

# CX1104: Linear Algebra for Computing

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}}_{x} = \underbrace{\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}}_{b}$$

Chap. No : **7.1.1**

Lecture : **Least Squares**

Topic : **Introduction**

Concept : **Consistency in a System of Equations**

Instructor: **A/P Chng Eng Siong**

TAs: **Zhang Su, Vishal Choudhari**

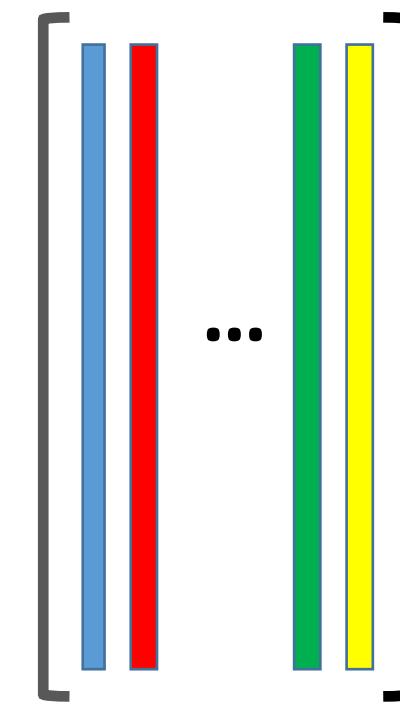
# Consistency in a System of Equations

Consider solving the system of equations:  $Ax = b$

Note:

- Matrix  $A \in R^{M \times N}$ , where
  - $M$  denotes no. of rows/equations
  - $N$  denotes no. of columns/unknowns
- $x \in R^N$
- $b \in R^M$
- The above system of equations can either be
  1. consistent (or)
  2. inconsistent.

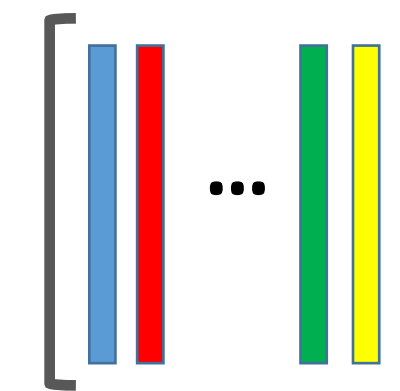
Based on  $M$  &  $N$ , there exist three cases:



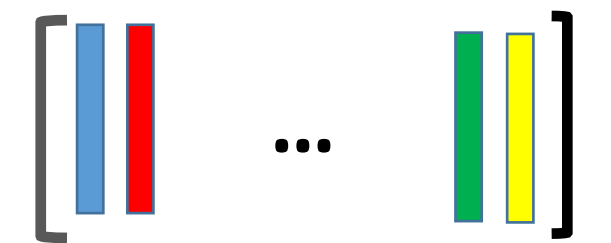
$$M \gg N$$

More equations,  
less unknowns.

Hence, **over-determined!**  
Typically this will result  
in inconsistent system of  
equations



$$M \approx N$$

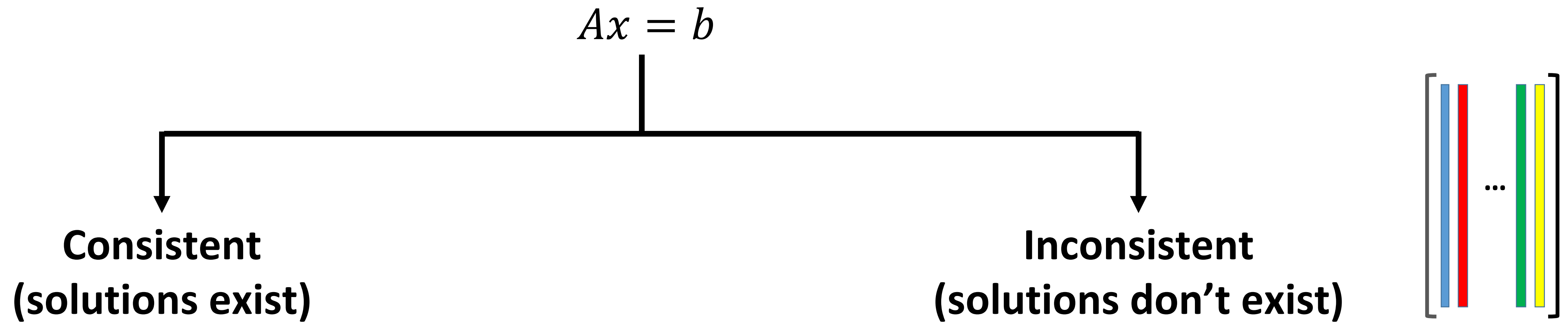


$$M \ll N$$

Less equations,  
more unknowns.

Hence, **under-determined!**  
Typically, this will  
result  
in infinite solutions

# Consistency in a System of Equations



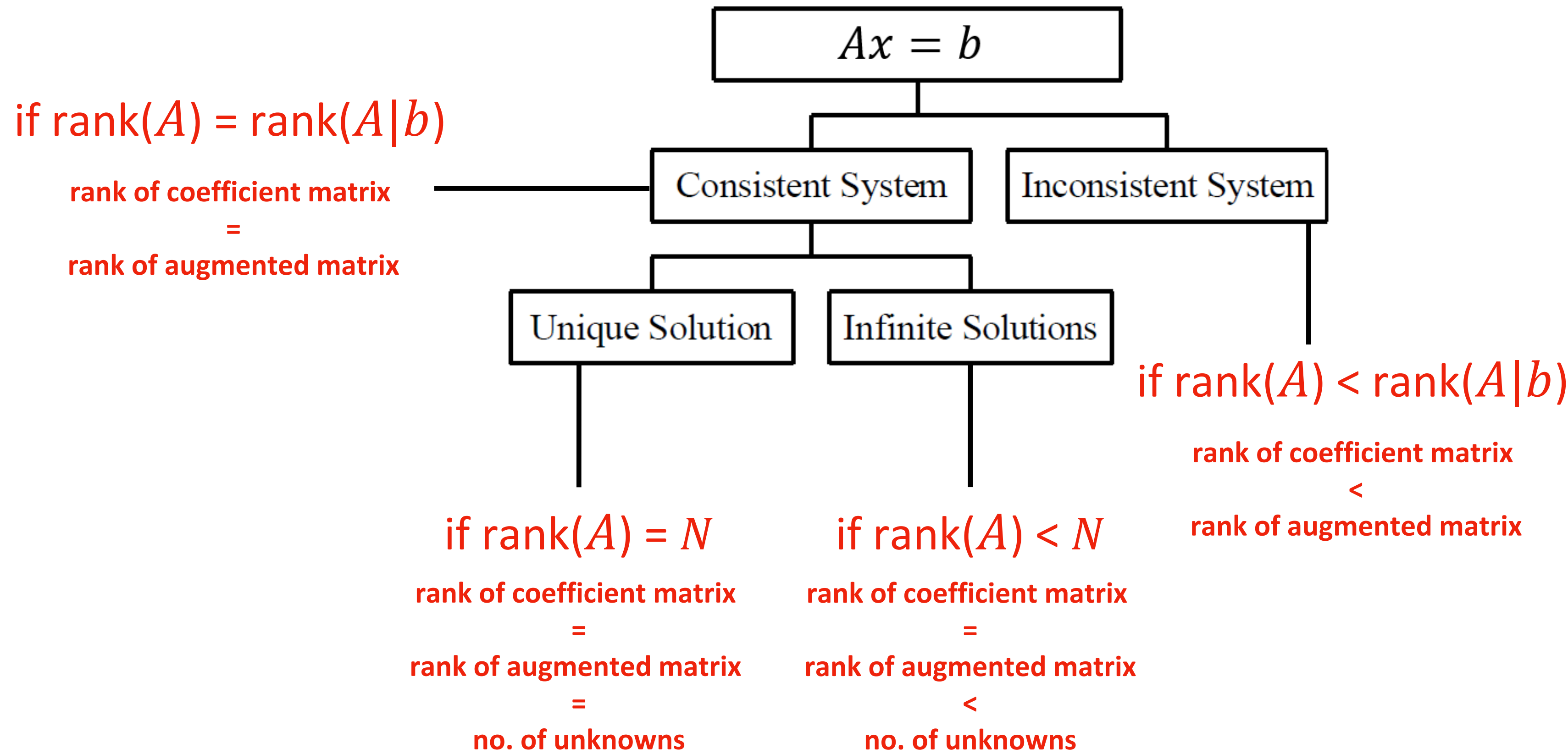
- $b$  is in column space of  $A$ , i.e,  
 $b$  is formed by linear combinations of  $A$ 's columns.
- $\text{Rank}(A) = \text{Rank}(A|b)$ , i.e,  
rank of  $A$  is same as that of the augmented matrix.

