MAT 3341

Applied Linear Algebra

Study Guide

winter 2024

$Ax = b$ $\qquad$ $Ax = \lambda x$

$A = LU$ $\qquad$ $PA = LU$ $\qquad$ $A = QR$

Matrix Arithmetic

- addition / subtraction:

  $A=(a_{ij})$ $B=(b_{ij})$ $m\times n$

  $A\pm B=(a_{ij}\pm b_{ij})$

- scalar multiplication:

  $A=(a_{ij})$ α is a scalar

  $\alpha A=(\alpha a_{ij})$

- matrix-vector multiplication:

  $A=(a_1\ a_2 \cdots a_n)$

  $a_1, a_2, \dots, a_n \in \mathbb{F}^m$

  $x \in \mathbb{F}^n$

  $Ax=\sum_{i=1}^{n} x_i a_i \in \mathbb{F}^m$

- matrix-matrix multiplication

  A: $m\times q$ matrix

  B: $q\times n$ matrix with columns $b_1, b_2, \dots, b_n \in \mathbb{F}^q$

  $AB=(Ab_1\ Ab_2 \cdots Ab_n)$

  or if $C=AB$, we have that

  $c_{ij}=\sum_{k=1}^{q} a_{ik}b_{kj}$

2 special Matrices

Zero matrix: $O_{m\times n}=\begin{pmatrix} 0 & 0 & \cdots & 0\\ 0 & 0 & \cdots & 0\\ \vdots & \vdots & & \vdots\\ 0 & 0 & \cdots & 0\end{pmatrix}\in\mathbb{R}^{m\times n}$

Identity matrix: $I_n=\begin{pmatrix} 1 & 0 & \cdots & 0\\ 0 & 1 & \cdots & 0\\ \vdots & & \ddots & \vdots\\ 0 & \cdots & \cdots & 1\end{pmatrix}\in\mathbb{R}^{n\times n}$

For a $m\times n$ matrix A:

- $A+O=O+A=A$
- $I_mA=AI_n=A$

Diagonal Matrix

$A=\mathrm{diag}(\alpha_1,\dots,\alpha_n)=\begin{pmatrix}\alpha_1 & 0 & \cdots & 0\\ \vdots & \ddots & & \vdots\\ 0 & \cdots & & \alpha_n\end{pmatrix}\in\mathbb{F}^{n\times n}$

Transpose

The transpose of a matrix A is a matrix A^T whose (i,j) entry is the (j,i) entry of A.

$A=(a_{ij})\in\mathbb{F}^{m\times n}$ $\quad A^T=(a_{ji})\in\mathbb{F}^{n\times m}$

$A^T=A \Rightarrow A$ is symmetric

Some relations:

- $(A^T)^T=A$
- $(A+B)^T=A^T+B^T$
- $(\alpha A)^T=\alpha A^T$
- $(AB)^T=B^TA^T$
- $(A^{-1})^T=(A^T)^{-1}$

Inverse

A matrix $A\in\mathbb{F}^{n\times n}$ is said to be invertible if $\exists X\in\mathbb{F}^{n\times n}$ s.t. $XA=AX=I_n$

X is an inverse of A, write A^{-1}

Proposition: The inverse of an invertible matrix is unique.

If A and B are $n\times n$ invertible matrices, then we have

$(AB)^{-1}=B^{-1}A^{-1}$

Link to Linear Map

A function $f:\mathbb{F}^n\to\mathbb{F}^m$ is a linear map if:

- $f(\vec{x}+\vec{y})=f(\vec{x})+f(\vec{y})$ $\quad\forall \vec{x},\vec{y}\in\mathbb{F}^n$
- $f(\alpha\vec{x})=\alpha f(\vec{x})$ $\quad\forall\alpha\in\mathbb{F},\ \vec{x}\in\mathbb{F}^n$

Proposition: Let $f:\mathbb{F}^n\to\mathbb{F}^m$ be a linear map. Then $\exists!\, A\in\mathbb{F}^{m\times n}$ s.t. $f(\vec{x})=A\vec{x}$ $\forall\vec{x}\in\mathbb{F}^n$. Conversely, if $A\in\mathbb{F}^{m\times n}$ then $f:\mathbb{F}^n\to\mathbb{F}^m$ is a linear map.

Gaussian Elimination

To solve the system $A\vec{x}=\vec{b}$, we can use Gaussian Elimination and backward substitution.

$$A\vec{x}=\vec{b}\to\underbrace{(A|\vec{b})}_{\text{aug. matrix}}\xrightarrow{\text{E.R.O}}(\underbrace{U}_{\text{Upper }\Delta}|\vec{c})\to\underbrace{\vec{x}=U^{-1}\vec{c}}_{\text{backward substitution}}$$

We use elementary row operations to do Gaussian Elimination

- Add a multiple of a row to another
- Exchange two rows
- Multiply a row by a non-zero scalar

Elementary Matrices

- $E_{ij}(\alpha)$: add α times row j to row i, $i\neq j$
- E_{ij}: exchange row i and j, $i\neq j$
- $E_i(\alpha)$: multiply row i by $\alpha\neq0$

Each elementary matrix is invertible and the inverse is of the same type

- $E_{ij}(\alpha)^{-1}=E_{ij}(-\alpha)$
- $E_{ij}^{-1}=E_{ij}$
- $E_i(\alpha)^{-1}=E_i\left(\frac{1}{\alpha}\right)$

LU Factorization

If A is an $n\times n$ matrix, invertible and can be transformed into an upper-triangular matrix U using only elementary row operations of type I

$E_k\cdots E_2E_1A=U \Rightarrow A=LU,\ L=(E_k\cdots E_1)^{-1}=E_1^{-1}\cdots E_k^{-1}$

To solve a linear system using LU factorization, we have

$$A\vec{x}=\vec{b}\Leftrightarrow LU\vec{x}=\vec{b}=\begin{cases}L\vec{y}=\vec{b} & \text{forward sub.}\\ U\vec{x}=\vec{y} & \text{back. sub.}\end{cases}$$

We also get $\det(A)=\prod_{i=1}^{n}u_{ii}$

Proposition: Let A be invertible. If $A=LU$ then this decomposition is unique.

Pivoting and Permutation

Definition: A matrix obtained from I by any row interchanges is called a permutation matrix

Equivalent Definition: A is a permutation matrix if each row and each column has exactly one 1, all the other entries being 0.

Proposition: Let P be a permutation matrix, then P is invertible and $P^{-1}=P^T$.

