

International University
School of Electrical Engineering

Introduction to Computers for Engineers

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Lecturely Topics

- Lecture 1 - Basics – variables, arrays, matrices
- Lecture 2 - Basics – matrices, operators, strings, cells
- Lecture 3 - Functions & Plotting
- Lecture 4 - User-defined Functions
- Lecture 5 - Relational & logical operators, if, switch statements
- Lecture 6 - For-loops, while-loops
- Lecture 7 - Review on Midterm Exam**
- Lecture 8 - Solving Equations & Equation System (Matrix algebra)
- Lecture 9 - Data Fitting & Integral Computation
- Lecture 10 - Representing Signal and System
- Lecture 11 - Random variables & Wireless System
- Lecture 12 - Review on Final Exam**

References: H. Moore, *MATLAB for Engineers*, 4/e, Prentice Hall, 2014
G. Recktenwald, *Numerical Methods with MATLAB*, Prentice Hall, 2000
A. Gilat, *MATLAB, An Introduction with Applications*, 4/e, Wiley, 2011

Matrix Algebra


- dot product
- matrix-vector multiplication
- matrix-matrix multiplication
- matrix inverse
- solving linear systems
- least-squares solutions
- determinant, rank, condition number
- vector & matrix norms
- iterative solutions of linear systems
- examples
- electric circuits
- temperature distributions

Operators and Expressions

operation	element-wise	matrix-wise
addition	+	+
subtraction	-	-
multiplication	.*	*
division	./	/
left division	.\	\
exponentiation	.^	^
transpose w/o complex conjugation		.'
transpose with complex conjugation		'

```
>> help /  
>> help precedence
```

used in matrix
algebra operations



```
>> A = [1 2; 3 4]
```

```
A =
```

```
    1    2
    3    4
```

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 7 & 10 \\ 15 & 22 \end{bmatrix}$$

```
>> [A, A.^2; A^2, A*A]
```

```
% form sub-blocks
```

```
ans =
```

```
    1    2    1    4
    3    4    9   16
-----
    7   10    7   10
   15   22   15   22
```

```
% note A^2 = A*A
```

```
>> B = 10.^A;
```

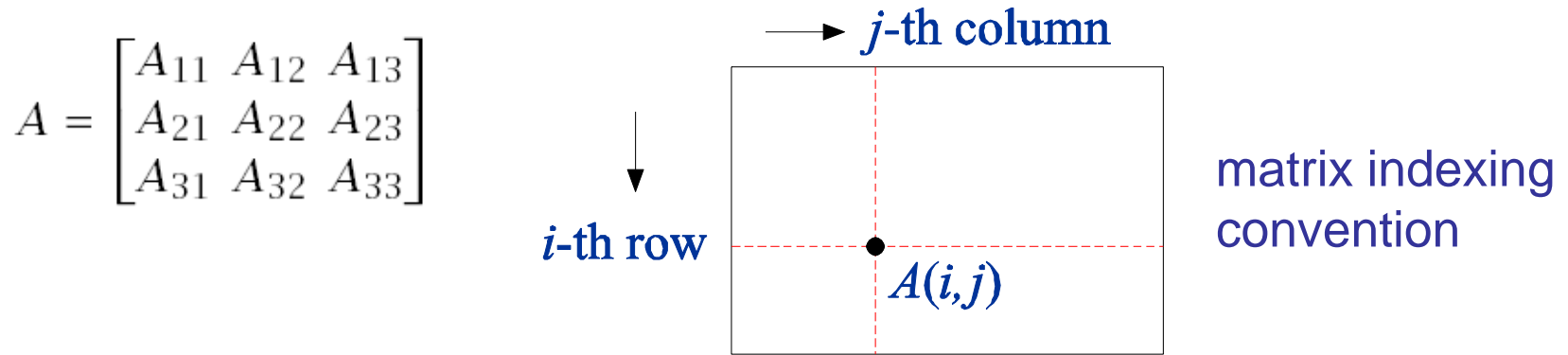
```
>> [B, log10(B)]
```

```
ans =
```

```
    10    100
  1000 10000
```

$$B = \begin{bmatrix} 10^1 & 10^2 \\ 10^3 & 10^4 \end{bmatrix}$$

```
    1    2
    3    4
```



```
>> A = [1 2 3; 2 0 4; 0 8 5]
```

```
A =
```

```
    1    2    3
    2    0    4
    0    8    5
```

```
>> size(A)           % [N,M] = size(A) , NxM matrix
```

```
ans =
```

```
    3    3
```

dot product

The **dot product** is the basic operation in matrix-vector and matrix-matrix multiplications

