CV5100 – MUDE

Modeling, Uncertainty, and Data for Engineers Ch4 – Linear Algebra

Course instructors:

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Numerical Modelling, Linear Algebra, Optimization

| Date | Day | Week | Lecture# | Topic | Topic summary | | | | |
|-----------|-----|------|----------|----------------------------|---|--|--|--|--|
| 28-Jul-25 | Mon | 1 | | • | NO CLASS | | | | |
| 29-Jul-25 | Tue | 1 | | | NO CLASS | | | | |
| 30-Jul-25 | Wed | 1 | 1 | Introduction lecture | motivation, course content, logistics, etc. | | | | |
| 31-Jul-25 | Thu | 1 | 2 | Modelling Concepts | sudheendra's part, course logistics; model classification | | | | |
| 4-Aug-25 | Mon | 2 | Asst-0 | | Software installation & github | | | | |
| 5-Aug-25 | Tue | 2 | 3 | Numerical Modelling | model decisions, verification vs. validation; differential equations in structural engg, examples, ODE types (linear, nonlinear, order) | | | | |
| 6-Aug-25 | Wed | 2 | 4 | Numerical Modelling | Analytical vs. Numerical solutions, code, algorithm | | | | |
| 7-Aug-25 | Thu | 2 | 5 | Numerical Modelling | Numerical derivative/Finite Differences, Taylor series, error, convergence, forward, backward difference | | | | |
| 11-Aug-25 | Mon | 3 | Asst-1 | | Finite difference, convergence rate, newton-raphson for finding roots (solving an equation) | | | | |
| 12-Aug-25 | Tue | 3 | 6 | Numerical Modelling | Central finite diff (1st &2nd order); Numerical integration; IVP example, accuracy/error, convergence, | | | | |
| 13-Aug-25 | Wed | 3 | 7 | Numerical Modelling | stability, explicit vs. implicit; BVP e.g. analytical, numerical/FDM, code implementation | | | | |
| 14-Aug-25 | Thu | 3 | 8 | Numerical Modelling | BVP matrix eqn; PDEs - types, gradient and laplacian operators, | | | | |
| 18-Aug-25 | Mon | 4 | Asst-2 | | IVP & BVP numerical solutions - explicit vs implicit and implementing matrix eq solving using inverse | | | | |
| 19-Aug-25 | Tue | 4 | 9 | Linear Algebra | Vector spaces, span, linear dependence, basis, dimension, examples, tensor vs. matrix | | | | |
| 20-Aug-25 | Wed | 4 | 10 | Linear Algebra | System of linear eqns, matrix form, solution approach-direct | | | | |
| 21-Aug-25 | Thu | 4 | 11 | Linear Algebra | matrix eqns solutions approach - iterative methods | | | | |
| 25-Aug-25 | Mon | 5 | Asst-3 | | - | | | | |
| 26-Aug-25 | Tue | 5 | - | Linear Algebra | NO CLASS | | | | |
| 28-Aug-25 | Thu | 5 | 12 | Linear Algebra | Eigenvalueproblem, solution approaches, compliexity/scaling; parallel computing? | | | | |
| 29-Aug-25 | Fri | 5 | 13 | | Quiz-1 @ 8am | | | | |
| 1-Sep-25 | Mon | 6 | Asst-4 | | Direct vs Iterative method implementation and comparison; convergence, error plot etc.; Eig vs Eigs | | | | |
| 2-Sep-25 | Tue | 6 | 14 | Optimization | Classification, Mathematical formulations, standard form, key concepts | | | | |
| 3-Sep-25 | Wed | 6 | 15 | Optimization | Gradient based approaches | | | | |
| 4-Sep-25 | Thu | 6 | 16 | Optimization | Non-gradient approaches | | | | |
| 8-Sep-25 | Mon | 7 | Asst-5 | | | | | | |
| 9-Sep-25 | Tue | 7 | 17 | Uncertainty and Estimation | random variables (rv), covariance, correlation; goodness of fit concepts | | | | |

Outline

- Vector space concepts
- System of linear equations
- Solution using direct methods
- Solution using indirect (iterative) methods
- Eigenvalue problem
- Orthogonality and orthogonalization

Vector space concepts

- Vector (Linear) space and subspace
- Span
- Linear dependence/independence
- Basis
- Dimension
- Orthogonal vs. non-orthogonal basis
- Column space, null space, rank

