

Matrix Factorizations

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Schedule for Lecture

- ▶ Introduction to Numerical Linear Algebra
 - What is the numerical linear algebra?
 - Why?
 - How?
- ▶ Matrix Factorizations
 - What are matrix factorizations?
 - Existence and uniqueness of matrix factorizations
 - Why?
 - How?

- ▶ Two matrices
 - LU, QR Factorizations
- ▶ Three matrices
 - Diagonalization
 - Jordan canonical form
 - Schur decompositions
 - Singular decomposition

Linear Algebra

Math.

Linear Algebra by S. Friedberg, A. Insel and L. Spence
Chapters 1, 2, 3, 4, 5, 6, 7

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Linear Algebra by S. Friedberg, A. Insel and L. Spence
Chapters 1, 2, 3, 4, 5, 6, 7

Eng.

Elementary Linear Algebra by H. Anton and C. Rorres
Chapters 1, 2, 3, 4, 5, 6, 7, 8

Mathematical Programming

Math.

Mathematica, Maple, MATLAB

Mathematical Programming

Math.

Mathematica, Maple, MATLAB

Eng.

Fortran, C, MATLAB

Errors

Definition

x : the true value

x^* : an approximation to x

- ▶ $|x - x^*|$: Absolute Error
- ▶ $\frac{|x - x^*|}{|x|}$ ($x \neq 0$): Relative Error

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Which one is better?

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Why?

Sources of Errors

- ▶ Errors in mathematical modelling: Simplifying and Assumptions

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- ▶ Errors in mathematical modelling: Simplifying and Assumptions
- ▶ Blunders (Programming Errors): Large programmes, Subprogrammes
- ▶ Errors in input: Errors in data transfer, uncertainties associated with measurements
- ▶ Machine errors by computer (Floating point arithmetic): Rounding and Chopping, Underflow and Overflow

Arithmetic

In 1985 IEEE(Institute for Electrical and Electronic Engineers) report: Binary Floating Point Arithmetic Standard 754.

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Single, Double and Extended Precisions

Algorithms

Examining approximation procedures involving **finite** sequence of calculations.

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Algorithms

Examining approximation procedures involving **finite** sequence of calculations.

- ▶ Stable: Small changes in the initial data
- ▶ Unstable: Otherwise
- ▶ Conditionally Stable: Stable only for certain of initial data

Convergence

$\{\alpha_n\}_{n=1}^{\infty}$, $\{\beta_n\}_{n=1}^{\infty}$: sequences

$$\lim_{n \rightarrow \infty} \beta_n = 0, \quad \lim_{n \rightarrow \infty} \alpha_n = \alpha.$$

If $\exists K > 0$ s. t. $|\alpha_n - \alpha| \leq |\beta_n|$ for large n then $\{\alpha_n\}_{n=1}^{\infty}$ converges to α with the rate of convergence $O(\beta_n)$.

$$\alpha_n = \alpha + O(\beta_n)$$



LU factorization

$$A = \mathbb{R}^{m \times n}$$

$$\parallel$$
$$LU$$

where $L \in \mathbb{R}^{m \times m}$: lower triangular matrix
with diagonal entries : 1

$U \in \mathbb{R}^{m \times n}$: Echelon form of A

If $m=n$

$$L \in \mathbb{R}^{n \times n}$$

$U \in \mathbb{R}^{n \times n}$: upper triangular matrix

< Theory >

- ① Existence
- ② Uniqueness
- ③ Why?
- ④ How can we find?

