

## Iterative method for Linear systems

So far we have discussed direct methods

(plu with pivoting)  $\begin{matrix} A = LU \\ A = LL^T \\ A = QR \\ A = U\Sigma V^T \end{matrix}$  Generally, these all cost  $\sqrt{O(n^3)}$

The challenge is how to solve  $Ax=b$  when  $A$  is a very large matrix.

Maybe we can forego finding solutions in finitely many steps and focus on "approximation"

Most large systems in applications are sparse. However, if the sparsity is unstructured, direct methods do not exploit the sparsity for computation.

Iterative Method sequence of approximations  $x^{(0)} \quad x^{(1)} \quad x^{(2)}$

$x^{(0)} \equiv$  Initial guess

$x^{(k)} \equiv$  k-th iterate

Typically,  $O(n)$  or  $O(n^2)$  per iteration useful when # of iterations  $= O(1)$

### Basic Idea

Formulate  $Ax=b$  as  $x = Bx + d$

Define  $x^{(k)}$  as follows

$$x^{(k)} = Bx^{(k)} + d \quad k=1,2,\dots$$

Goal i) Does sequence converge?

ii) How to pick  $x^{(0)}$ ?

Stopping criterion

$$\frac{\|x^{(k+1)} - x^{(k)}\|}{\|x^{(k)}\|} < \epsilon$$

$$\|b - Ax^{(k)}\| < \epsilon$$

Residual at the k-th iteration

$$\equiv b - Ax^{(k)} = r^{(k)}$$

## Jacobi iteration

$A \in \mathbb{R}^{n \times n}$  invertible

$$Ax = b$$

$D \equiv$  Diagonal matrix

$$D = \begin{pmatrix} d_{11} & & \\ & d_{22} & \\ & & \ddots \\ & & & d_{nn} \end{pmatrix} \quad d_{ii} = A_{ii}$$

Assume  $D$  is invertible.

True solution:  $A^{-1}b$

Approximate solution:  $x^{(k-1)}$   
at  $(k-1)$ -th iteration

$$\text{Error} = e^{(k-1)} = A^{-1}b - x^{(k-1)}$$

Assume "magically" I know the error

$$\begin{aligned} x^{(k)} &= x^{(k-1)} + e^{(k-1)} \\ &= x^{(k-1)} + A^{-1}b - x^{(k-1)} \end{aligned}$$

Could we estimate the error?

$$Ae^{(k-1)} = AA^{-1}b - Ax^{(k-1)}$$

$$Ae^{(k-1)} = b - Ax^{(k-1)} = r^{(k-1)}$$

To find the error, we solve

$$Ae^{(k-1)} = r^{(k-1)}$$

Assume  $A \approx D$

$$De^{(k-1)} = r^{(k-1)}$$

$$e^{(k-1)} = D^{-1}r^{(k-1)}$$

$$x^{(k)} = x^{(k-1)} + e^{(k-1)}$$

$$= x^{(k-1)} + D^{-1}r^{(k-1)}$$

$$= x^{(k-1)} + D^{-1}(b - Ax^{(k-1)})$$

Jacobi iteration

Proposition If the limit  $\lim_{k \rightarrow \infty} x^{(k)}$  exists, it solves

$$Ax = b. \quad \text{That is } A \lim_{k \rightarrow \infty} x^{(k)} = b$$



proof

$$\lim_{k \rightarrow \infty} x^{(k)} = \lim_{k \rightarrow \infty} x^{(k-1)} + D^{-1} \left( b - A \lim_{k \rightarrow \infty} x^{(k-1)} \right)$$

The same

$$\text{Therefore, } D^{-1} \left( b - A \lim_{k \rightarrow \infty} x^{(k-1)} \right) = 0$$

$$D^{-1} z = 0 \Rightarrow z = 0$$

$$\therefore A \lim_{k \rightarrow \infty} x^{(k-1)} = b \quad \text{as desired} \quad \underline{\square}$$

