

# Matrices

CS5691 : PRML - Linear Algebra – basics;

CS6015- LARP;

CS6464

# Matrix Arithmetic and Operation

- **Equality:**  $A = B$  provided *dimensions of A and B are equal* and  $a_{ij} = b_{ij}$  for all  $i$  and  $j$ .  
*Matrices of different sizes cannot be equal.*
- **Addition, Subtraction:**  $A_{n \times m} \pm B_{n \times m} = [a_{ij} \pm b_{ij}]$ . *Matrices of different sizes cannot be added or subtracted.*
- **Scalar Multiple:**  $cA = [ca_{ij}]$ ;  $c$  is any number.
- **Multiplication:**  $A_{n \times p} * B_{p \times m} = A \cdot B_{n \times m}$
- **Transpose:**  $A = [a_{ij}]_{n \times m}$  then  $A^T = [a_{ji}]_{m \times n} \forall i, j$
- **Trace:**  $tr(A) = \sum_{i=1}^n a_{ii}$ . *If A is not square then trace is not defined.*

## Properties of Matrix Arithmetic and the Transpose

- $A + B = B + A$
- $A + (B + C) = (A + B) + C$
- $A(BC) = (AB)C$
- $A(B \pm C) = AB \pm AC$
- $(B \pm C)A = BA \pm CA$
- $a(B \pm C) = aB \pm aC$
- $(a \pm b)C = aC \pm bC$
- $(ab)C = a(bC)$
- $a(BC) = (aB)C = B(aC)$
- $A(B) \neq B(A)$ , in general.

Letters in caps define matrices, while that in small denote scalars.

## Properties of Matrix Arithmetic and the Transpose

- $A + 0 = 0 + A = A$
- $A - A = 0$
- $0 - A = -A$
- $0A = 0$  and  $A0 = 0$
- $A^n A^m = A^{n+m}$
- $(A^n)^m = A^{nm}$
- $(A^T)^T = A$
- $(A \pm B)^T = A^T \pm B^T$
- $(cA)^T = cA^T$
- $(AB)^T = B^T A^T$

Letters in caps define matrices, while that in small denote scalars.

**Theorem**      **Traces of  $AB$  and  $BA$  are equal. If  $AB$  and  $BA$  are each square, then  $\text{tr}(AB) = \text{tr}(BA)$**

# Important properties of the inverse matrix

Suppose that  $A$  and  $B$  are invertible matrices of the same size. Then,

a)  $AB$  is invertible and  $(AB)^{-1} = B^{-1}A^{-1}$

b)  $A^{-1}$  is invertible and  $(A^{-1})^{-1} = A$

c) For  $n = 0, 1, 2, \dots$   $A^n$  is invertible and  $(A^n)^{-1} = A^{-n} = (A^{-1})^n$

d) If  $c$  is any non zero scalar then  $cA$  is invertible and  $(cA)^{-1} = \frac{1}{c}A^{-1}$ .

e)  $A^T$  is invertible and  $(A^T)^{-1} = (A^{-1})^T$

# Inverse Calculation

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

will be ***invertible*** if  $ad - bc \neq 0$

and ***singular*** if  $ad - bc = 0$ .

- If the matrix is invertible its inverse will be,

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

The properties of these operations are (assuming that  $r, s$  are scalars and the sizes of the matrices  $A, B, C$  are chosen so that each operation is well defined):

$$r(AB) = (rA)B = A(rB),$$

$$I_m A = A = A I_n;$$

$$(A^T)^T = A,$$

$$(A + B)^T = A^T + B^T,$$

$$(rA)^T = rA^T,$$

$$(AB)^T = B^T A^T,$$

$$(I_n)^T = I_n;$$

$$AA^{-1} = A^{-1}A = I_n,$$

$$(rA)^{-1} = r^{-1}A^{-1}, \quad r \neq 0,$$

$$(AB)^{-1} = B^{-1}A^{-1},$$

$$(I_n)^{-1} = I_n,$$

$$(A^T)^{-1} = (A^{-1})^T,$$

$$(A^{-1})^{-1} = A.$$

$$A + B = B + A, \quad (1)$$

$$(A + B) + C = A + (B + C), \quad (2)$$

$$A + 0 = A, \quad (3)$$

$$r(A + B) = rA + rB, \quad (4)$$

$$(r + s)A = rA + sA, \quad (5)$$

$$r(sA) = (rs)A; \quad (6)$$

$$A(BC) = (AB)C, \quad (7)$$

$$A(B + C) = AB + AC, \quad (8)$$

$$(B + C)A = BA + CA, \quad (9)$$

$$\text{Tr}(A + B) = \text{Tr}(A) + \text{Tr}(B)$$

$$\text{Tr}(E) = n \quad (\text{trace of identity matrix})$$

$$\text{Tr}(O) = 0 \quad (\text{trace of zero matrix})$$

$$\text{Tr}(ABC) = \text{Tr}(CAB) = \text{Tr}(BCA)$$

$$\text{Tr}(cA) = c\text{Tr}(A) \quad c \in \mathbb{C}$$

$$\text{Tr}(A^T) = \text{Tr}(A)$$

# Special Matrices : Diagonal Matrix

- **Diagonal Matrix:** A square matrix is called **diagonal** if it has the following form

$$D = \begin{bmatrix} d_1 & 0 & \dots & 0 \\ 0 & d_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & d_n \end{bmatrix}$$

- Suppose  $D$  is a diagonal matrix and  $d_i, i = 1, \dots, n$  are the entries on the main diagonal.
- If one or more of the  $d_i$ 's are zero then the matrix is singular.