③ Why?

$$Ax = b$$

$$LUx = b.$$

$$\text{Let } Ux = y \text{ then } LUx = Ly = b$$

↓
← y : forward substitution
↓
 x : backward substitution



\Leftrightarrow all eigenvalues $> 0 \Leftrightarrow$ all leading principal submatrices: positive determinant

A : symmetric positive definite ($A=A^T$, $x^T A x > 0 \quad \forall x \in \mathbb{R}^n$)

$\Rightarrow A$: nonsingular ($\det(A) > 0$)

$$a_{ii} > 0$$

$$(a_{ij})^2 < a_{ii} a_{jj}$$

$$A: \det(A(1:k)) \neq 0, \quad A: \text{nonsingular}$$

$$k=1, \dots, n-1$$

\therefore Exists, is unique.

$$A = U^T U \quad (\text{Cholesky Factorization})$$

$A \in \mathbb{R}^{m \times n}$ $\alpha \subset \{1, \dots, m\}$
 $\beta \subset \{1, \dots, n\}$
 $A(\alpha, \beta)$: submatrix
 If $m=n$, $\alpha=\beta$
 principal submatrix
 leading principal submatrix

proof 1.

$$A = LU \quad \text{and} \quad A^T = (LU)^T = U^T L^T$$

$$\therefore A = A^T \Rightarrow LU = U^T L^T \quad \therefore L = U^T \quad A = U^T U$$

not true.

proof 2.

By induction.

$$(i) \quad n=1. \quad a = \sqrt{a} \sqrt{a} = (-\sqrt{a})(-\sqrt{a})$$

$$\therefore \exists! \quad U \in \mathbb{R}^{n \times n} \text{ with } \underline{\text{positive diagonal entries}} \text{ s.t. } A = U^T U.$$

(ii) Assume that it is true for $n-1$.

A : symmetric positive definite

\Rightarrow leading principal submatrix A_{n-1} : symmetric positive definite

$$\left[\begin{array}{c|c} A_{n-1} & \\ \hline & \end{array} \right]$$

$$\text{unique Cholesky factorization: } A_{n-1} = U_{n-1}^T U_{n-1}.$$



Show: $A = U^T U$

Let $A = \begin{bmatrix} A_{n-1} & c \\ c^T & \alpha \end{bmatrix}$ where $c \in \mathbb{R}^{n-1}$, $\alpha \in \mathbb{R}$

$$\text{" } \begin{bmatrix} U_{n-1}^T & 0 \\ r^T & \beta \end{bmatrix} \begin{bmatrix} U_{n-1} & r \\ 0 & \beta \end{bmatrix} = U^T U$$

$$\text{" } \begin{bmatrix} U_{n-1}^T U_{n-1} & U_{n-1}^T r \\ r^T U_{n-1} & r^T r + \beta^2 \end{bmatrix}$$

If $U_{n-1}^T r = c$ and $r^T r + \beta^2 = \alpha$

(i) r : unique ($\because U_{n-1}^T$: nonsingular)

then $\beta^2 = \alpha - r^T r > 0$?

(ii) $0 < \det(A) = \det(U^T)(U) = \det(U_{n-1})^2 \beta^2$

$\therefore \beta^2 > 0$

Thus, $\exists! \beta > 0$

Algorithm

for $j = 1:n$

for $i = 1:j-1$

$$u_{ij} = (a_{ij} - \sum_{k=1}^{i-1} u_{ki} u_{kj}) / r_{ii}$$

end

$$u_{jj} = (a_{jj} - \sum_{k=1}^{j-1} u_{kj}^2)^{1/2}$$

end

$$\frac{n^3}{3} \text{ flops.}$$



< QR factorization >

$$A \in \mathbb{R}^{m \times n} \quad \text{and} \quad \{a_1, a_2, \dots, a_n\} : \text{linearly independent}$$

" (m ≥ n)

$$[a_1 \ a_2 \ \dots \ a_n]$$

$$\Rightarrow A = QR \quad \text{where} \quad Q \in \mathbb{R}^{m \times n} \quad \text{with} \quad \{q_1, q_2, \dots, q_n\}.$$

