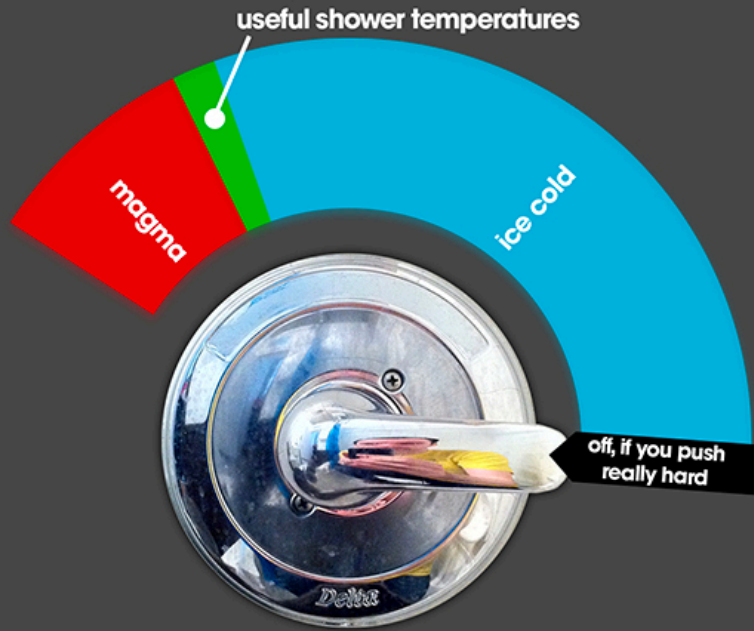


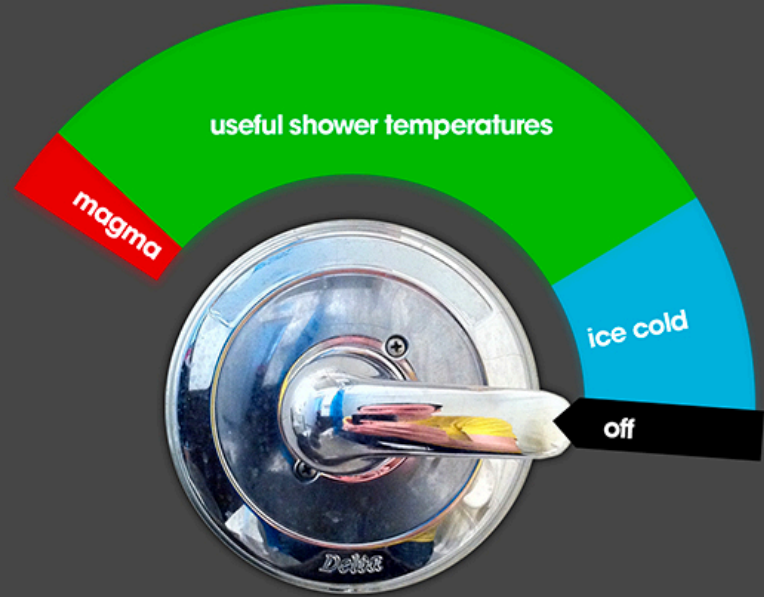
# Linear System of Equations - Conditioning

# the shower faucet

how they are:



how they should be:



**WHAT IT LOOKS LIKE**



**WHAT IT FEELS LIKE**



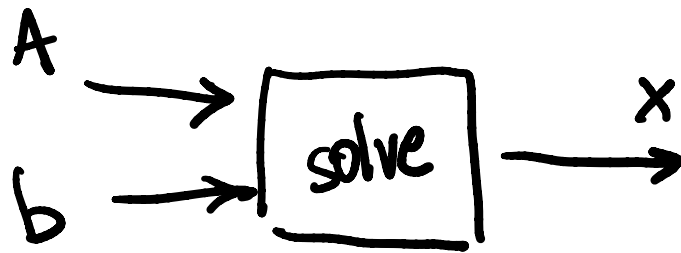
# Numerical experiments

**Input** has uncertainties:

- Errors due to representation with finite precision
- Error in the sampling

Once you select your numerical method , how much error should you expect to see in your **output**?

*Is your method sensitive to errors (perturbation) in the input?*



$$A x = b$$

① Defining  $A$   
( $N \times N$ )

A) random

B) Hilbert

② Start with a known exact solution:

$$x_{\text{true}} = [1, 1, \dots, 1] \quad (\text{np.ones}(N))$$

③ Compute  $b = A @ x_{\text{true}}$

④ Solve  $\begin{matrix} A \\ b \end{matrix} \begin{matrix} \longrightarrow \\ \longrightarrow \end{matrix} \boxed{\phantom{0000}} \longrightarrow x_{\text{solve}}$

⑤ Compute error  $\| x_{\text{solve}} - x_{\text{true}} \|$

# Sensitivity of Solutions of Linear Systems

Suppose we start with a non-singular system of linear equations  $A x = b$ .