$$\mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

\mathbf{a}, \mathbf{b} must have the same dimension

$$\mathbf{a}^T \mathbf{b} = [a_1, a_2, a_3] \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = a_1 b_1 + a_2 b_2 + a_3 b_3$$

$$\mathbf{a}^T \mathbf{b} = \mathbf{a}' \mathbf{b} = \mathbf{a} \cdot \mathbf{b} = \mathbf{a}.' * \mathbf{b}$$

math
notations

MATLAB
notation

dot product
for complex-valued vectors

complex-conjugate transpose,
or, hermitian conjugate of \mathbf{a}

$$\mathbf{a}^\dagger \mathbf{b} = [a_1^*, a_2^*, a_3^*] \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = a_1^* b_1 + a_2^* b_2 + a_3^* b_3$$

$$\mathbf{a}^\dagger \mathbf{b} = \mathbf{a}^H \mathbf{b} = \mathbf{a}' * \mathbf{b}$$

math
notations

MATLAB
notation

for real-valued vectors, the
operations $'$ and $.*'$
are equivalent

$$\mathbf{a} = \begin{bmatrix} 1 \\ 2 \\ -3 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 4 \\ -5 \\ 2 \end{bmatrix}$$

$$[1, 2, -3] \begin{bmatrix} 4 \\ -5 \\ 2 \end{bmatrix} = 1 \times 4 + 2 \times (-5) + (-3) \times 2 = -12$$

```
>> a = [1; 2; -3];  b = [4; -5; 2];  
>> a'*b  
ans =  
    -12  
>> dot(a,b)        % built-in function  
ans =                % same as sum(a.*b)  
    -12
```

matrix-vector multiplication

$$[4, 1, 2] \begin{bmatrix} 5 \\ -4 \\ -7 \end{bmatrix} = 2$$

$$[1, -1, 1] \begin{bmatrix} 5 \\ -4 \\ -7 \end{bmatrix} = 2$$

$$[2, 1, 1] \begin{bmatrix} 5 \\ -4 \\ -7 \end{bmatrix} = -1$$

combine three dot product operations into a single **matrix-vector** multiplication

$$\Rightarrow \begin{bmatrix} 4 & 1 & 2 \\ 1 & -1 & 1 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5 \\ -4 \\ -7 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ -1 \end{bmatrix}$$

matrix-vector multiplication

combine three dot product operations into a **single** matrix-vector multiplication

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + a_{12}x_2 + a_{13}x_3 \\ a_{21}x_1 + a_{22}x_2 + a_{23}x_3 \\ a_{31}x_1 + a_{32}x_2 + a_{33}x_3 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

$$\mathbf{A} \mathbf{x} = \mathbf{b}$$

matrix-matrix multiplication

$$\begin{bmatrix} 4 & 1 & 2 \\ 1 & -1 & 1 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5 \\ -4 \\ -7 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ -1 \end{bmatrix}$$

$$\begin{bmatrix} 4 & 1 & 2 \\ 1 & -1 & 1 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 3 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ -2 \\ 3 \end{bmatrix}$$

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

combine three matrix-vector
multiplications into a single
matrix-matrix multiplication

$$\begin{bmatrix} 4 & 1 & 2 \\ 1 & -1 & 1 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5 & -1 & -3 \\ -4 & 3 & 1 \\ -7 & 2 & 6 \end{bmatrix} = \begin{bmatrix} 2 & 3 & 1 \\ 2 & -2 & 2 \\ -1 & 3 & 1 \end{bmatrix}$$