- $b$  is NOT in column space of  $A$ , i.e,  
 $b$  is NOT formed by linear combinations of  $A$ 's columns.
- **Typically** occurs when  $M \gg N$  (**over-determined**), i.e,  
there exist more equations than unknowns.
- The rows of  $A$  are dependent but,  
their corresponding  $b$  values are not consistent.
- $\text{Rank}(A) < \text{Rank}(A|b)$ , i.e,  
rank of  $A$  is less than that of the augmented matrix.

# Consistency in a System of Equations

A system of equations can be consistent or inconsistent. What does that mean?

A system of equations  $Ax = b$  is consistent if there is a solution, and it is inconsistent if there is no solution. However, consistent system of equations does not mean a unique solution, that is, a consistent system of equation may have a unique solution or infinite solutions.



**NOTE:** Rank (A) is the maximum number of independent rows or columns of A.

You can find number of independent row or columns by:

1. row reduction process
2. rank(A) in MATLAB

**Note:** rank (A) > rank (A|b) is never possible. Why?

# Examples

$\text{rank}(A) = \text{rank}(A|b) = N$

**Consistent and Unique Solution**

a) The system of equations

$$\begin{bmatrix} 2 & 4 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 6 \\ 4 \end{bmatrix}$$

is a consistent system of equations as it has a unique solution, that is,

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

```
>> A_b = [ 2 4 6; 1 3 4]

A_b =

     2     4     6
     1     3     4

>> rank(A_b)

ans =

     2
```

**Consistent and Having Infinite Solutions**

b) The system of equations

$$\begin{bmatrix} 2 & 4 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 6 \\ 3 \end{bmatrix}$$

is also a consistent system of equations but it has infinite solutions as given as follows.

Expanding the above set of equations,

$$\begin{aligned} 2x + 4y &= 6 \\ x + 2y &= 3 \end{aligned}$$

you can see that they are the same equation. Hence any combination of  $(x,y)$  that satisfies

$$2x + 4y = 6$$

is a solution. For example  $(x,y)=(1,1)$  is a solution and other solutions include  $(x,y)=(0.5,1.25)$ ,  $(x,y)=(0, 1.5)$  and so on.

```
>> A_b = [ 2 4 6; 1 2 3]

A_b =

     2     4     6
     1     2     3

>> rank(A_b)

ans =

     1
```

**Inconsistent and No solutions Exist**

c) The system of equations

$$\begin{bmatrix} 2 & 4 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 6 \\ 4 \end{bmatrix}$$

$\text{rank}(A) < \text{rank}(A|b)$

```
>> A = [2 4; 1 2]

A =

     2     4
     1     2

>> rank(A)

ans =

     1

>> A_b = [ 2 4 6; 1 2 4]

A_b =

     2     4     6
     1     2     4

>> rank(A_b)

ans =

     2
```

$\text{rank}(A) = \text{rank}(A|b) < N$



# CX1104: Linear Algebra for Computing

$$\underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{mn} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}}_{x} = \underbrace{\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}}_{b}$$

Chap. No : **7.1.2**

Lecture : **Least Squares**

Topic : **Introduction**

Concept : **The Least Squares Problem**

Instructor: **A/P Chng Eng Siong**

TAs: **Zhang Su, Vishal Choudhari**

# Consistency in a System of Equations

$$Ax = b$$

**Consistent**  
(solutions exist)

- $b$  is in column space of  $A$ , i.e.,  $b$  is formed by linear combinations of  $A$ 's columns.
- $\text{Rank}(A) = \text{Rank}(A|b)$ , i.e., rank of  $A$  is same as that of the augmented matrix.

**Consider**

**Inconsistent**  
(solutions don't exist)

- $b$  is NOT in column space of  $A$ , i.e.,  $b$  is NOT formed by linear combinations of  $A$ 's columns.
- **Typically** occurs when  $M \gg N$  (**over-determined**), i.e., there exist more equations than unknowns.
- The rows of  $A$  are dependent but, their corresponding  $b$  values are not consistent.
- $\text{Rank}(A) < \text{Rank}(A|b)$ , i.e., rank of  $A$  is less than that of the augmented matrix.

$$\begin{bmatrix} | & | & | & \dots & | & | \\ \hline | & | & | & \dots & | & | \\ \hline \end{bmatrix}$$

$M \gg N$

# Least Squares Solution for Inconsistent Equations

Consider solving the system of equations:  $Ax = b$

Note:

- Matrix  $A \in R^{M \times N}$ , where
  - $M$  denotes no. of rows/equations
  - $N$  denotes no. of columns/unknowns
- $x \in R^N$
- $b \in R^M$
- When  $M \gg N$ ,
  - the system is over-determined
  - the equations may be inconsistent
  - there may be no solution

**Best we can do?**

**Find  $x$  such that  $Ax$  is as close to  $b$  as possible!**

If  $A$  is  $m \times n$  and  $\mathbf{b}$  is in  $\mathbb{R}^m$ , a **least-squares solution** of  $A\mathbf{x} = \mathbf{b}$  is an  $\hat{\mathbf{x}}$  in  $\mathbb{R}^n$  such that

