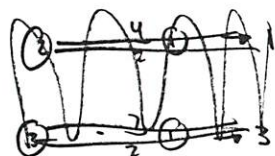


# Gaussian Elimination

$$-\frac{4}{2} \times \begin{pmatrix} 2 & 2 & 3 \\ 4 & 5 & 6 \\ 8 & 8 & 9 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 4 \\ 2 \\ 3 \end{pmatrix}$$



$$-\frac{4}{2} \textcircled{1} + \textcircled{2} \rightarrow \textcircled{2}$$

$$-\frac{8}{2} \textcircled{1} + \textcircled{3} \rightarrow \textcircled{3}$$

$$\begin{pmatrix} 2 & 2 & 3 & | & 4 \\ 0 & -1 & 0 & | & 6 \\ 0 & - & - & | & - \end{pmatrix}$$

Pivot element

$$E_j - \frac{a_{ji}}{a_{ii}} E_i \rightarrow E_j$$

$$\textcircled{j} - \frac{a_{ji}}{a_{ii}} \textcircled{i} \rightarrow \textcircled{j}$$

Gaussian Elimination

$$\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ 0 & a_{22} & & \\ & & a_{33} & \\ & 0 & 0 & \dots & 0 & a_{nn} \end{pmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_n \end{bmatrix}$$

Now solve for:

$$x_n = \frac{b_n}{a_{nn}}$$

$$x_{n-1} = \frac{b_{n-1} - a_{n-1,n} x_n}{a_{n-1,n-1}}$$

$$x_i = \frac{b_i - \sum_{j=i+1}^n a_{ij} x_j}{a_{ii}}$$

Back Substitution

If you continued the elimination process  
would get to the point

$$\left[ \begin{array}{ccc|c} a_{11} & & & b_1 \\ & a_{22} & & b_2 \\ & & \ddots & \vdots \\ 0 & & & a_{nn} & b_n \end{array} \right]$$

$$x_n = b_n / a_{nn}$$

$$x_i = b_i / a_{ii}$$

Gauss-Jordan Method.

Is ok but requires more calculations!

Round-off errors

$$\left( \begin{array}{cccc|c} 10 & 7 & 8 & 7 & 32 \\ 7 & 5 & 6 & 5 & 23 \\ 8 & 6 & 10 & 9 & 33 \\ 7 & 5 & 9 & 10 & 31 \end{array} \right) = \left( \begin{array}{c} 32 \\ 23 \\ 33 \\ 31 \end{array} \right)$$

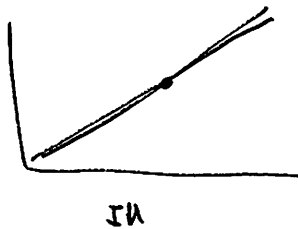
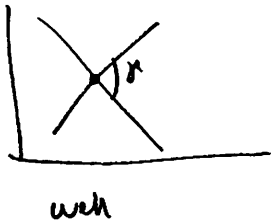
can get  $\hat{x} = \begin{pmatrix} -7.2 \\ 14.6 \\ -2.5 \\ 3.1 \end{pmatrix}$   $A\hat{x} = \begin{pmatrix} 31.9 \\ 23.1 \\ 32.9 \\ 31.1 \end{pmatrix}$

but  $\hat{x} = \begin{pmatrix} 0.18 \\ 2.36 \\ 0.65 \\ 1.21 \end{pmatrix}$   $A\hat{x} = \begin{pmatrix} 31.99 \\ 23.01 \\ 32.99 \\ 31.01 \end{pmatrix}$

Real solns  $x = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} !$

Can define Residual  $r = b - A\hat{x}$   
 $r = 0 = b - A x_{\text{exact}}$

### III - Condition



$$\begin{cases} 0.9999x - 1.0001y = 1 \\ x - y = 1 \end{cases} \quad \begin{cases} x = 0.5 \\ y = 0.5 \end{cases}$$

But

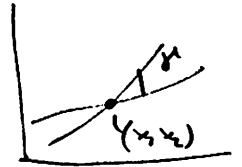
$$\begin{cases} 0.9999x - 1.0001y = 1 \\ x - y = 1 + \epsilon \end{cases} \quad \begin{cases} x = 0.5 + 5000\epsilon \\ y = 0.5 + 4999.5\epsilon \end{cases}$$

So small change in  $\epsilon$  greatly changes solution

5

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \quad \underline{\underline{Ax=b}}$$

is intersects between two lines



turns out that

$$\tan \theta = \frac{a_{11}a_{22} - a_{12}a_{21}}{a_{11}a_{21} + a_{12}a_{22}}$$

So if  $\theta \rightarrow 0$  ( $\frac{\text{numerator}}{\text{denominator}} \rightarrow 0 \Rightarrow \text{numerator} \rightarrow 0$ )

but numerator is  $\det A$ .

So apparently ill-conditioned  $\sim$  close to singular!

singular  $\Rightarrow$  lines are close to co-linear  
- i.e. linearly dependent equations

6

- If the RHS values come from a formula just use more significant figure

- If RHS was experimental data - trouble will not get good solution.

- Symptoms of ill conditioning

-  $|\det A| \ll |a_{ij}|_{\max}$  or  $|b_i|_{\max}$

- Poor approximate solutions will give small residuals

- Elements of  $A^{-1}$  are large compared to elements of  $A$ .