Jacobi iteration computation

$$x^{(k)} = x^{(k-1)} + D^{-1} (b - A x^{(k-1)})$$

$$\begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \\ \vdots \\ x_m^{(k)} \end{bmatrix} = \begin{bmatrix} x_1^{(k-1)} \\ x_2^{(k-1)} \\ \vdots \\ x_m^{(k-1)} \end{bmatrix} + \begin{bmatrix} 1/a_{11} & & \\ & 1/a_{22} & \\ & & \ddots \\ & & & 1/a_{nn} \end{bmatrix} \begin{bmatrix} b_1 - [A x^{(k-1)}]_1 \\ b_2 - [A x^{(k-1)}]_2 \\ \vdots \\ b_m - [A x^{(k-1)}]_m \end{bmatrix}$$

$$x_i^{(k)} = x_i^{(k-1)} + \frac{1}{a_{ii}} \left( b_i - [A x^{(k-1)}]_i \right)$$

$$x_i^{(k)} = x_i^{(k-1)} + \frac{1}{a_{ii}} \left( b_i - \sum_j a_{ij} x_j^{(k-1)} \right)$$

$$= \underbrace{x_i^{(k-1)}}_{(1)} + \frac{1}{a_{ii}} \left( b_i - \sum_{j \neq i} a_{ij} x_j^{(k-1)} - \underbrace{a_{ii} x_i^{(k-1)}}_{(4)} \right)$$

$$\text{Note } (1) - \frac{1}{a_{ii}} (4) = 0$$

$$x_i^{(k)} = \frac{1}{a_{ii}} \left[ b_i - \sum_{j \neq i} a_{ij} x_j^{(k-1)} \right]$$

## Iterative Methods

$$x^{(k)} = B x^{(k-1)} + d$$

Jacobi: 
$$x^{(k)} = x^{(k-1)} + D^{-1} (b - A x^{(k-1)})$$
$$= \underbrace{[I - D^{-1} A]}_B x^{(k-1)} + \underbrace{D^{-1} b}_d$$

Explicit form: 
$$x_i^{(k)} = \frac{b_i - \sum_{j \neq i} a_{ij} x_j^{(k-1)}}{a_{ii}} \quad 1 \leq i \leq m$$

Exercise What is the computational complexity of Jacobi?

For general  $A \Rightarrow O(m^2)$

If  $A$  is sparse with  $O(1)$  non-zero entries  $\Rightarrow O(m)$  in each row

### Algorithm

Input:  $x^{(0)} \in \mathbb{R}^m$

For  $k = 1$ : max-iterations

for  $i = 1:m$

$$x_i^{(k)} = \frac{b_i - \sum_{j \neq i} a_{ij} x_j^{(k-1)}}{a_{ii}}$$

### convergence of Jacobi iteration

$A$  is row diagonally dominant if

$$|a_{ii}| > \sum_{\substack{j=1 \\ j \neq i}}^m |a_{ij}| \quad i=1, 2, \dots, m$$

Theorem If  $A$  is row-diagonally dominant, Jacobi iteration converges for any arbitrary choice of  $x^{(0)}$ .

Example Is  $A = \begin{pmatrix} -3 & 1 & 0 \\ 2 & -7 & 1 \\ 0 & 1 & 2 \end{pmatrix}$  row diagonally dominant?

(Yes!)

Numerical convergence

$$\frac{\|x^{(k)} - x^{(k-1)}\|}{\|x^{(k)}\|} < \epsilon$$
$$\|b - Ax^{(k)}\| < \delta$$

$\epsilon, \delta$  tolerances

Example

$$\begin{aligned} 5x_1 - 2x_2 + 3x_3 &= -1 \\ -3x_1 + 9x_2 + x_3 &= 2 \\ 2x_1 - x_2 - 7x_3 &= 3 \end{aligned}$$

