

# ECEn 671: Mathematics of Signals and Systems

Randal W. Beard

Brigham Young University

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# Section 1

## Matrix Inverses

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## Definition

$A \in \mathbb{C}^{m \times n}$  has a left inverse if  $\exists B \in \mathbb{C}^{n \times m}$  such that

$$\underset{n \times m}{B} \underset{m \times n}{A} = \underset{n \times n}{I}$$

## Definition

$A \in \mathbb{C}^{m \times n}$  has a right inverse if  $\exists D \in \mathbb{C}^{n \times m}$  such that

$$\underset{m \times n}{A} \underset{n \times m}{C} = \underset{m \times m}{I}$$

## Matrix Inverses, cont

### Example

The matrix

$$A = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 7 & 0 \end{pmatrix}.$$

has an infinite number of right inverses, namely

$$C = \begin{pmatrix} \frac{1}{2} & 0 \\ 0 & \frac{1}{7} \\ c_1 & c_2 \end{pmatrix} \quad \forall c_1, c_2 \in \mathbb{R}$$

since

$$AC = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}.$$

## Matrix Inverses, cont

- ▶ Suppose  $A$  has a left inverse, then

$$Ax = b \iff BAx = Bb \iff x = Bb$$

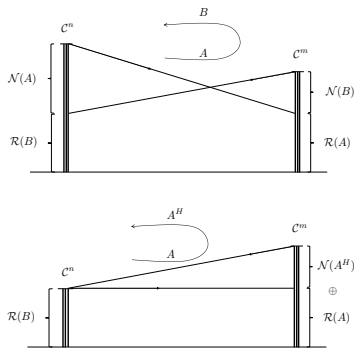
- ▶ Suppose  $A$  has a right inverse, then let

$$x = Cb \Rightarrow Ax = ACb = b$$

so  $x = Cb$  is a solution.

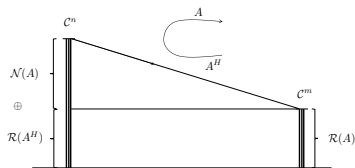
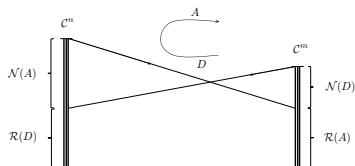
# Left Inverse

- ▶ Let  $B$  be a left inverse of  $A$ .
- ▶ Then  $BA = I : \mathbb{C}^n \rightarrow \mathbb{C}^n$ .
- ▶ Of necessity we must have that  $\mathcal{N}(A) = \{0\}$ , otherwise there are vectors  $x \in \mathcal{N}(A) \subseteq \mathbb{C}^n$  such that  $BAx = B0 = 0 \neq x$ , i.e.,  $BA \neq I$ .
- ▶ Therefore  $Ax = b$  has at most one solution (since  $b$  may not be in  $\mathcal{R}(A)$ ).



# Right Inverse

- ▶ Let  $D$  be a right inverse of  $A$ .
- ▶ Then  $AD = I : \mathbb{C}^m \rightarrow \mathbb{C}^m$ .
- ▶ Of necessity we must have that  $\mathcal{N}(A^H) = \{0\}$ , otherwise  $D^H A^H = I$  is impossible.
- ▶  $\mathcal{N}(A)$  may be nontrivial therefore if  $\hat{x}$  is a solutions so is  $\hat{x} + x_n$  where  $x_n \in \mathcal{N}(A)$  since  $A(\hat{x} + x_n) = A\hat{x} = b$ . Therefore, there is at least one solution.



# Right and Left Inverses

## Lemma

1. *If  $A$  has a left inverse then  $Ax = b$  has at most one solution.*
2. *If  $A$  has a right inverse then  $Ax = b$  has at least one solution.*



# Regular Inverse

If  $A \in \mathbb{C}^{n \times n}$  when the following statements are equivalent:

1.  $A^{-1}$  exists
2.  $\mathcal{N}(A) = \{0\}$  and  $\mathcal{N}(A^H) = \{0\}$ .
3.  $\text{rank}(A) = n$
4.  $\det(A) \neq 0$
5. (right inverse of  $A$ ) = (left inverse of  $A$ ) =  $A^{-1}$
6. there are no zero eigenvalues of  $A$
7.  $A^H A$  is positive definite
8.  $A$  is nonsingular

## Regular Inverse, cont.

If  $A^{-1}$  exists then

$$A^{-1} = \frac{\text{adj}(A)}{\det(A)}$$

where  $\text{adj}(A)$  is the adjugate of  $A$  where  $\text{adj}(A) = [B_{ij}]^T$  and  $B_{ij} = (-1)^{i+j} \det(M_{ij})$  and  $M_{ij}$  is the  $(i,j)^{th}$  minor of  $A$ .

