

Lecture 07 – Solving Linear Systems (Part 1)

Prof. Brendan Kochunas

NERS/ENGR 570 - Methods and Practice of Scientific Computing (F20)



Outline

- Solution of Linear Systems
- Direct Methods and ~~Matrix Factorizations~~
- Iterative Methods
- ~~Third Party Libraries~~

Learning Objectives: By the end of Today's Lecture you should be able to

- ~~(Skill) Perform Conflict Resolution (but just in git)~~
- ~~(Knowledge) Interpretate meaning of some vector norms~~
- ~~(Value/Knowledge) explain how to think about programming equations in linear algebra~~
- (Knowledge) know when to use direct vs. iterative solution algorithms
- (Knowledge) implement LU factorization
- (Knowledge) how to implement some iter. & understand convergence

Basic Linear Algebra Operations

Residual and Norms of Vectors

$$\mathbf{r} = \mathbf{Ax} - \mathbf{b}$$

residual

$$\|\mathbf{r}\|_1 = \sum_i |r_i|$$

1-norm

$$\|\mathbf{r}\|_2 = \sqrt{\sum_i r_i^2}$$

2-norm ("average error")

$$\|\mathbf{r}\|_\infty = \max_i (|r_i|)$$

∞ -norm ("max local error")

$$\|\mathbf{r}\|_p = \left(\sum_i |r_i|^p \right)^{1/p}$$

p -norm

$$A \cdot X = b$$

Inner/Dot Product (vector-vector multiply)

$$\mathbf{u}^T \cdot \mathbf{v} = \sum_i u_i v_i$$

Matrix-vector Multiply

$$\mathbf{Ax} = \mathbf{b} \rightarrow b_i = \sum_j a_{i,j} x_j$$

Matrix-Matrix Multiply

$$\mathbf{AB} = \mathbf{C} \rightarrow c_{i,j} = \sum_k a_{i,k} b_{k,j}$$



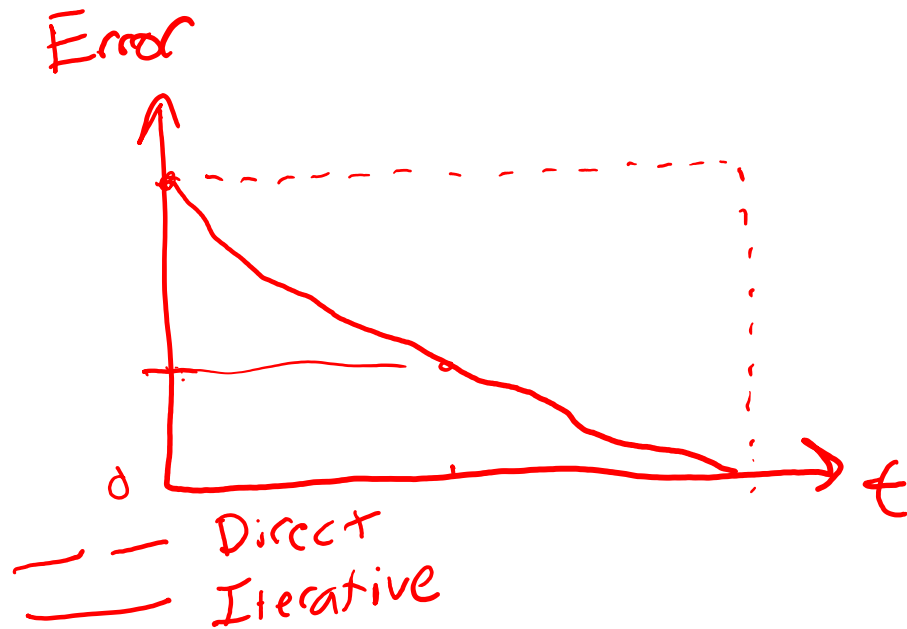
Solving Linear Systems

How do we solve linear systems?