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

```
A =
```

4	1	2
1	-1	1
2	1	1

```
>> B = [5 -1 -3; -4 3 1; -7 2 6]
```

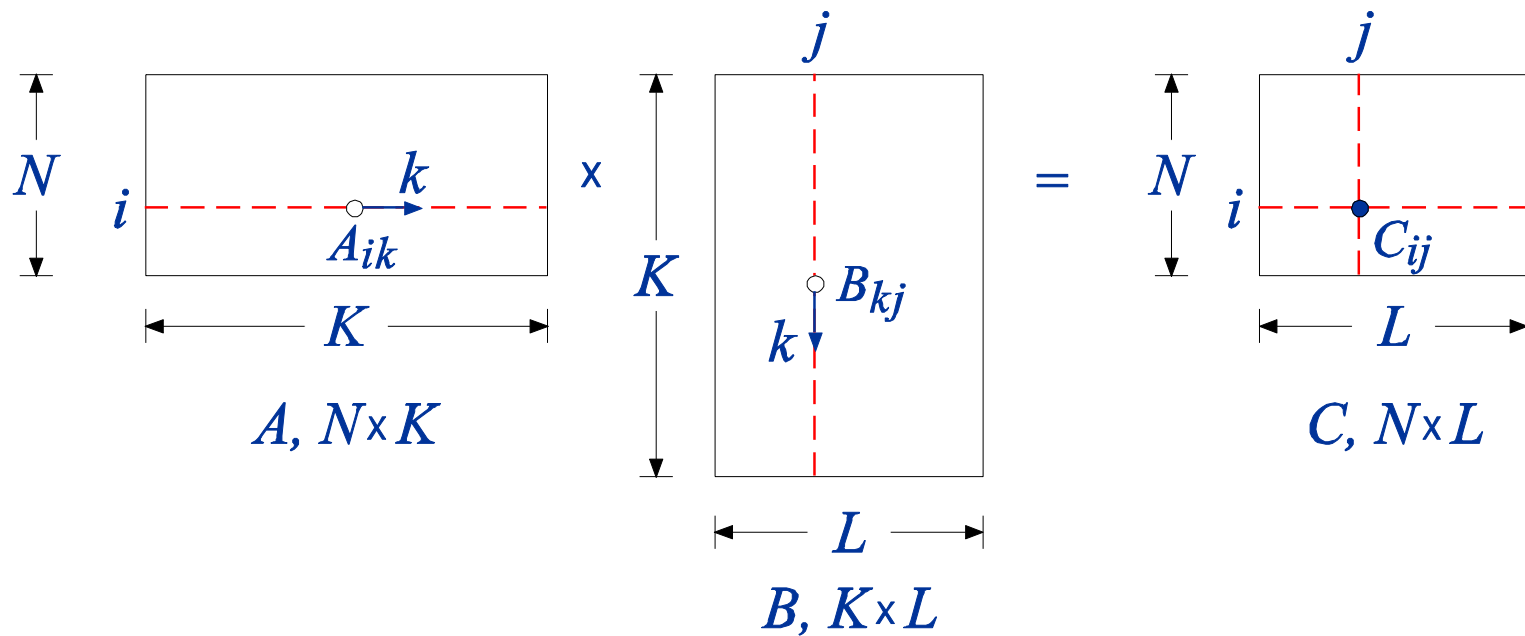
```
B =
```

5	-1	-3
-4	3	1
-7	2	6

```
>> C = A*B
```

```
C =
```

2	3	1
2	-2	2
-1	3	1



$$C_{ij} = \sum_{k=1}^K A_{ik} B_{kj}, \quad 1 \leq i \leq N, \quad 1 \leq j \leq L$$

$C(i,j)$ is the dot product of i -th row of A with j -th column of B

$$\begin{bmatrix} 4 & 1 & 2 \\ 1 & -1 & 1 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5 & -1 & -3 \\ -4 & 3 & 1 \\ -7 & 2 & 6 \end{bmatrix} = \begin{bmatrix} 2 & 3 & 1 \\ 2 & -2 & 2 \\ -1 & 3 & 1 \end{bmatrix}$$

note:

$$\mathbf{A} * \mathbf{B} \neq \mathbf{B} * \mathbf{A}$$

$$2 \times (-1) + 1 \times 3 + 1 \times 2 = 3$$

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} = \left[\begin{array}{c|c} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} \\ \hline a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} \end{array} \right]$$

Rule of thumb:

$$(N \times K) \times (K \times M) \longrightarrow N \times M$$

A is $N \times K$

B is $K \times M$

then, $A \times B$ is $N \times M$

vector-vector multiplication

$$[a_1, a_2, a_3] \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = a_1 b_1 + a_2 b_2 + a_3 b_3$$

$(1 \times 3) \times (3 \times 1) \rightarrow 1 \times 1 = \text{scalar}$
row * column = scalar

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} [b_1, b_2, b_3] = \begin{bmatrix} a_1 b_1 & a_1 b_2 & a_1 b_3 \\ a_2 b_1 & a_2 b_2 & a_2 b_3 \\ a_3 b_1 & a_3 b_2 & a_3 b_3 \end{bmatrix}$$

$(3 \times 1) \times (1 \times 3) \rightarrow 3 \times 3$
column * row = matrix

vector-vector multiplication

```
>> [1, 2, 3] * [2 -3 -1]'
```

```
ans =
```

```
-7
```

```
>> [1, 2, 3]' * [2 -3 -1]
```

```
ans =
```

```
2    -3    -1
4    -6    -2
6    -9    -3
```

row \times column
= scalar

column \times row
= matrix

solving linear systems

$$\mathbf{A} \mathbf{x} = \mathbf{b}$$

Linear equations have a very large number of applications in engineering, science, social sciences, and economics

