

# Summary Sheet: MATH 3NA3 - Numerical Linear Algebra

## Floating Point (FP) Number Systems

FP system definition:  $\begin{cases} \beta & : \text{Base} \\ P & : \text{Precision} \\ L & : \text{Exponent min} \\ U & : \text{Exponent max} \end{cases}$

$$x = \pm(d_0.d_1d_2\dots d_{P-1}) \times \beta^E, \quad E \in [L, U]$$

$$x = \pm \left( \sum_{i=0}^{P-1} \frac{d_i}{\beta^i} \right) \beta^E, \quad d_i \in [0, \beta - 1]$$

$$\epsilon_{mach} = \beta^{1-P}$$

$$\text{Absolute rounding error} = |fl(x) - x| \leq |x| \epsilon_{mach}$$

$$\text{RRE (Relative representation error)} = \frac{|fl(x) - x|}{|x|}$$

$$\text{maxRRE}(x) = \begin{cases} \epsilon_{mach} & \text{if round up/down} \\ \frac{\epsilon_{mach}}{2} & \text{if round to nearest} \end{cases} \leq \epsilon_{mach}$$

$$fl(x) = x(1 + \delta), \delta = \frac{fl(x) - x}{x}, |\delta| \leq \epsilon_{mach}$$

$$\text{Min value representable} > 0 = \beta^L$$

$$\text{Max value representable} = \beta^{U+1}(1 - \beta^{-P})$$

$$|\mathbb{F}| = 2(\beta - 1)(\beta^{P-1})(U - L + 1) + 1$$

### Properties of FP systems:

1. Finite:  $\exists$  overflow and underflow
2. Discrete:  $\exists$  gaps btwn nums  $\in \mathbb{F}$
3. Non-Uniform: Nums  $\in \mathbb{F} \neg$  (evenly distributed)

## Floating Point Operations

$$x \oplus y := fl(x \star y) = (x \star y)(1 + \delta) \quad |\delta| < \epsilon$$

$$\text{Fundamental Axiom: } \frac{|x \oplus y - (x \star y)|}{|x \star y|} \leq \epsilon = \frac{1}{2} \epsilon_{mach}$$

**Cancellation Error:** subtract similar sized nums

## General Algebra

$$\sum_{i=1}^n i = \frac{n(n+1)}{2}$$

eigvals of  $A^T A \in \mathbb{R}^{n \times n} = [\sigma_1 \dots \sigma_n]^2$  from  $A$ 's SVD

- $a^2 - b^2 = (a - b)(a + b)$
- Singular matrix:= not invertible

### SPD:

- $A$  SPD iff  $A^T = A$  & (strict diag. dom  $\Leftrightarrow \lambda_{min} > 0$ )
- $A$  SPD iff  $B^T A B$  is SPD for nonsingular  $B$
- if  $A$  SPD, principle submatrices SPD

### Gershgorin's thm:

- any eigenvalue of  $A$  is in at least one of the closed disks  $D(a_{ii}, R_{ii})$ ,  $R_{ii} = \sum_{j \neq i} |A_{ij}|$

**Diagonal dominance:** properties:

1. If  $A$  strict diag dom,  $A$  invertible
2.  $A^T = A$ , if  $A$  strict diag dom, and  $A_{ii} > 0$ , then  $A$  SPD.

pf of 1 by contradiction: sps non-invertible, then  $\exists$  row of 0's, that row's diag not greater than sum of others, so contradiction.

## Matrix Norms & SVD

### Matrix Norm Properties:

1.  $\|A\| \geq 0, \|A\| = 0$  iff  $A = 0$
2.  $\|cA\| = |c| \times \|A\|$
3.  $\|A + B\| \leq \|A\| + \|B\|$

$$\|A\|_p = \max_{\|\vec{x}\|_p=1} \|A\vec{x}\|_p = \max_{\vec{x} \neq 0} \frac{\|A\vec{x}\|_p}{\|\vec{x}\|_p}$$

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^m |a_{ij}| \quad (\text{max abs col sum})$$

$$\|A\|_\infty = \max_{1 \leq i \leq m} \sum_{j=1}^n |a_{ij}| \quad (\text{max abs row sum})$$

$$\|A\|_2 = \sqrt{\lambda_{max}(A^T A)} = \sigma_{max}(A)$$

$$\|AA^T\|_2 = \|A^T A\|_2 = \lambda_{max}(A^T A) = \sigma_{max}(A)^2$$

### Induced Matrix Norm Properties:

1.  $\|A\vec{x}\| \leq \|A\| \times \|\vec{x}\|$
2.  $\|AB\| \leq \|A\| \times \|B\|$
3.  $\|Q_1 A Q_2\|_2 = \|A\|_2$
4.  $\|Q\|_2 = 1$
5.  $\|A^T\|_2 = \|A\|_2$
6.  $\|I\| = 1$