System of Linear Equations

Algebraic to Matrix form

$$egin{array}{lll} y_1 &=& a_{11}x_1 + a_{12}x_2 + \ldots + a_{1n}x_n \ y_2 &=& a_{21}x_1 + a_{22}x_2 + \ldots + a_{2n}x_n \ dots & & dots \ y_m &=& a_{m1}x_1 + a_{m2}x_2 + \ldots + a_{mn}x_n \end{array} \qquad egin{bmatrix} y_1 \ y_2 \ dots \ y_m \end{bmatrix} = egin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \ a_{21} & a_{22} & \ldots & a_{2n} \ dots & dots & dots \ a_{m1} & a_{m2} & \ldots & a_{mn} \end{bmatrix} egin{bmatrix} x_1 \ x_2 \ dots \ x_n \end{bmatrix}$$

$$y = Ax$$

$$\mathbf{y} = egin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{m1} \end{bmatrix} x_1 + egin{bmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{m2} \end{bmatrix} x_2 + \cdots + egin{bmatrix} a_{1n} \\ a_{2n} \\ \vdots \\ a_{mn} \end{bmatrix} x_n$$
 Give an example of linear equation in structural engineering

y is an element of the range space of A: $y \in \mathcal{R}(A)$

Solution using direct methods

Gaussian Elimination

Elementary row operations to get row echelon form:

- 1.Interchanging two rows.
- 2. Multiplying a row by a non-zero scalar.
- 3. Adding a scalar multiple of one row to another.

$$2x + y - z = 8 \qquad (L_1)$$

$$-3x - y + 2z = -11$$
 (L₂)

$$-2x + y + 2z = -3$$
 (L₃)

| System of equations | Row operations | Augmented matrix | | | |
|---------------------|----------------|------------------|----|----|---|
| 2x+y- $z=$ 8 | | | 1 | -1 | 8 |
| -3x - y + 2z = -11 | | -3 | -1 | 2 | $\left[egin{array}{c} 8 \ -11 \ -3 \end{array} ight]$ |
| -2x + y + 2z = -3 | | ig ig -2 | 1 | 2 | $\begin{bmatrix} -3 \end{bmatrix}$ |

Solution using direct methods

LU decomposition

$$egin{bmatrix} a_{11} & a_{12} & a_{13} \ a_{21} & a_{22} & a_{23} \ a_{31} & a_{32} & a_{33} \end{bmatrix} = egin{bmatrix} \ell_{11} & 0 & 0 \ \ell_{21} & \ell_{22} & 0 \ \ell_{31} & \ell_{32} & \ell_{33} \end{bmatrix} egin{bmatrix} u_{11} & u_{12} & u_{13} \ 0 & u_{22} & u_{23} \ 0 & 0 & u_{33} \end{bmatrix}$$

- Decomposes matrix A into:
 - L: Lower triangular matrix
 - U: Upper triangular matrix
- Solves AX=B by solving LY=B and then UX=Y.

- Useful for multiple RHS e.g.?
- What if A is symmetric?
 LU → LL^T Cholesky

Solution using direct methods

- Gaussian Elimination Computational efficiency
 - Eliminate elements of first column nxn ops
 - For every subsequent column reduce n by 1
 - Sum of squares of n natural number O(n^3)
- Run time scaling
- Memory scaling (storing the matrix); 8 bytes per number in 64-bit (double precision) – 15 decimals
- Triangular matrix solved sequentially (not efficient for parallel computing)
- Finds the exact solution in a finite number of steps

Eigenvalue problem

- Definition and details
- Computational complexity/scaling
- eig vs. eigs eigensolvers (numpy vs scipy) full vs sparse matrices – direct vs indirect/iterative methods
- Inverse and pseudoinverse
- Energy and eigenvalues

 Where do we come across eigenvalues in structural engineering?

Orthogonalization

Gram-Schmidt process

Given k nonzero linearly-independent vectors $\mathbf{v}_1, \dots, \mathbf{v}_k$ the Gram–Schmidt process defines the vectors $\mathbf{u}_1, \dots, \mathbf{u}_k$ as follows:

$$egin{aligned} \mathbf{u}_1 &= \mathbf{v}_1, \ \mathbf{u}_2 &= \mathbf{v}_2 - \operatorname{proj}_{\mathbf{u}_1}(\mathbf{v}_2), \ \mathbf{u}_3 &= \mathbf{v}_3 - \operatorname{proj}_{\mathbf{u}_1}(\mathbf{v}_3) - \operatorname{proj}_{\mathbf{u}_2}(\mathbf{v}_3), \ \mathbf{u}_4 &= \mathbf{v}_4 - \operatorname{proj}_{\mathbf{u}_1}(\mathbf{v}_4) - \operatorname{proj}_{\mathbf{u}_2}(\mathbf{v}_4) - \operatorname{proj}_{\mathbf{u}_3}(\mathbf{v}_4), \ &dots \ \mathbf{u}_k &= \mathbf{v}_k - \sum_{i=1}^{k-1} \operatorname{proj}_{\mathbf{u}_j}(\mathbf{v}_k), \end{aligned}$$

