define x_ε as the unique vector solving

$$A_\varepsilon x_\varepsilon = b_\varepsilon$$

Question: What can we say about $\|x - x_\varepsilon\|_2$ as $\varepsilon \rightarrow 0$?

We are going to estimate the derivative of x_ε with respect to the parameter $\varepsilon \in (-\varepsilon_0, \varepsilon_0)$. This is indeed a differentiable funct. of ε since

$$x_\varepsilon = A_\varepsilon^{-1} b_\varepsilon$$

and $\varepsilon \mapsto A_\varepsilon$, $\varepsilon \mapsto b_\varepsilon$ are differentiable and A_0 is invertible so $\varepsilon \mapsto A_\varepsilon^{-1}$ is differentiable (in fact, it is infinitely differentiable in ε as long as $\varepsilon \in (-\varepsilon_0, \varepsilon_0)$)

Let us write $\tilde{x} := \left. \frac{d}{d\varepsilon} \right|_{\varepsilon=0} x_\varepsilon$, what can we say about \tilde{x} ?

$$\frac{d}{d\varepsilon} (A_\varepsilon x_\varepsilon) = \frac{d}{d\varepsilon} (b_\varepsilon) \quad \forall \varepsilon$$

$$\frac{d}{d\varepsilon} \left((A + \varepsilon \dot{A}) x_\varepsilon \right) = \frac{d}{d\varepsilon} (b + \varepsilon \dot{b})$$

$$\frac{d}{d\varepsilon} (A x_\varepsilon + \varepsilon \dot{A} x_\varepsilon) = \dot{b}$$

$$A \frac{d}{d\varepsilon} x_\varepsilon + \dot{A} x_\varepsilon + \varepsilon \dot{A} \frac{d}{d\varepsilon} x_\varepsilon = \dot{b}$$

For $\varepsilon=0$, we obtain

$$A \tilde{x} + \dot{A} x = \dot{b}$$

Solving for \tilde{x} ,

$$\tilde{x} = A^{-1} (\dot{b} - \dot{A} x)$$

From here we can estimate the size of $x - x_\varepsilon$ since

$$x_\varepsilon = x + \varepsilon \tilde{x} + O(\varepsilon^2)$$

$$\begin{aligned}
\Rightarrow \quad \|x - x_\epsilon\| &= \|\epsilon \tilde{x} + O(\epsilon^2)\| \\
&\leq \|\epsilon \tilde{x}\| + O(\epsilon^2) \\
&= |\epsilon| \|\tilde{x}\| + O(\epsilon^2)
\end{aligned}$$

In scientific computing we have about two ways of estimating errors: absolute error and relative error.

$$\text{Absolute error} := \|x - x_\epsilon\|$$

$$\text{Relative error} := \frac{\|x - x_\epsilon\|}{\|x\|}$$

Let's estimate the relative error for our problem.

$$\frac{\|x - x_\epsilon\|}{\|x\|} \leq \frac{|\epsilon| \|\tilde{x}\|}{\|x\|} + O(\epsilon^2)$$

Recall our formula for \tilde{x} ,

$$\tilde{x} = A^{-1}(\dot{b} - \dot{A}x)$$

$$\begin{aligned}
\|\tilde{x}\|_2 &= \|A^{-1}(\dot{b} - \dot{A}x)\|_2 \\
&\leq \|A^{-1}\|_{op} \|\dot{b} - \dot{A}x\|_2
\end{aligned}$$

$$\begin{aligned}\Rightarrow \| \tilde{x} \|_2 &\leq \| A^{-1} \|_{op} (\| \tilde{b} \|_2 + \| \dot{A} x \|_2) \\ &\leq \| A^{-1} \|_{op} (\| \tilde{b} \|_2 + \| \dot{A} \| \| x \|_2)\end{aligned}$$

Putting this estimate back in our relative error estimation,

$$\frac{\| x - x_\varepsilon \|_2}{\| x \|_2} \leq |\varepsilon| \left(\frac{\| A^{-1} \|_{op} \| \tilde{b} \|_2}{\| x \|_2} + \frac{\| A^{-1} \|_{op} \| \dot{A} \|_{op} \cancel{\| x \|_2}}{\cancel{\| x \|_2}} \right) + O(\varepsilon^2)$$

We want to estimate the LHS in term of the relative error made when A, b are replaced with $A_\varepsilon, b_\varepsilon$, i.e. we want to estimate things by

$$\frac{\| \dot{A} \|_{op}}{\| A \|_{op}} \quad \text{and} \quad \frac{\| \tilde{b} \|_2}{\| b \|_2}$$

For the second term, observe that

$$\| A^{-1} \|_{op} \| \dot{A} \|_{op} = \left(\| A \|_{op} \cdot \| \tilde{A}^{-1} \|_{op} \right) \cdot \frac{\| \dot{A} \|_{op}}{\| A \|_{op}}$$

Meanwhile, for the first term, we observe that

$$b = Ax$$

$$\Rightarrow \| b \|_2 \leq \| A \|_{op} \cdot \| x \|_2$$

$$\text{i.e.} \quad \frac{1}{\| x \|_2} \leq \frac{\| A \|_{op}}{\| b \|_2}$$

We conclude that

$$\frac{\|x - x_\varepsilon\|}{\|x\|} \leq |\varepsilon| \left(\|A\|_{op} \|A^{-1}\|_{op} \frac{\|\tilde{b}\|_2}{\|b\|_2} + \|A\|_{op} \|\tilde{A}^{-1}\|_{op} \frac{\|\tilde{A}\|_{op}}{\|A\|_{op}} \right) + O(\varepsilon^2)$$

Gathering the common factor,

$$\frac{\|x - x_\varepsilon\|_2}{\|x\|_2} \leq \left(\|A\|_{op} \|A^{-1}\|_{op} \right) \left(\frac{|\varepsilon| \|\tilde{b}\|_2}{\|b\|_2} + \frac{|\varepsilon| \|\tilde{A}\|_{op}}{\|A\|_{op}} \right) + O(\varepsilon^2)$$

(Alternative way of writing this, using that

$$A_\varepsilon - A = \varepsilon \tilde{A}, \quad b_\varepsilon - b = \varepsilon \tilde{b}$$

$$\frac{\|x - x_\varepsilon\|_2}{\|x\|_2} \leq \left(\|A\|_{op} \|A^{-1}\|_{op} \right) \left(\frac{\|b - b_\varepsilon\|_2}{\|b\|_2} + \frac{\|A - A_\varepsilon\|_{op}}{\|A\|_{op}} \right) + O(\varepsilon^2)$$

Definition. Given a $n \times n$ matrix A we

define its condition number, $\text{cond}(A)$, by

$$\text{cond}(A) = \begin{cases} \|A\|_{op} \|A^{-1}\|_{op} & \text{if } A \text{ is invertible} \\ +\infty & \text{if } A \text{ is not invertible.} \end{cases}$$

Remarks : * If $A = \lambda I$, $\lambda \neq 0$, then

$$\begin{aligned}\text{cond}(A) &= \|\lambda I\|_{op} \cdot \|\lambda^{-1} I\|_{op} \\ &= |\lambda| \cdot |\lambda^{-1}| = 1\end{aligned}$$

* More generally, if A is invertible and $\lambda \neq 0$, then

$$\text{cond}(\lambda A) = \text{cond}(A)$$

Why! Since $\|\lambda A\|_{op} = |\lambda| \|A\|_{op}$
 $\|(\lambda A)^{-1}\|_{op} = |\lambda^{-1}| \|A^{-1}\|_{op}$