Linear Programming – Management Science

Computer Aided Design – aerodynamics of cars, planes

Signal Processing, Communications, Control, Radar, Sonar, Electromagnetics, Oil Exploration, Computer Vision, Pattern & Face Recognition

Chip Design – millions of transistors on a chip

Economic Models, Finance, Statistical Models, Data Mining, Social Models, Financial Engineering

Markov Models – Speech, Biology, Google Pagerank

Scientific Computing – solving very large problems

the only practical way to solve very large systems is iteratively

solving linear systems

$$\begin{array}{rcl} 2x_1 + x_2 & = & 4 \\ x_1 + 5x_2 - x_3 & = & 8 \\ x_1 - 2x_2 + 4x_3 & = & 9 \end{array} \Rightarrow \begin{bmatrix} 2 & 1 & 0 \\ 1 & 5 & -1 \\ 1 & -2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 4 \\ 8 \\ 9 \end{bmatrix}$$

matrix
inverse

$$A\mathbf{x} = \mathbf{b}$$

$$A\mathbf{x} = \mathbf{b} \Rightarrow \mathbf{x} = A^{-1}\mathbf{b} = A \setminus \mathbf{b}$$

always use the **backslash** operator to solve a linear system, instead of **inv(A)**

solving linear systems (using backslash)

$$\begin{array}{rcl} 2x_1 + x_2 & = & 4 \\ x_1 + 5x_2 - x_3 & = & 8 \\ x_1 - 2x_2 + 4x_3 & = & 9 \end{array} \Rightarrow \begin{bmatrix} 2 & 1 & 0 \\ 1 & 5 & -1 \\ 1 & -2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 4 \\ 8 \\ 9 \end{bmatrix}$$

```
>> A = [2 1 0; 1 5 -1; 1 -2 4];  
>> b = [4 8 9]';  
>> x = A\b  
x =  
    1  
    2  
    3  
  
>> norm(A*x-b) % test - should be zero  
ans =  
    0 % or, of the order of eps
```

solving linear systems (using inv)

```
>> A = [2 1 0; 1 5 -1; 1 -2 4];
>> b = [4 8 9]';
>> inv(A)                                % same as A^(-1)
ans =
    0.5806    -0.1290    -0.0323
   -0.1613     0.2581     0.0645
   -0.2258     0.1613     0.2903

>> x = inv(A) * b                        % but prefer backslash
x =                                       % same as x = A^-1 * b
    1.0000
    2.0000
    3.0000

>> norm(A*x-b)
ans =
    1.8310e-015
```

```
>> inv(sym(A))
ans =
[ 18/31, -4/31, -1/31]
[ -5/31,  8/31,  2/31]
[ -7/31,  5/31,  9/31]
```

solving linear systems – back-slash and forward-slash

A of size **N×N** and invertible

X of size **N×K**

B of size **N×K**

equivalent

$$\mathbf{AX} = \mathbf{B} \quad \longrightarrow \quad \mathbf{X} = \mathbf{A} \backslash \mathbf{B} = \text{inv}(\mathbf{A}) * \mathbf{B}$$

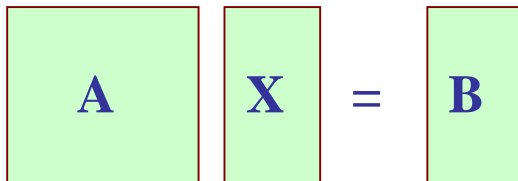
A of size **N×N** and invertible

X of size **K×N**

B of size **K×N**

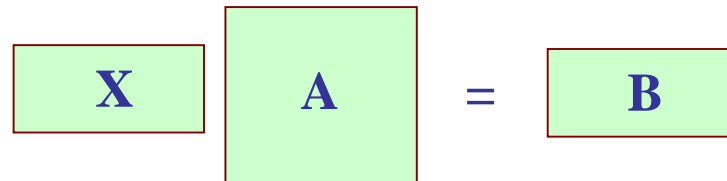
equivalent

$$\mathbf{XA} = \mathbf{B} \quad \longrightarrow \quad \mathbf{X} = \mathbf{B} / \mathbf{A} = \mathbf{B} * \text{inv}(\mathbf{A})$$



A diagram showing three light green rectangular boxes. The first box contains the letter 'A' and is wider than it is tall. The second box contains the letter 'X' and is taller than it is wide. These two boxes are followed by an equals sign and a third box containing the letter 'B', which is the same width as 'A' and taller than 'X'.

$$\mathbf{A} \mathbf{X} = \mathbf{B}$$



A diagram showing three light green rectangular boxes. The first box contains the letter 'X' and is taller than it is wide. The second box contains the letter 'A' and is wider than it is tall. These two boxes are followed by an equals sign and a third box containing the letter 'B', which is the same width as 'A' and taller than 'X'.

