



# Linear Algebra

CSCI 2820

Lecture 18

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ECES 122

# Today

- More on Inverses
- Solving Systems of Equations
- Computing the inverse
- Pseudoinverse

# Inverse examples

Reminder: T.F.A.E: (for non-zero matrix)

- $A$  is invertible
- $A$  has Q.ind. columns
- $A$  has Q.ind. rows
- $A$  has left inverse
- $A$  has right inverse

• eg3:  $A = \begin{bmatrix} 1 & -2 & 3 \\ 0 & 2 & 2 \\ -3 & -4 & -1 \end{bmatrix}$ ,  $\tilde{A} = \frac{1}{30} \begin{bmatrix} 0 & -20 & -10 \\ -6 & 5 & -2 \\ 6 & 10 & 2 \end{bmatrix}$

check  $AA' = A'A = I$ .

• eg4:  $2 \times 2$  matrices :  $A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$ ,  $A' = \frac{1}{\underbrace{A_{11}A_{22} - A_{12}A_{21}}_{\text{determinant}}} \begin{bmatrix} A_{22} - A_{12} \\ -A_{21}A_{11} \end{bmatrix}$

Invertible iff:  $A_{11}A_{22} - A_{12}A_{21} \neq 0$

• eg5: Orthogonal matrix:  $\tilde{A}'A = I$ ,  $\tilde{A}' = \tilde{A}^T$

eg. 1:  $I, I' = I$

$$I \cdot I = I$$

eg2:

$$I = \begin{bmatrix} a_1 & 0 & 0 & \dots & 0 \\ 0 & \ddots & & & \\ 0 & & \ddots & & 0 \\ \vdots & & & \ddots & \\ 0 & & & & a_n \end{bmatrix}$$

$\text{diag}(a_1, \dots, a_n)$

when is it invertible?

all  $a_i$ 's  $\neq 0$

$$I' = \begin{bmatrix} 1/a_1 & 0 & \dots & 0 \\ 0 & \ddots & & \\ 0 & & \ddots & 0 \\ \vdots & & & \ddots \\ 0 & & & & 1/a_n \end{bmatrix}$$

$$= \text{diag}(1/a_1, \dots, 1/a_n)$$

# Inverse examples

## Inverse of Transpose:

$$(A^T)^{-1} = (A^{-1})^T \quad (= A^{-T})$$

- Inverse of product:  $A\beta$  non invertible

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

(check:  $AB \cdot B^{-1}A^{-1} = AIA^{-1} = AA^{-1} = I$ )

Question: Can  $A, B$  st either  $A$  or  $B$  not invertible, yet  $AB$  invertible? (ex. for home)

- Dual basis:  $A \in \mathbb{R}^{n \times n}$  invertible,  $B = A'$ ,  $A = [\vec{a}_1 \dots \vec{a}_n]$

$$B = \left[ \begin{array}{c} b_1^T \\ \vdots \\ b_n^T \end{array} \right] \Rightarrow \left\{ \underbrace{\vec{b}_1, \dots, \vec{b}_n}_{B^2} \right\} \text{ basis}$$

$$\begin{aligned} A &= [\vec{a}_1 \dots \vec{a}_n] \\ &\Rightarrow \underbrace{\{\vec{a}_1, \dots, \vec{a}_n\}}_{B_1} \text{ basis} \end{aligned}$$

$B_1, B_2$  are dual bases

$\vec{a} = \beta_1 \vec{d}_1 + \dots + \beta_n \vec{d}_n$  : find  $\beta_i$ 's via dual basis  $B_2$