We change the right-hand side vector  $b$  (input) by a small amount  $\Delta b$ .

How much the solution  $x$  (output) changes, i.e., how large is  $\Delta x$ ?

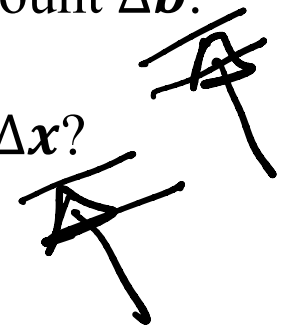
$$\frac{\text{Output Relative error}}{\text{Input Relative error}} = \frac{\|\Delta x\|/\|x\|}{\|\Delta b\|/\|b\|} = \frac{\|\Delta x\| \|b\|}{\|\Delta b\| \|x\|}$$

$$Ax = b \rightarrow \text{exact}$$

$$A \hat{x} = \hat{b} \rightarrow \text{pert}$$

$$\hat{x} = x + \Delta x \quad \hat{b} = b + \Delta b$$

$$A(x + \Delta x) = b + \Delta b \rightarrow \boxed{A \Delta x = \Delta b}$$



# Sensitivity of Solutions of Linear Systems

$$\frac{\text{Output Relative error}}{\text{Input Relative error}} = \frac{\|\Delta x\|/\|x\|}{\|\Delta b\|/\|b\|} = \frac{\|\Delta x\| \|b\|}{\|\Delta b\| \|x\|}$$

$Ax = b$   
 $A\Delta x = \Delta b$   
 $\Delta x = A^{-1}\Delta b$

$$\frac{\text{Output Relative error}}{\text{Input Relative error}} = \frac{\|A^{-1}\Delta b\| \|b\|}{\|\Delta b\| \|x\|} \leq \frac{\|A^{-1}\| \|\Delta b\| \|b\|}{\|\Delta b\| \|x\|} =$$

$$\|A^{-1}\Delta b\| \leq \|A^{-1}\| \|\Delta b\|$$

$$= \frac{\|A^{-1}\| \|b\|}{\|x\|} = \frac{\|A^{-1}\| \|Ax\|}{\|x\|} \leq \frac{\|A^{-1}\| \|A\| \|x\|}{\|x\|}$$

$$\|Ax\| \leq \|A\| \|x\|$$

$\frac{\text{out}}{\text{inp}} \leq \|A^{-1}\| \|A\|$

# Sensitivity of Solutions of Linear Systems

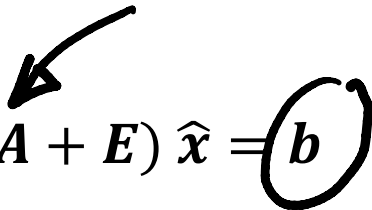
$$\frac{\text{out}}{\text{inp}} \leq \underline{\hspace{2cm}}$$

$$\underbrace{\frac{\|\Delta x\|}{\|x\|}}_{\text{cyan}} \leq \underbrace{\|A^{-1}\| \|A\|}_{\text{pink}} \underbrace{\frac{\|\Delta b\|}{\|b\|}}_{\text{green}}$$

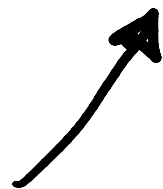
$\text{cond}(A)$

# Sensitivity of Solutions of Linear Systems

We can also add a perturbation to the matrix  $A$  (input) by a small amount  $E$ , such that

$$(A + E) \hat{x} = b$$


and in a similar way obtain:

$$\frac{\|\Delta x\|}{\|x\|} \leq \underbrace{\|A^{-1}\| \|A\|}_{\text{cond}(A)} \frac{\|E\|}{\|A\|}$$




# Condition number

The condition number is a measure of sensitivity of solving a linear system of equations to variations in the input.

The condition number of a matrix  $A$ :

$$\text{cond}(A) = \underbrace{\|A^{-1}\|} \underbrace{\|A\|}$$

Recall that the induced matrix norm is given by

$$\|A\|_p = \max_{\|x\|=1} \|Ax\|_p$$

And since the condition number is relative to a given norm, we should be precise and for example write:

$$\text{cond}_2(A) \text{ or } \text{cond}_\infty(A)$$

# Condition number

$$A \rightarrow \text{sing} \\ \underline{\underline{\text{cond}(A) = \infty}}$$

$$\frac{\|\Delta x\|}{\|x\|} \leq \text{cond}(A) \frac{\|\Delta b\|}{\|b\|}$$

Small condition numbers mean not a lot of error amplification. Small condition numbers are good!