$$\mathbf{X} \mathbf{A} = \mathbf{B}$$

solving linear systems – least-squares solutions

A of size **NxM**

x of size **Mx1** column

b of size **Nx1** column

$$\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$$

pseudo-inverse

$$\mathbf{x} = \text{pinv}(\mathbf{A}) * \mathbf{b};$$

```
>> help \  
>> help pinv
```

will be used in
in weeks 11 & 12

$\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$ is a solution of $\mathbf{Ax} = \mathbf{b}$

in a **least-squares** sense,

i.e., \mathbf{x} minimizes the norm squared
of the error $\mathbf{e} = \mathbf{b} - \mathbf{A} * \mathbf{x}$:

$$(\mathbf{b} - \mathbf{Ax})' * (\mathbf{b} - \mathbf{Ax}) = \min$$

\mathbf{x} may or may not be unique
depending on whether the linear
system $\mathbf{Ax} = \mathbf{b}$ is over-determined,
under-determined, or whether \mathbf{A} has
full rank or not

least-squares solutions - summary

Fundamental Theorem of
Linear Algebra – what is it?

$\mathbf{A} = \mathbf{N} \times \mathbf{M}$ matrix

$\mathbf{A}' = \mathbf{M} \times \mathbf{N}$ matrix

$\mathbf{x} = \mathbf{M} \times 1$ column

$\mathbf{A}' * \mathbf{A} = \mathbf{M} \times \mathbf{M}$ matrix

$\mathbf{b} = \mathbf{N} \times 1$ column

$\mathbf{A}' * \mathbf{b} = \mathbf{M} \times 1$ column

Assuming **full rank** for \mathbf{A} , we have the following cases:

1. $\mathbf{N} > \mathbf{M}$, **overdetermined case**, (most common in practice)

$\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$ = unique least-squares solution, same as

$\mathbf{x} = \text{pinv}(\mathbf{A}) * \mathbf{b}$, and

$\mathbf{x} = (\mathbf{A}' * \mathbf{A})^{(-1)} * (\mathbf{A}' * \mathbf{b})$

$\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$ is numerically
the most accurate method

2. $\mathbf{N} < \mathbf{M}$, **underdetermined case**, (there are many solutions)

$\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$, $\mathbf{x} = \text{pinv}(\mathbf{A}) * \mathbf{b}$, are two possible solutions

3. $\mathbf{N} = \mathbf{M}$, **square invertible case**, \mathbf{x} is unique

$\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$ is equivalent to $\mathbf{x} = \mathbf{A}^{(-1)} * \mathbf{b}$

least-squares solutions - example

```
% overdetermined
% full-rank example

A = [1 2; 3 4; 5 6]
b = [4, 3, 8]';

x = A\b
% x = pinv(A)*b
% x = (A'*A)\(A'*b)

x =
    -1
     2
```

overdetermined system of
3 equations in 2 unknowns

$$x_1 + 2x_2 = 4$$

$$3x_1 + 4x_2 = 3$$

$$5x_1 + 6x_2 = 8$$

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix}$$

$$e = b - Ax = \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 - x_1 - 2x_2 \\ 3 - 3x_1 - 4x_2 \\ 8 - 5x_1 - 6x_2 \end{bmatrix} = \text{error}$$

least-squares solutions - example

$$J = e^T e = (b - Ax)^T (b - Ax) = x^T (A^T A) x - 2x^T (A^T b) + b^T b = \min$$

$$\frac{\partial J}{\partial x} = 2A^T(Ax - b) = 0 \quad \Rightarrow \quad x_{\text{opt}} = (A^T A)^{-1} A^T b$$

inverse exists because A was assumed to have full rank

$$J_{\min} = J|_{x=x_{\text{opt}}} = b^T b - b^T A (A^T A)^{-1} A^T b$$

minimized value of J
achieved at $x = x_{\text{opt}}$

$$J = (x - x_{\text{opt}})^T (A^T A) (x - x_{\text{opt}}) + J_{\min} \geq J_{\min}$$

strictly positive-definite quadratic form because of full rank of A , vanishes only at $x = x_{\text{opt}}$

least-squares solutions - example

```
A = [1 2; 3 4; 5 6]
b = [4, 3, 8]';

x_opt = (A'*A) \ (A'*b)

J_min = b'*b - ...
        b'*A*inv(A'*A)*A'*b

x_opt =
    -1
     2
J_min =
     6
```

