

1 Matrix Factorizations

Basic Matrix Facts

- Range, Kernel
- Fundamental Theorem of Linear Algebra
 $Ran(A)(+)Ker(A^*) = C^m, Ran(A) \perp Ker(A^*)$
 $Ran(A^*)(+)Ker(A) = C^n, Ran(A^*) \perp Ker(A)$
- Norms - vector norms, matrix norms

$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \max_{\|x\|=1} \|Ax\|$$
 Unitary invariance of 2-norm:
 - Q is unitary if $Q \in C^{m \times n}, Q^*Q = I$
 - $\|Qx\|_2 = \|x\|_2, \|QA\|_2 = \|A\|_2 = \|AQ\|_2$ (does not hold for 1-norm)
- Vector norm axioms
 - positivity: $\|x\| \geq 0, \|x\| = 0 \Leftrightarrow x = 0$
 - scaling: $\|ax\| = |a|\|x\|$
 - triangle inequality: $\|x + y\| \leq \|x\| + \|y\|$
- Submultiplicativity:
 For all induced matrix norms: $\|AB\| \leq \|A\|\|B\|$
- Projectors and Reflectors
 - P is a projector $\Leftrightarrow P^2 = P$
 - P is an orthogonal projector $\Leftrightarrow P = P^*, P^2 = P$
 - Householder reflectors: reflects across the $span\{v\}^\perp$
 - * $H(v)x = (I - 2P)x$
 $= (I - \frac{vv^*}{v^*v})x$ (Orthog projection onto $span\{v\} : P = \frac{vv^*}{v^*v}$)
 - * $H(v)$ is Hermitian, and $H(v)$ is unitary ($H(v)^*H(v) = I$)

$$\rightarrow Rx = (Q^*b)$$

Solve via backsubstitution.

$$\text{Cost of Householder QR: } 2mn^2 - 2/3n^3$$

Cost of back substitution: n^2 Discrete Least Squares problems:

$$\min_x \|b - Ax\|_2, A \in \mathbb{R}^{m \times n}, m \geq n$$

- Floating Point Arithmetic

~~How many bits are in the IEEE Floating point mantissa?~~

Basic axioms: $fl(X + Y) = (X + Y)(1 + \delta), |\delta| \leq \epsilon_{mach}$

Nothing on the floating point format.

- Stability and conditioning

Condition number for solving linear systems

$$Ax = b, (A + \delta A)(x + \delta x) = b, \frac{\|\delta x\|}{\|x\|} \leq \underbrace{\|A\| \|A^{-1}\|}_{\text{Condition\#}} \frac{\|\delta A\|}{\|A\|}$$

\log_{10} of condition # is the number of digits you'll lose.

Could use SVD to construct worst case situation for the condition number.

– HALFWAY POINT –

2 Interpolation

Basic problem:

Given $f \in C[a, b]$, find $p_n \in P_n$

$$p_n(x_j) = f(x_j)$$

at the prescribed points x_0, \dots, x_n .

Given a basis $\phi_0, \phi_1, \dots, \phi_n$ for P_n .

$$\text{Write } p_n(x) = \sum_{j=0}^n c_j \phi_j(x)$$

$$p_n(x_k) = \sum_{j=0}^n c_j \phi_j(x_k) = f(x_k), k = 0, \dots, n$$

$$\begin{bmatrix} \phi_0(x_0) & \phi_1(x_0) & \dots & \phi_n(x_0) \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ \phi_0(x_n) & \phi_1(x_n) & \dots & \phi_n(x_n) \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_n \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ \vdots \\ f(x_n) \end{bmatrix}$$

Some notable bases for P_n :

- $\phi_j(x) = x^j$ monomial basis \rightarrow Vandermonde matrix \rightarrow ill-conditioned

- $\phi_j(x) = \prod_{l=0}^{j-1} (x - x_l)$ Newton \rightarrow Lower triangular
- $\phi_j(x) = \frac{\prod_{l=0, l \neq j}^n (x - x_l)}{\prod_{l=0, l \neq j}^n (x_j - x_l)}$ Lagrange, Identity Matrix

Error Formula: If $f \in C^{n+1}[a, b]$, then for each $x \in (a, b)$ there exists some $\xi \in (a, b)$ such that

$$f(x) - p_n(x) = \frac{f^{(n+1)}(\xi)}{(n+1)!} \prod_{j=0}^n (x - x_j)$$

$$\|f - p_n\|_{L^\infty} \leq \frac{\|f^{(n+1)}\|_{L^\infty}}{(n+1)!} \left\| \prod_{j=0}^n (x - x_j) \right\|_{L^\infty}$$

Runge's function: $f(x) = \frac{1}{1+x^2} x \in [-5, 5]$ Key Point: High Degree Interpolation at uniformly spaced points can fail to converge.

(Chebyshev points are much better.) Hermite Interpolation (Don't memorize formulas) $h_n \in P_{2n+1}$ such that:

$$h_n(x_j) = f(x_j)$$

$$h'_n(x_j) = f'(x_j) \quad j = 0, \dots, n \text{ Piecewise Polynomial Approximation}$$

- Piecewise linear (matches $f(x_j) \Rightarrow C^0$)
- Piecewise cubic Hermite (matches $f(x_j), f'(x_j) \Rightarrow C^1$)
- Splines match $f(x_j)$ use extra degrees of freedom to achieve maximum smoothness (Like a razor commercial).