Theorem: Any invertible matrix A has a permuted LU factorization, namely $PA=LU$

- P: permutation matrix
- L: lower unitriangular matrix
- U: Upper triangular matrix

We use the permuted LU factorization because sometimes row interchanges are necessary if the pivot is 0

Partial Pivoting

Even if not needed, it is a good idea to use row interchanges

Let $A^{(k-1)}$ be the matrix at step k of Gaussian elimination

Pick j s.t. $|a_{jk}^{(k-1)}|=\max_{k\le i\le n}|a_{ik}^{(k-1)}|$ and do

$R_j\leftrightarrow R_k$

LDV Factorization

Let A be invertible and assume $A=LU$

$A=LU=LDV$ $\quad D=\mathrm{diag}(u_{11},u_{22},\dots,u_{nn})$ $\quad V=D^{-1}U$ (upper uni-Δ)

Remark: i) If $A=LDV$, then $A^T=(LDV)^T=V^TDL^T$

ii) If $A^T=A$, then $A=LDL^T=V^TDV$

If $A=LDV$ then

$$A\vec{x}=\vec{b}\Leftrightarrow LDV\vec{x}=\vec{b}\Leftrightarrow\begin{cases}L\vec{y}=\vec{b} & \text{forward substitution}\\ D\vec{z}=\vec{y} & \text{"rescaling" } z_i=\frac{1}{d_i}y_i\\ V\vec{x}=\vec{z} & \text{backward substitution}\end{cases}$$

For permuted LDV factorization, we have $PA=LDV$

General Linear Systems

We can generalize LU decomposition to general matrix A

L is square lower unitriangular

U is in row echelon form where:

- all nonzero rows are above zero rows
- for each nonzero row, the leading entry is strictly on the right of the leading entries of rows above it

Example: $\begin{pmatrix}1 & 2 & 3 & 4\\ 0 & 0 & 4 & 5\\ 0 & 0 & 0 & 0\end{pmatrix}$ is in row echelon form

Inner Product

Let V be a vector space over $\mathbb{F}$. A map $\langle \cdot,\cdot \rangle : V\times V \to \mathbb{F}$ is said to be an inner product if

i) $\langle \alpha\vec{u}+\beta\vec{v}, \vec{w}\rangle = \alpha\langle \vec{u},\vec{w}\rangle + \beta\langle \vec{v},\vec{w}\rangle$

$\forall \vec{u},\vec{v},\vec{w}\in V \quad \forall \alpha,\beta\in\mathbb{F}$

ii) $\langle \vec{u},\vec{v}\rangle = \overline{\langle \vec{v},\vec{u}\rangle} \quad \forall \vec{u},\vec{v}\in V$

iii) $\langle \vec{u},\vec{u}\rangle \geq 0 \quad \forall \vec{u}\in V$

$\langle \vec{u},\vec{u}\rangle = 0$ iff $\vec{u}=\vec{0}$

From i) and ii), we get

$\langle \vec{w}, \alpha\vec{u}+\beta\vec{v}\rangle = \bar{\alpha}\langle \vec{w},\vec{u}\rangle + \bar{\beta}\langle \vec{w},\vec{v}\rangle$

Vector Norm

Let V be a vector space over $\mathbb{F}$. A map $\|\cdot\| : V \to \mathbb{R}$ is said to be a norm if

i) $\|\vec{u}\| \geq 0 \quad \forall \vec{u}\in V$ and $\|\vec{u}\|=0$ iff $\vec{u}=\vec{0}$

ii) $\|\alpha\vec{u}\| = |\alpha|\,\|\vec{u}\| \quad \forall \vec{u}\in V \quad \forall\alpha\in\mathbb{F}$

iii) $\|\vec{u}+\vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\| \quad \forall \vec{u},\vec{v}\in V$

Any inner product induce a norm

$\|\vec{u}\| = \sqrt{\langle \vec{u},\vec{u}\rangle}, \quad \vec{u}\in V$

Cauchy-Schwarz inequality: Let $\langle \cdot,\cdot\rangle$ be an inner product on V and let $\|\cdot\| = \sqrt{\langle \cdot,\cdot\rangle}$. Then,

$|\langle \vec{u},\vec{v}\rangle| \leq \|\vec{u}\|\,\|\vec{v}\| \quad \forall \vec{u},\vec{v}\in V$

P-norm: Let $1\leq p\leq\infty$. The p-norm on $\mathbb{F}^n$ is defined by

- if $p<\infty$: $\|\vec{x}\|_p = \left(\sum_{i=1}^{n} |x_i|^p\right)^{1/p}, \quad \vec{x}\in\mathbb{F}^n$
- if $p=\infty$: $\|\vec{x}\|_\infty = \max_{1\leq i\leq n} |x_i|$

Matrix Norm

Frobenius norm: Let $A=(a_{ij})\in\mathbb{F}^{m\times n}$

$$\|A\|_F = \left(\sum_{i=1}^{m}\sum_{j=1}^{n} |a_{ij}|^2\right)^{1/2}$$

Induced Matrix Norm: Let $\|\cdot\|_a$ and $\|\cdot\|_b$ be norms on $\mathbb{F}^m$ and $\mathbb{F}^n$, respectively. Then

$$\|A\|_{a,b} = \sup_{\substack{\vec{x}\in\mathbb{F}^n \\ \vec{x}\neq\vec{0}}} \frac{\|A\vec{x}\|_b}{\|\vec{x}\|_a} = \sup_{\|\vec{x}\|_a=1} \|A\vec{x}\|_b$$

Proposition: For any induced matrix norm, we have

i) $\|A\vec{x}\| \leq \|A\|\,\|\vec{x}\| \quad \forall\vec{x}\in\mathbb{F}^n \quad \forall A\in\mathbb{F}^{m\times n}$

ii) $\|I_n\| = 1$

iii) $\|AB\| \leq \|A\|\,\|B\| \quad \forall A\in\mathbb{F}^{m\times k} \quad \forall B\in\mathbb{F}^{k\times n}$

P-norm: let $A\in\mathbb{F}^{m\times n}$ then

$\forall 1\leq p\leq\infty, \quad \|A\|_p = \sup_{\vec{x}\neq\vec{0}} \frac{\|A\vec{x}\|}{\|\vec{x}\|}$