# Inverse examples

$$AB = I$$

$$\vec{x} = \underbrace{AB}_{I} \vec{x} = [\vec{a}_1 \dots \vec{a}_n] \begin{bmatrix} \vec{b}_1^T \\ \vdots \\ \vec{b}_n^T \end{bmatrix} \vec{x}$$

$$= \underbrace{\langle b_1, x \rangle}_{\beta_1} \vec{a}_1 + \dots + \underbrace{\langle b_n, x \rangle}_{\beta_n} \vec{a}_n$$

$$A = \begin{bmatrix} \vec{a}_1 & \vec{a}_2 \\ 1 & -1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} \vec{a}_1 & \vec{a}_2 \end{bmatrix}$$

$$B = \left[ \vec{a}_1 \quad \vec{a}_2 \right]^{-1} = \begin{pmatrix} -1/2 & 1/2 \\ 1/2 & -1/2 \end{pmatrix} = \vec{b}_1^T \quad \vec{b}_2^T$$

check:  $\begin{pmatrix} -5 \\ 1 \end{pmatrix} = -2 \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} - 3 \cdot \begin{pmatrix} 1 \\ -2 \end{pmatrix} \leq \begin{pmatrix} -5 \\ 1 \end{pmatrix}$

Quick note

$A_{n \times n}$  invertible

$K \in \mathbb{R}$

$$(A^K)^{-1} = (\bar{A})^k = \bar{A}^{-k}$$

$$\bar{A}^2 = A \cdot A$$

$$(A^2)^{-1} = (A \cdot A)^{-1} = \bar{A}^2 \cdot \bar{A}^2 = (A^2)^{-1} = \bar{A}^{-2}$$

$\{\vec{a}_1, \vec{a}_2\}$  and  $\{\vec{b}_1, \vec{b}_2\}$  dual bases

$$\vec{x} = \begin{pmatrix} -5 \\ 1 \end{pmatrix}, \vec{a} = \beta_1 \vec{a}_1 + \beta_2 \vec{a}_2$$

$$\beta_1 = \frac{\langle b_1, x \rangle}{\langle b_1, b_1 \rangle} = -2$$

$$\beta_2 = \frac{\langle b_2, x \rangle}{\langle b_2, b_2 \rangle} = -3$$

$$\begin{pmatrix} -5 \\ 1 \end{pmatrix} = -2 \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} - 3 \cdot \begin{pmatrix} 1 \\ -2 \end{pmatrix} \leq \begin{pmatrix} -5 \\ 1 \end{pmatrix}$$

# Triangular Matrix

Claim: L triangular matrix is invertible if it has non-zero diag. elements.

Proof: Assume L is lower triangular. We will

show L.I columns. I.e.  $\vec{L}\vec{x} = \vec{0} \Leftrightarrow \vec{x} = \vec{0}$

$$\vec{L}\vec{x} = \vec{0} \Leftrightarrow L_{11}x_1 = 0 \Rightarrow x_1 = 0 \quad (L_{11} \neq 0)$$

$$" \quad L_{21}x_1 + L_{22}x_2 = 0 \Rightarrow x_2 = 0$$

$$L_{31}x_1 + L_{32}x_2 + L_{33}x_3 = 0 \Rightarrow x_3 = 0 \text{ etc}$$

$$\vdots \quad \vec{x} = \vec{0}$$

$$\begin{bmatrix} L_{11} & & & \\ L_{21} & L_{22} & & 0 \\ \vdots & & \ddots & \\ L_{n1} & \dots & \dots & L_{nn} \end{bmatrix}$$

Upper triangular R: repeat proof or  $L = R^T$  lower triag.

$R^T$  invertible by previous part,  $(R^T)^T$  invertible.

# Inverse via QR factorization

$$A = Q \cdot R \quad (\text{assume } A \text{ nxn invertible})$$

↓ ↳ upper-triangular

orthogonal

$$\cdot A^{-1} = (Q \cdot R)^{-1} = \underbrace{R^{-1} Q^{-1}}_{\text{easy}} = \underbrace{R^{-1} \cdot \underbrace{Q^{-1}}_{\text{easy}}}$$

↓  
algorithm shortly

# Solving linear equations

$\vec{R}\vec{x} = \vec{b}$ ,  $R$  upper-triangular  $n \times n$   
non-zero diag.