The vector projection of a vector ${f v}$ on a nonzero vector ${f u}$ is defined

$$ext{proj}_{\mathbf{u}}(\mathbf{v}) = rac{\langle \mathbf{v}, \mathbf{u}
angle}{\langle \mathbf{u}, \mathbf{u}
angle} \, \mathbf{u}$$

Solution using indirect methods

Jacobi iteration

 $\mathbf{A} = \mathbf{D} + \mathbf{R}$

Let $A\mathbf{x} = \mathbf{b}$ be a square system of *n* linear equations, where:

$$A=egin{bmatrix} a_{11}&a_{12}&\cdots&a_{1n}\ a_{21}&a_{22}&\cdots&a_{2n}\ dots&dots&\ddots&dots\ a_{n1}&a_{n2}&\cdots&a_{nn} \end{bmatrix}, \qquad \mathbf{x}=egin{bmatrix} x_1\ x_2\ dots\ x_n \end{bmatrix}, \qquad \mathbf{b}=egin{bmatrix} b_1\ b_2\ dots\ b_n \end{bmatrix}.$$

$$\mathbf{x} = egin{bmatrix} x_1 \ x_2 \ dots \ x_n \end{bmatrix}, \qquad \mathbf{b} = egin{bmatrix} b_1 \ b_2 \ dots \ b_n \end{bmatrix}.$$

$$egin{align} \mathbf{g}(\mathbf{x}) &= \mathbf{D}^{-1}(\mathbf{b} - \mathbf{R}\mathbf{x}) \ \mathbf{f}(\mathbf{x}) &= \mathbf{g}(\mathbf{x}) - \mathbf{x} \ \mathbf{e}(\mathbf{x}) &= \mathbf{x} - \mathbf{x}^* & \mathbf{e}(\mathbf{x}_{k+1}) &= \left(\mathbf{I} - \mathbf{D}^{-1}\mathbf{A}\right)\mathbf{e}(\mathbf{x}_k) \ \mathbf{x}_{k+1} &= \mathbf{g}(\mathbf{x}_k) & \|\mathbf{I} - \mathbf{D}^{-1}\mathbf{A}\| < 1 \ \end{aligned}$$

$$\mathbf{x}_{k+1} = (1-\omega)\mathbf{x}_k + \omega\mathbf{g}(\mathbf{x}_k)$$
 $\|\mathbf{I} - \omega\mathbf{D}^{-1}\mathbf{A}\| < 1$

- Fixed-point iteration
- Residual vs. Error
- L² norm
- Condition number
- Spectral radius

$$\kappa(A) = \|A\| \cdot \|A^{-1}\|$$

$$\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2$$

 $\rho(A) = \max\{|\lambda| : \lambda \text{ is an eigenvalue of } A\}$

Solution using indirect methods

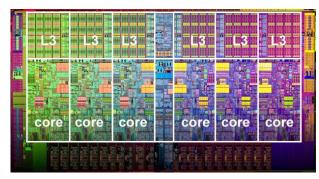
- Gauss-Seidel Method
- Conjugate Gradient Method
- GMRES
- Preconditioned Conjugate Gradient (PCG)
- Multigrid methods
- Anderson-Jacobi
- Alternating Anderson Jacobi

Pratapa, P. P., Suryanarayana, P., & Pask, J. E. (2016). Anderson acceleration of the Jacobi iterative method: An efficient alternative to Krylov methods for large, sparse linear systems. *Journal of Computational Physics*, *306*, 43-54.

High Performance & Parallel Computing







```
b_i = A_{i1}x_1 + A_{i2}x_2 + \ldots + A_{in}x_n = \sum_{j=1}^n A_{ij}x_j

% Given, Matrix A of size n x n.
% Given, Vector x of size n x 1.
% Find, Vector b = A*x.

for i=1:n

S = 0;

computers

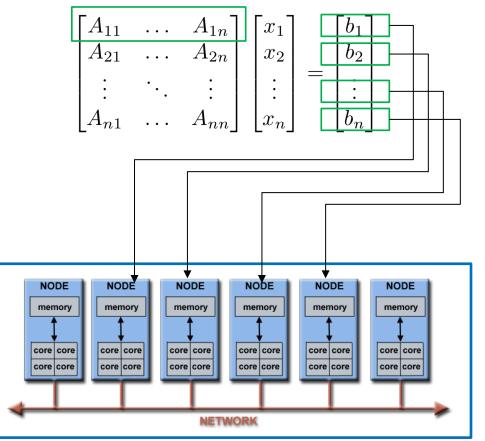
for j=1:n

S = S + A(i,j)*x(j);

end

b(i) = S;

end
```



Computer Cluster

Other things if you are curious

- Scientific/High-performance computing
- Profiling
- BLAS
- LAPACK
- MPI
- PETSc
- Threading
- Parallel scaling, parallel computing
- Cache, retrieval
- Communication
- Petaflops, Exaflops, Supercomputers