Special cases for $p=1$ and $p=\infty$

$$\|A\|_1 = \max_{1\leq j\leq n}\left\{\sum_{i=1}^{m} |a_{ij}|\right\}$$

$$\|A\|_\infty = \max_{1\leq i\leq m}\left\{\sum_{j=1}^{n} |a_{ij}|\right\}$$

Conditioning

Let $\|\cdot\|$ denote the vector norm and its induced matrix norm. Then for any nonsingular matrix A we define

$$K(A) = \|A\|\,\|A^{-1}\|$$

the condition number of A

Properties:

- $K(A)\geq 1$
- $\forall\alpha\in\mathbb{F}, \alpha\neq 0 \quad K(\alpha A) = K(A)$

If $K(A)\gg 1$, we say A is ill-conditioned (well-conditioned if $K(A)$ "close" to 1)

$K(A)$ depends on norm: $K_1(A)$, $K_2(A)$, $K_\infty(A)$

System Perturbation

Exact system: $A\vec{x}=\vec{b}$ (*)

Perturbed system: $A\tilde{\vec{x}} = \vec{b}+\vec{\delta b}$ (**)

Theorem: Let $\vec{x}$ be the solution to (*) with $\vec{b}\neq\vec{0}$ and let $\tilde{\vec{x}}$ be the solution to (**). Then

$$\frac{1}{K(A)}\frac{\|\vec{\delta b}\|}{\|\vec{b}\|} \leq \frac{\|\tilde{\vec{x}}-\vec{x}\|}{\|\vec{x}\|} \leq K(A)\frac{\|\vec{\delta b}\|}{\|\vec{b}\|}$$

Positive Definite Matrices

A symmetric matrix $K\in\mathbb{R}^{n\times n}$ is said to be positive definite if

$$\vec{x}^T K\vec{x} > 0 \quad \forall\vec{x}\in\mathbb{R}^n, \vec{x}\neq\vec{0}$$

Theorem: Any inner product on $\mathbb{R}^n$ is of the form

$$\langle\vec{x},\vec{y}\rangle = \vec{x}^T K\vec{y}$$

for some symmetric positive definite matrix K

Remark: K positive definite $\Rightarrow \ker(K)=\{\vec{0}\}$

Quadratic Forms

A function $q:\mathbb{R}^n\longrightarrow\mathbb{R}$ of the form

$$q(\vec{x}) = q(x_1,x_2,\dots,x_n) = \sum_{i\leq j} c_{ij}x_ix_j$$

is called a quadratic form.

Proposition: For any quadratic form on $\mathbb{R}^n$, there exists a unique symmetric matrix $K\in\mathbb{R}^{n\times n}$ s.t. $q(\vec{x}) = \vec{x}^T K\vec{x}$

Determine Positive Definite

Method 1: Complete the square

Let $K\in\mathbb{R}^{n\times n}$ be symmetric

Then take its quadratic form $q(\vec{x})=\vec{x}^TK\vec{x}$ and expand it. Then complete the square.

If the quadratic form is strictly greater than 0 for all $\vec{x}\neq\vec{0}$ and 0 for $\vec{x}=\vec{0}$, then K is positive definite.

Continued:

For a general 2x2 matrix, let

$$K = \begin{pmatrix} a & b \\ b & c\end{pmatrix}$$

Then K is positive definite iff $a>0$ and $c-\frac{b^2}{a}>0$

Method 2: LDL^T factorization

Theorem: A matrix $A\in\mathbb{R}^{n\times n}$ is symmetric positive definite if and only if $A=LDL^T$ with L lower uni Δ and $D=\operatorname{diag}(d_{11},\dots,d_{nn})$ with $d_{ii}>0 \quad \forall 1\leq i\leq n$

Conjugate Transpose

Definition: Let $A\in\mathbb{C}^{m\times n}$. The conjugate transpose of A, written A^H, is

$$A^H = (\bar{A})^T\in\mathbb{C}^{n\times m}$$

$A=(a_{ij}), \quad A^H = (\overline{a_{ji}})$

Properties:

- $(A+B)^H = A^H+B^H$
- $(\alpha A)^H = \bar{\alpha}A^H$
- $(A^H)^H = A$
- $(AB)^H = B^HA^H$

Definition: A matrix $A\in\mathbb{C}^{n\times n}$ is said to be Hermitian if $A^H=A$

If $A=A^H$

- $a_{ii}\in\mathbb{R}$
- $\vec{x}^HA\vec{x}\in\mathbb{R} \quad \forall x\in\mathbb{C}^n$

Positive Definite Matrices: Complex Case

Definition: A Hermitian matrix $A\in\mathbb{C}^{n\times n}$ is said to be positive definite if

$$x^HAx>0 \quad \forall x\in\mathbb{C}^n, \ x\neq 0$$

- For any inner product on $\mathbb{C}^n$ $\langle\cdot,\cdot\rangle$ can be written $\langle x,y\rangle = x^TK\bar{y}$ for some K SPD
- A is HPD if $A=LDL^H$, L lower unitriangular, $D=\operatorname{diag}(d_{11},\dots,d_{nn})\in\mathbb{R}^{n\times n}$, $d_{ii}>0$

Cholesky Factorization

If A is HPD, then we can get the following decomposition:

$$A=LDL^H = (L\sqrt{D})(\sqrt{D}L^H) = MM^H$$

where $M=L\sqrt{D}$, $\sqrt{D}=\operatorname{diag}(\sqrt{d_{11}},\dots,\sqrt{d_{nn}})$

This is called the Cholesky factorization

In practice, we don't go through Gaussian Elimination to get MM^H

we can find m_{ij} using this algorithm

for $j=1,\dots,n$ do

  $m_{jj} = \sqrt{a_{jj} - \sum_{k=1}^{j-1} m_{jk}\overline{m_{jk}}}$

  for $i=j+1,\dots,n$ do

    $m_{ij} = \frac{1}{m_{jj}}\left(a_{ij} - \sum_{k=1}^{j-1} m_{ik}\overline{m_{jk}}\right)$

  end for

end for

Orthogonal and Orthonormal Basis

V vector space over $\mathbb{F}$, $\langle\cdot,\cdot\rangle$ inner product, $\|\cdot\| = \sqrt{\langle\cdot,\cdot\rangle}$

Definition: we say that $\vec{u},\vec{v}\in V$ are orthogonal if $\langle\vec{u},\vec{v}\rangle=0$

we say that a set $\{v_1,\dots,v_n\}$ is

- orthogonal if $\langle v_i,v_j\rangle=0 \quad \forall i\neq j$
- orthonormal if $\langle v_i,v_j\rangle = \delta_{ij} = \begin{cases}1 & i=j\\ 0 & i\neq j\end{cases}$

Proposition: If $\{\vec{v}_1,\dots,\vec{v}_n\}$ is an orthogonal set of nonzero vectors, then they are linearly independent

Proposition: Let $\{\vec{v}_1,\dots,\vec{v}_n\}$ be an orthogonal basis of a subspace W of V.