Back substitution:

$$R_{11}x_1 + R_{12}x_2 + \dots + R_{1n}x_n = b_1$$

⋮

⋮

$$R_{n-1,n-1}x_{n-1} + R_{n-1,n}x_n = b_{n-1} \quad \begin{matrix} x_{n-1} = (b_{n-1} - R_{n-1,n}x_n) / R_{n-1,n-1} \\ R_{nn}x_n = b_n \Rightarrow x_n = b_n / R_{nn} \end{matrix}$$

algo: for  $i=n, \dots, 1$  :  $x_i = (b_i - R_{i,i+1}x_{i+1} - \dots - R_{i,n}x_n) / R_{ii}$

computes the solution of  $R\vec{x} = \vec{b}$ ,  $\vec{x} = \vec{R}^{-1}\vec{b}$

# Solving linear equations-QR

**Algorithm 11.2** SOLVING LINEAR EQUATIONS VIA QR FACTORIZATION  
given an  $n \times n$  invertible matrix  $A$  and an  $n$ -vector  $b$ .

1. *QR factorization.* Compute the QR factorization  $A = QR$ .
2. Compute  $Q^T b = \vec{y}$
3. *Back substitution.* Solve the triangular equation  $Rx = Q^T b$  using back substitution.

$(A)^{-1} = (QR)^{-1} = R^{-1}Q^T$ . Method for solving linear eq. for any  $n \times n$  invertible matrix  $A$ .  $A\vec{x} = \vec{b}$ .

solution is  $\vec{x} = A^{-1}\vec{b} = \underbrace{R^{-1}Q^T\vec{b}}_{\text{compute } Q^T\vec{b} = \vec{y}}$

solve upper-triang. system  $R\vec{x} = \vec{y}$   
by back-sub.

# Solving linear equations

# Solving linear equations

$$\left. \begin{array}{l} \vec{A}\vec{x}_1 = \vec{b}_1 \\ \vec{A}\vec{x}_2 = \vec{b}_2 \\ \vdots \\ \vec{A}\vec{x}_k = \vec{b}_k \end{array} \right\} \quad \begin{array}{l} AX = B, A \text{ invertible} \\ X = [\vec{x}_1 \dots \vec{x}_k] \\ B = [\vec{b}_1 \dots \vec{b}_k] \end{array}$$

$$X = \tilde{A}^{-1}B \quad \text{solution}$$

gostter method:  $A = QR$  (11.3)

$$\vec{y}_k = Q^T \vec{b}_k, \quad R \vec{x}_k = \vec{y}_k$$

# Computing matrix inverse

**Algorithm 11.3** COMPUTING THE INVERSE VIA QR FACTORIZATION  
given an  $n \times n$  invertible matrix  $A$ .

1. *QR factorization.* Compute the QR factorization  $A = QR$ .
2. For  $i = 1, \dots, n$ ,  
Solve the triangular equation  $Rb_i = \tilde{q}_i$  using back substitution.

$A_{n \times n}$  invertible ,  $\underbrace{A^{-1}}_B = ?$      $A = QR$  ,  $\underbrace{A^{-1} = R^{-1}Q^{-1}}_{R \cdot B = Q^T} \Rightarrow$

$R \cdot B = Q^T$

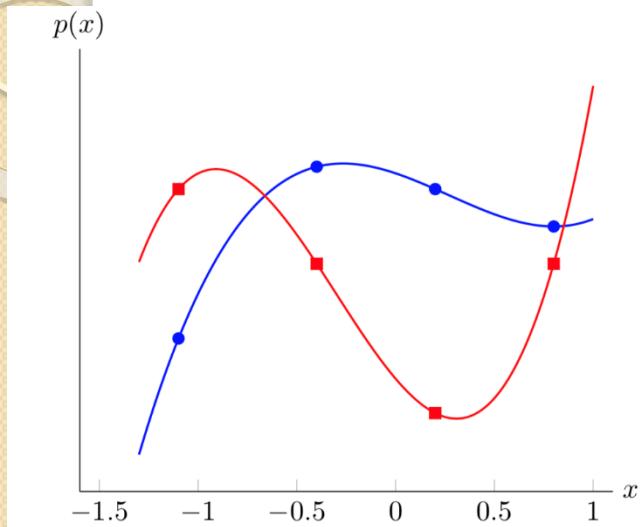
$\underbrace{\{ R \cdot b_i = \tilde{q}_i \}}$