" $[q_1 \ q_2 \ \dots \ q_n]$ orthonormal

- (i) $\|q_i\| = 1$ for $i=1, \dots, n$
- (ii) $\{q_1, q_2, \dots, q_n\} : \text{orthogonal set.}$

$$\Rightarrow Q^T Q = I \in \mathbb{R}^{n \times n}$$

$$R \in \mathbb{R}^{n \times n} : \text{nonsingular}$$

upper triangular

Proof. By applying the Gram-Schmidt Process to A with normalizations

$$\{a_1, a_2, \dots, a_n\} : \text{linearly independent set}$$

$$\Rightarrow \{q_1, q_2, \dots, q_n\} : \text{orthonormal set}$$

For each $k=1, 2, \dots, n$,

$$\text{Span}(a_1, \dots, a_i) = \text{Span}(q_1, \dots, q_i)$$

$$\begin{aligned} \text{Span}(a_1) &= \text{Span}(q_1) \\ \text{Span}(a_1, a_2) &= \text{Span}(q_1, q_2) \\ &\vdots \end{aligned}$$

$$\text{Span}(a_1, a_2, \dots, a_n) = \text{Span}(q_1, q_2, \dots, q_n)$$

Therefore, $\exists y_{1i}, y_{2i}, \dots, y_{ni}$ s.t.

$$\begin{cases} a_1 = y_{11} q_1 \\ a_2 = y_{12} q_1 + y_{22} q_2 \\ \vdots \\ a_n = y_{1n} q_1 + y_{2n} q_2 + \dots + y_{nn} q_n \end{cases}$$

$$A = [a_1 \ a_2 \ \dots \ a_n] = [q_1 \ q_2 \ \dots \ q_n] \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1n} \\ 0 & y_{22} & \dots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & y_{nn} \end{bmatrix} = QR$$



- Show: (i) Q has orthonormal columns.
i.e. $\{q_1, q_2, \dots, q_n\}$: orthonormal set: o.k.
- (ii) R : nonsingular
 $r_{ii} \neq 0$ for $i=1, 2, \dots, n$.
- (iii) R : upper triangular : o.k

(ii) R : nonsingular

If $r_{ii} = 0$ then $a_i = r_{i1}q_1 + \dots + r_{i,i-1}q_{i-1} + \underbrace{r_{ii}q_i}_{=0}$

$\therefore a_i$ is a linear combination of q_1, \dots, q_{i-1} .

Hence $a_i \in \text{Span}(q_1, \dots, q_{i-1}) = \text{Span}(a_1, \dots, a_{i-1})$.

But a_1, \dots, a_{i-1}, a_i : linearly independent, contradiction

Thus $r_{ii} \neq 0$ for $i=1, 2, \dots, n$.

Since R : upper triangular, R : nonsingular.

Note: Gram-Schmidt Process

$\{x_1, \dots, x_k\}$: a basis of a subspace W
 $W \subset \mathbb{R}^n$

$$v_1 = x_1$$

$$v_2 = x_2 - \left(\frac{v_1 \cdot x_2}{v_1 \cdot v_1} \right) v_1$$

\vdots

$$v_k = x_k - \left(\frac{v_1 \cdot x_k}{v_1 \cdot v_1} \right) v_1 - \left(\frac{v_2 \cdot x_k}{v_2 \cdot v_2} \right) v_2 - \dots - \left(\frac{v_{k-1} \cdot x_k}{v_{k-1} \cdot v_{k-1}} \right) v_{k-1}$$

$$W_i = \text{Span}(x_1, \dots, x_i) \quad \text{for } i=1, \dots, k$$

Then for each $i=1, \dots, k$, $\{v_1, \dots, v_i\}$: orthogonal basis for W_i .



7.1.2 Decoupling 7.1.3 The Basic Unitary Decompositions.

Theorem 7.1.3 (Schur Decomposition)

$$A \in \mathbb{C}^{n \times n}$$

$$\exists Q \in \mathbb{C}^{n \times n}, \text{ unitary s.t. } Q^H A Q = T = D + N$$

where $D = \text{diag}(\lambda_1, \dots, \lambda_n)$ and $N \in \mathbb{C}^{n \times n}$, strictly upper triangular.

proof.