Then $\forall\vec{w}\in W$, we have

$$\vec{w} = \sum_{i=1}^{n}\frac{\langle\vec{w},\vec{v}_i\rangle}{\|\vec{v}_i\|^2}\vec{v}_i$$

If it is an ONB, then $\vec{w} = \sum_{i=1}^{n}\langle\vec{w},\vec{v}_i\rangle\vec{v}_i$

Gram-Schmidt

The Gram-Schmidt algorithm transforms any basis $\{\vec{w}_1,\dots,\vec{w}_n\}$ into an orthogonal basis

Goal: Transform a basis $\{\vec{w}_1,\dots,\vec{w}_n\}$ into an orthogonal basis $\{\vec{v}_1,\dots,\vec{v}_n\}$

- $\vec{v}_1 = \vec{w}_1$
- $\vec{v}_2 = \vec{w}_2 - \frac{\langle\vec{w}_2,\vec{v}_1\rangle}{\|\vec{v}_1\|^2}\vec{v}_1$
- $\vec{v}_3 = \vec{w}_3 - \frac{\langle\vec{w}_3,\vec{v}_1\rangle}{\|\vec{v}_1\|^2}\vec{v}_1 - \frac{\langle\vec{w}_3,\vec{v}_2\rangle}{\|\vec{v}_2\|^2}\vec{v}_2$

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

$$\vec{v}_k = \vec{w}_k - \sum_{i=1}^{k-1}\frac{\langle\vec{w}_k,\vec{v}_i\rangle}{\|\vec{v}_i\|^2}\vec{v}_i$$

We can turn $\{\vec{v}_1,\dots,\vec{v}_k\}$ into an ONB by setting $\vec{u}_i = \frac{1}{\|\vec{v}_i\|}\vec{v}_i$

QR Decomposition

Let $V=\mathbb{F}^m$. $\{\vec{w}_1,\dots,\vec{w}_n\}$ a basis and $\{\vec{v}_1,\dots,\vec{v}_n\}$ an orthogonal basis

Then we get

$$\underbrace{\left(\vec{w}_1\middle|\vec{w}_2\middle|\cdots\middle|\vec{w}_n\right)}_{A \quad m\times n} = \underbrace{\left(\vec{v}_1\middle|\vec{v}_2\middle|\cdots\middle|\vec{v}_n\right)}_{\text{orthogonal columns}}\underbrace{\begin{pmatrix}1 & \alpha_{12} & \alpha_{13} & \cdots\\ & 1 & \alpha_{23} & \cdots\\ & & 1 & \cdots\\ & & & 1\end{pmatrix}}_{n\times n}$$

$$\alpha_{ik} = \frac{\langle\vec{w}_k,\vec{v}_i\rangle}{\|v_i\|^2}$$

The QR factorization is

$$A=QR$$

where $A = (\vec{w}_1|\vec{w}_2|\cdots|\vec{w}_n)$

$Q = (\vec{u}_1|\vec{u}_2|\cdots|\vec{u}_n)$

$$R = \begin{pmatrix}\|\vec{v}_1\| & & 0\\ & \ddots & \\ 0 & & \|\vec{v}_n\|\end{pmatrix}\begin{pmatrix}1 & \alpha_{12} & \cdots & \alpha_{1n}\\ & 1 & & \vdots\\ 0 & & \ddots & \alpha_{n-1,n}\\ & & & 1\end{pmatrix}$$

Some remarks:

For $A\in\mathbb{F}^{m\times n}$ with LI columns we have $\underset{m\times n}{A} = \underset{m\times n}{Q}\,\underset{n\times n}{R}$

i) $Q^HQ = I_n$

ii) R is upper triangular and invertible

iii) $A^HA = R^HR$ (Cholesky for A^HA)

Unitary (Orthogonal) Matrices

Definition: A matrix $Q\in\mathbb{C}^{n\times n}$ is called unitary if $Q^HQ = QQ^H = I_n$.

Proposition: Let Q and S be unitary (orthogonal) matrices of size $n\times n$.

Then

i) The columns of Q is an ONB for $\mathbb{C}^n$ ($\mathbb{R}^n$)

ii) $|\det(Q)|=1$

iii) QS is unitary (orthogonal)

iv) $\langle Q\vec{x},Q\vec{y}\rangle = \langle\vec{x},\vec{y}\rangle \quad \forall\vec{x},\vec{y}\in\mathbb{C}^n$ ($\mathbb{R}^n$)

Orthogonal Complement

Let $\{\vec{v}_1, \dots, \vec{v}_n\}$ be an orthogonal basis for W subspace of V. The orthogonal complement of W in V is

$$W^{\perp} = \{\vec{v} \in V,\ \langle \vec{v}, \vec{w} \rangle = 0 \ \ \forall \vec{w} \in W\}$$

Orthogonal Projection

Let $\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$ be an orthogonal basis for W subspace of V. The orthogonal projection of $\vec{v} \in V$ onto W is

$$\mathrm{Proj}_W(\vec{v}) = \sum_{i=1}^{n} \frac{\langle \vec{v}, \vec{v}_i \rangle}{\|\vec{v}_i\|_2} \vec{v}_i$$

If $W = \{\vec{0}\}$ then we set $\mathrm{Proj}_W(\vec{v}) = \vec{0}$

Remarks:

- $\vec{v} \in W \iff \vec{v} = \mathrm{Proj}_W(\vec{v})$
- $\vec{v}_k = \vec{w}_k - \sum_{i=1}^{k-1} \frac{\langle \vec{w}_k, \vec{v}_i \rangle}{\|\vec{v}_i\|^2} \vec{v}_i$

$$= \vec{w}_k - \mathrm{Proj}_{\mathrm{span}\{\vec{v}_1, \dots, \vec{v}_k\}}(\vec{w}_k)$$

Proposition: Let W be a subspace of V and let $\vec{p} = \mathrm{Proj}_W(\vec{v})$ for some $\vec{v}$. Then

i) $\vec{p} \in W$ and $\vec{v} - \vec{p} \in W^{\perp}$

ii) $\|\vec{v} - \vec{p}\| < \|\vec{v} - \vec{w}\| \ \ \forall \vec{w} \in W, \vec{w} \neq \vec{p}$

Projection Matrix

$V = \mathbb{F}^m$, let $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$ be an orthonormal basis of $W \subseteq V$ and $Q = (\vec{u}_1 | \cdots | \vec{u}_n)$

Then for any $\vec{v} \in V$, we get

$$QQ^H \vec{v} = \mathrm{Proj}_W(\vec{v})$$

The matrix $P = QQ^H$ is called a projection matrix and satisfies

i) P is Hermitian

ii) $P^2 = P$ (P idempotent)

Solving Linear System using QR decom.

