

# Introduction to Applied Scientific Computing using MATLAB

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# 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    1    2
 1000 10000    3    4
```

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

## 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

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

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

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

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

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

```
>> 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]
```

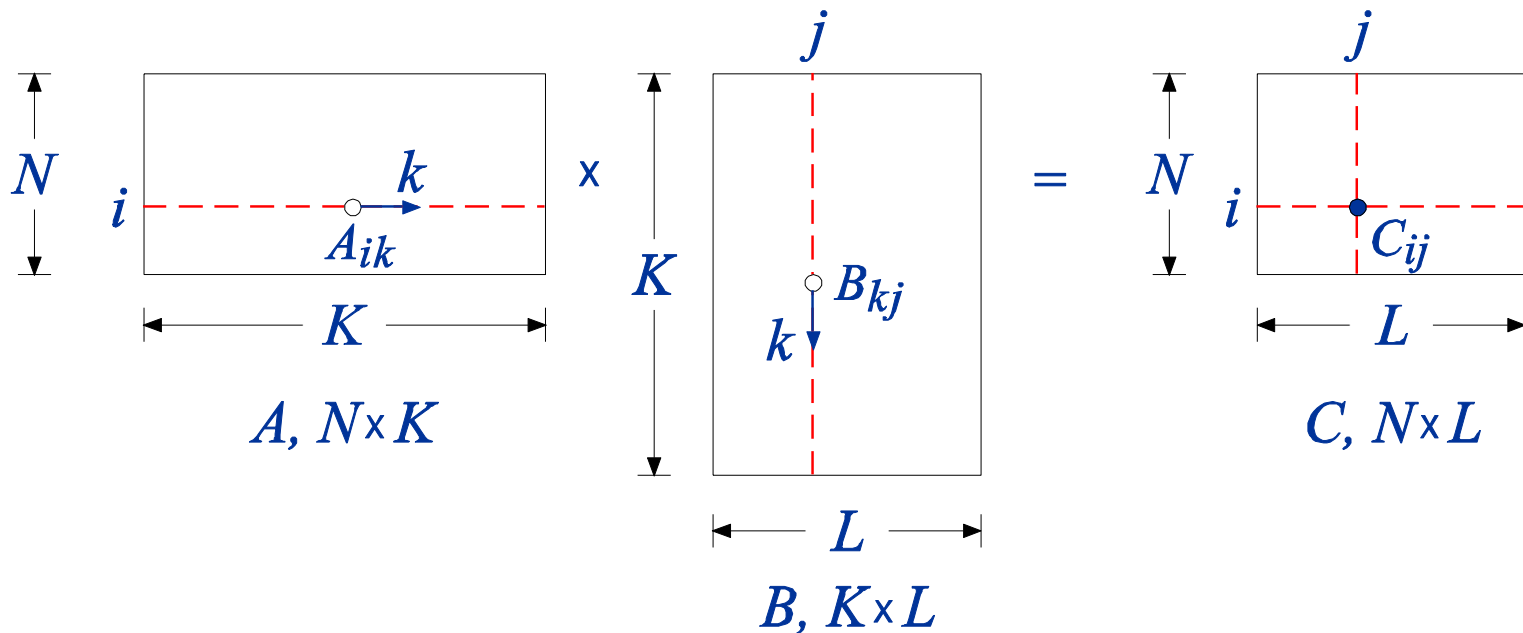
```
B =
```

```
    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  $B$**

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

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

note:  
 **$A * B \neq B * A$**

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

Rule of thumb:

**$(N \times K) \times (K \times M) \rightarrow N \times M$**

**A is  $N \times K$**

**B is  $K \times M$**

**then,  $A * B$  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

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

matrix  
inverse

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

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

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



## 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 **NxN** and invertible

**X** of size **NxK**

**B** of size **NxK**

equivalent

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

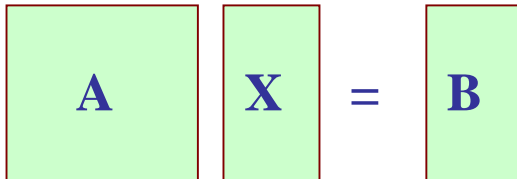
**A** of size **NxN** and invertible

**X** of size **KxN**

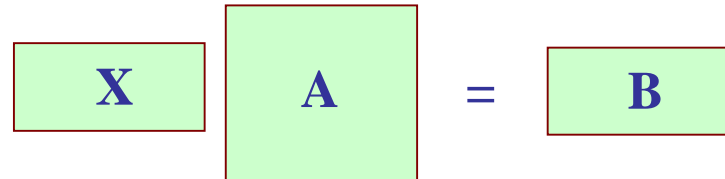
**B** of size **KxN**

equivalent

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



A diagram illustrating the matrix equation  $\mathbf{AX} = \mathbf{B}$ . It consists of three light green rectangular boxes with dark red borders. The first box contains the letter 'A', the second contains 'X', and the third contains 'B'. They are arranged horizontally with an equals sign between the second and third boxes.