(i) $n=1$: obvious

(ii) $n-1$: holds $[\tilde{U}^H C \tilde{U} = \tilde{T}]$

$$\text{Show : } Q^H A Q = T$$

$$\text{Find } Q = U \begin{bmatrix} 1 & 0 \\ 0 & \tilde{U} \end{bmatrix}$$

U : unitary.

$$Q^H A Q = \begin{bmatrix} 1 & 0 \\ 0 & \tilde{U}^H \end{bmatrix} \underbrace{U^H A U}_{\Pi} \begin{bmatrix} 1 & 0 \\ 0 & \tilde{U} \end{bmatrix} = T$$

$$\begin{bmatrix} \lambda & w^H \\ 0 & C \end{bmatrix}_{n-1}^1$$

Question : (i) existence
(ii) $\lambda, w = ?$

$$\parallel \begin{bmatrix} \lambda & w^H \tilde{U} \\ 0 & \tilde{U}^H C \tilde{U} \end{bmatrix}$$

$Ax = \lambda x \quad x \neq 0$
with $B = \lambda$.

Lemma 7.1.2

$$A \in \mathbb{C}^{n \times n}, \quad B \in \mathbb{C}^{p \times p}, \quad X \in \mathbb{C}^{n \times p}$$

$$AX = XB, \quad \text{rank}(X) = p.$$

$$\Rightarrow \exists Q \in \mathbb{C}^{n \times n} \text{ unitary s.t. } Q^H A Q = T = \begin{bmatrix} T_{11} & T_{12} \\ 0 & T_{22} \end{bmatrix} \begin{matrix} p \\ n-p \end{matrix}$$

where $\lambda(T_{11}) = \lambda(A) \cap \lambda(B)$

$$\text{proof. Let } X = Q \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \quad Q \in \mathbb{C}^{n \times n}, \quad R_1 \in \mathbb{C}^{p \times p}$$

: QR factorization of X .



$$\text{Let } Q^H A Q = \begin{bmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{bmatrix} \begin{matrix} p \\ n-p \end{matrix} = T$$

$$\begin{aligned} \begin{bmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{bmatrix} \begin{bmatrix} R_1 \\ 0 \end{bmatrix} &\stackrel{p}{=} \stackrel{n-p}{T} \stackrel{Q^H A Q}{=} Q^H A Q \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \stackrel{X=QR}{=} Q^H A X \stackrel{AX=XB}{=} Q^H X B \stackrel{X=QR}{=} Q^H Q \begin{bmatrix} R_1 \\ 0 \end{bmatrix} B \\ &= \begin{bmatrix} R_1 \\ 0 \end{bmatrix} B. \end{aligned}$$

Since R_1 : nonsingular, $T_{21} R_1 = 0$ and $T_{11} R_1 = R_1 B$.

$$R_1^{-1} T_{11} R_1 = B$$

T_{11} is similar to B .

$$\therefore T_{21} = 0 \quad \text{and} \quad \lambda(T_{11}) = \lambda(B)$$

Show : $\lambda(T) = \lambda(A) \cap \lambda(B)$

Suppose $\lambda(A) = \lambda(T) = \lambda(T_{11}) \cup \lambda(T_{22})$: we need to prove

O.K.

$$\Rightarrow \lambda(A) \cap \lambda(B) = (\lambda(T_{11}) \cup \lambda(T_{22})) \cap \lambda(T_{11}) = \lambda(T_{11}).$$

Lemma 7.1.1.

$$T \in \mathbb{C}^{n \times n}$$

||

$$\begin{bmatrix} T_{11} & T_{12} \\ 0 & T_{22} \end{bmatrix} \begin{matrix} p \\ q \end{matrix}$$

$$\Rightarrow \lambda(T) = \lambda(T_{11}) \cup \lambda(T_{22}).$$

proof.

$$T \lambda = \begin{bmatrix} T_{11} & T_{12} \\ 0 & T_{22} \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} = \lambda \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} \quad \text{where } \lambda_1 \in \mathbb{C}^p \quad \lambda_2 \in \mathbb{C}^q$$