**Vector Norms:**  $\|\vec{x}\|_p = (\sum_{i=1}^n |x_i|^p)^{\frac{1}{p}}$

1.  $\|\vec{x}\| \geq 0, \|\vec{x}\| = 0$  iff  $\vec{x} = 0$
2.  $\|\vec{x} + \vec{y}\| \leq \|\vec{x}\| + \|\vec{y}\|$
3.  $\|\alpha \vec{x}\| = |\alpha| \times \|\vec{x}\|$

- $\|\cdot\|_a, \|\cdot\|_b$  equiv. iff  $\exists c$ 's s.t.

$c_1 \|\vec{x}\|_b \leq \|\vec{x}\|_a \leq c_2 \|\vec{x}\|_b$ , meaning can exchange in p-norm applications

$$\|\vec{x}\|_\infty = \max_{1 \leq j \leq n} |x_j|$$

$$\|\vec{x}\|_2 \leq \|\vec{x}\|_1 \leq \sqrt{n} \|\vec{x}\|_2$$

$$\|\vec{x}\|_\infty \leq \|\vec{x}\|_1 \leq n \|\vec{x}\|_\infty$$

### SVD:

$$A = U \Sigma V^T \Leftrightarrow A^{-1} = V \Sigma^{-1} U^T$$

$A$  symm. pos. definite  $\Rightarrow$  diagonalization = SVD

- Singular values of  $AA^T = A^T A = \sigma_1^2, \dots, \sigma_n^2$
- $\det(A) = \prod_{i=1}^n \sigma_i$

## MATLAB

Command	Purpose
realmax/realmin	return max/min float
eps	return $\epsilon_{mach}$
norm( $\vec{x}, p$ ), norm( $A, p$ )	$\ \vec{x}\ _p, \ A\ _p$
cond( $A, p$ )	$\kappa_p(A)$
pinv( $A$ )	pseudo-inv $A$

## Error, Sensitivity & Big O

input/output perturbation:  $x + \delta x, f + \delta f$

**Absolute Condition Number:**  $\hat{\kappa} = \|f'(x)\|$

**Relative Condition Number:**  $\kappa = \frac{\|f'(x)\| \|x\|}{\|f(x)\|}$

**Absolute Error:**  $\|\tilde{f}(x) - f(x)\|$ ,  $\tilde{f} :=$  num mthd output

**Relative Error:**  $\frac{\|\tilde{f}(x) - f(x)\|}{\|f(x)\|}$

Algo accurate iff  $\frac{\|\tilde{f}(x) - f(x)\|}{\|f(x)\|} = O(\epsilon_{mach})$

**Backward Error:**  $|\tilde{x} - x|$

- Attribute output err to  $\Delta$  inp
- $\tilde{f}(x) = f(\tilde{x})$ , solve for  $\tilde{x}$
- rel fwd err  $\leq \kappa$  rel back err

## Solutions of Linear Equations 1

**Condition Number:**  $\kappa_p(A) = \|A\|_p \|A^{-1}\|_p$

1.  $\kappa_p(A) \geq 1$
2.  $\kappa_p(I) = 1$
3.  $\kappa_p(\alpha A) = \kappa_p(A) \forall$  scalars  $\alpha$

$$\bullet \kappa_2(A) = \frac{\sigma_{max}}{\sigma_{min}}$$

**Condition Number of solving  $A\vec{x} = \vec{b}$ :**

Math:  $f(A, \vec{b}) = \vec{x} \Leftrightarrow A\vec{x} = \vec{b}$

Compute:  $\tilde{f}(A, \vec{b}) = \tilde{\vec{x}} = \vec{x} + \delta \vec{x} \Leftrightarrow (A + \delta A) = \vec{b} + \delta \vec{b}$

- Relative Error:  $\frac{\|\delta \vec{x}\|}{\|\vec{x}\|}$
- Relative Backward Error:  $\frac{\|\delta \vec{b}\|}{\|\vec{b}\|}, \frac{\|\delta A\|}{\|A\|}$
- Algo Backward Stable iff  $\frac{\|\delta \vec{b}\|}{\|\vec{b}\|}, \frac{\|\delta A\|}{\|A\|} = O(\epsilon_{mach})$