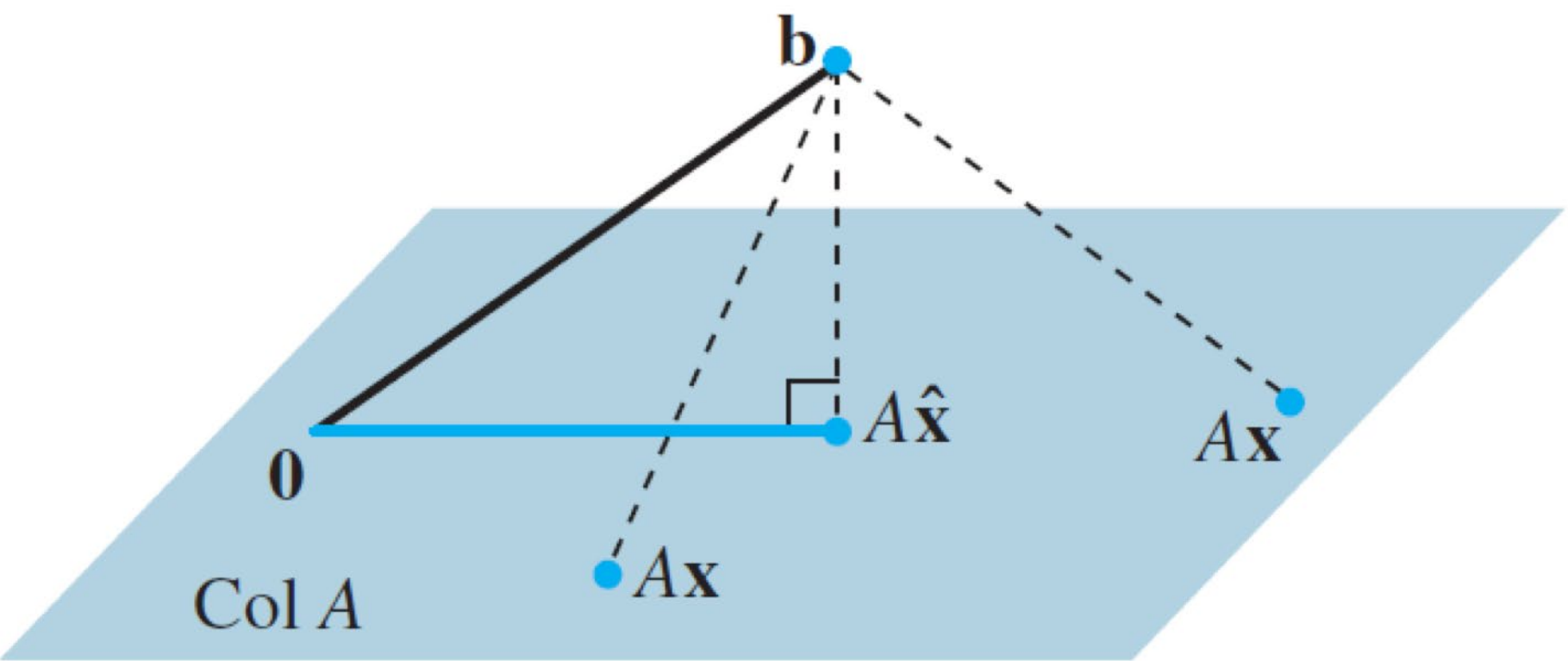
$$\|\mathbf{b} - A\hat{\mathbf{x}}\| \leq \|\mathbf{b} - A\mathbf{x}\|$$

for all  $\mathbf{x}$  in  $\mathbb{R}^n$ .

Think of  $A\mathbf{x}$  as an *approximation* to  $\mathbf{b}$ . The smaller the distance between  $\mathbf{b}$  and  $A\mathbf{x}$ , given by  $\|\mathbf{b} - A\mathbf{x}\|$ , the better the approximation. The **general least-squares problem** is to find an  $\mathbf{x}$  that makes  $\|\mathbf{b} - A\mathbf{x}\|$  as small as possible. The adjective “least-squares” arises from the fact that  $\|\mathbf{b} - A\mathbf{x}\|$  is the square root of a sum of squares.



# Definitions



**FIGURE 1** The vector  $\mathbf{b}$  is closer to  $A\hat{\mathbf{x}}$  than to  $A\mathbf{x}$  for other  $\mathbf{x}$ .

The most important aspect of the least-squares problem is that no matter what  $\mathbf{x}$  we select, the vector  $A\mathbf{x}$  will necessarily be in the column space,  $\text{Col } A$ . So we seek an  $\mathbf{x}$  that makes  $A\mathbf{x}$  the closest point in  $\text{Col } A$  to  $\mathbf{b}$ . See Fig. 1. (Of course, if  $\mathbf{b}$  happens to be in  $\text{Col } A$ , then  $\mathbf{b}$  is  $A\mathbf{x}$  for some  $\mathbf{x}$ , and such an  $\mathbf{x}$  is a “least-squares solution.”)

If a linear system is consistent, then its exact solutions are the same as its least squares solutions, in which case the least squares error is zero.

**NOTE:**  
When the linear system  $Ax = b$  is inconsistent,  $b$  does not lie in the column space of  $A$ .

To explain the terminology in this problem, suppose that the column form of  $\mathbf{b} - A\mathbf{x}$  is

$$\mathbf{b} - A\mathbf{x} = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{bmatrix}$$

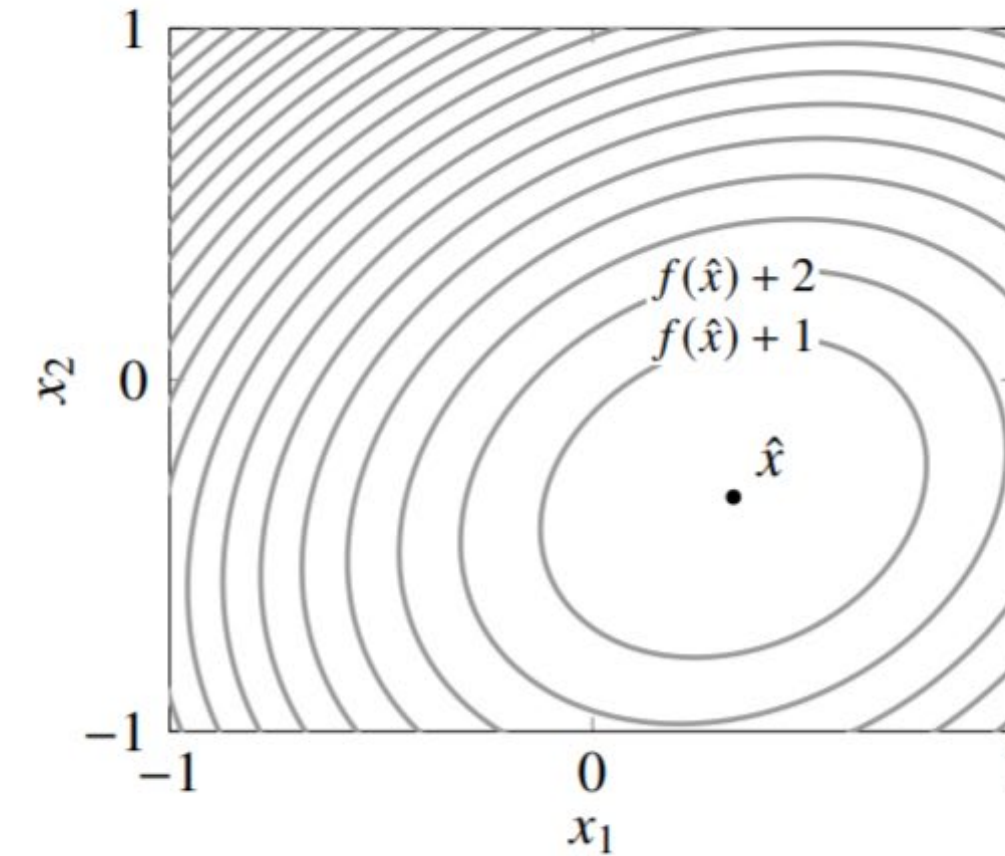
The term “least squares solution” results from the fact that minimizing  $\|\mathbf{b} - A\mathbf{x}\|$  also has the effect of minimizing  $\|\mathbf{b} - A\mathbf{x}\|^2 = e_1^2 + e_2^2 + \cdots + e_m^2$ .