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

np.solv(A, b, x)

MATLAB $A \setminus b = x$
 $\underline{A^{-1}} A = I = A \underline{A^{-1}}$



Direct Methods: Matrix Factorizations
 Operation count $\sim O(? n^3)$

Iterative methods

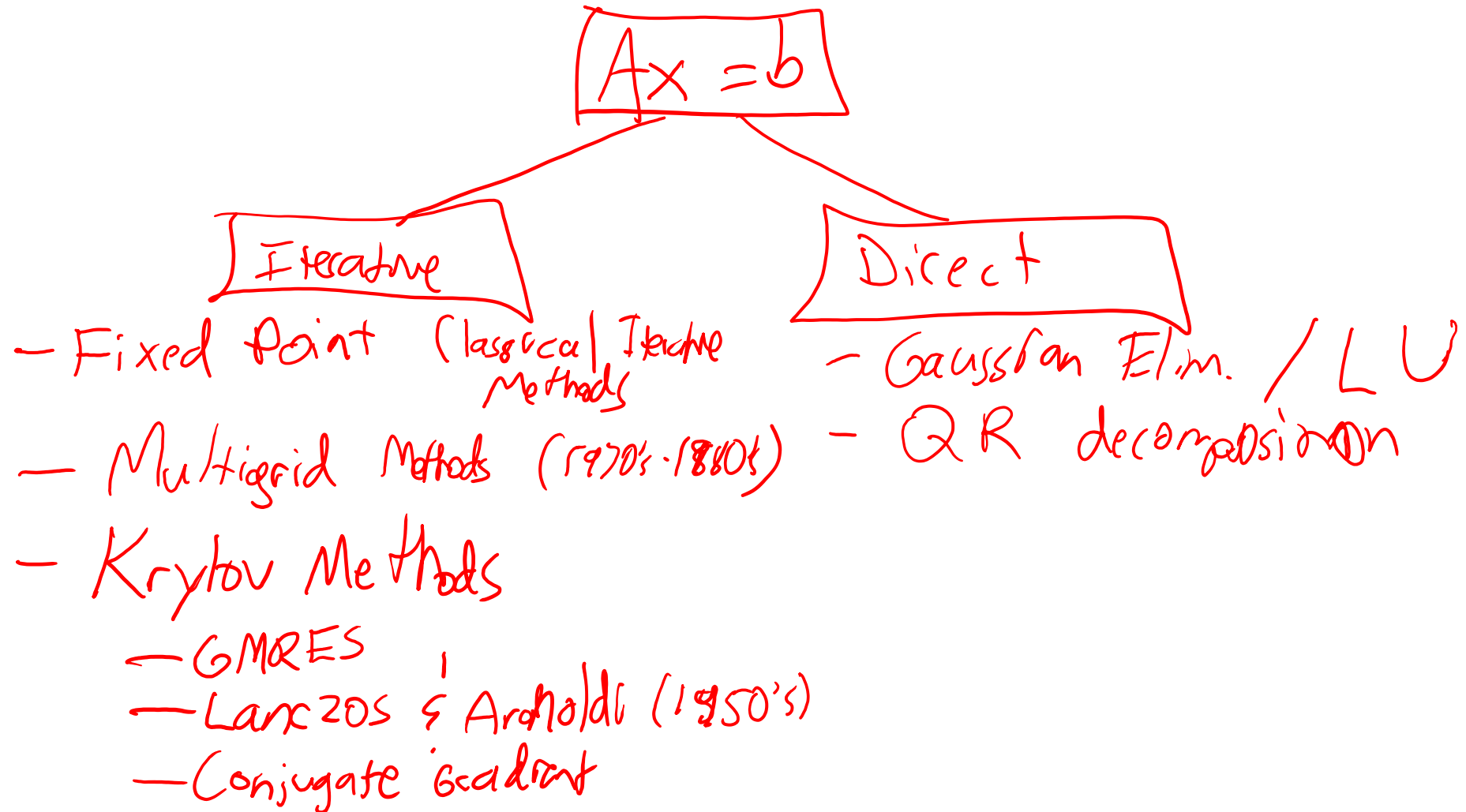
repetitive application
 of Mat-vec

$$\sim O(? n^2) \times m$$

$m < n$

$$(8\text{-bytes})(10^{12}) = 8 \text{ TB GB}$$

Overview of Solution Methods



Types of Matrices

1. Identity Matrix
2. Triangular
3. Diagonal
4. Symmetric
5. Tri-diagonal
6. Diagonally Dominant
7. Sparse/Dense
8. Square
9. Unitary
10. Positive definite
11. Invertible
12. scalar
13. Hermitian
14. Orthonormal