## Diagonal Matrix (contd.)

- On the other hand if  $d_i \neq 0, \forall i$  then the matrix is invertible and the inverse is,

$$D^{-1} = \begin{bmatrix} \frac{1}{d_1} & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{d_2} & 0 & \dots & 0 \\ 0 & 0 & \frac{1}{d_3} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \frac{1}{d_n} \end{bmatrix}$$

# Triangular matrix

$$U = \begin{bmatrix} u_{11} & u_{12} & u_{13} & \cdots & u_{1n} \\ 0 & u_{22} & u_{23} & \cdots & u_{2n} \\ 0 & 0 & u_{33} & \cdots & u_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & u_{nn} \end{bmatrix}_{n \times n}$$

**Upper Triangular Matrix**

$$L = \begin{bmatrix} l_{11} & 0 & 0 & \cdots & 0 \\ l_{21} & l_{22} & 0 & \cdots & 0 \\ l_{31} & l_{32} & l_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ l_{n1} & l_{n2} & l_{n3} & \cdots & l_{nn} \end{bmatrix}_{n \times n}$$

**Lower Triangular Matrix**

- *If  $A$  is a triangular matrix with main diagonal entries  $a_{11}, a_{22}, \dots, a_{nn}$  then if one or more of the  $a_{ii}$ 's are zero the matrix will be **singular**.*
- *On the other hand if  $a_{ii} \neq 0 \forall i$  then the matrix is **invertible**.*

# Symmetric and anti-symmetric matrices

Suppose that  $A$  is an  $n \times m$  matrix, then  $A$  will be called **symmetric** if  $A = A^T$ .

Some properties of symmetric matrices are:

- a) *For any matrix  $A$ , both  $AA^T$  and  $A^T A$  are symmetric.*
- b) *If  $A$  is an invertible symmetric matrix then  $A^{-1}$  is also symmetric.*
- c) *If  $A$  is invertible then  $AA^T$  and  $A^T A$  are both invertible.*

## ***Anti-Symmetric or Skew-Symmetric:***

*An anti-symmetric matrix is a square matrix that satisfies the identity  $\mathbf{A} = -\mathbf{A}^T$ .*

## **Other Special forms of matrices:**

- **Toeplitz matrix**
- **Block Circulant Matrix**
- **Orthogonal (also, -skew -sym)**
- **PD, PSD, ...**
- **Tri-diagonal system**
- **Hessian**
- **Jacobian**
- **Adjoint and Adjugate matrices**
- **(skew-) Hermitian (or self-adjoint ) matrix**
- **Covariance matrix**
- **Periodic matrices**
- **Compound Matrix**
- **g-inv & Pseudo-inv**
- **GRAM matrix**
- **Kernel of matrix**
- **Schur Complement**
- **PERM (n)**
- **Skew-symmetric**
- **DFT Matrix**
- **Idempotent Matrices**
- **Vandermonde Matrices**

# Matrix Multiplication

1. The order makes a difference...AB is different from BA.
2. **Rule** : The number of columns in first matrix must equal number of rows in second matrix.

In other words, the **inner dimensions** must be equal.

3. **Dimension of product** : The answer will be number of rows in first matrix by number of columns in second matrix.

In other words, the **outer dimensions**.

$$\begin{array}{c} \begin{bmatrix} 4 \\ 2 \end{bmatrix} \times \begin{bmatrix} 3 & 1 \end{bmatrix} = \begin{bmatrix} \square & \square \\ \square & \square \end{bmatrix} \\ \underbrace{2 \times 1 \quad 1 \times 2} \end{array}$$