# Example

## Example

$$A = \begin{bmatrix} 2 & 0 \\ -1 & 1 \\ 0 & 2 \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$



- the least squares solution  $\hat{x}$  minimizes

$$f(x) = \|Ax - b\|^2 = (2x_1 - 1)^2 + (-x_1 + x_2)^2 + (2x_2 + 1)^2$$

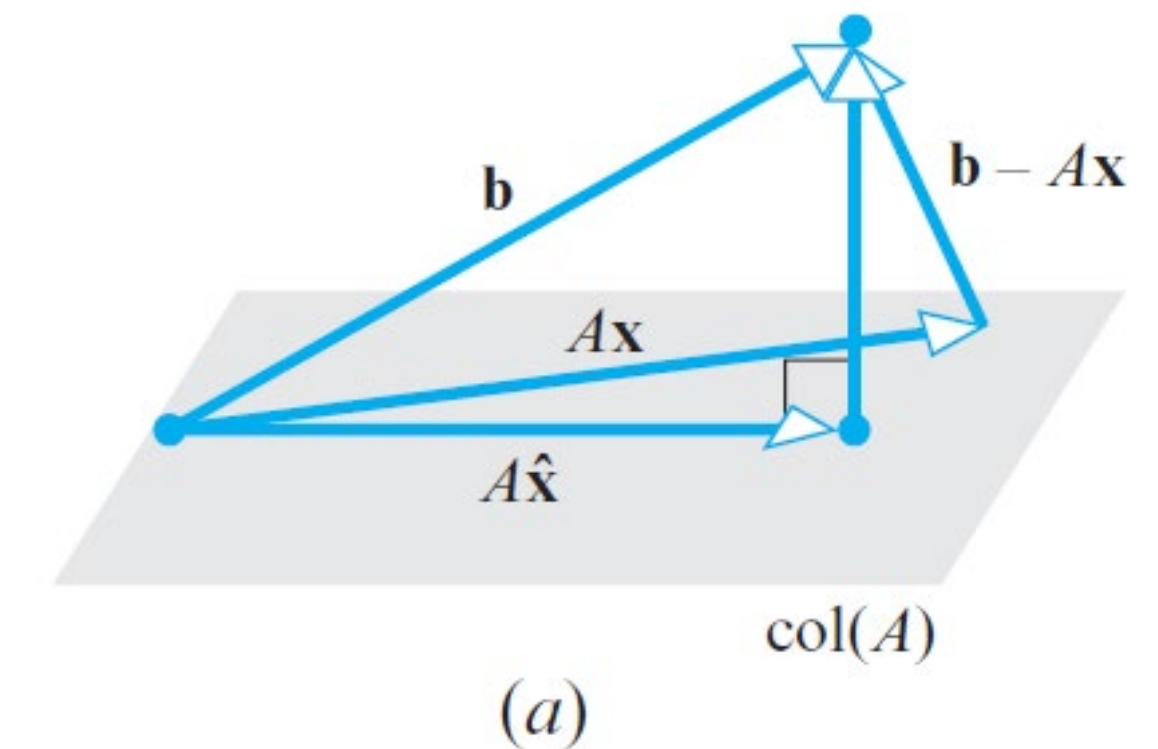
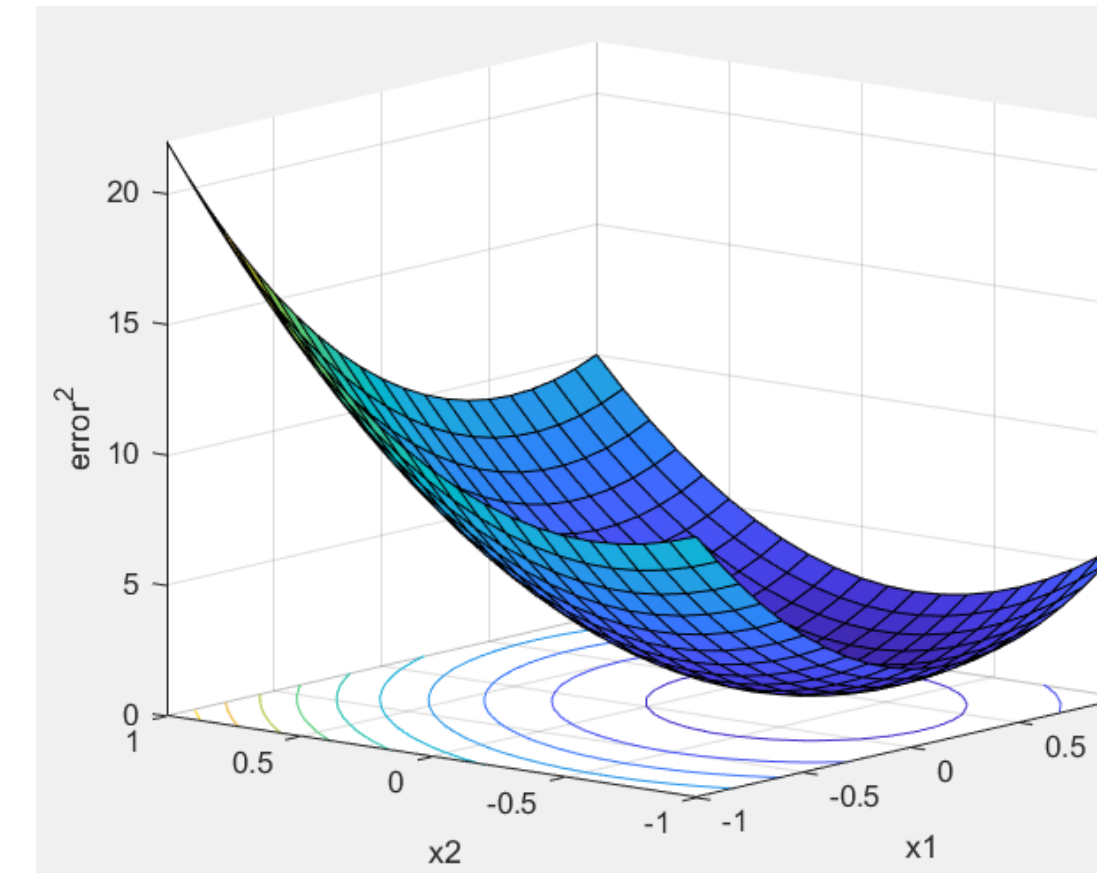
- to find  $\hat{x}$ , set derivatives with respect to  $x_1$  and  $x_2$  equal to zero:

$$10x_1 - 2x_2 - 4 = 0, \quad -2x_1 + 10x_2 + 4 = 0$$

solution is  $(\hat{x}_1, \hat{x}_2) = (1/3, -1/3)$

Least squares

8.3



opStr =

'x1=0.30, x2=-0.30, err^2=0.680 '

```
%ch6_4_Ex1.m
%Chng Eng Siong, plotting the error wrt x
close all; clear all;
A = [2 0; -1 1; 0 2];
b = [1 0 -1]';
[x1,x2] = meshgrid(-1:0.1:1, -1:0.1:1);
[m,n] = size(x1);
z = zeros(m,n);
for i=1:m
    for j=1:n
        z(i,j) = norm(b - (x1(i,j)*A(:,1)+x2(i,j)*A(:,2))).^2;
    end
end
surf(x1,x2,z)
xlabel('x1'); ylabel('x2'); zlabel('error^2');

% Lets print the min value and the x vector
minIdx = find(z == min(z(:)));
x1(minIdx), x2(minIdx), z(minIdx)
opStr = sprintf('x1=%0.2f, x2=%0.2f, err^2=%0.3f ',x1(minIdx),x2(minIdx),z(minIdx))
```