### Example

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

$$\text{adj}(A) = \begin{pmatrix} (-1)^2 |d| & (-1)^3 |c| \\ (-1)^3 |b| & (-1)^4 |a| \end{pmatrix} = \begin{pmatrix} d & -c \\ -b & a \end{pmatrix}$$

$$\text{so } A^{-1} = \frac{\begin{pmatrix} d & -c \\ -b & a \end{pmatrix}}{\det(A)} = \frac{\begin{pmatrix} d & -c \\ -b & a \end{pmatrix}}{ad - cb}$$

# Matrix Rank

## Lemma

Let  $A : \mathbb{C}^n \rightarrow \mathbb{C}^m$  then

$$\text{rank}\left(\begin{smallmatrix} A \\ m \times n \end{smallmatrix}\right) = \text{rank}\left(\begin{smallmatrix} A^H \\ n \times m \end{smallmatrix}\right) = \text{rank}\left(\begin{smallmatrix} A^H A \\ n \times n \end{smallmatrix}\right) = \text{rank}\left(\begin{smallmatrix} A A^H \\ m \times m \end{smallmatrix}\right)$$

Proof.

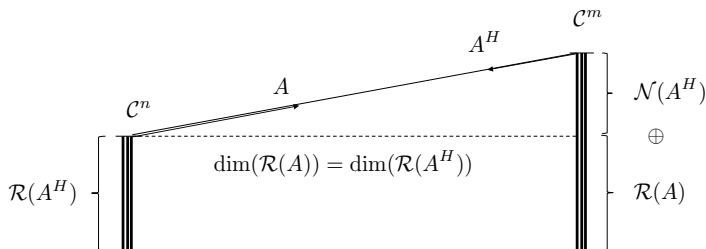
$$\begin{aligned} \text{rank}(B) &= \# \text{ of linearly independent columns} = \dim(\mathcal{R}(B)) \\ &= \# \text{ of linearly independent rows} = \dim(\mathcal{R}(B^H)). \end{aligned}$$

Therefore

$$\begin{aligned} \text{rank}(A) &= \dim(\mathcal{R}(A)) = \dim(\mathcal{R}(A^H)) = \text{rank}(A^H) \\ &= \dim(\mathcal{R}(A A^H)) = \text{rank}(A A^H) \text{ Since } \mathcal{R}(A^*) = \mathcal{R}(A A^*) \\ &= \dim(\mathcal{R}(A^H A)) = \text{rank}(A^H A) \text{ Since } \mathcal{R}(A) = \mathcal{R}(A^* A) \end{aligned}$$

## Left Inverse: Least Squares

- ▶ Consider the solution of  $Ax = b$  where  $m > n$ , i.e.,  $A$  is tall.
- ▶ Assume  $A$  is full rank, i.e.,  $\text{rank}(A) = n$ .
- ▶ Assume  $b \in \mathcal{R}(A)$



- ▶ Map  $b$  to  $\mathcal{R}(A^*)$ :  $A^H b = A^H A x$
- ▶ Since  $\text{rank}(A) = n \iff \text{rank}(A^H A) = n$  so  $(A^H A)^{-1}$  exists

$$\Rightarrow \boxed{x = (A^H A)^{-1} A^H b}$$

## Left Inverse: Least Squares, cont.

What if  $b \notin \mathcal{R}(A)$ ? This is the least squares problem, e.g.

$$\underbrace{\begin{pmatrix} a_1 & 1 \\ a_2 & 1 \\ \vdots & \vdots \\ a_n & 1 \end{pmatrix}}_A \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_x = \underbrace{\begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix}}_b$$

linear regression

Since there is no solution, it is reasonable to find  $x$  that minimizes  $\|e\|_2$  where

$$e = Ax - b$$

.