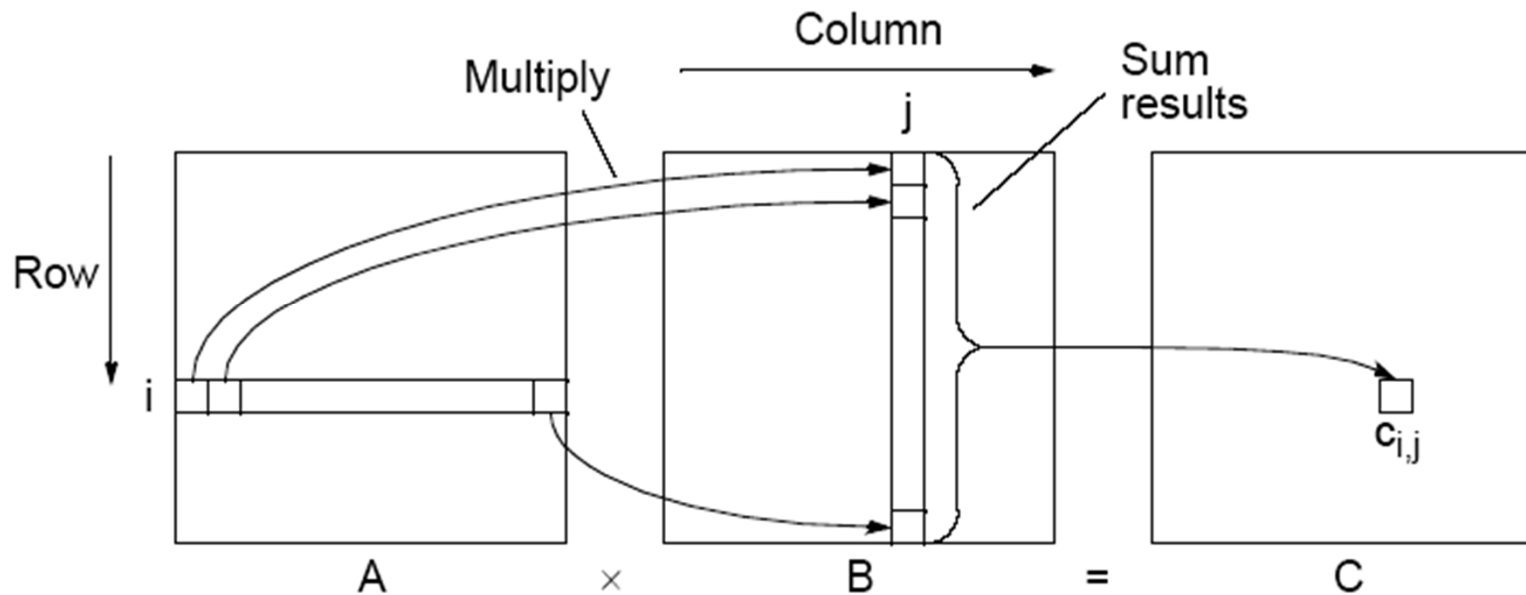
$$\begin{array}{c} \begin{bmatrix} 3 & 1 \end{bmatrix} \times \begin{bmatrix} 4 \\ 2 \end{bmatrix} = \begin{bmatrix} \square \end{bmatrix} \\ \underbrace{1 \times 2 \quad 2 \times 1} \end{array}$$

# Matrix Multiplication

Multiplication of two matrices, **A** and **B**, produces the matrix **C** whose elements,  $c_{i,j}$  ( $0 \leq i < n, 0 \leq j < m$ ), are computed as follows:

$$c_{i,j} = \sum_{k=0}^{l-1} a_{i,k} b_{k,j}$$

where **A** is an  $n \times p$  matrix and **B** is an  $p \times m$  matrix.



# Matrix Notation and Matrix Multiplication

Nine co-efficients

$$2u + v + w = 5$$

Three unknowns

$$4u - 6v = -2$$

Three right-hand sides

$$-2u + 7v + 2w = 9$$

$$Ax = b$$

$$A = \begin{bmatrix} 2 & 1 & 1 \\ 4 & -6 & 0 \\ -2 & 7 & 2 \end{bmatrix}$$

$$x = \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

$$b = \begin{bmatrix} 5 \\ -2 \\ 9 \end{bmatrix}$$

Co-efficient matrix

Solution vector

constant vector

There are two ways to multiply a matrix  $A$  and a vector  $x$ .

- One way is a row at a time, each row of  $A$  combines with  $x$  to give a component of  $Ax$ . There are three inner products when  $A$  has three rows:

$$Ax \text{ by rows} \quad \begin{bmatrix} 1 & 1 & 6 \\ 3 & 0 & 1 \\ 1 & 1 & 4 \end{bmatrix} \begin{bmatrix} 2 \\ 5 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \cdot 2 + 1 \cdot 5 + 6 \cdot 0 \\ 3 \cdot 2 + 0 \cdot 5 + 3 \cdot 0 \\ 1 \cdot 2 + 1 \cdot 5 + 4 \cdot 0 \end{bmatrix} = \begin{bmatrix} 7 \\ 6 \\ 7 \end{bmatrix}$$

- Second way, multiplication a column at a time. The product  $Ax$  is found all at once, as a combination of the three columns of  $A$ :

$$Ax \text{ by columns} \quad 2 \begin{bmatrix} 1 \\ 3 \\ 1 \end{bmatrix} + 5 \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} + 0 \begin{bmatrix} 6 \\ 3 \\ 4 \end{bmatrix} = \begin{bmatrix} 7 \\ 6 \\ 7 \end{bmatrix}$$