$$A^T A = \begin{bmatrix} 1 & 3 & 5 \\ 2 & 4 & 6 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} = \begin{bmatrix} 35 & 44 \\ 44 & 56 \end{bmatrix}$$

$$A^T b = \begin{bmatrix} 1 & 3 & 5 \\ 2 & 4 & 6 \end{bmatrix} \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix} = \begin{bmatrix} 53 \\ 68 \end{bmatrix}$$

$$b^T b = [4, 3, 8] \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix} = 89$$

$$x_{\text{opt}} = (A^T A)^{-1} A^T b = \begin{bmatrix} -1 \\ 2 \end{bmatrix}, \quad J_{\text{min}} = b^T b - b^T A^T (A^T A)^{-1} A b = 6$$

least-squares solutions - example

$$e = b - Ax = \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 4 - x_1 - 2x_2 \\ 3 - 3x_1 - 4x_2 \\ 8 - 5x_1 - 6x_2 \end{bmatrix} = \text{error}$$

$$J = (4 - x_1 - 2x_2)^2 + (3 - 3x_1 - 4x_2)^2 + (8 - 5x_1 - 6x_2)^2$$

$$= [x_1, x_2] \begin{bmatrix} 35 & 44 \\ 44 & 56 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - 2 \cdot [53, 68] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + 89$$

$$= 35x_1^2 + 88x_1x_2 + 56x_2^2 - 106x_1 - 136x_2 + 89$$

$$= 35(x_1 + 1)^2 + 88(x_1 + 1)(x_2 - 2) + 56(x_2 - 2)^2 + 6$$

$$= [x_1 + 1, x_2 - 2] \begin{bmatrix} 35 & 44 \\ 44 & 56 \end{bmatrix} \begin{bmatrix} x_1 + 1 \\ x_2 - 2 \end{bmatrix} + 6, \quad x - x_{\text{opt}} = \begin{bmatrix} x_1 + 1 \\ x_2 - 2 \end{bmatrix}$$

least-squares solutions - example

$$J = 35(x_1 + 1)^2 + 88(x_1 + 1)(x_2 - 2) + 56(x_2 - 2)^2 + 6 \geq 6$$

J is minimized at $x_1 = -1$, $x_2 = 2$, with minimum value, $J = 6$

```
% we can also minimize J with fminsearch,  
% i.e., the multivariable version of fminbnd  
  
J = @(x) 35*(x(1)+1).^2 +...  
        88*(x(1)+1).*(x(2)-2)+...  
        56*(x(2)-2).^2 + 6;  
  
x0 = [0,0]';    % arbitrary initial search point  
  
[xmin,Jmin] = fminsearch(J,x0)  
  
% xmin =                % Jmin = 6  
%      -1.0000  
%      2.0000
```

Invertibility, rank, determinants, condition number

The inverse **inv**(**A**) of an **NxN** square matrix **A** exists if its **determinant** is non-zero, or, equivalently if it has **full rank**, i.e., when its **rank** is equal to the row or column dimension **N**

```
>> doc inv  
>> doc det  
>> doc rank  
>> doc cond
```

```
a = [1 2 3]'; b = [4 5 6]';  
A = [a, a+b, b]
```

```
A =  
  
     1     5     4  
     2     7     5  
     3     9     6
```

det(**A**) = 0

```
>> det(A)  
  
ans =  
  
     0  
  
>> rank(A)  
  
ans =  
  
     2
```

Invertibility, rank, determinants, condition number

The larger the **cond(A)** the more ill-conditioned the linear system, and the less reliable the solution.

```
A = [1, 5, 4  
      2, 7 + 1e-8, 5  
      3, 9, 6];
```

```
>> cond(A)  
ans =  
      3.3227e+009
```

```
A\[1; 2; 3]
```

```
ans =  
      1  
      0  
      0
```

```
A\[1.001; 2.0002; 3.000003]
```

```
ans =  
      30150.999185  
     -30150.000183  
      30150.000683
```

```
det(A) = -6.0000e-008
```

Determinant and inverse of a 2x2 matrix

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

$$A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

$$\det(A) = ad - bc$$

Example: $\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}^{-1} = \frac{1}{4 - 6} \begin{bmatrix} 4 & -2 \\ -3 & 1 \end{bmatrix} = \begin{bmatrix} -2 & 1 \\ 1.5 & -0.5 \end{bmatrix}$