Basis splines (B-splines) $B_{j,k}(x)$

"compact support" - zero except for a small subinterval that depends on j and k .

- Trigonometric Interpolation

Find $t_n \in \text{span}\{e^{0x}, e^{ix}, e^{-ix} \dots e^{inx}, e^{-inx}\}$

such that $t_n(x_j) = f(x_j) \quad j = 0, \dots, 2n$

x_j are uniformly spaced on $[0, 2\pi)$

f is 2π -periodic.

The coefficients of t_n are the discrete Fourier coefficients of $f(x_0), \dots, f(x_{2n})$

3 Approximation Theory

(# SVD problems ≥ 1)

- Discrete Least Squares

$$A \in C^{m \times n}, m \geq n, \min_{x \in C^n} \|b - Ax\|_2$$

$$b = b_R + b_k$$

$$\|b - Ax\|_2^2 = \underbrace{\|b_R - Ax\|_2^2}_{\in \text{Ran}(A)} + \underbrace{\|b_k\|_2^2}_{\in \text{Ker}(A^*)} = \|b_R - Ax\|_2^2 + \|b_k\|_2^2$$

Whitman - "Do I contradict myself? Very well, then I contradict myself, I am large, I contain multitudes."

Pick $Ax = b_r$

Note that $A^*b = A^*(b_R + b_k) = A^*b_R + \underbrace{A^*b_k}_{=0} = A^*b_R$

Normal Equations: $A^*Ax = A^*b$ $A^*A \in C^{n \times n}$, invertible $\Leftrightarrow A$ is full rank.

Alternative: $A = QR = [Q_1 Q_2] \begin{bmatrix} R_1 \\ 0 \end{bmatrix} = Q_1 R_1$

$$\|b - Ax\|_2^2 = \|b - QRx\|_2^2 = \|QQ^*b - QRx\|_2^2 = \|Q^*b - Rx\|_2^2$$

$$= \left\| \begin{bmatrix} Q_1^* \\ Q_2^* \end{bmatrix} b - \begin{bmatrix} R_1 \\ 0 \end{bmatrix} x \right\|_2^2 = \left\| \begin{bmatrix} Q_1^*b - R_1x \\ Q_2^*b \end{bmatrix} \right\|_2^2$$

$$= \|Q_1^*b - R_1x\|_2^2 + \|Q_2^*b\|_2^2$$

Find x s.t. $R_1x = Q_1^*b$

- Singular Value decomposition $A \in C^{m \times n}$,

- $A = U\Sigma V^*$
- $UU^* = I_m$
- $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_{\min(m,n)})$
- $V^*V = I_n$
- $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_{\min(m,n)}$

Dyadic Decomposition: $A = \sum_{j=1}^r \sigma_j u_j v_j^*$, $r = \text{rank}(A)$

E.g., if $m=n=r=2$,

$$A = U\Sigma V^* = [U_1 U_2] \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix} \begin{bmatrix} v_1^* \\ v_2^* \end{bmatrix} = [\sigma_1 u_1 \sigma_2 u_2] \begin{bmatrix} v_1^* \\ v_2^* \end{bmatrix}$$

$$= \sigma_1 u_1 v_1^* + \sigma_2 u_2 v_2^*$$

Fundamental subspaces:

$$\text{Ran}(A) = \text{span}\{u_1, \dots, u_r\}$$

$$\text{Ran}(A^*) = \text{span}\{v_1, \dots, v_r\}$$

$$\text{Ker}(A) = \text{span}\{u_{r+1}, \dots, u_m\}$$

$$\text{Ker}(A^*) = \text{span}\{u_{r+1}, \dots, u_n\}$$
 Pseudoinverse: $A^+ = \sum_{j=1}^r \frac{1}{\sigma_j} v_j u_j^*$

$$= (A^*A)^{-1}A^* \text{ if } A \text{ is full rank}$$

Best Low Rank Approximation:

$$\min_{x \in C^{m \times n}, \text{rank}(x) \leq k} \|A - X\|_2 = \sigma_{k+1}$$

- Continuous Least Squares and Orthogonal Polynomials Problem: $\min_{p \in P_n} \|f - p\|_L^2$

$$\|p\|_L^2 = \min_{p \in P_n} \left(\int_a^b (f(x) - p(x))^2 dx \right)^{1/2}$$

$$\text{Inner product: } \langle f, g \rangle = \int_a^b f(x)g(x)w(x)dx$$

$$\text{Optimal Polynomial: } p_*(x) = \sum c_j \phi_j(x)$$

$$\rightarrow \begin{bmatrix} \langle \phi_0, \phi_0 \rangle & \dots & \langle \phi_n, \phi_0 \rangle \\ \vdots & \ddots & \vdots \\ \langle \phi_0, \phi_n \rangle & \dots & \langle \phi_n, \phi_n \rangle \end{bmatrix} \begin{bmatrix} c_0 \\ \vdots \\ c_n \end{bmatrix} = \begin{bmatrix} \langle f, \phi_0 \rangle \\ \vdots \\ \langle f, \phi_n \rangle \end{bmatrix}$$

Best choice for ϕ_0, \dots, ϕ_n : for orthogonal polynomials

ϕ_j has exact degree j if $j \neq k$

$$\Rightarrow c_j = \langle f, \phi_j \rangle / \langle \phi_j, \phi_j \rangle$$

Can be built via Gram Schmidt.

Three Term Recurrence!