# Properties of matrix multiplication

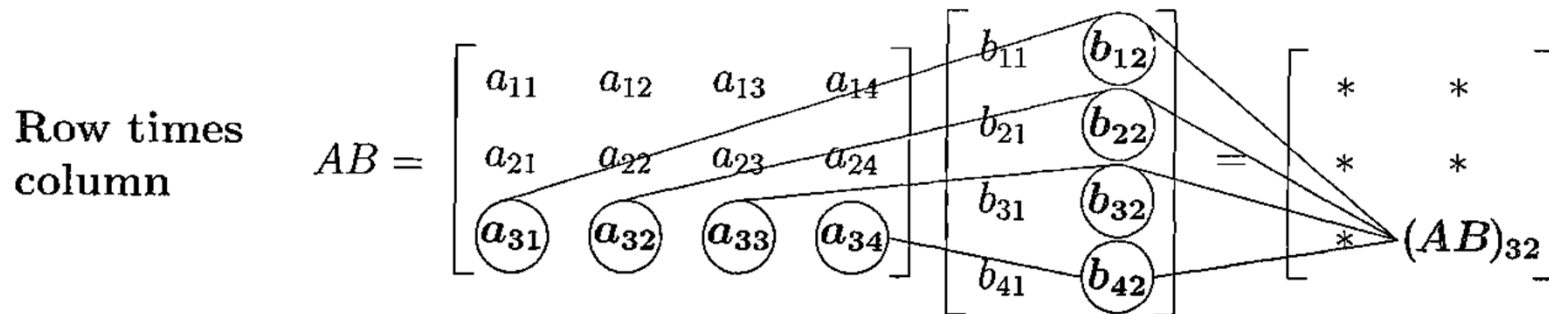
- Every product  $Ax$  can be found using whole columns. Therefore  $Ax$  is a combination of the columns of  $A$ . The coefficients are the components of  $x$ .
- The identity matrix  $I$ , with 1s on the diagonal and 0s everywhere else, leaves every vector unchanged.

**Identity matrix**  $IA = A$  and  $BI = B$ .

# Properties of matrix multiplication

- The  $i, j$  entry of  $AB$  is the inner product of the  $i$ -th row of  $A$  and the  $j$ -th column of  $B$

$$(AB)_{32} = a_{31}b_{12} + a_{32}b_{22} + a_{33}b_{32} + a_{34}b_{42}$$



# Properties of matrix multiplication

- Each entry of  $AB$  is the product of a row and a column:

$$(AB)_{ij} = (\text{row } i \text{ of } A) \text{ times } (\text{column } j \text{ of } B)$$

- Each column of  $AB$  is the product of a matrix and a column:

$$\text{column } j \text{ of } AB = A \text{ times } (\text{column } j \text{ of } B)$$

- Each row of  $AB$  is the product of a row and a matrix:

$$\text{row } i \text{ of } AB = (\text{row } i \text{ of } A) \text{ times } B$$

# Properties of matrix multiplication

- For matrices  $A, B, C, D, E$  and  $F$ ,
- Matrix multiplication is **associative**:

$$(AB)C = A(BC)$$

- Matrix operations are **distributive**:

$$A(B + C) = AB + AC \text{ and } (B + C)D = BD + CD$$

- Matrix multiplication is **not commutative**: Usually  
 $FE \neq EF$

Exception :

$$E = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad EF = \begin{bmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} = FE$$

# Norms

To meter the lengths of vectors in a vector space we need the idea of a **norm**.

Norm is a function that maps  $x$  to a nonnegative real number

$$\| \cdot \|: F \rightarrow R^+$$

A Norm must satisfy following properties:

1 – Positivity  $\|x\| > 0, \forall x \neq 0$

2 – Homogeneity  $\|\alpha x\| = |\alpha| \|x\|, \forall x \in F \text{ and } \forall \alpha \in C$

3 – Triangle inequality  $\|x + y\| \leq \|x\| + \|y\|, \forall x, y \in F$

# Norm of vectors

**p-norm** is:  $\|x\|_p = \left( \sum_i |a_i|^p \right)^{\frac{1}{p}} \quad p \geq 1$

For  $p=1$  we have **1-norm** or **sum norm**  $\|x\|_1 = \left( \sum_i |a_i| \right)$

For  $p=2$  we have **2-norm** or **euclidian norm**  $\|x\|_2 = \left( \sum_i |a_i|^2 \right)^{1/2}$

For  $p=\infty$  we have  **$\infty$ -norm** or **max norm**  $\|x\|_\infty = \max_i \{ |a_i| \}$

## The $l_p$ -Norm

The  $l_p$ - Norm for a vector  $x$  is defined as ( $p \geq 1$ ):

$$\|x\|_{l_p} = \left( \sum_{i=1}^n |x_i|^p \right)^{1/p}$$

Examples:

- for  $p=2$  we have the ordinary euclidian norm:  $\|x\|_{l_2} = \sqrt{x^T x}$

- for  $p= \infty$  the definition is  $\|x\|_{l_\infty} = \max_{1 \leq i \leq n} |x_i|$

- a norm for matrices is induced via  $\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|}$