Given a system $A\vec{x} = \vec{b}$

Then

$$A\vec{x} = \vec{b} \iff QR\vec{x} = \vec{b}$$
$$\Rightarrow Q^H QR\vec{x} = Q^H \vec{b}$$
$$\Rightarrow R\vec{x} = Q^H \vec{b}$$

$\vec{x} = R^{-1} Q^H \vec{b}$ is not always solution to the system $A\vec{x} = \vec{b}$

- If $QQ^H \vec{b} = b$, namely $b \in \mathrm{col}(A)$, then $\vec{x} = R^{-1} Q^H \vec{b}$ is solution to $A\vec{x} = \vec{b}$
- If $QQ^H \vec{b} \neq \vec{b}$, namely $\vec{b} \notin \mathrm{col}(A)$, then $A\vec{x} = \vec{b}$ has no solution

Least Squares Minimization

Let $A \in \mathbb{F}^{m \times n}$ with rank n. The least squares minimization problem is when the system $A\vec{x} = \vec{b}$ has no solutions and we want to find $\vec{x}$ that solves

$$\min_{\vec{x} \in \mathbb{F}^n} \|A\vec{x} - \vec{b}\|_2^2$$

We want to find $\vec{y} = A\vec{x} \in \mathrm{col}(A)$ that is closest to $\vec{b}$.

We have $\vec{y} = \mathrm{Proj}_{\mathrm{col}(A)} \vec{b}$. Therefore, we can find the solution to the least squares minimization problem using the reduced QR factorization.

$$A\vec{x}^* = QQ^H \vec{b} \iff R\vec{x}^* = Q^H \vec{b}$$

$\vec{x}^*$ is the least squares solution to $A\vec{x} = \vec{b}$

Eigenvalues and Eigenvectors

Let $A \in \mathbb{F}^{n \times n}$. Recall that a scalar λ is an eigenvalue if $A\vec{v} = \lambda\vec{v}$ for some nonzero vector $\vec{v} \neq \vec{0}$. Then $\vec{v}$ is called an eigenvector corresponding to λ. We call $(\lambda, \vec{v})$ an eigenpair.

To compute $(\lambda, \vec{v})$, we have

$$A\vec{v} = \lambda\vec{v} \iff (A - \lambda I)\vec{v} = 0$$

has a nonzero solution iff $A - \lambda I$ is singular, namely $\det(A - \lambda I) = 0$

We define the characteristic polynomial

$$P_A(\lambda) = \det(A - \lambda I)$$
$$= (\lambda_1 - \lambda)^{m_{\lambda_1}} (\lambda_2 - \lambda)^{m_{\lambda_2}} \cdots (\lambda_k - \lambda)^{m_{\lambda_k}}$$

where $\lambda_1, \lambda_2, \dots, \lambda_k$ are distinct eigenvalues and m_{λ_j} is the algebraic multiplicity of λ_j

V_{λ_j} is the eigenspace corresponding to λ_j, defined by $V_{\lambda_j} = \ker(A - \lambda_j I)$, where $\dim(V_{\lambda_j})$ is the geometric multiplicity of λ_j

We have $m_{\lambda_1} + m_{\lambda_2} + \dots + m_{\lambda_k} = n$ and $1 \leq \dim(V_{\lambda_j}) \leq m_{\lambda_j}$

Proposition: Let $A \in \mathbb{F}^{n \times n}$

1) A is singular $\iff \lambda = 0$ is an eigenvalue

2) A and A^T have the same eigenvalues, but different eigenvectors in general

3) If A is real and $(\lambda, \vec{w}) = (\alpha + i\beta, \vec{u} + i\vec{v})$ is an eigenpair, then $(\alpha - i\beta, \vec{u} - i\vec{v})$ is also an eigenpair.

4) $\det(A) = \prod_{i=1}^{n} \lambda_i$ and $\mathrm{tr}(A) = \sum_{i=1}^{n} \lambda_i$, where λ_i are eigenvalues of A.

5) For every induced matrix norm, $|\lambda_i| \leq \|A\|$ for all $i = 1, \dots, n$. In particular, we have

$$\rho(A) = \max_{1 \leq j \leq n} |\lambda_j| \leq \|A\|$$

where $\rho(A)$ is the spectral radius of A.

Invariant Subspace

We say that a subspace W of a vector space V is invariant from a linear map $L: V \to V$ if $L(\vec{w}) \in W \ \ \forall \vec{w} \in W$

For a matrix $A \in \mathbb{R}^{n \times n}$, we say that $W \subset \mathbb{R}^n$ is invariant for A if $A\vec{w} \in W \ \ \forall \vec{w} \in W$

Gershgorin Circle Theorem

Definition: For $i = 1, 2, \dots, n$, the i^{th} Gershgorin disk is defined by

$$D_i = D(a_{ii}, r_i) = \{z \in \mathbb{C},\ |z - a_{ii}| \leq r_i\},$$
$$r_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} |a_{ij}|$$

We call $D_A = \bigcup_{i=1}^{n} D_i$ the Gershgorin domain.

Theorem: All the eigenvalues of A lies in its Gershgorin domain D_A.

Theorem: Let S_1 be the union of k Gershgorin disks of A and let $S_2 = D_A \setminus S_1$, the union of the $n-k$ remaining ones. If $S_1 \cap S_2 = \emptyset$, then S_1 contains k eigenvalues and S_2 contains $n-k$ eigenvalues.

Strictly Diagonally Dominant Matrices

A square matrix A is said to be strictly diagonally dominant (by row) if

$$|a_{ii}| > \sum_{\substack{j=1 \\ j \neq i}}^{n} |a_{ij}| = r_i \quad \forall i = 1, 2, \dots, n$$

Theorem: If A is strictly diagonally dominant, then A is invertible

Similar Matrices

Definition: Two matrices A and B are said to be similar if there exists an invertible matrix S s.t.

$$S^{-1}AS = B \quad (A = SBS^{-1})$$

Two similar matrices have the same eigenvalues

Diagonalization

A square matrix is said to be diagonalizable if it is similar to a diagonal matrix.

$$S^{-1}AS = \Lambda$$

Λ is a diagonal matrix with the eigenvalues of A on the diagonal.