**But how small?**

$$\text{cond}(A) = \|A\| \|A^{-1}\|$$

$$1) \|x\| > 0 \longrightarrow \text{cond}(A) > 0$$
$$2) \|xy\| \leq \|x\| \|y\| \longrightarrow \| \underbrace{A A^{-1}} \| \leq \|A\| \|A^{-1}\|$$
$$\|A\| \|A^{-1}\| > \|I\|$$

$$\|I\| = \max_{\|x\|=1} \|Ix\| = 1$$

$$\boxed{\|A\| \|A^{-1}\| \geq 1}$$

# Condition number

$$\frac{\|\Delta \mathbf{x}\|}{\|\mathbf{x}\|} \leq \mathit{cond}(\mathbf{A}) \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|}$$

Small condition numbers mean not a lot of error amplification. Small condition numbers are good!

Recall that

$$\|\mathbf{I}\| = \max_{\|\mathbf{x}\|=1} \|\mathbf{I} \mathbf{x}\| = 1$$

Which provides with a lower bound for the condition number:

$$\mathit{cond}(\mathbf{A}) = \|\mathbf{A}^{-1}\| \|\mathbf{A}\| \geq \|\mathbf{A}^{-1} \mathbf{A}\| = \|\mathbf{I}\| = 1$$

If  $\mathbf{A}^{-1}$  does not exist, then  $\mathit{cond}(\mathbf{A}) = \infty$  (by convention)

# Recall Induced Matrix Norms

$$\|\mathbf{A}\|_1 = \max_j \sum_{i=1}^n |A_{ij}|$$

Maximum absolute column sum of the matrix  $\mathbf{A}$

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$$\|\mathbf{A}\|_\infty = \max_i \sum_{j=1}^n |A_{ij}|$$

Maximum absolute row sum of the matrix  $\mathbf{A}$

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$$\|\mathbf{A}\|_2 = \max_k \sigma_k$$

$\sigma_k$  are the singular value of the matrix  $\mathbf{A}$

# Condition Number of a Diagonal Matrix

What is the 2-norm-based condition number of the diagonal matrix

$$A = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 13 & 0 \\ 0 & 0 & 0.5 \end{bmatrix} ?$$

$$\{ 100, 13, 0.5 \}$$

$$A^{-1} = \begin{bmatrix} 1/100 & & \\ & 1/13 & \\ & & 1/0.5 \end{bmatrix}$$

$$\{ \frac{1}{100}, \frac{1}{13}, \frac{1}{0.5} \}$$

$$\|A\|_2 = 100$$

$$\|A^{-1}\|_2 = 2$$

$$\text{cond}(A) = 100 \times 2 = 200 //$$

# Condition Number of Orthogonal Matrices

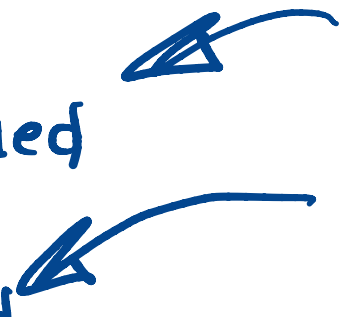
What is the 2-norm condition number of an orthogonal matrix  $A$ ?

$$\text{cond}(A) = \|A^{-1}\|_2 \|A\|_2 = \|A^T\|_2 \|A\|_2 = 1$$

That means orthogonal matrices have optimal conditioning.

They are very well-behaved in computation.

$\text{cond}(A)$   $\left\{ \begin{array}{l} \text{small} \rightarrow \text{well-conditioned} \\ \text{large} \rightarrow \text{ill-conditioned} \end{array} \right.$



# About condition numbers

1. For any matrix  $A$ ,  $cond(A) \geq 1$
2. For the identity matrix  $I$ ,  $cond(I) = 1$
3. For any matrix  $A$  and a nonzero scalar  $\gamma$ ,  $cond(\gamma A) = cond(A)$
4. For any diagonal matrix  $D$ ,  $cond(D) = \frac{\max |d_i|}{\min |d_i|}$
5. The condition number is a measure of how close a matrix is to being singular: a matrix with large condition number is nearly singular, whereas a matrix with a condition number close to 1 is far from being singular
6. The determinant of a matrix is NOT a good indicator is a matrix is near singularity  
 $\det(A) = 0 \rightarrow \text{sing}$

# Residual versus error

Our goal is to find the solution  $x$  to the linear system of equations  $Ax = b$