- for  $l_2$  this means :  
 $\|A\|_2 = \text{maximum eigenvalue of } A^T A$

# Properties of Matrix Norms

- These induced matrix norms satisfy:

$$\|A\| > 0 \text{ if } A \neq 0$$

$$\|\gamma A\| = |\gamma| \cdot \|A\| \text{ for any scalar } \gamma$$

$$\|A + B\| \leq \|A\| + \|B\| \text{ (triangle inequality)}$$

$$\|AB\| \leq \|A\| \cdot \|B\|$$

$$\|Ax\| \leq \|A\| \cdot \|x\| \text{ for any vector } x$$



# Condition Number

- If  $A$  is square and nonsingular, then

$$\text{cond}(A) = \|A\| \cdot \|A^{-1}\|$$

- If  $A$  is singular, then  $\text{cond}(A) = \infty$
- If  $A$  is nearly singular, then  $\text{cond}(A)$  is large.
- The condition number measures the ratio of maximum expansion to maximum shrinkage:

$$\|A\| \cdot \|A^{-1}\| = \left( \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} \right) \cdot \left( \min_{x \neq 0} \frac{\|Ax\|}{\|x\|} \right)^{-1}$$

## Condition Number of the Matrix

$$A = \begin{bmatrix} 100 & -200 \\ -200 & 401 \end{bmatrix}$$

$$A^{-1} = \begin{bmatrix} 4.01 & 2 \\ 2 & 1 \end{bmatrix}$$

Row - sum norm of  $A = \|A\| = \text{Max}(300, 601) = 601$ .

Row - sum norm of  $A^{-1} = \|A^{-1}\| = \text{Max}(6.01, 3) = 6.01$ .

Condition Number  $k(A) = 601(6.01) = 3612$  (large).

$A$  is ill - conditioned.

# The Gaussian Elimination Method

- The Gaussian elimination method is a **technique** for **solving systems of linear equations** of any size.
- The operations of the Gaussian elimination method are:
  1. **Interchange** any two equations.
  2. **Replace** an equation by a **nonzero constant multiple** of itself.
  3. **Replace** an equation by the **sum** of that equation and a **constant multiple of any other equation**.

# Row-Reduced Form of a Matrix

- Each row consisting entirely of **zeros** lies **below** all rows having **nonzero entries**.
- The **first nonzero entry** in each nonzero row is **1** (called a **leading 1**).
- In any two successive (nonzero) rows, the **leading 1** in the lower row lies **to the right** of the **leading 1** in the **upper row**.
- If a column contains a **leading 1**, then the other entries in that column are **zeros**.

# Row Operations

1. Interchange any two rows.
2. Replace any row by a nonzero constant multiple of itself.
3. Replace any row by the sum of that row and a constant multiple of any other row.

# Terminology for the Gaussian Elimination Method

## Unit Column

- A column in a coefficient matrix is in unit form if **one** of the entries in the column is a **1** and the **other** entries are **zeros**.

## Pivoting

- The **sequence** of **row operations** that **transforms** a **given column** in an augmented matrix into a **unit column**.

# Notation for Row Operations

- Letting  $R_i$  denote the  $i$ -th row of a matrix, we write

Operation 1:  $R_i \leftrightarrow R_j$  to mean:  
Interchange row  $i$  with row  $j$ .

Operation 2:  $cR_i$  to mean:  
replace row  $i$  with  $c$  times row  $i$ .

Operation 3:  $R_i + aR_j$  to mean:  
Replace row  $i$  with the sum of row  $i$  and  $a$  times row  $j$ .

## Example

- Pivot the matrix about the circled element

$$\begin{bmatrix} 3 & 5 & 9 \\ 2 & 3 & 5 \end{bmatrix}$$

### Solution:

$$\begin{bmatrix} 3 & 5 & | & 9 \\ 2 & 3 & | & 5 \end{bmatrix} \xrightarrow{\frac{1}{3}R_1} \begin{bmatrix} 1 & 5/3 & | & 3 \\ 2 & 3 & | & 5 \end{bmatrix} \xrightarrow{R_2 - 2R_1} \begin{bmatrix} 1 & 5/3 & | & 3 \\ 0 & -1/3 & | & -1 \end{bmatrix}$$

# The Gaussian Elimination Method

1. Write the **augmented matrix** corresponding to the linear system.
2. **Interchange rows**, if necessary, to obtain an augmented matrix in which the **first entry** in the **first row** is **nonzero**. Then **pivot** the matrix about this entry.
3. **Interchange** the **second row** with any row below it, if necessary, to obtain an augmented matrix in which the **second entry** in the **second row** is **nonzero**. **Pivot** the matrix about this entry.
4. **Continue** until the final matrix is in **row-reduced form**.