S has the eigenvectors corresponding to the eigenvalues on its columns.

$$\Lambda = \mathrm{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$$

$$S = (\vec{v}_1 | \vec{v}_2 | \cdots | \vec{v}_n)$$

$(\lambda_i, \vec{v}_i)$ eigenpairs

S^{-1} has the left eigenvectors of A corresponding to the eigenvalues on its rows.

Theorem: Let $A \in \mathbb{C}^{n \times n}$. The following statements are equivalent:

i) There exists a basis of $\mathbb{C}^n$ consisting of eigenvectors of A

ii) $m_\lambda = \dim(V_\lambda)$ for all eigenvalues λ of A

iii) A is diagonalizable

Corollary: If all the eigenvalues of A are distinct then A is diagonalizable.

Remark: If $A \in \mathbb{R}^{n \times n}$ and all the eigenvalues are real and satisfy $m_\lambda = \dim(V_\lambda)$, then we can take $S, \Lambda \in \mathbb{R}^{n \times n}$ and we say A is diagonalizable over $\mathbb{R}$.

Exponentials of Matrices

$$e^A = \sum_{k=0}^{\infty} \frac{1}{k!} A^k = I + A + \frac{1}{2} A^2 + \frac{1}{3!} A^3 + \dots$$

If A is diagonalizable, we have

$$A = S\Lambda S^{-1}$$
$$e^A = S\,\mathrm{diag}(e^{\lambda_1}, \dots, e^{\lambda_n})\,S^{-1}$$

Eigenvalues and Eigenvectors of Hermitian matrices

Proposition: Let $A \in \mathbb{C}^{n \times n}$. If A is Hermitian then all the eigenvalues are real.

Proposition: Let $A \in \mathbb{C}^{n \times n}$. If A is Hermitian then eigenvectors corresponding to distinct eigenvalues are orthogonal

Unitarily Diagonalizable Matrices

A matrix $A \in \mathbb{C}^{n \times n}$ is said to be unitarily diagonalizable if $\exists U \in \mathbb{C}^{n \times n}$ unitary and $\Lambda \in \mathbb{C}^{n \times n}$ diagonal s.t. $U^H A U = \Lambda$.

Spectral Theorem: If A is Hermitian then A is unitarily diagonalizable.

Principal Axes Theorem: Let $A \in \mathbb{R}^{n \times n}$. The following are equivalent

(a) A has an orthonormal set of n eigenvectors in $\mathbb{R}^n$.

(b) A is orthogonally diagonalizable.

(c) A is symmetric.

Positive Definite Matrices (eigenvalues)

Theorem: A Hermitian Matrix is positive definite $\iff$ all eigenvalues are positive.

2-norm of Hermitian Matrices

Proposition: Let $A \in \mathbb{C}^{n \times n}$. For any unitary matrix $U \in \mathbb{C}^{n \times n}$ we have

$$\|UA\|_2 = \|A\|_2 = \|AU\|_2$$

Proposition: Let $A \in \mathbb{C}^{n \times n}$ be Hermitian and let $\lambda_1, \dots, \lambda_n$ be its eigenvalues. Then

$$\|A\|_2 = \max_{1 \leq i \leq n} |\lambda_i| = \rho(A)$$

We also get that if a matrix A is Hermitian positive definite, we get

$$\|A\|_2 = \lambda_{max}, \quad \|A^{-1}\|_2 = \frac{1}{\lambda_{min}}, \quad \kappa(A) = \frac{\lambda_{max}}{\lambda_{min}}$$

Rayleigh Quotient

Let $A \in \mathbb{C}^{n \times n}$ be Hermitian

Let $r_A: \mathbb{C}^n \setminus \{\vec{0}\} \longrightarrow \mathbb{R}$ be defined by

$$r_A(\vec{v}) = \frac{\langle A\vec{v}, \vec{v} \rangle}{\langle \vec{v}, \vec{v} \rangle}$$

we can use this to find an eigenvalue λ_i corresponding to a given eigenvector $\vec{v}_i$ of A.

$$\lambda_i = \frac{\vec{v}_i^H A \vec{v}_i}{\vec{v}_i^H \vec{v}_i} = \frac{\langle A\vec{v}_i, \vec{v}_i \rangle}{\langle \vec{v}_i, \vec{v}_i \rangle} = r_A(v_i)$$

we also have $\lambda_1 \leq r_A(\vec{v}) \leq \lambda_n \ \ \forall \vec{v} \in \mathbb{C}^n \setminus \{\vec{0}\}$ and $\exists \vec{v}_1, \vec{v}_n$ s.t. $r_A(\vec{v}_1) = \lambda_1$ and $r_A(\vec{v}_n) = \lambda_n$

Schur Decomposition

Theorem: Let $A \in \mathbb{C}^{n\times n}$. Then there exists a unitary matrix such that

$$U^H A U = T \qquad (A = UTU^H)$$

where $T \in \mathbb{C}^{n\times n}$ is upper triangular. Moreover, the diagonals of T are eigenvalues of A.

Normal Matrices

A matrix A is said to be normal if $A^H A = AA^H$

Theorem: Let $A \in \mathbb{C}^{n\times n}$. Then A is normal if and only if it is unitarily diagonalizable.

Jordan Matrix

Given a scalar λ and an integer n, the Jordan block $J_{\lambda,n}$ is the $n\times n$ matrix with λ on the diagonal, 1 on the upper diagonal, and 0 everywhere else, namely

$$J_{\lambda,1} = (\lambda), \quad J_{\lambda,2} = \begin{pmatrix} \lambda & 1 \\ 0 & \lambda \end{pmatrix}, \quad J_{\lambda,3} = \begin{pmatrix} \lambda & 1 & 0 \\ 0 & \lambda & 1 \\ 0 & 0 & \lambda \end{pmatrix}$$

and so on

A Jordan matrix is a block diagonal matrix of the form

$$J = \operatorname{diag}(J_{\lambda_1,n_1}, J_{\lambda_2,n_2}, \dots, J_{\lambda_k,n_k})$$

$$= \begin{pmatrix} J_{\lambda_1,n_1} & & & \\ & J_{\lambda_2,n_2} & & 0 \\ & 0 & \ddots & \\ & & & J_{\lambda_k,n_k} \end{pmatrix}$$

Jordan Canonical Form Decomposition

Theorem: Let $A \in \mathbb{C}^{n\times n}$. Then A is similar to a Jordan matrix, namely there exists an invertible matrix such that

$$S^{-1} A S = J = \operatorname{diag}(J_{\lambda_1,n_1}, J_{\lambda_2,n_2}, \dots, J_{\lambda_\ell,n_\ell})$$

where the $\lambda_1, \lambda_2, \dots, \lambda_\ell$ are eigenvectors of A.