A diagram illustrating the matrix equation  $\mathbf{XA} = \mathbf{B}$ . It consists of three light green rectangular boxes with dark red borders. The first box contains 'X', the second contains 'A', and the third contains 'B'. They are arranged horizontally with an equals sign between the second and third boxes.

# 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
```

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

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

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

$$x_{\text{opt}} = (A^T A)^{-1} A^T b$$

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  $x = x_{\text{opt}}$



# least-squares solutions - example

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

$$b = \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix};$$

$$x_{\text{opt}} = (A^T A)^{-1} (A^T b)$$

$$J_{\text{min}} = b^T b - \dots \\ b^T A (A^T A)^{-1} A^T b$$

$$x_{\text{opt}} =$$

$$-1$$

$$2$$

$$J_{\text{min}} =$$

$$6$$

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

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

$$b^T b = \begin{bmatrix} 4 & 3 & 8 \end{bmatrix} \begin{bmatrix} 4 \\ 3 \\ 8 \end{bmatrix} = 89$$

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

## 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.

The *condition number* of a matrix measures the sensitivity of the solution of a system of linear equations to errors in the data

```
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 $L_\infty$ 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

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

$L_\infty$  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);

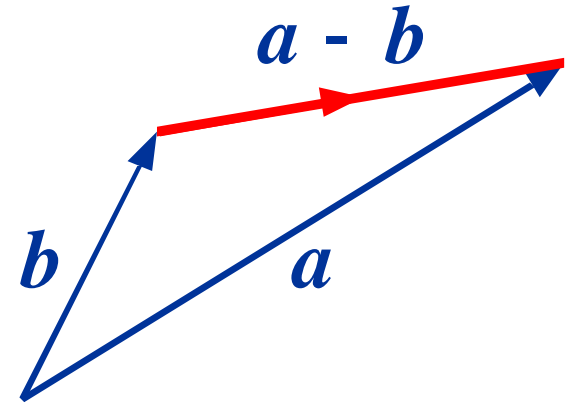
% N = norm(x,2);