# CX1104: Linear Algebra for Computing

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Chap. No : **7.1.3**

Lecture : **Least Squares**

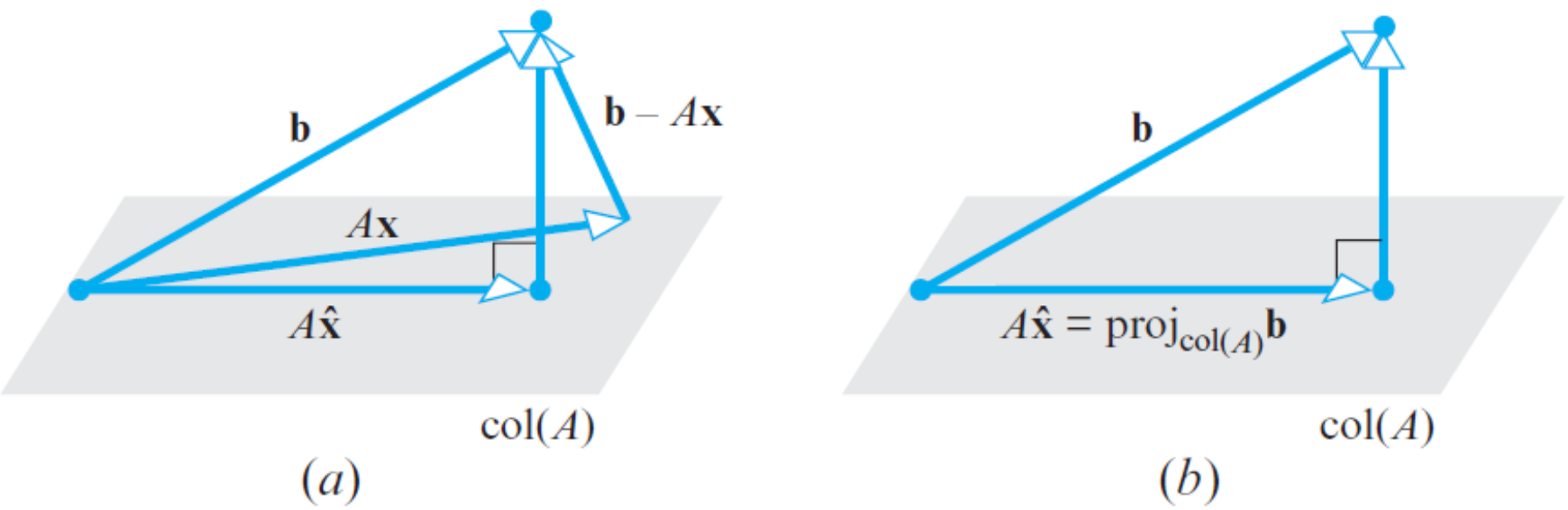
Topic : **Solving the Least Squares Problem**

Concept : **Best Approx. Theorem and Normal Equation**

Instructor: **A/P Chng Eng Siong**

TAs: **Zhang Su, Vishal Choudhari**

# Best Approximation Theorem



**THEOREM 6.4.1 Best Approximation Theorem**  
*If  $W$  is a finite-dimensional subspace of an inner product space  $V$ , and if  $\mathbf{b}$  is a vector in  $V$ , then  $\text{proj}_W \mathbf{b}$  is the **best approximation** to  $\mathbf{b}$  from  $W$  in the sense that*

$$\|\mathbf{b} - \text{proj}_W \mathbf{b}\| < \|\mathbf{b} - \mathbf{w}\|$$

*for every vector  $\mathbf{w}$  in  $W$  that is different from  $\text{proj}_W \mathbf{b}$ .*

**Proof** For every vector  $\mathbf{w}$  in  $W$ , we can write

$$\mathbf{b} - \mathbf{w} = (\mathbf{b} - \text{proj}_W \mathbf{b}) + (\text{proj}_W \mathbf{b} - \mathbf{w})$$

But  $\text{proj}_W \mathbf{b} - \mathbf{w}$ , being a difference of vectors in  $W$ , is itself in  $W$ ; and since  $\mathbf{b} - \text{proj}_W \mathbf{b}$  is orthogonal to  $W$ , the two terms on the right side of (1) are orthogonal. Thus, it follows from the Theorem of Pythagoras (Theorem 6.2.3) that

$$\|\mathbf{b} - \mathbf{w}\|^2 = \|\mathbf{b} - \text{proj}_W \mathbf{b}\|^2 + \|\text{proj}_W \mathbf{b} - \mathbf{w}\|^2$$

If  $\mathbf{w} \neq \text{proj}_W \mathbf{b}$ , it follows that the second term in this sum is positive, and hence that

$$\|\mathbf{b} - \text{proj}_W \mathbf{b}\|^2 < \|\mathbf{b} - \mathbf{w}\|^2$$

Since norms are nonnegative, it follows (from a property of inequalities) that

$$\|\mathbf{b} - \text{proj}_W \mathbf{b}\| < \|\mathbf{b} - \mathbf{w}\| \quad \blacktriangleleft$$



# The Normal Equation

$$Ax = b$$

Multiplying both sides by  $A^T$

$$A^T A x = A^T b$$

Normal Equation!

The set of least-squares solutions of  $Ax = b$  coincides with the nonempty set of solutions of the normal equations  $A^T A x = A^T b$ .

Proved in the next slide!

## Solution of the General Least-Squares Problem

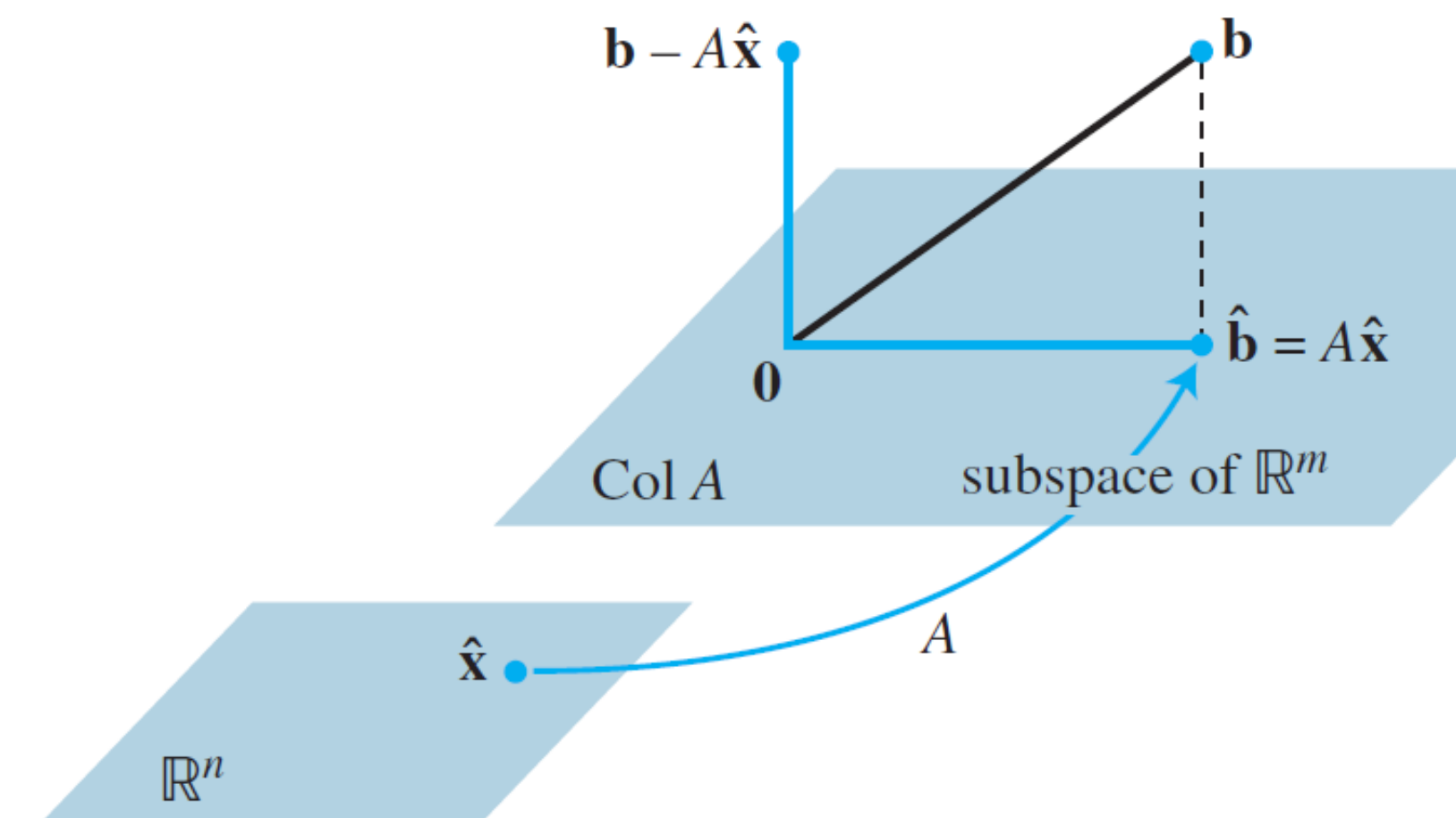
Given  $A$  and  $b$  as above, apply the Best Approximation Theorem in Section 6.3 to the subspace  $\text{Col } A$ . Let