# Augmented Matrices

- Matrices are **rectangular arrays of numbers** that can aid us by **eliminating the need to write the variables** at each step of the reduction.
- For example, the **system**

$$2x + 4y + 6z = 22$$

$$3x + 8y + 5z = 27$$

$$-x + y + 2z = 2$$

may be represented by the **augmented matrix**

$$\left[ \begin{array}{ccc|c} 2 & 4 & 6 & 22 \\ 3 & 8 & 5 & 27 \\ -1 & 1 & 2 & 2 \end{array} \right]$$

**Augmented matrix**  
**[C|B]**

**Coefficient**  
**Matrix [C]**

# Matrices and Gaussian Elimination

- **Every step** in the **Gaussian elimination method** can be expressed with **matrices**, rather than systems of equations, thus simplifying the whole process:

- Steps expressed as **systems of equations**:

$$2x + 4y + 6z = 22$$

$$3x + 8y + 5z = 27$$

$$-x + y + 2z = 2$$

- Steps expressed as **augmented matrices**:

$$\left[ \begin{array}{ccc|c} 2 & 4 & 6 & 22 \\ 3 & 8 & 5 & 27 \\ -1 & 1 & 2 & 2 \end{array} \right]$$

$$\begin{aligned} 2x + 4y + 6z &= 22 \\ 3x + 8y + 5z &= 27 \\ -x + y + 2z &= 2 \end{aligned}$$

$$\begin{aligned} x + 2y + 3z &= 11 \\ 3x + 8y + 5z &= 27 \\ -x + y + 2z &= 2 \end{aligned}$$

$$\begin{aligned} x + 2y + 3z &= 11 \\ 2y - 4z &= -6 \\ -x + y + 2z &= 2 \end{aligned}$$


$$\begin{aligned} x + 2y + 3z &= 11 \\ 2y - 4z &= -6 \\ 3y + 5z &= 13 \end{aligned}$$

$$\left[ \begin{array}{ccc|c} 2 & 4 & 6 & 22 \\ 3 & 8 & 5 & 27 \\ -1 & 1 & 2 & 2 \end{array} \right]$$


$$\left[ \begin{array}{ccc|c} 1 & 2 & 3 & 11 \\ 3 & 8 & 5 & 27 \\ -1 & 1 & 2 & 2 \end{array} \right]$$

$$\left[ \begin{array}{ccc|c} 1 & 2 & 3 & 11 \\ 0 & 2 & -4 & -6 \\ -1 & 1 & 2 & 2 \end{array} \right]$$


$$\left[ \begin{array}{ccc|c} 1 & 2 & 3 & 11 \\ 0 & 2 & -4 & -6 \\ 0 & 3 & 5 & 13 \end{array} \right]$$




$$R'_1 = \frac{1}{2}R_1$$



$$R'_2 = R_2 - 3R_1$$



$$R'_3 = R_3 + R_1$$



$$R'_2 = \frac{1}{2}R_2$$

$$\begin{aligned} x + 2y + 3z &= 11 \\ y - 2z &= -3 \\ 3y + 5z &= 13 \end{aligned}$$

$$\begin{aligned} x + 7z &= 11 \\ y - 2z &= -3 \\ 3y + 5z &= 13 \end{aligned}$$

$$\begin{aligned} x + 7z &= 11 \\ y - 2z &= -3 \\ 11z &= 22 \end{aligned}$$


$$\begin{aligned} x + 7z &= 11 \\ y - 2z &= -3 \\ z &= 2 \end{aligned}$$

$$\begin{bmatrix} 1 & 2 & 3 & 11 \\ 0 & 1 & -2 & -3 \\ 0 & 3 & 5 & 13 \end{bmatrix}$$


$$\begin{bmatrix} 1 & 0 & 7 & 17 \\ 0 & 1 & -2 & -3 \\ 0 & 3 & 5 & 13 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 7 & 17 \\ 0 & 1 & -2 & -3 \\ 0 & 0 & 11 & 22 \end{bmatrix}$$


$$\begin{bmatrix} 1 & 0 & 7 & 17 \\ 0 & 1 & -2 & -3 \\ 0 & 0 & 1 & 2 \end{bmatrix}$$




$$R'_2 = \frac{1}{2}R_2$$




$$R'_1 = R_1 - 2R_2$$



$$R'_3 = R_3 - 3R_2$$




$$R'_3 = \frac{1}{11}R_3$$




$$R'_1 = R_1 - 7R_3$$

$$\begin{array}{l}
 x = 3 \\
 y - 2z = -3 \\
 z = 2
 \end{array}
 \quad \left| \quad \begin{array}{ccc|c}
 1 & 0 & 0 & 3 \\
 0 & 1 & -2 & -3 \\
 0 & 0 & 1 & 2
 \end{array} \right.$$

  $R'_1 = R_1 - 7R_3$

$$\begin{array}{l}
 x = 3 \\
 y = -3 \\
 z = 2
 \end{array}
 \quad \left| \quad \begin{array}{ccc|c}
 1 & 0 & 0 & 3 \\
 0 & 1 & 0 & 1 \\
 0 & 0 & 1 & 2
 \end{array} \right.$$

  $R'_2 = R_2 + 2R_3$

**Row Reduced Form  
of the Matrix**

Thus, the **solution** to the system is  $x = 3$ ,  $y = 1$ ,  
and  $z = 2$ .

## Gaussian Elimination in the case of unique solution

- With a full set of  $n$  pivots, there is only one solution.
- The system is non singular, and it is solved by forward elimination and back-substitution.

# Systems with no Solution

- If there is a **row** in the augmented matrix containing **all zeros** to the **left** of the **vertical line** and a **nonzero** entry to the **right** of the **line**, then the system of equations has **no solution**.