$\begin{matrix} \vec{b}_i & \text{columns of } B \\ \vec{q}_i & \text{columns of } Q^T \end{matrix}$

do at home: read section 11.4 (how to compute inverses)

# Computing matrix inverse

# Examples



# Examples

# Pseudo-inverse

- $m \times n$  matrix  $A$  l.i. independent columns (tall/square)

iff  $n \times n$  Gram matrix  $\bar{A}^T A$  is invertible

$\Rightarrow$  columns of  $A$  l.i. let  $\vec{z}$  n-vector

$$(\bar{A}^T A) \vec{z} = \vec{0} \Rightarrow \text{Need to show } \vec{z} = \vec{0}$$

$$\vec{z}^T (\bar{A}^T A) \vec{z} = 0 \Rightarrow$$

$$\vec{z}^T \bar{A}^T A \vec{z} = 0 \Rightarrow \|A \vec{z}\|^2 = 0 \Rightarrow A \vec{z} = \vec{0} \Rightarrow \vec{z} = \vec{0} \quad (\text{implies } \bar{A}^T A \text{ invert})$$

$\Leftarrow$  columns of  $A$  are l.i. dependent. Need to show

$\bar{A}^T A$  is singular.

$$\exists \vec{z} \neq \vec{0} \text{ s.t. } A \vec{z} = \vec{0} \Rightarrow (\bar{A}^T A) \vec{z} = \vec{0} \Rightarrow \text{columns of } \bar{A}^T A \\ L.D., \bar{A}^T A \text{ singular}$$

# Pseudo-inverse

claim : if  $A$  (square or tall) has linearly indep. columns then it has a left inverse.

Proof : Assume  $A$  has L.I. columns, then  $A^T A$  is invertible. Observe

$(A^T A)^{-1} \cdot A^T$  is a left-inverse of  $A$

check :  $\left[ (A^T A)^{-1} \cdot A^T \right] A = (A^T A)^{-1} (A^T A) = I$

pseudo-inverse (Moore-Penrose inverse)

if  $A$  square  $\overset{A^+}{A} = \overset{A^-}{A} : \overset{A^+}{A} = (\overset{A^T}{A} \overset{-1}{A}) \overset{T}{A} = \overset{-1}{A} \overset{T}{A} \overset{-1}{A} = \overset{-1}{A}$

# Pseudo-inverse

Transpose all equations for wide matrices.

If a wide matrix  $A$  has L.I rows  
then it has right inverses

$\tilde{A}^T (A\tilde{A}^T)^{-1}$ , pseudo inverse,  $\tilde{A}^+$

$A\tilde{x} = \tilde{b}$  systems

• over-determined systems with A L.I columns,

and  $\exists$  solution:  $\vec{\tilde{x}} = \tilde{A}^+ \vec{b}$

• under-det : rows of A L.I ,  $\vec{\tilde{x}} = \tilde{A}^+ \vec{b}$ .

# Pseudo-inverse

# Exercise

**11.5 Inverse of a block matrix.** Consider the  $(n + 1) \times (n + 1)$  matrix

$$A = \begin{bmatrix} I & a \\ a^T & 0 \end{bmatrix},$$

where  $a$  is an  $n$ -vector.

- (a) When is  $A$  invertible? Give your answer in terms of  $a$ . Justify your answer.
- (b) Assuming the condition you found in part (a) holds, give an expression for the inverse matrix  $A^{-1}$ .