$$\hat{b} = \text{proj}_{\text{Col } A} b$$

Because  $\hat{b}$  is in the column space of  $A$ , the equation  $Ax = \hat{b}$  is consistent, and there is an  $\hat{x}$  in  $\mathbb{R}^n$  such that

$$A\hat{x} = \hat{b} \quad (1)$$

Since  $\hat{b}$  is the closest point in  $\text{Col } A$  to  $b$ , a vector  $\hat{x}$  is a least-squares solution of  $Ax = b$  if and only if  $\hat{x}$  satisfies (1). Such an  $\hat{x}$  in  $\mathbb{R}^n$  is a list of weights that will build  $\hat{b}$  out of the columns of  $A$ . See Fig. 2. [There are many solutions of (1) if the equation has free variables.]



**FIGURE 2** The least-squares solution  $\hat{x}$  is in  $\mathbb{R}^n$ .

Why called “Normal”?

Ref: <https://mathworld.wolfram.com/NormalEquation.html>

Lay, Linear Algebra and its Applications (4<sup>th</sup> Edition)

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# The Normal Equation Proof

Suppose  $\hat{\mathbf{x}}$  satisfies  $A\hat{\mathbf{x}} = \hat{\mathbf{b}}$ . By the Orthogonal Decomposition Theorem in Section 6.3, the projection  $\hat{\mathbf{b}}$  has the property that  $\mathbf{b} - \hat{\mathbf{b}}$  is orthogonal to  $\text{Col } A$ , so  $\mathbf{b} - A\hat{\mathbf{x}}$  is orthogonal to each column of  $A$ . If  $\mathbf{a}_j$  is any column of  $A$ , then  $\mathbf{a}_j \cdot (\mathbf{b} - A\hat{\mathbf{x}}) = 0$ , and  $\mathbf{a}_j^T (\mathbf{b} - A\hat{\mathbf{x}}) = 0$ . Since each  $\mathbf{a}_j^T$  is a row of  $A^T$ ,

$$A^T (\mathbf{b} - A\hat{\mathbf{x}}) = \mathbf{0} \quad (2)$$

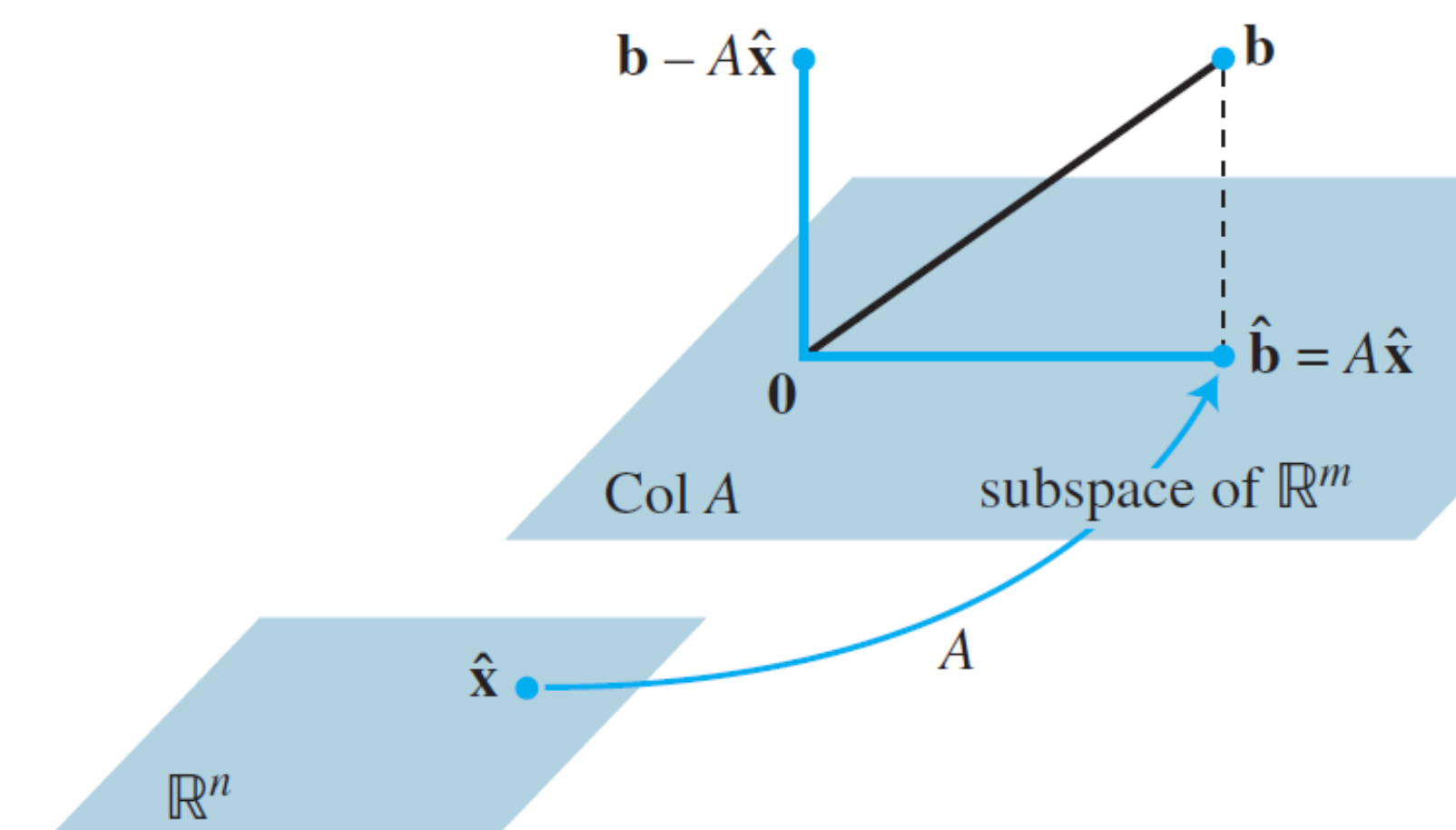
(This equation also follows from Theorem 3 in Section 6.1.) Thus

$$\begin{aligned} A^T \mathbf{b} - A^T A \hat{\mathbf{x}} &= \mathbf{0} \\ A^T A \hat{\mathbf{x}} &= A^T \mathbf{b} \end{aligned}$$

These calculations show that each least-squares solution of  $A\mathbf{x} = \mathbf{b}$  satisfies the equation

$$A^T A \mathbf{x} = A^T \mathbf{b} \quad (3)$$

The matrix equation (3) represents a system of equations called the **normal equations** for  $A\mathbf{x} = \mathbf{b}$ . A solution of (3) is often denoted by  $\hat{\mathbf{x}}$ .



**FIGURE 2** The least-squares solution  $\hat{\mathbf{x}}$  is in  $\mathbb{R}^n$ .

## THEOREM 14

Let  $A$  be an  $m \times n$  matrix. The following statements are logically equivalent:

- The equation  $A\mathbf{x} = \mathbf{b}$  has a unique least-squares solution for each  $\mathbf{b}$  in  $\mathbb{R}^m$ .
- The columns of  $A$  are linearly independent.
- The matrix  $A^T A$  is invertible.