(i) $\lambda_2 \neq 0$

$$T_{22} \lambda_2 = \lambda \lambda_2 \Rightarrow \lambda \in \lambda(T_{22})$$

(ii) $\lambda_2 = 0$

$$T_{11} \lambda_1 = \lambda \lambda_1 \Rightarrow \lambda \in \lambda(T_{11})$$

$$\therefore \lambda(T) \subset \lambda(T_{11}) \cup \lambda(T_{22})$$



General version of Lemma 7.1.5

Theorem 7.1.6 (Block Diagonal Decomposition)

$$A \in \mathbb{C}^{n \times n}$$

$$(i) \quad Q^H A Q = T = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1q} \\ & T_{22} & \cdots & T_{2q} \\ & & \ddots & \\ 0 & & & T_{qq} \end{bmatrix}, \quad T_{ii} : \text{square for } i=1, \dots, q$$

$$(ii) \quad \lambda(T_{ii}) \text{ and } \lambda(T_{jj}) : \text{disjoint whenever } i \neq j$$

$$\Rightarrow \exists X : \text{nonsingular s.t. } X^{-1} A X = \text{diag}(T_{11}, \dots, T_{qq})$$

Sketch of proof.

By induction

$$(i) \quad 2 \times 2 \text{ block : } Q^H A Q = T = \begin{bmatrix} T_{11} & T_{12} \\ 0 & T_{22} \end{bmatrix} \quad \lambda(T_{11}) \cap \lambda(T_{22}) = \emptyset, \quad T_{11}, T_{22} : \text{square}$$

$$\text{then } \exists Y \text{ s.t. } Y^{-1} T Y = \text{diag}(T_{11}, T_{22})$$

$$(ii) \quad 3 \times 3 \text{ block : } Q^H A Q = T = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ 0 & T_{22} & T_{23} \\ 0 & 0 & T_{33} \end{bmatrix}$$

$$\text{then } \exists Y_1 \text{ s.t. } Y_1^{-1} T Y_1 = \begin{bmatrix} T_{11} & T_{12} & 0 \\ 0 & T_{22} & 0 \\ 0 & 0 & T_{33} \end{bmatrix}$$

$$\exists Y_2 \text{ s.t. } Y_2^{-1} (Y_1^{-1} T Y_1) Y_2 = \begin{bmatrix} T_{11} & 0 & 0 \\ 0 & T_{22} & 0 \\ 0 & 0 & T_{33} \end{bmatrix}$$

(iii) 4×4 block



Lecture 4. The Singular Value Decomposition

A Geometric Observation

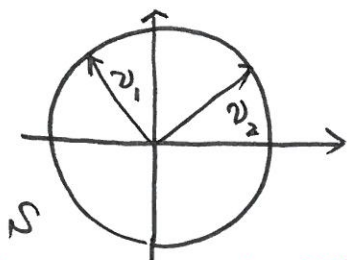
The image of the unit sphere under any $m \times n$ matrix is a hyperellipse.

m -dimensional generalization of an ellipse.

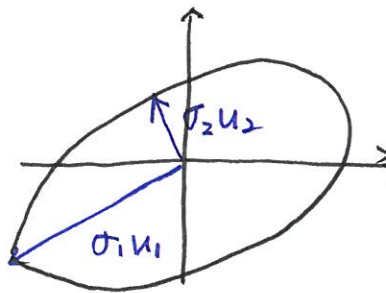
Consider the unit sphere in \mathbb{R}^n .

orthogonal directions $u_1, \dots, u_m \in \mathbb{R}^m$ $\|u_i\| = 1$.