solve for  $x_1 \Rightarrow x_1 = \frac{-1 + 2x_2 - 3x_3}{5}$

solve for  $x_2$   
 $x_2 = \frac{2 + 3x_1 - x_3}{9}$

solve for  $x_3$   
 $x_3 = \frac{3 - 2x_1 + x_2}{7}$

$$x_1^{(0)} = x_2^{(0)} = x_3^{(0)} = 0$$

First approximation

$$x_1^{(1)} = -1/5$$

$$x_2^{(1)} = 2/9$$

$$x_3^{(1)} = -3/7$$

Jacobi iteration

$$A \approx D$$

$$x^{(k)} = x^{(k-1)} + D^{-1}(b - Ax^{(k-1)})$$

Decompose

A

as

$$A = L + D + U$$

upper triangular

$$A \approx L + D$$

Lower triangular

Diagonal entries are zero

$$x^{(k)} \approx x^{(k-1)} + (L + D)^{-1} [b - Ax^{(k-1)}]$$

Gauss-Seidel iteration

Assume diagonal entries of A are non-zero

$(L + D)$  is invertible

Explicit form

$$x_i^{(k)} = \frac{b_i - \sum_{j \neq i} a_{ij} x_j^{(k)} - \sum_{j > i} x_j^{(k-1)}}{a_{ii}} \quad 1 \leq i \leq n$$



## Iterative methods: Analysis

Theorem If  $A$  is row-diagonally dominant, Gauss-Seidel converges for any choice of  $x^{(0)}$ .

Theorem also holds for positive definite matrix.

$$x^{(k)} = x^{(k-1)} + (L+D)^{-1} (b - Ax^{(k-1)})$$

$$x^{(k)} = \underbrace{[I - (L+D)^{-1}A]}_B x^{(k-1)} + \underbrace{(L+D)^{-1}b}_d$$

Is this a good approximation of  $I$ ?

Example

$$\begin{aligned} 5x_1 - 2x_2 + 3x_3 &= -1 \\ -3x_1 + 9x_2 + x_3 &= 2 \\ 2x_1 - x_2 - 7x_3 &= 3 \end{aligned}$$

Gauss-Seidel  $x_1^{(0)} = x_2^{(0)} = x_3^{(0)} = 0$

$$x_1^{(1)} = \frac{-1 + 2x_2^{(0)} - 3x_3^{(0)}}{5} = -\frac{1}{5}$$

$$x_2^{(1)} = \frac{2 + 3x_1^{(1)} - x_3^{(0)}}{9} = \frac{2 - \frac{3}{5}}{9} = \frac{7}{45}$$

$$x_3^{(1)} = \frac{3 - 2x_1^{(1)} + x_2^{(1)}}{7}$$

$$= \frac{3 + \frac{2}{5} + \frac{7}{45}}{7} = \frac{32}{63}$$

Repeat above until convergence

Diagonal  $\Rightarrow$  invertibility  
Dominance

$$Ax = \lambda x$$

Consider an eigenvector  $\bar{x} \in \mathbb{R}^m$

choose an index as follows:  $i = \arg \max_{1 \leq j \leq m} (\bar{x}_j)$

Rescale  $\bar{x}$  as follows:

$$x = \frac{\bar{x}}{\bar{x}_i}$$

Not  $x$  is an eigenvector

$$Ax = \lambda x$$

$$(Ax)_i = (\lambda x)_i$$

$$\sum_j A_{ij} x_j = \lambda x_i$$

$$\Rightarrow \sum_j A_{ij} x_j = \lambda$$

$$\sum_{j=i} A_{ij} x_i + \sum_{j \neq i} A_{ij} x_j = \lambda$$

one term

$$A_{ii} + \sum_{j \neq i} A_{ij} x_j = \lambda$$

$$\lambda - A_{ii} = \sum_{j \neq i} A_{ij} x_j$$

$$|\lambda - A_{ii}| \leq \sum_{j \neq i} |A_{ij}| |x_j| \leq \sum_{j \neq i} |A_{ij}| = R_i$$

Every eigenvalue of  $A$  lies within at least one of the discs  $D(a_{ii}, R_i)$

Def  $B_k, k=1, 2, 3, \dots$  matrices in  $\mathbb{R}^{m \times m}$

$$\lim_{k \rightarrow \infty} B_k = 0$$

(All entries of  $B_k$  converge to zero)