When these statements are true, the least-squares solution  $\hat{\mathbf{x}}$  is given by

$$\hat{\mathbf{x}} = (A^T A)^{-1} A^T \mathbf{b} \quad (4)$$

# Examples

**EXAMPLE 1** Find a least-squares solution of the inconsistent system  $A\mathbf{x} = \mathbf{b}$  for

$$A = \begin{bmatrix} 4 & 0 \\ 0 & 2 \\ 1 & 1 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 2 \\ 0 \\ 11 \end{bmatrix}$$

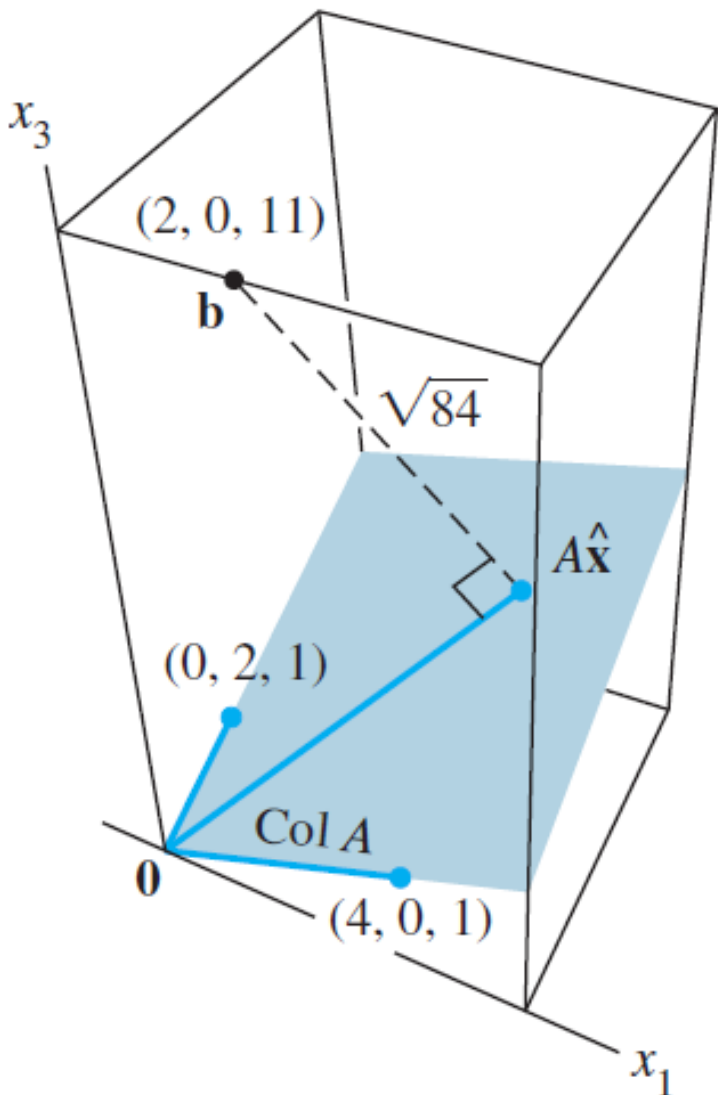
**SOLUTION** To use normal equations (3), compute:

$$A^T A = \begin{bmatrix} 4 & 0 & 1 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 2 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 17 & 1 \\ 1 & 5 \end{bmatrix}$$

$$A^T \mathbf{b} = \begin{bmatrix} 4 & 0 & 1 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 0 \\ 11 \end{bmatrix} = \begin{bmatrix} 19 \\ 11 \end{bmatrix}$$

Then the equation  $A^T A \mathbf{x} = A^T \mathbf{b}$  becomes

$$\begin{bmatrix} 17 & 1 \\ 1 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 19 \\ 11 \end{bmatrix}$$



Row operations can be used to solve this system, but since  $A^T A$  is invertible and  $2 \times 2$ , it is probably faster to compute

$$(A^T A)^{-1} = \frac{1}{84} \begin{bmatrix} 5 & -1 \\ -1 & 17 \end{bmatrix}$$

and then to solve  $A^T A \mathbf{x} = A^T \mathbf{b}$  as

$$\begin{aligned} \hat{\mathbf{x}} &= (A^T A)^{-1} A^T \mathbf{b} \\ &= \frac{1}{84} \begin{bmatrix} 5 & -1 \\ -1 & 17 \end{bmatrix} \begin{bmatrix} 19 \\ 11 \end{bmatrix} = \frac{1}{84} \begin{bmatrix} 84 \\ 168 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \end{aligned}$$

In many calculations,  $A^T A$  is invertible, but this is not always the case. The next

FIGURE 3

# Examples

**EXAMPLE 3** Given  $A$  and  $\mathbf{b}$  as in Example 1, determine the least-squares error in the least-squares solution of  $A\mathbf{x} = \mathbf{b}$ .

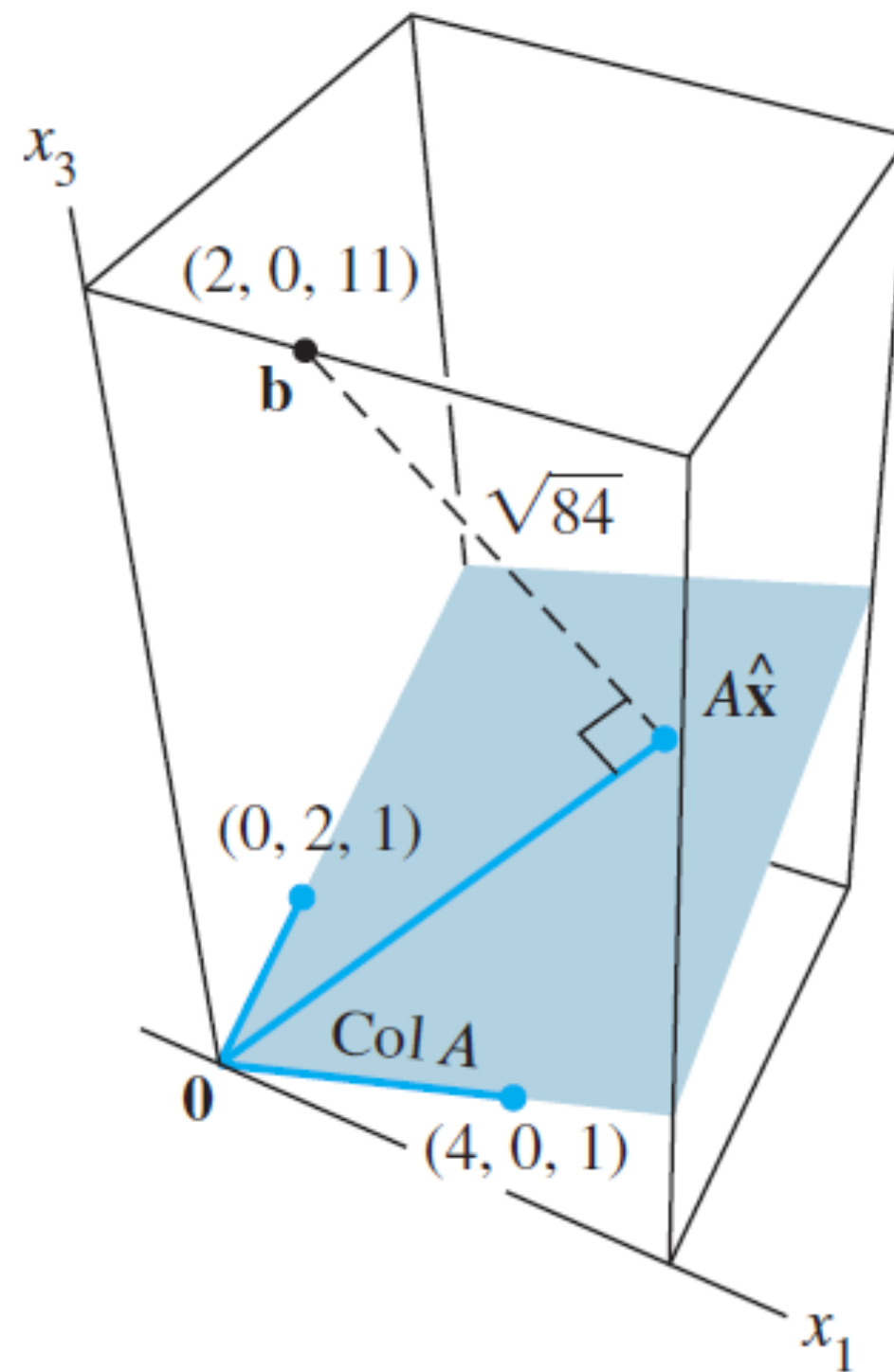


FIGURE 3

**SOLUTION** From Example 1,

$$\mathbf{b} = \begin{bmatrix} 2 \\ 0 \\ 11 \end{bmatrix} \quad \text{and} \quad A\hat{\mathbf{x}} = \begin{bmatrix} 4 & 0 \\ 0 & 2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \\ 3 \end{bmatrix}$$