Matrix Exponential

Used widely in solving linear dynamic systems

$$\exp(A) = \sum_{n=0}^{\infty} \frac{A^n}{n!} = 1 + A + \frac{A^2}{2!} + \frac{A^3}{3!} + \dots$$

```
>> A = [1 2; 3 4];
```

$$A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$

```
>> expm(A)           % matrix exponential
```

```
ans =
```

```
    51.9690    74.7366  
   112.1048   164.0738
```

```
>> exp(A)            % element-wise exponential
```

```
ans =
```

```
    2.7183    7.3891  
   20.0855   54.5982
```

```
>> doc expm  
>> doc exp
```

Vector & Matrix Norms

>> doc norm

L_1 , L_2 , and L_∞ norms of a vector

$$\mathbf{x} = [x_1, x_2, \dots, x_N]$$

$$\|\mathbf{x}\|_1 = \sum_{n=1}^N |x_n|$$

L_1 norm

$$\|\mathbf{x}\|_2 = \sqrt{\sum_{n=1}^N |x_n|^2}$$

Euclidean, L_2 norm

$$\|\mathbf{x}\|_\infty = \max(|x_1|, |x_2|, \dots, |x_N|)$$

L_∞ norm

$$d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|$$

used as distance
measure between
two vectors or
matrices

```
x = [1, -4, 5, 3]; p = inf;
```

```
switch p
```

```
    case 1
```

```
        N = sum(abs(x));
```

```
    case 2
```

```
        N = sqrt(sum(abs(x).^2));
```

```
    case inf
```

```
        N = max(abs(x));
```

```
    otherwise
```

```
        N = sqrt(sum(abs(x).^2));
```

```
end
```

equivalent calculation using
the built-in function **norm** :



```
% N = norm(x,1);
```

```
% N = norm(x,2);
```

```
% N = norm(x,inf);
```

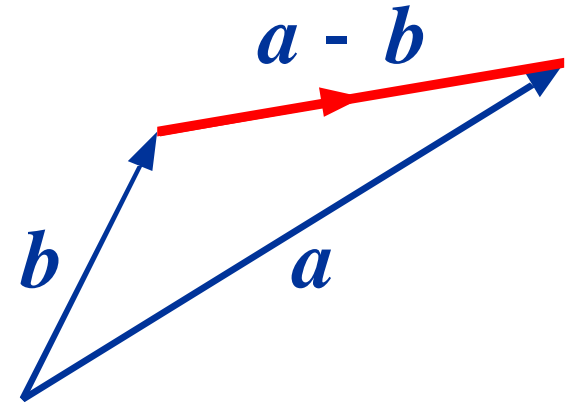
```
% N = norm(x,2);
```

useful for comparing two vectors or matrices

```
>> norm(a-b)           % a,b vectors of same size
```

```
>> norm(A-B)           % A,B matrices of same size
```

$$\mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$



$$\|\mathbf{a} - \mathbf{b}\|_2 = \text{norm}(\mathbf{a} - \mathbf{b})$$

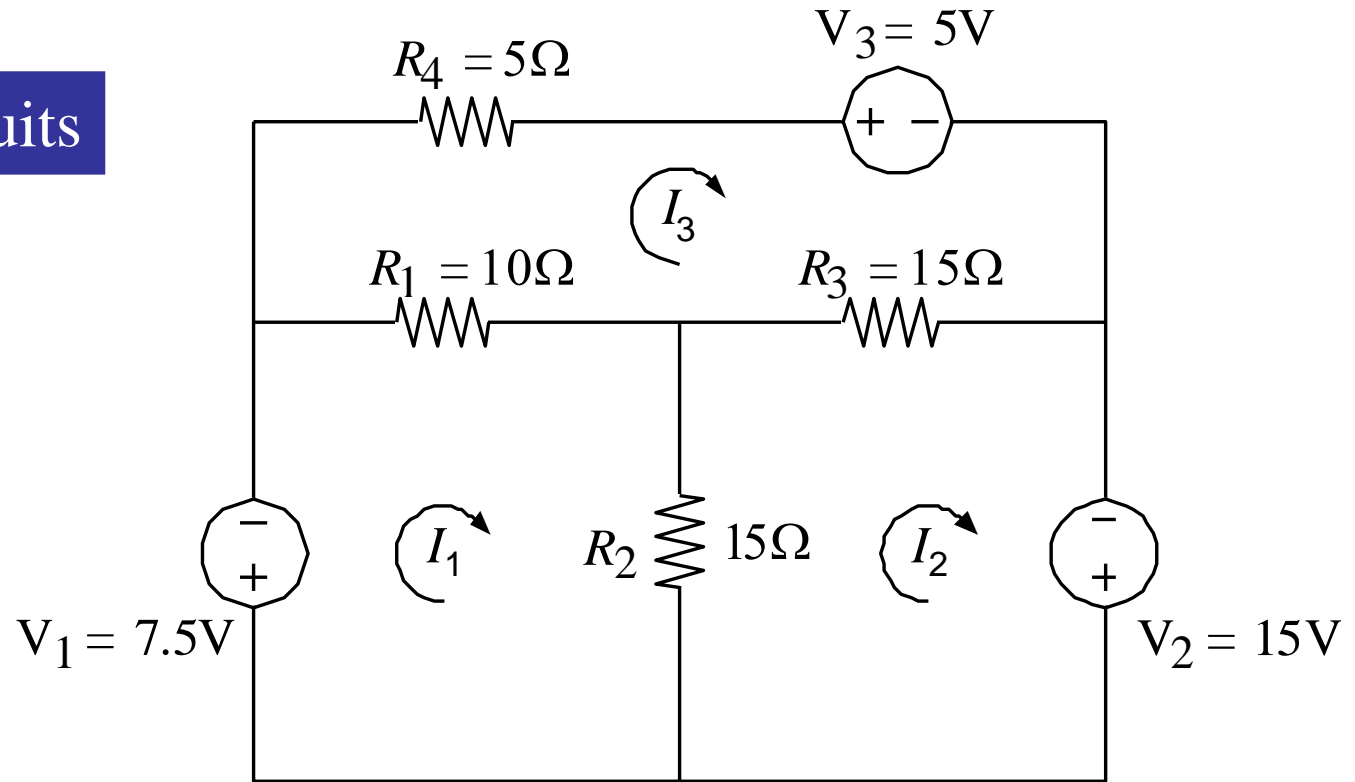
$$= \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2}$$