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
```

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



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

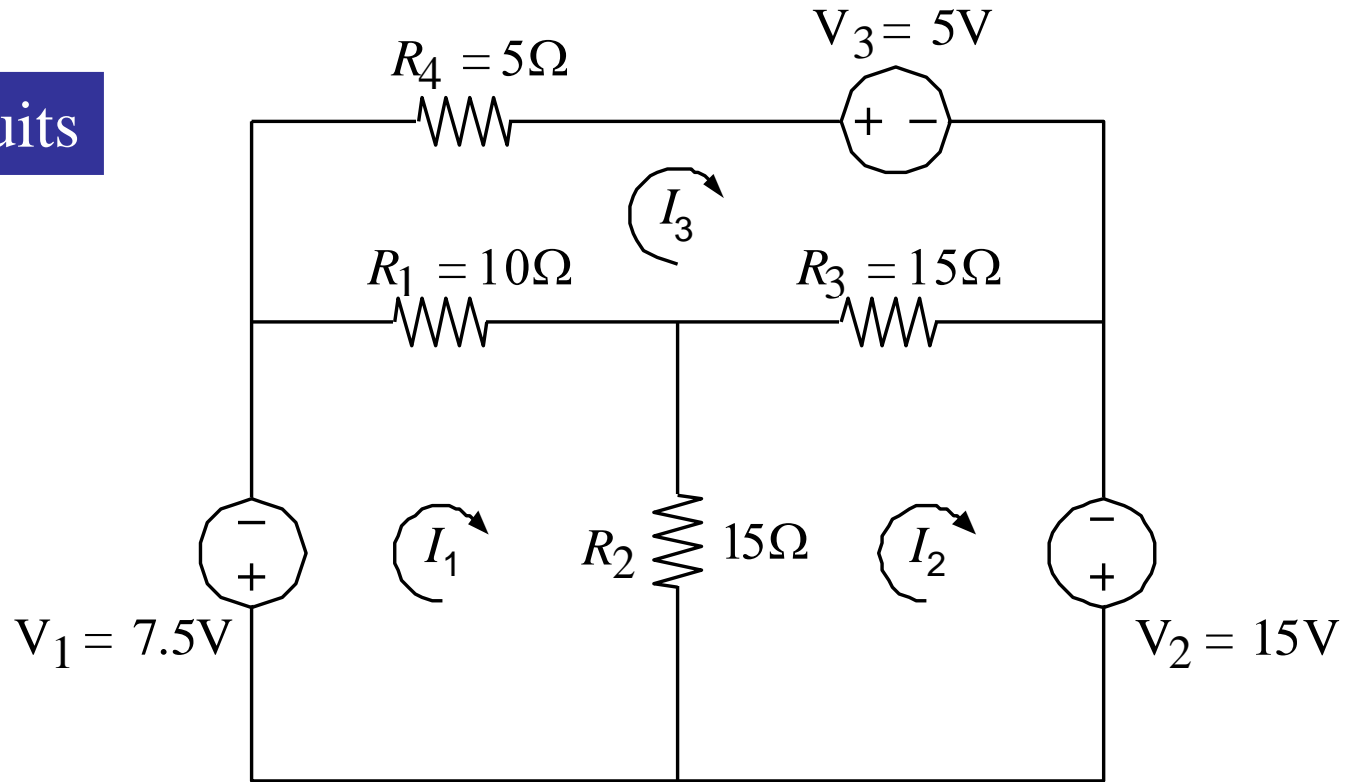
$$= \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2}$$

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

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]`

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

# Iterative solutions of linear systems $Ax=b$

the only practical way to solve very large linear systems is **iteratively**

Methods:

- 
1. Jacobi method
  2. Gauss-Seidel method
  3. Relaxation methods
  4. Conjugate Gradient method
  5. Others

G. H. Golub and C. F. Van Loan, *Matrix Computations*, 3/e, JHU Press, 1996.

D. S. Watkins, *Fundamentals of Matrix Computations*, 2/e, Wiley, 2002.

L. N. Trefethen and D. Bau, *Numerical Linear Algebra*, SIAM, 1997.

A. Bjork, *Numerical Methods for Least Squares Problems*, SIAM, 1996.



rearrange

$$3x = 12$$

$$2x + x = 12$$

scalar example  
illustrating the  
Jacobi method

rearrange

$$2x = -x + 12$$

$$x = -0.5x + 6$$

turn it into a recursion

for  $k = 1, 2, 3, \dots$

$$x(k + 1) = -0.5x(k) + 6$$

start with any  $x(1)$ ,

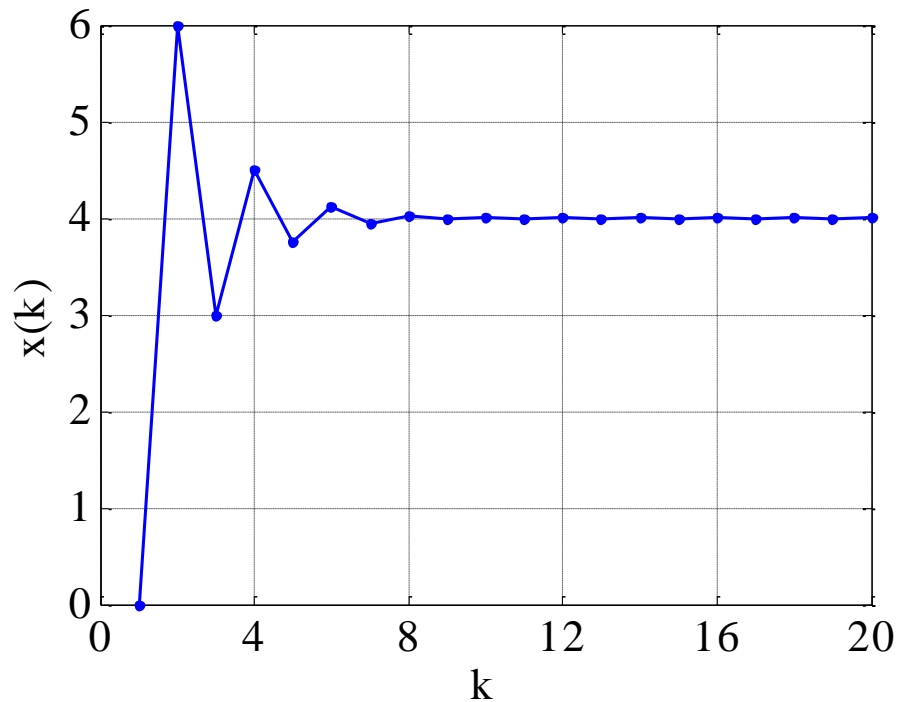
$$x(2) = -0.5x(1) + 6$$

$$x(3) = -0.5x(2) + 6$$

$$x(4) = -0.5x(3) + 6, \quad \text{etc.}$$

```
x(1)=0;           % arbitrary
for k=1:19
    x(k+1) = -0.5*x(k) + 6;
end

k=1:20; plot(k,x,'b.-');
```



```
>> [k; x]'
```

1	0.0000
2	6.0000
3	3.0000
4	4.5000
5	3.7500
6	4.1250
7	3.9375
8	4.0313
9	3.9844
10	4.0078
11	3.9961
12	4.0020
13	3.9990
14	4.0005
15	3.9998
16	4.0001
17	3.9999
18	4.0000
19	4.0000
20	4.0000

```
tol=1e-10; x0=0;
x=x0; k=1;
while 1
    xnew = -0.5*x + 6;
    if abs(xnew-x)<=tol
        break;
    end
    x = xnew;
    k = k+1;
end
```

k, abs(x-4)

k =

37

ans =

5.8208e-011

forever  
while loop

```
tol=1e-10; x0=0;
x=x0; k=1;
xnew = -0.5*x+6;
while abs(xnew-x)>tol
    x = xnew;
    k = k+1;
    xnew = -0.5*x + 6;
end
```

k, abs(x-4)

k =

37

ans =

5.8208e-011

conventional  
while loop