- Well-conditioned

-  $|(\text{diagonal elements})| \gg |(\text{off diagonal elements})|$

- elements of  $A$  are  $10^{-10}$  and elements of  $A^{-1}$  are  $10^{10}$

What to do before <sup>reducing</sup> using Gauss-Elimination

1) Reformulate problem if necessary!

ADVANCE

1) Want largest coeff in rows to be of comparable magnitude. So multiply through by appropriate constants

ADVANCE

2) Rearrange equations by rows and columns (switch order of variables) to place largest elements on diagonal.

In progress

3) Re-order rows to see that  $a_{ii}$  is the largest of  $a_{ij}$  for  $j > i$ . If not re-order.

(If you get all zeros, you do not have a unique solution!)

# Iterative Techniques Gauss-Seidel Method.

9

- Same comments apply to pre-processing of A.

$$\left\{ \begin{array}{l} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \\ \vdots \\ a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n \end{array} \right\} \text{ system of linear eqns.}$$

Given for  $x_i$ :

$$x_1 = \frac{b_1 - a_{12}x_2 - \dots - a_{1n}x_n}{a_{11}}$$

$$x_i = \frac{b_i - a_{i1}x_1 - \dots - a_{i,i-1}x_{i-1} - a_{i,i+1}x_{i+1} - \dots - a_{in}x_n}{a_{ii}}$$

$$x_n = \frac{b_n - a_{n1}x_1 - a_{n2}x_2 - \dots - a_{nn-1}x_{n-1}}{a_{nn}}$$

$$x_i = \frac{b_i - \sum_{j=1, j \neq i}^n a_{ij}x_j}{a_{ii}}$$

Can start with first approx

10

$$\left\{ \begin{array}{l} x_1 = b_1/a_{11} \\ \vdots \\ x_i = b_i/a_{ii} \\ \vdots \\ x_n = b_n/a_{nn} \end{array} \right\}$$

and put into R.H.s to predict new  $x_i$

$$x_i^* = \frac{b_i - \sum_{j=1, j \neq i}^n a_{ij}x_j}{a_{ii}}$$

Can improve iteration by using good values for some of the  $x_i$ 's.

$$x_i^* = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j^* - \sum_{j=i+1}^n a_{ij}x_j}{a_{ii}} \quad \text{Gauss-Seidel Method.}$$

Residuals

$$r = b - Ax$$

$$r=0 = b - Ax_c$$

$$\text{So } r_i = b_i - \sum_{j=1}^n a_{ij} x_j$$

$$= b_i - \left[ \sum_{j=1}^{i-1} a_{ij} x_j + a_{ii} x_i + \sum_{j=i+1}^n a_{ij} x_j \right]$$

↑ can also be  $x_j^*$

$$= b_i - a_{ii} x_i - \left[ \sum_{j=1}^{i-1} a_{ij} x_j^* + \sum_{j=i+1}^n a_{ij} x_j \right]$$

But real Gauss-Seidel  $x_i^* = \frac{b_i - \sum_{j=1}^{i-1} a_{ij} x_j^* - \sum_{j=i+1}^n a_{ij} x_j}{a_{ii}}$

so

$$r_i = a_{ii} x_i^* - a_{ii} x_i$$

$$x_i^* - x_i = \frac{r_i}{a_{ii}}$$

$$x_i^* = x_i + \frac{r_i}{a_{ii}}$$

12.

when  $r_i = b_i - \sum_{j=1}^{i-1} a_{ij} x_j^* - \sum_{j=i+1}^n a_{ij} x_j$  (use best into possible)

Can also be used as an iteration scheme.

Goal is to reduce the Residual vector.

ie as  $\epsilon \rightarrow 0$  then  $x$  converge.

Modified - Relaxation Methods.

$$x_i^* = x_i + \omega \frac{r_i}{a_{ii}}$$

$\omega$  is the relaxation parameter.

$0 < \omega < 1$  under-relaxation  
 $1 < \omega$  over-relaxation

13

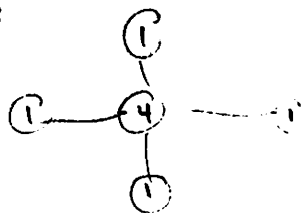
- Some systems do not converge (quickly) using Gauss Seidel but will do so for  $0 < \omega < 1$ .

- When using systems to solve PDE's can use over-relaxation to speed convergence.

$$\left. \begin{aligned} \frac{\partial^2 f}{\partial x^2} &= 0 \\ \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} &= 0 \end{aligned} \right\} \text{Boundary Value Problems.}$$

$$\frac{1}{\omega} [f_{i,j} - 2f_{i,j} + f_{i,j}] \quad \frac{1}{\omega} [f_{i,j} - 2f_{i,j} + f_{i,j}]$$

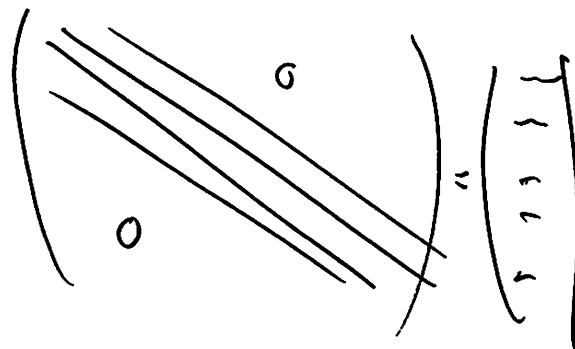
①-②-③



stencil

Get big system of equations for values of  $f_{i,j}$ . Often quickly solved using iterative techniques.

Will get systems with diagonals that are zero.



END