$\sigma_1, \dots, \sigma_m$ (possibly zero)



AS



Reduced SVD $A \in \mathbb{C}^{m \times n}$ ($m \geq n$)

$$A v_j = \sigma_j u_j \quad 1 \leq j \leq n.$$

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n > 0$$

$$A \begin{bmatrix} v_1 & v_2 & \dots & v_n \end{bmatrix} =$$

$$= \begin{bmatrix} u_1 & u_2 & \dots & u_n \end{bmatrix} \begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_n & \end{bmatrix}$$

$$AV = \hat{U} \hat{\Sigma}$$

$$A = \hat{U} \hat{\Sigma} V^* \quad (V: \text{unitary}).$$

$$\begin{matrix} \uparrow & \uparrow & \uparrow \\ m \times n & n \times n & n \times n \end{matrix}$$

(A : assumed full rank n)



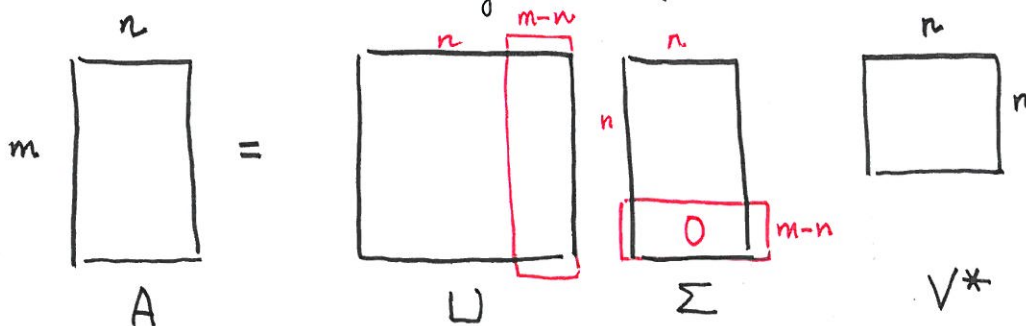
Full SVD

① $A \in \mathbb{C}^{m \times n}$

② $m \geq n$

$$A = U \Sigma V^*$$

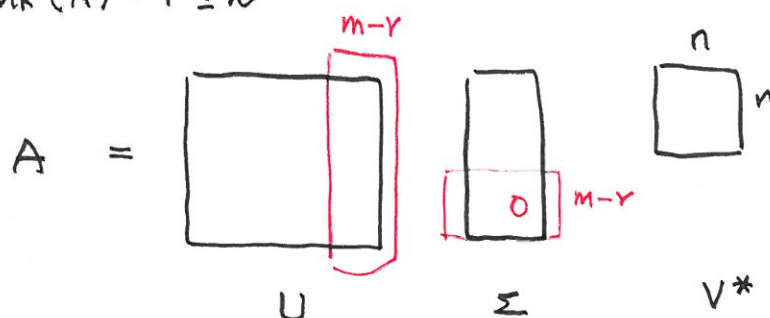
U : $m \times m$ unitary
 Σ : $m \times n$ diagonal with positive real entries
 V : $n \times n$ unitary



n : singular vectors of A

③ A is not assumed to have full rank n .
(A is rank-deficient. $\text{rank}(A) \leq n$)

Let $\text{rank}(A) = r \leq n$



Note: $m-n \leq m-r \therefore$ more "0" rows.



Theorem

- ① The nonzero singular values of A
= the square roots of the nonzero eigenvalues of A^*A or AA^* .

$$A^*A = (U\Sigma V^*)^*(U\Sigma V^*) = V\Sigma^*U^*U\Sigma V^* = V(\Sigma^*\Sigma)V^*$$

- ② If $A = A^*$ then the singular values $\sigma_1^2, \dots, \sigma_r^2$ of A are the absolute values of the eigenvalues of A .

③ $A \in \mathbb{C}^{m \times m}$, $|\det(A)| = \prod_{i=1}^m \sigma_i$

$$\begin{aligned} \text{//} \\ |\det(U\Sigma V^*)| &= |\det(U)| |\det(\Sigma)| |\det(V^*)| = |\det(\Sigma)| \\ &= \prod_{i=1}^m \sigma_i \end{aligned}$$