Proposition  $\lim_{k \rightarrow \infty} B_k = 0$  iff  $\lim_{k \rightarrow \infty} B_k u = 0 \quad \forall u$

proof  $\Rightarrow$  Easy  $\Leftarrow$  use "good"  $u$ 's

consider convergence of

$M, M^2, M^3, \dots$  what is  $\lim_{k \rightarrow \infty} M^k = ?$

$$\lim_{k \rightarrow \infty} M^k = 0 \Rightarrow \lim_{k \rightarrow \infty} M^k u = 0 \quad \forall u$$

Let  $u$  be an eigenvector of  $M$  with  $|\lambda| > 1$

$$M^k u = \lambda^k u$$

$$\lim_{k \rightarrow \infty} \lambda^k u \neq 0$$



- $M$  has eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_m$   
 $|\lambda_i| < 1$

Now, consider  $M^k x$  for any  $x$

CASE 1 Diagonalizable

$$M^k x = c_1 \lambda_1^k u_1 + c_2 \lambda_2^k u_2 + \dots + c_m \lambda_m^k u_m$$

$$\lim_{k \rightarrow \infty} M^k x = 0 \quad \text{since } |\lambda_i| < 1$$

Conclusion  $\lim_{k \rightarrow \infty} M^k = 0$  iff all eigenvalues are strictly smaller than 1

Exercise  $M = \begin{pmatrix} 0 & 1 \\ -2 & -3 \end{pmatrix}$  Find  $\lim_{k \rightarrow \infty} M^k$

$$\lambda_1 = -1 \quad \lambda_2 = -2$$

$$\therefore \lim_{k \rightarrow \infty} M^k \neq 0$$

Exercise  $M = \begin{pmatrix} 1/2 & 0 & 0 \\ 0 & -1/4 & 0 \\ -11 & 7 & 0 \end{pmatrix}$  Find  $\lim_{k \rightarrow \infty} M^k$

$$\lambda_1 = 1/2; \quad \lambda_2 = -1/4; \quad \lambda_3 = 0$$

$$\lim_{k \rightarrow \infty} M^k = 0$$

Spectral radius  $\rho(M) = \max \{ |\lambda|; \lambda \text{ is eigenvalue of } M \}$

Need to find all eigenvalues of  $M$

Lemma If  $\|\cdot\|$  is an induced matrix norm,  $\rho(A) \leq \|A\|$

Proof  $A \in \mathbb{R}^{m \times m}$  Eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_m$

Eigenvectors  $x_1, x_2, \dots, x_m$

$$Ax_1 = \lambda_1 x_1 \quad Ax_2 = \lambda_2 x_2 \quad \dots \quad Ax_m = \lambda_m x_m$$

$$X = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \dots & x_m \\ | & | & & | \end{bmatrix} \quad AX = \Lambda X \equiv AX = \lambda x_1$$

$$|\lambda_1| \|x\| = \|\lambda_1 x\| = \|Ax\| \leq \|A\| \|x\| \quad \Rightarrow \quad |\lambda_1| \leq \|A\|$$



Argue similarly for all eigenvalues to get  
 $\rho(A) \leq \|A\|$

Jacobi:  $x^{(k)} = x^{(k-1)} + D^{-1}(b - Ax^{(k-1)})$  (1)

Exact  
solution

$$Ax = b$$

$$D^{-1}Ax = D^{-1}b$$

$$D^{-1}(b - Ax) = 0$$

$$x = x + D^{-1}(b - Ax) \quad (2)$$

$$(2) - (1)$$

$$\underbrace{x - x^{(k)}}_{e^{(k)}} = \underbrace{x - x^{(k-1)}}_{e^{(k-1)}} - D^{-1}A \underbrace{(x - x^{(k-1)})}_{e^{(k-1)}}$$

$$e^{(k)} = (I - D^{-1}A) e^{(k-1)}$$

$\Downarrow$   
Linear

Similarly for Gauss Seidel, we have

$$e^{(k)} = [I - (L+D)^{-1}A] e^{(k-1)}$$