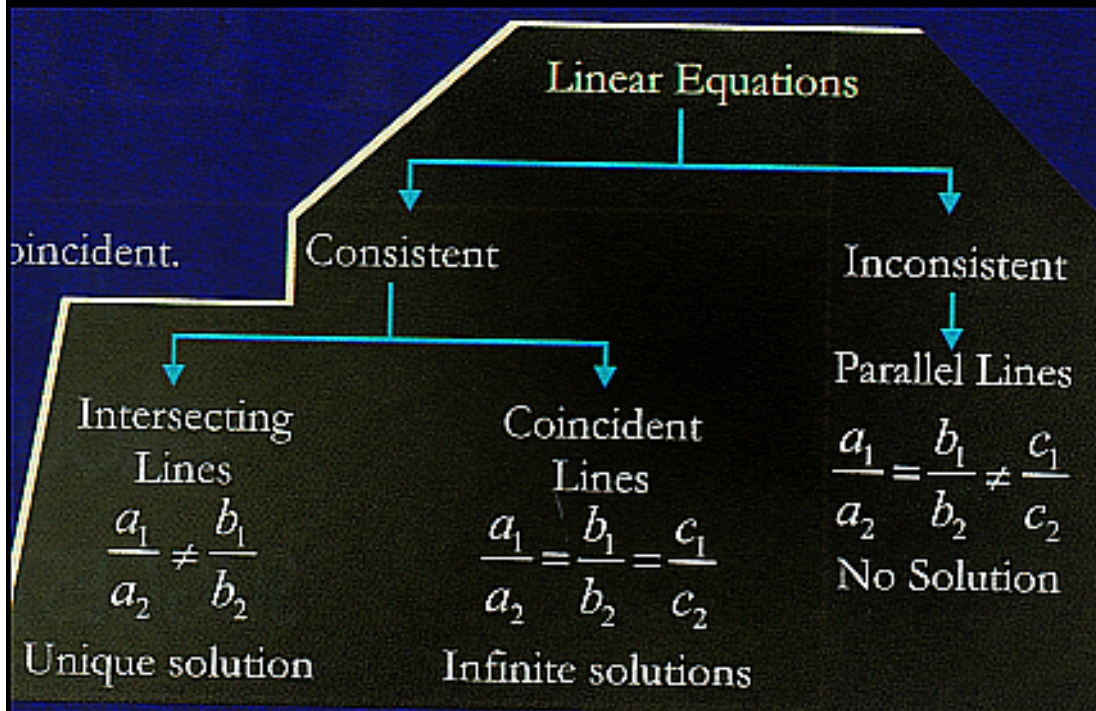
# Theorem

- a. If the **number of equations** is **greater** (**over-determined system**) than or equal to the **number of variables** in a linear system, then one of the following is true:
  - i. The system has **no solution**.
  - ii. The system has **exactly one solution**.
  - iii. The system has **infinitely many solutions**.
  
- b. If there are **fewer equations than variables** (**under-determined system**) in a linear system, then the system either has **no solution** or it has **infinitely many solutions**.



## Linear Equation

An equation of the form  $ax + by + c = 0$ , where  $a, b, c$  are real numbers,  $a \neq 0, b \neq 0$  and  $x, y$  are variables; is called a linear equation in two variables.



## Example for Solving Equations with Zero Solutions

Determine whether the following equation has zero, one, or infinitely many solutions.