Hence

$$\mathbf{b} - A\hat{\mathbf{x}} = \begin{bmatrix} 2 \\ 0 \\ 11 \end{bmatrix} - \begin{bmatrix} 4 \\ 4 \\ 3 \end{bmatrix} = \begin{bmatrix} -2 \\ -4 \\ 8 \end{bmatrix}$$

and

$$\|\mathbf{b} - A\hat{\mathbf{x}}\| = \sqrt{(-2)^2 + (-4)^2 + 8^2} = \sqrt{84}$$

The least-squares error is  $\sqrt{84}$ . For any  $\mathbf{x}$  in  $\mathbb{R}^2$ , the distance between  $\mathbf{b}$  and the vector  $A\mathbf{x}$  is at least  $\sqrt{84}$ . See Fig. 3. Note that the least-squares solution  $\hat{\mathbf{x}}$  itself does not appear in the figure. ■



# Examples

**EXAMPLE 2** Find a least-squares solution of  $A\mathbf{x} = \mathbf{b}$  for

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} -3 \\ -1 \\ 0 \\ 2 \\ 5 \\ 1 \end{bmatrix}$$

- Note the linear dependency in the rows and columns of  $A$ :**
- Column 1 = Column 2 + Column 3 + Column 4
  - Rows 1 & 2 are same, but their corresponding  $b$  values are different (inconsistent)
  - Rows 3 & 4 are same, but their corresponding  $b$  values are different (inconsistent)
  - Rows 5 & 6 are same, but their corresponding  $b$  values are different (inconsistent)

**SOLUTION** Compute

$$A^T A = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 6 & 2 & 2 & 2 \\ 2 & 2 & 0 & 0 \\ 2 & 0 & 2 & 0 \\ 2 & 0 & 0 & 2 \end{bmatrix}$$

$$A^T \mathbf{b} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} -3 \\ -1 \\ 0 \\ 2 \\ 5 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ -4 \\ 2 \\ 6 \end{bmatrix}$$

**Note that  $A^T A$  is always a square matrix.**

The augmented matrix for  $A^T A \mathbf{x} = A^T \mathbf{b}$  is

Reduced to

$$\begin{bmatrix} 6 & 2 & 2 & 2 & 4 \\ 2 & 2 & 0 & 0 & -4 \\ 2 & 0 & 2 & 0 & 2 \\ 2 & 0 & 0 & 2 & 6 \end{bmatrix} \sim \begin{bmatrix} 1 & 0 & 0 & 1 & 3 \\ 0 & 1 & 0 & -1 & -5 \\ 0 & 0 & 1 & -1 & -2 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$A^T A$        $A^T b$

The general solution is  $x_1 = 3 - x_4$ ,  $x_2 = -5 + x_4$ ,  $x_3 = -2 + x_4$ , and  $x_4$  is free. So the general least-squares solution of  $A\mathbf{x} = \mathbf{b}$  has the form

$$\hat{\mathbf{x}} = \begin{bmatrix} 3 \\ -5 \\ -2 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

**Note:** Here, there are infinitely many solutions with the same least square error. **Note:** Here,  $A^T A$  is not invertible (its determinant is 0).

$A^T A$  may not be invertible if:

- some columns are linearly dependent (i.e. we have redundant features) (as in this example)
  - solution: remove the linear dependency
- too many features ( $m < n$ )
  - solution: delete some features, there are too many features for the amount of data we have

Ref: [http://mlwiki.org/index.php/Normal\\_Equation](http://mlwiki.org/index.php/Normal_Equation)

Ref: Andrew Ng discussing this phenomenon-  
<https://www.coursera.org/lecture/machine-learning/normal-equation-noninvertibility-zSiE6>

# Examples

```
% pg 362 Lay's book, Example 2 - Least Squares, when A'A is singular
close all; clear all;
A = [1 1 0 0; 1 1 0 0; 1 0 1 0; 1 0 1 0; 1 0 0 1; 1 0 0 1];
b = [-3 -1 0 2 5 1]';

AtA = A'*A
rank_Ata = rank(AtA) % A'*A is singular, we check its rank

% Ax = b;
x1 = pinv(A)*b
x2 = inv(A'*A)*A'*b % This is what we think we should do
% compare inv(A'*A) bs pinv(A'*A)
disp("using normal inverser (A'*A):");
inv(A'*A)
disp("using pinverser (A'*A):");
pinv(A'*A)

x3 = pinv(A'*A)*A'*b % This is what Andy Ng suggest to d
```

AtA =

6	2	2	2
2	2	0	0
2	0	2	0
2	0	0	2

rank\_Ata =

3

x1 =

0.5000
-2.5000
0.5000
2.5000

x2 =

1
-3
0
2

Warning: Matrix is close to singular or badly scaled.  
> In [Lay\\_example2\\_pg362](#) (line 8)

$A^T A$

ans =

1.0e+15 *			
1.5012	-1.5012	-1.5012	-1.5012
-1.5012	1.5012	1.5012	1.5012
-1.5012	1.5012	1.5012	1.5012
-1.5012	1.5012	1.5012	1.5012

$A^T A$  is non-invertible. Hence MATLAB computes its inverse as a very large value  $\Rightarrow \infty$

ans =

0.0938	0.0312	0.0313	0.0313
0.0313	0.3437	-0.1562	-0.1563
0.0312	-0.1562	0.3438	-0.1562
0.0313	-0.1562	-0.1563	0.3438

x3 =

0.5000
-2.5000
0.5000
2.5000

NOTE: Pseudo-inverse (pinv) will be introduced later.



# Reference

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## Some Useful readings:

- 1) Fogel: Learning Goals: find the best solution (by one measure, anyway) of inconsistent equation. Learn to apply the algebra, geometry, and calculus of projections to this problem.  
<http://staff.imsa.edu/~fogel/LinAlg/PDF/33%20Least%20Squares.pdf>
- 2) Why normal equation always have a solution: unique or infinite even if A has dependent column
  - a) <https://math.stackexchange.com/questions/2920398/how-do-the-normal-equations-always-have-a-solution>
  - b) <https://math.stackexchange.com/questions/72222/existence-of-least-squares-solution-to-ax-b>
  - c) <https://stats.stackexchange.com/questions/63143/question-about-a-normal-equation-proof>
- 3) Prof Walker, Worcester Polytechnic Institute: [https://users.wpi.edu/~walker/MA3257/HANDOUTS/least-squares\\_handout.pdf](https://users.wpi.edu/~walker/MA3257/HANDOUTS/least-squares_handout.pdf)

# Reference

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- 3) Prof Walker, Worcester Polytechnic Institute: [https://users.wpi.edu/~walker/MA3257/HANDOUTS/least-squares\\_handout.pdf](https://users.wpi.edu/~walker/MA3257/HANDOUTS/least-squares_handout.pdf)