Moreover, the Jordan matrix is unique up to a permutation of the Jordan blocks.

Suppose that $\lambda_1, \dots, \lambda_k$ are distinct eigenvalues of A and m_{λ_j} be their algebraic multiplicities. $\dim(V_{\lambda_j})$ are their geometric multiplicities.

Then we have

i) The matrix is diagonalizble if and only if all the Jordan blocks are of size 1×1.

ii) For $j = 1, 2, \dots, k$, the sum of the size of the Jordan blocks with λ_j on the diagonal

iii) The number of Jordan blocks ℓ is equal to $\sum_{j=1}^{k} \dim(V_{\lambda_j})$. More precisely, for $j = 1, 2, \dots, k$, there are $\dim(V_{\lambda_j})$ blocks with λ_j on the diagonal.

iv) Write $S = (\vec{w}_1 | \vec{w}_2 | \cdots | \vec{w}_n)$

$$S^{-1} A S = J \implies AS = SJ$$

If we look at the n_1 vectors associated with the first Jordan block satisfy

$$\begin{aligned} A\vec{w}_1 &= \lambda_1 \vec{w}_1 & (A - \lambda_1 I)\vec{w}_1 &= \vec{0} \\ A\vec{w}_2 &= \vec{w}_1 + \lambda_1 \vec{w}_2 & (A - \lambda_1 I)\vec{w}_2 &= \vec{w}_1 \\ &\vdots & &\vdots \\ A\vec{w}_{n_1} &= w_{n_1 - 1} + \lambda_1 \vec{w}_{n_1} & (A - \lambda_1 I)\vec{w}_{n_1} &= w_{n_1-1} \end{aligned}$$

That is, $\vec{w}_1$ is an eigenvector while $\vec{w}_2, \dots, \vec{w}_{n_1}$ are generalized eigenvectors of index $2, \dots, n_1$, respectively.

$\{\vec{w}_1, \vec{w}_2, \dots, \vec{w}_{n_1}\}$ is a Jordan chain of length n_1. The same holds true for the other Jordan blocks.

Generalized Eigenvector

Let $A \in \mathbb{C}^{n\times n}$. A vector $\vec{w} \neq \vec{0}$ is called a generalized eigenvector corresponding to an eigenvalue λ is

$$(A - \lambda I)^q \vec{w} = \vec{0} \quad \text{for some integer } q \geq 1$$

The smallest q is called the index.

Applications of Jordan Canonical Forms

i) Prove Cayley-Hamilton Theorem

$$P_A(\lambda) = \det(A - \lambda I) = (\lambda_1 - \lambda)^{m_{\lambda_1}} (\lambda_2 - \lambda)^{m_{\lambda_2}} \cdots (\lambda_k - \lambda)^{m_{\lambda_k}}$$

$$\Rightarrow P_A(A) = (\lambda_1 I - A)^{m_{\lambda_1}} (\lambda_2 I - A)^{m_{\lambda_2}} \cdots (\lambda_k I - A)^{m_{\lambda_k}} = 0$$

ii) Compute power of $A \in \mathbb{C}^{n\times n}$

$$A^k = (SJS^{-1})^k = SJ^kS^{-1} = S\operatorname{diag}(J_1^k, \dots, J_\ell^k) S^{-1}$$

$$J_{\lambda,1}^k = (\lambda^k) \qquad J_{\lambda,2}^k = \begin{pmatrix} \lambda^k & k\lambda^{k-1} \\ 0 & \lambda^k \end{pmatrix}, \quad k \geq 1$$

ii) Compute exponential of $A \in \mathbb{C}^{n\times n}$, or tA.

$$e^A = S \operatorname{diag}(e^{J_1}, e^{J_2}, \dots, e^{J_\ell}) S^{-1}$$

$$e^{J_{\lambda,m}} = e^{\lambda I + J_{0,m}} = e^{\lambda I} e^{J_{0,m}} = e^{\lambda} I e^{J_{0,m}}$$

$$= e^{\lambda} \sum_{k=0}^{m-1} \frac{1}{k!} (J_{0,m})^k$$

Singular Value Decomposition

Let $A \in \mathbb{C}^{m\times n}$. A singular value decomposition of A is a decomposition of the form

$$A = P \Sigma Q^H$$

where

- $r \leq \min\{m, n\}$ is the rank of A
- $P = (\vec{p}_1 | \vec{p}_2 | \cdots | \vec{p}_r) \in \mathbb{C}^{m\times r}$ a matrix of left singular vectors and satisfies $P^H P = I_r$
- $Q = (\vec{q}_1 | \vec{q}_2 | \cdots | \vec{q}_r) \in \mathbb{C}^{n\times r}$ a matrix of right singular vectors and satisfies $Q^H Q = I_r$
- $\Sigma = \operatorname{diag}(\sigma_1, \sigma_2, \dots, \sigma_r) \in \mathbb{R}^{r\times r}$ is the matrix of singular values which are assumed to be listed in non-increasing order, namely

$$\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r > 0$$

We then call σ_1 the dominant singular value.

We can write A as the sum of r rank one matrices

$$A = \sum_{i=1}^{r} \sigma_i \vec{p}_i \vec{q}_i^H$$

Rank k approximation of A

The best rank k approximation of A is obtained by the following:

$$A_k = \sum_{i=1}^{k} \sigma_i \vec{p}_i \vec{q}_i^H$$

A_k also satisfies

$$\|A - B\| \geq \|A - A_k\| \quad \forall B \in \mathbb{C}^{m\times n} \text{ of rank } k$$

Some Properties

$A = P\Sigma Q^H \iff A\vec{q}_i = \sigma_i \vec{p}_i, \quad i = 1, \dots, r$

$A = P\Sigma Q^H \iff A^H\vec{p}_i = \sigma_i \vec{q}_i, \quad i = 1, \dots, r$

This leads to

- $A^H A \vec{q}_i = \sigma_i A^H \vec{p}_i = \sigma_i^2 \vec{q}_i$
- $AA^H \vec{p}_i = \sigma_i A\vec{q}_i = \sigma_i^2 \vec{p}_i$

which means that

$(\sigma_i^2, \vec{q}_i)$ is an eigenpair of $A^H A$

$(\sigma_i^2, \vec{p}_i)$ is an eigenpair of AA^H

Singular Values

Let $A \in \mathbb{C}^{m\times n}$. The singular values of A are the roots of the positive eigenvalues of $A^H A$.