**Residual Properties:**  $\vec{r} = \vec{b} - \tilde{\vec{x}}$

1.  $\frac{\|\delta \vec{x}\|}{\|\vec{x}\|} \leq \kappa(A) \frac{\vec{r}}{\vec{b}}$
  2.  $\frac{\|\delta A\|}{\|A\|} \geq \frac{\vec{r}}{A \vec{x}}$
- Problem:  $A\vec{x} = \vec{b}$
  - Computation:  $(A + \delta A)\tilde{\vec{x}} = \vec{b}(1 + \delta)$
  - $\tilde{\vec{x}} = \vec{x} + \delta \vec{x}$

## Solutions of Linear Equations 2: LU

**LU factorization:**  $A_{n \times n} = LU$

**Steps:**

1. Initialize  $L$  as identity matrix.
2. Initialize  $U$  as zero matrix.
3. For each column  $j$ :
  - a. Set elements of  $U$  in row  $i$  up to  $j$ .
  - b. Set elements of  $L$  from row  $j+1$  to  $n$ .

**Pivoting:**

With partial pivoting:  $PA = LU$ .

$P$  - Permutation matrix.

$$M_k = \begin{bmatrix} 1 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 1 & \vdots & \dots & 0 \\ 0 & \dots & -m_{k+1} & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & -m_n & 0 & \dots & 1 \end{bmatrix}$$

- $L_k = M_k^{-1} = I + \vec{m}_k \vec{e}_k^T$
- $U = M_{n-1} M_{n-2} \dots M_2 M_1 A$
- $L = M_1^{-1} M_2^{-1} \dots M_{n-2}^{-1} M_{n-1}^{-1}$
- LU factorization not backw stable, PLU is.
- LU factorization  $O(\frac{2}{3}n^3)$  flops

**Cholesky:**  $A = LL^T$  (unique, for SPD A)

$$l_{jj} = \sqrt{a_{jj} - \sum_{k=1}^{j-1} l_{jk}^2} \text{ diag elements}$$

$$l_{ij} = \frac{a_{ij} - \sum_{k=1}^{j-1} l_{ik} l_{kj}}{l_{jj}} \text{ other elements}$$

- Cholesky factorization  $O(\frac{1}{3}n^3)$  flops

$$A = \begin{bmatrix} a & b \\ b & c \end{bmatrix} L = \begin{bmatrix} \sqrt{a} & 0 \\ \frac{b}{\sqrt{a}} & \sqrt{c - \left(\frac{b}{\sqrt{a}}\right)^2} \end{bmatrix}$$

## Iterative Methods

$A = M - N$ ,  $M$  nonsingular

$$\vec{x}^{(k+1)} = M^{-1} N \vec{x}^{(k)} + M^{-1} \vec{b} = G \vec{x}^{(k)} + \vec{c}$$

Terminate when  $\|\vec{r}^{(k)}\| = \|\vec{b} - A \vec{x}^{(k)}\| \leq \text{tol}$

**Properties of  $\rho(A)$ :**

1.  $\rho(A) \leq \|A\|_k \forall k$
2. Spectral radius  $\rho(A) = \max |\lambda(A)|$
3.  $\lim_{n \rightarrow \infty} A_{n \times n}^n = 0$  iff  $\rho(A) < 1$
4. Iterative mthd converges iff  $\rho(G) < 1$ 
  - Iter mthd converges iff  $\|G\|_a < 1$  for some  $a$

**Jacobi Mthd:**  $A = D + L + U$  ( $D = M, L + U = -N$ )

- each iter  $O(2kn^2)$ , good for large, sparse  $A$
- $D :=$  Diag entries of  $A$
- $D :=$  Strictly lower diagonal entries of  $A$
- $D :=$  Strictly upper diagonal entries of  $A$
- $\vec{x} = D^{-1}(- (L + U) \vec{x} + \vec{b})$
- $\vec{x}^{(k+1)} = D^{-1}(- (L + U) \vec{x}^{(k)} + \vec{b})$
- $G_j = D^{-1}(L + U)$

**Gauss-Seidel Mthd:**  $L + D = M, -U = N$

- $\vec{x}^{(k+1)} = D^{-1}(\vec{b} - L \vec{x}^{(k+1)} - U \vec{x}^{(k)})$
- $\vec{x}^{(k+1)} = (L + D)^{-1}(\vec{b} - U \vec{x}^{(k)})$
- $G_{gs} = -(L + D)^{-1}U$
- $\vec{c}_{gs} = (L + D)^{-1}\vec{b}$