Direct Solution Methods *SuperLU*

aka Matrix Factorizations

LU Factorization

$$A = \underbrace{L} U \quad L = \begin{bmatrix} 1 & 0 \\ \text{ } & 1 \end{bmatrix} \quad U = \begin{bmatrix} \text{ } & \text{ } \\ 0 & 1 \end{bmatrix}$$

$$Ax = b \rightarrow LUx = b$$

$$\cancel{L}^{-1} L U x = \cancel{L}^{-1} b = y$$

$$\begin{cases} Ux = y & - \text{Backward Subs. (2)} \\ Ly = b & - \text{Forward Elim. (1)} \end{cases}$$

LU: Forward Elimination

$$Ly = b$$

$$L = \begin{bmatrix} \times & & \\ & \times & \\ & & \times \end{bmatrix}$$

$$a_{1,1} = l_{1,1} \quad x_1 = b_1 \quad \Rightarrow \quad x_1 = \frac{b_1}{l_{1,1}}$$

$$l_{1,1}x_1 + l_{2,1}x_2 = b_2 \quad \Rightarrow \quad x_2 = \frac{b_2 - l_{2,1}x_1}{l_{2,1}}$$

$$x_i = \left(b_i - \sum_{j=1, i-1}^i l_{i,j}x_j \right) / l_{i,i}$$

LU: Backward Substitution

$$Ux = y \quad U = \begin{bmatrix} \times & & \\ & \times & \\ & & \times \end{bmatrix}$$

$$a_{n,n} x_n = y_n \Rightarrow x_n = \frac{y_n}{a_{n,n}}$$

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

$$x_i = \left(y_i - \sum_{j=i+1}^n a_{ij} x_j \right) / a_{i,i}$$



Classical Iterative Methods

aka Fixed Point Iteration Schemes

Classical Iteration Schemes

Jacobi

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

Diagram illustrating the Jacobi iteration scheme. A large circle contains the summation term $\sum_{j=1, j \neq i}^n a_{ij} x_j^{(e)}$. Arrows point from this circle to two separate summation terms: $-\sum_{j=1}^{i-1} a_{ij} x_j^{(e)}$ and $-\sum_{j=i+1}^n a_{ij} x_j^{(e)}$.

$$\underline{x}^{(e+1)} = -\underline{D}^{-1}(\underline{L} + \underline{U})\underline{x}^{(e)} + \underline{D}^{-1}\underline{b}$$

$$\underline{F} = -\underline{D}^{-1}(\underline{L} + \underline{U})$$

Gauss-Siedel

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

$$A = L + D + U$$

$$L = \begin{bmatrix} 0 & & \\ a_{21} & 0 & \\ a_{31} & a_{32} & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} a_{11} & & \\ & a_{22} & \\ & & a_{33} \end{bmatrix}$$

$$U = \begin{bmatrix} & a_{12} & a_{13} \\ & & a_{23} \\ & & & a_{33} \end{bmatrix}$$

$$\underline{x}^{(e+1)} = -(\underline{D} + \underline{L})^{-1}\underline{U}\underline{x}^{(e)} + (\underline{D} + \underline{L})^{-1}\underline{b}$$

$$\underline{x}^{(e+1)} = \underline{F}\underline{x}^{(e)} + \underline{c} \quad \text{where } \underline{c} = (\underline{D} + \underline{L})^{-1}\underline{b}$$

Do they converge?

- Fixed point iteration

$$\mathbf{x}^{(\ell+1)} = \mathbf{F}\mathbf{x}^{(\ell)} + \mathbf{c}$$

- Express iterate as combination of exact solution and error

$$\mathbf{x} + \boldsymbol{\varepsilon}^{(\ell+1)} = \mathbf{F}(\mathbf{x} + \boldsymbol{\varepsilon}^{(\ell)}) + \mathbf{c} \quad x = Fx + c$$

- If the method converges then:

$$\lim_{\ell \rightarrow \infty} \boldsymbol{\varepsilon}^{(\ell)} = 0$$



Hands on Python Examples