Let us recall the solution of the perturbed problem

$$\hat{x} = (x + \Delta x)$$

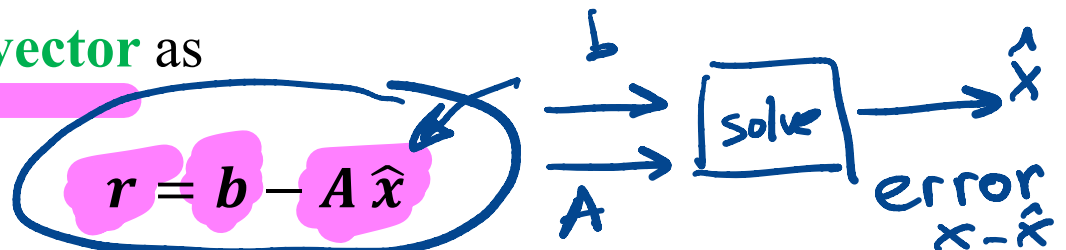
which could be the solution of

$$A\hat{x} = (b + \Delta b), \quad (A + E)\hat{x} = b, \quad (A + E)\hat{x} = (b + \Delta b)$$

And the **error vector** as

$$e = \Delta x = \hat{x} - x$$

We can write the **residual vector** as





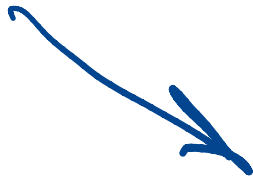


**Relative residual:**  $\frac{\|r\|}{\|A\|\|x\|}$

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(How well the solution satisfies the problem)

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**Relative error:**  $\frac{\|\Delta x\|}{\|x\|}$

(How close the approximated solution is from the exact one)

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# Residual versus error

It is possible to show that the residual satisfy the following inequality:

$$\frac{\|r\|}{\|A\|\|\hat{x}\|} \leq c \epsilon_m$$

Where  $c$  is “large” constant when LU/Gaussian elimination is performed without pivoting and “small” with partial pivoting.

Therefore, Gaussian elimination with partial pivoting yields **small relative residual regardless of conditioning of the system.**

**When solving a system of linear equations via LU with partial pivoting, the relative residual is guaranteed to be small!**

# Residual versus error

$$Ax = b \Rightarrow x = A^{-1}b$$

Let us first obtain the norm of the error:

$$\|\Delta x\| = \|\hat{x} - x\| = \|\underbrace{A^{-1}A}_{I} \hat{x} - A^{-1}b\| = \|A^{-1}(\underbrace{A\hat{x} - b}_r)\|$$

$$\frac{\|\Delta x\|}{\|x\|} = \frac{\|A^{-1}r\|}{\|x\|} \leq \frac{\|A^{-1}\| \|r\|}{\|x\|} \frac{\|A\|}{\|A\|}$$

$$\frac{\|\Delta x\|}{\|x\|} \leq \underbrace{\|A^{-1}\| \|A\|}_{\text{cond}(A)} \frac{\|r\|}{\|x\| \|A\|}$$

$$\frac{\|\Delta x\|}{\|x\|} \leq \text{cond}(A) \frac{\|r\|}{\|x\| \|A\|}$$

# Rule of thumb for conditioning

Suppose we want to find the solution  $\mathbf{x}$  to the linear system of equations  $\mathbf{A}\mathbf{x} = \mathbf{b}$  using LU factorization with partial pivoting and backward/forward substitutions.

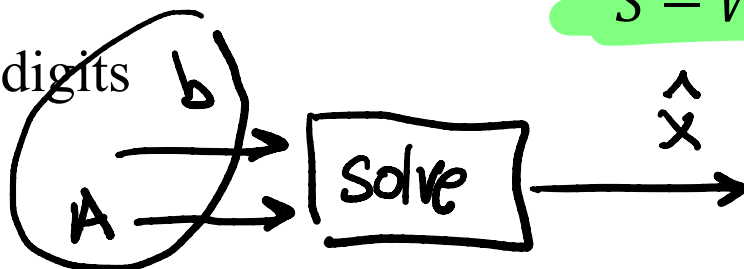
Suppose we compute the solution  $\hat{\mathbf{x}}$ .

If the entries in  $\mathbf{A}$  and  $\mathbf{b}$  are accurate to  $S$  decimal digits,

and  $\text{cond}(\mathbf{A}) = 10^W$ ,

then the elements of the solution vector  $\hat{\mathbf{x}}$  will be accurate to about

decimal digits



$S - W$

$$e_r = \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|} \leq 10^{-S}$$

$$e_r = \frac{\|\Delta \mathbf{x}\|}{\|\mathbf{x}\|} \leq \text{cond}(\mathbf{A}) \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|}$$

$$e_r \leq 10^W 10^{-S} = 10^{-(S-W)}$$