**SOR Mthd:** (equivalent to GS mthd for  $\omega = 1$ )

$$G_{sor} = (D + \omega L)^{-1}((1 - \omega)D - \omega U) \vec{x}^{(k)} + \omega(D + \omega L)^{-1}\vec{b}$$

- $G_{sor} = (D + \omega L)^{-1}((1 - \omega)D - \omega U)$
- if SOR converges, then  $0 < \omega < 2$

**Convergence:**

- Convergence rate  $\rho(G) = \gamma = \lim_{k \rightarrow \infty} \frac{\|\vec{x}^{(k+1)} - \vec{x}^{(*)}\|}{\|\vec{x}^{(k)} - \vec{x}^{(*)}\|^q}$
- $\lim_{k \rightarrow \infty} \vec{x}^{(k)} = \vec{x}^{(*)}$
- $q = 1, 0 < \gamma < 1$  linear convergence
- each iter gain  $-\log_{10}(\gamma)$  correct digits
- smaller  $\gamma \Rightarrow$  faster convergence
- A strict diag. dom.  $\Rightarrow$  Jacobi & G-S convrg (1)
- A SPD  $\Rightarrow$  SOR converges iff  $0 < \omega < 2$

pf of (1)J (G-S) same idea - end of soln's lin eqns:

by contr. sps.  $G_J$  has  $|\lambda| \geq 1 \Rightarrow \det(\lambda I - G_J) = 0$

- Tridiagonal  $A$ :  $\omega_{opt} = \frac{2}{1 + \sqrt{1 - \rho(G_J)^2}}$
- $\rho(G_{sor \omega_{opt}}) = \frac{1 - \sqrt{1 - \rho(G_J)^2}}{1 + \sqrt{1 - \rho(G_J)^2}}$

## Least Squares

Goal: find  $\underset{\vec{x} \in \mathbb{R}^n}{\text{argmin}} \|\vec{b} - A \vec{x}\|_2$

Solution set:  $\chi_{ls} = \{\vec{x} \in \mathbb{R}^n : \vec{x} = \underset{\vec{x} \in \mathbb{R}^n}{\text{argmin}} \|\vec{b} - A \vec{x}\|_2\}$

$$\chi_{ls} = \vec{x}_{ls} + \text{null}(A^T A) = \vec{x}_{ls} + \text{null}(A)$$

**Theorems:**

- $\vec{x} \in \chi_{ls} \Leftrightarrow A^T A \vec{x} = A^T \vec{b}$  (normal equations)
- $\exists$  unique solution if  $\text{rank}(A) = n$

**Pseudo-Inverse:**

- $A^\dagger = V \Sigma^\dagger U^T$ ,  $\sigma_i^\dagger = \frac{1}{\sigma_i}$  if  $\sigma_i \neq 0$ , else 0
- $\vec{x}_{ls} = A^\dagger \vec{b}$

**QR factorization:**  $A = [Q_1 \ Q_2] \begin{bmatrix} R \\ 0 \end{bmatrix} = Q_1 R$

- $A \in \mathbb{R}^{m \times n}, m \geq n \Rightarrow A$  has  $QR$  factorization
- $Q_{m \times m} = [Q_{1 \mathbb{R}^{m \times n}} \ Q_{2 \mathbb{R}^{m \times m-n}}]$  orthogonal
- $R_{m \times n} = \begin{bmatrix} \hat{R} \\ 0 \end{bmatrix}$ ,  $\hat{R}_{n \times n}$  upper triangular
- $\vec{x}_{ls} = R^{-1} Q_1^T \vec{b}$
- $\|\vec{b} - \vec{x}_{ls}\| = \|Q_2^T \vec{b}\|_2$

**Householder Transformation:**

idea:  $H_n \dots H_2 H_1 A = R$  (upper triangular),  $H_{m \times m}$

- $H \vec{x}$  is reflection of  $\vec{x}$  in plane orthog to  $\vec{v}$
- $H$  is orthogonal
- $H = I - 2 \vec{v} \vec{v}^T / \vec{v}^T \vec{v}$ ,  $\|\vec{v}\|_2 = 1$
- $H = H_1^T H_2^T \dots H_n^T$
- $Q = H_1 H_2 \dots H_n$