## Left Inverse: Least Squares, cont.

- ▶ Note that  $b = b_r + b_n$  where  $b_r \in \mathcal{R}(A)$  and  $b_n \in \mathcal{N}(A^H)$  so  $e = Ax - b_r - b_n$ .
- ▶ Since  $Ax - b_r \in \mathcal{R}(A) \perp \mathcal{N}(A^H)$  the best we can do is make  $Ax = b_r \Rightarrow e = b_n$ .
- ▶ Since  $b_n \in \mathcal{N}(A^H)$  we have

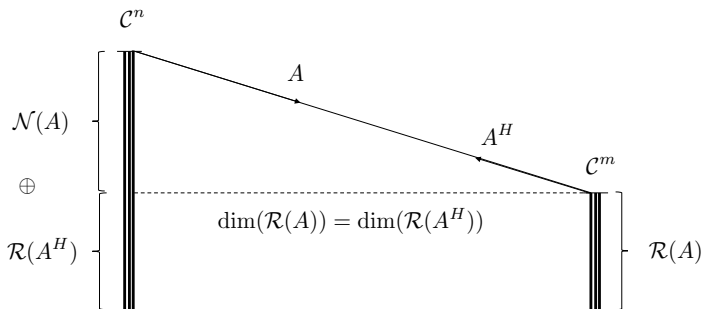
$$\begin{aligned} 0 &= A^H Ax - A^H b_r \\ \Rightarrow \underbrace{A^H Ax}_{\text{projection of } x \text{ onto } \mathcal{R}(A^H)} &= A^H b_r = \underbrace{A^H b}_{\text{projection of } b \text{ onto } \mathcal{R}(A^H)} \end{aligned}$$

- ▶ Since  $\text{rank}(A^H A) = \text{rank}(A) = n$  we have

$$\underbrace{x = (A^H A)^{-1} A^H b}_{\text{least square solution}}$$

## Right Inverse: Min-Norm Solution

- ▶ Consider the solution of  $Ax = b$  where  $m < n$ , i.e.,  $A$  is fat.
- ▶ Assume  $A$  is full rank, i.e.,  $\text{rank}(A) = m$ .



We would like to solve  $Ax = b$  note that since  $x = x_r + x_n$  where  $x_r \in \mathcal{R}(A^H)$  and  $x_n \in \mathcal{N}(A)$  and  $\mathcal{N}(A) \neq \{0\}$  there are an infinite number of solutions (i.e. add any thing in  $\mathcal{N}(A)$  to a solution). The minimum norm solution will be the element of  $\mathcal{R}(A^H)$  that satisfies  $Ax_r = b$ .

## Right Inverse: Min-norm Solution, cont.

$$x_r \in \mathcal{R}(A^H) \Rightarrow x_r = A^H y \text{ where } y \in \mathbb{C}^m$$

so we need to solve

$$\begin{pmatrix} A & A^H \\ m \times n & n \times m \end{pmatrix} \begin{matrix} y \\ m \times 1 \end{matrix} = \begin{matrix} b \\ m \times 1 \end{matrix}$$

Since  $\text{rank}(A) = \text{rank}(AA^H) = m$ ,  $(AA^H)^{-1}$  exists.

$$\Rightarrow y = (AA^H)^{-1}b$$

$$\Rightarrow \boxed{x_r = A^H(AA^H)^{-1}b}$$

Note that this is the same solution as

$$\begin{aligned} \min \quad & \|x\|_2 \\ \text{s.t.} \quad & Ax = b \end{aligned}$$



# Right and Left Inverses

## Lemma

If  $A \in \mathbb{C}^{m \times n}$  where  $m > n$  and  $A$  is full rank, then  $(A^H A)^{-1} A^H$  is a left inverse of  $A$ .

Proof.

$$(A^H A)^{-1} A^H A = I_n \quad \square$$

## Lemma

If  $A \in \mathbb{C}^{m \times n}$  where  $m < n$  and  $A$  is full rank, then  $A^H (A A^H)^{-1} A$  is a right inverse of  $A$ .

Proof.

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

- ▶ Both are examples of pseudo-inverses.
- ▶  $A^H (A A^H)^{-1} A$  is called the Moore-Penrose pseudo-inverse.
- ▶ In Matlab type `pinv(A)`.