$$= \sqrt{(\mathbf{a} - \mathbf{b})' (\mathbf{a} - \mathbf{b})}$$

Euclidean distance

dot product

Electric Circuits



Kirchhoff's Voltage Law

$$R_1(I_1 - I_3) + R_2(I_1 - I_2) + V_1 = 0$$

$$R_2(I_2 - I_1) + R_3(I_2 - I_3) - V_2 = 0$$

$$R_4 I_3 + R_3(I_3 - I_2) + R_1(I_3 - I_1) + V_3 = 0$$

Electric Circuits

$$(R_1 + R_2)I_1 - R_2I_2 - R_1I_3 = -V_1$$

$$-R_2I_1 + (R_2 + R_3)I_2 - R_3I_3 = V_2$$

$$-R_1I_1 - R_3I_2 + (R_1 + R_3 + R_4)I_3 = -V_3$$

$$\begin{bmatrix} R_1 + R_2 & -R_2 & -R_1 \\ -R_2 & R_2 + R_3 & -R_3 \\ -R_1 & -R_3 & R_1 + R_3 + R_4 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} -V_1 \\ V_2 \\ -V_3 \end{bmatrix}$$

$$R_1 = 10, \quad R_2 = 15, \quad R_3 = 15, \quad R_4 = 5$$

$$V_1 = 7.5, \quad V_2 = 15, \quad V_3 = 10$$

$$\begin{bmatrix} R_1 + R_2 & -R_2 & -R_1 \\ -R_2 & R_2 + R_3 & -R_3 \\ -R_1 & -R_3 & R_1 + R_3 + R_4 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} -V_1 \\ V_2 \\ -V_3 \end{bmatrix}$$

$$\begin{bmatrix} 25 & -15 & -10 \\ -15 & 30 & -15 \\ -10 & -15 & 30 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} -7.5 \\ 15 \\ -5 \end{bmatrix}$$

$$\mathbf{A} \mathbf{x} = \mathbf{b}$$


```
A = [25, -15, -10; -15, 30, -15; -10, -15, 30]
```

```
b = [-7.5; 15; -5]
```

```
A =
```

```
    25    -15    -10  
   -15     30   -15  
   -10    -15     30
```

```
b =
```

```
   -7.5000  
   15.0000  
   -5.0000
```

```
x = A\b
```

```
x =
```

```
    0.5000  
    1.0000  
    0.5000
```

$$\mathbf{x} = \begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 1.0 \\ 0.5 \end{bmatrix}$$

`inv(A)`

`ans =`

0.2571	0.2286	0.2000
0.2286	0.2476	0.2000
0.2000	0.2000	0.2000

`inv(sym(A)) --> (1/105) * [27 24 21`
 `24 26 21`
 `21 21 21]`

$$\mathbf{x} = A^{-1}\mathbf{b} = \frac{1}{105} \begin{bmatrix} 27 & 24 & 21 \\ 24 & 26 & 21 \\ 21 & 21 & 21 \end{bmatrix} \begin{bmatrix} -7.5 \\ 15 \\ -5 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 1.0 \\ 0.5 \end{bmatrix}$$