Proposition: Let $A \in \mathbb{C}^{m\times n}$. The rank of A is the number of positive eigenvalues of $A^H A$.

SVD Method

Proposition: The rank of $A \in \mathbb{C}^{m\times n}$ is the number of positive eigenvalues of $A^H A$ (counted with multiplicities).

Theorem: Let $A \in \mathbb{C}^{m\times n}$ be nonzero and of rank r. Then we can write

$$A = P\Sigma Q^H$$

where $P \in \mathbb{C}^{m\times r}$, $P^H P = I_r$, $Q \in \mathbb{C}^{n\times r}$, $Q^H Q = I_r$, $\Sigma = \operatorname{diag}(\sigma_1, \dots, \sigma_r)$, $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$. Moreover, Σ is unique.

To compute SVD of $A \in \mathbb{C}^{m\times n}$

Method based on $A^H A$

1. Compute the positive eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_r > 0$ of $A^H A$.
2. Find an orthonormal set $\{\vec{q}_1, \dots, \vec{q}_r\}$ such that
   $(A^H A)\vec{q}_i = \lambda_i \vec{q}_i \quad i = 1, 2, \dots, r$
3. For $i = 1, 2, \dots, r$, set
   $\sigma_i = \sqrt{\lambda_i}$ and $\vec{p}_i = \frac{1}{\sigma_i} A\vec{q}_i$

Method based on AA^H

1. Compute the positive eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_r > 0$ of AA^H.
2. Find an orthonormal set $\{\vec{p}_1, \dots, \vec{p}_r\}$ such that
   $(AA^H)\vec{p}_i = \lambda_i \vec{p}_i \quad i = 1, 2, \dots, r$
3. For $i = 1, 2, \dots, r$, set
   $\sigma_i = \sqrt{\lambda_i}$ and $\vec{q}_i = \frac{1}{\sigma_i} A^H\vec{p}_i$

Then we get

$$P = (\vec{p}_1 \ \vec{p}_2 \ \cdots \ \vec{p}_r)$$

$$\Sigma = \operatorname{diag}(\sigma_1, \sigma_2, \dots, \sigma_r)$$

$$Q = (\vec{q}_1 \ \vec{q}_2 \ \cdots \ \vec{q}_r)$$

$\{\vec{p}_1, \dots, \vec{p}_r\}$ orthonormal basis for $\operatorname{col}(A)$

$\{\vec{q}_1, \dots, \vec{q}_r\}$ orthonormal basis for $\operatorname{col}(A^H)$

To get a full SVD we do the following:

- Find an orthonormal basis of $\ker(A)$: $\{\vec{q}_{r+1}, \vec{q}_{r+2}, \dots, \vec{q}_n\}$
- Find an orthonormal basis of $\ker(A^H)$: $\{\vec{p}_{r+1}, \vec{p}_{r+2}, \dots, \vec{p}_m\}$
- Set

$$\hat{P} = (\vec{p}_1 \ \vec{p}_2 \ \cdots \ \vec{p}_m)$$

$$\hat{\Sigma} = \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix}$$

$$\hat{Q} = (\vec{q}_1 \ \vec{q}_2 \ \cdots \ \vec{q}_n)$$

Singular Values and Norms

Proposition: Let $A \in \mathbb{C}^{m\times n}$ and let $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$ be its (positive) singular values. Then

$$\|A\|_2 = \sigma_1 \qquad \|A\|_F = \sqrt{\sigma_1^2 + \sigma_2^2 + \dots + \sigma_r^2}$$

$$\|A - A_k\|_2 = \sigma_{k+1} \qquad \|A - A_k\|_F = \sqrt{\sigma_{k+1}^2 + \dots + \sigma_r^2}$$

Pseudoinverse

Let $A \in \mathbb{C}^{m\times n}$. The pseudoinverse (Moore-Penrose inverse) of A is the unique matrix $A^+ \in \mathbb{C}^{n\times m}$ such that

i) $AA^+A = A$ ii) $A^+AA^+ = A^+$

iii) A^+A and AA^+ are Hermitian

The pseudoinverse of $O_{m\times n}$ is its transpose $O_{n\times m}$. For a nonzero matrix $A \in \mathbb{C}^{m\times n}$, its pseudoinverse can be obtained from an SVD:

If $A = P\Sigma Q^H$, then $A^+ = Q\Sigma^{-1}P^H$,

where $\Sigma^{-1} = \operatorname{diag}\left(\frac{1}{\sigma_1}, \frac{1}{\sigma_2}, \dots, \frac{1}{\sigma_r}\right)$

Lemma: Let $A \in \mathbb{C}^{m\times n}$

i) If $\operatorname{rank}(A) = n$, then A^+ is a left inverse of A and $A^+ = (A^H A)^{-1} A^H$

ii) If $\operatorname{rank}(A) = m$, then A^+ is a right inverse of A and $A^+ = A^H (AA^H)^{-1}$

Pseudoinverse and Least Squares

We have that in the case that $\operatorname{rank}(A) = n$, the unique least-squares solution to $A\vec{x} = \vec{b}$ is $\vec{x}^* = A^+\vec{b}$

When we have that $\operatorname{rank}(A) < n$, $\ker(A) \neq \{\vec{0}\}$ and the least-squares solution is no longer unique.

Proposition: Let $A \in \mathbb{C}^{m\times n}$ be a matrix of $\operatorname{rank}(A) < n$ and let A^+ be its pseudoinverse. Then $\vec{x}^* = A^+\vec{b}$ is the least-squares solution to $A\vec{x} = \vec{b}$ that has the smallest 2-norm.

THE END

you made it

MAT 3341

winter 2024

$A\vec{x} = \vec{b}$ $A = LU$

$A = P\Sigma Q^H$ $A\vec{x} = \lambda\vec{x}$

$S^{-1}AS = \Lambda$

Good Luck on the exam!!