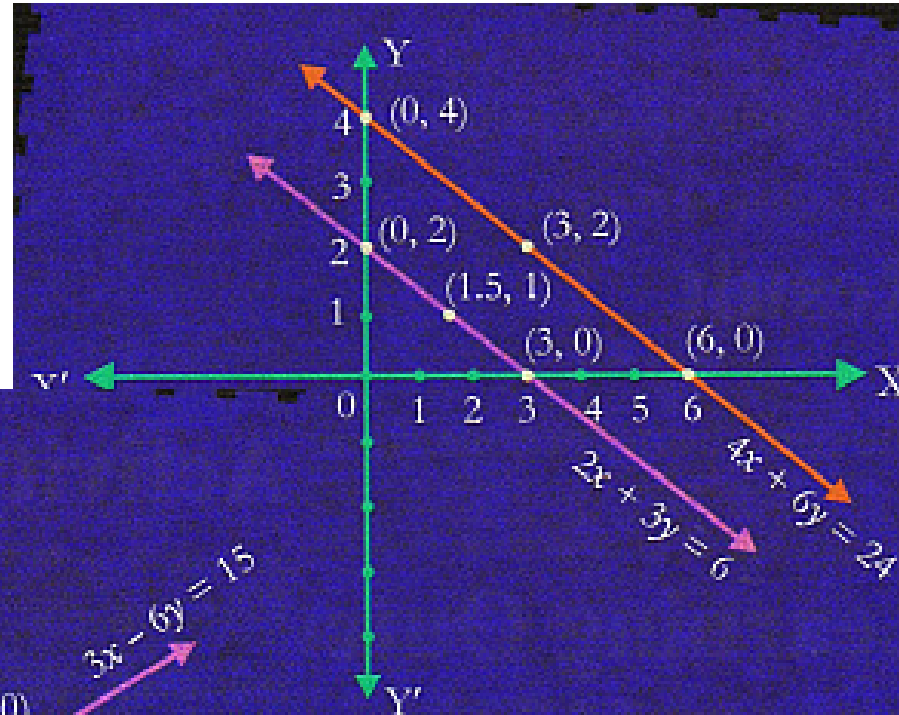
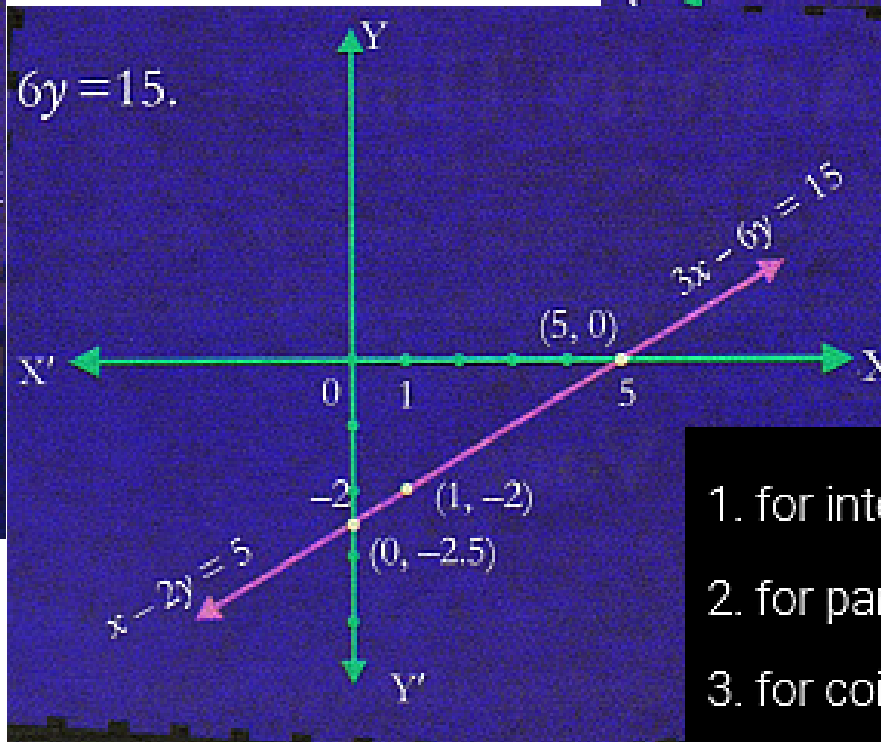
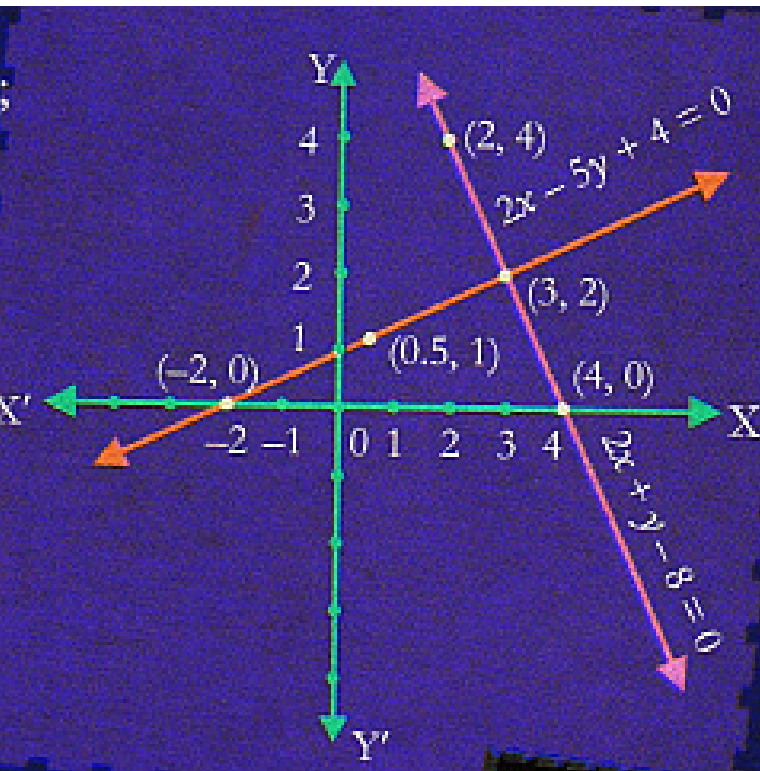
$$3x + 9x + 8 = 14x - 2x + 9$$

Consider the three pairs of linear equations

1<sup>st</sup> pair:  $2x - 5y + 4 = 0$ ,  $2x + y - 8 = 0$

2<sup>nd</sup> pair:  $4x + 6y = 24$ ,  $2x + 3y = 6$

3<sup>rd</sup> pair:  $x - 2y = 5$ ,  $3x - 6y = 15$



1. for intersecting lines,  $\frac{a_1}{a_2} \neq \frac{b_1}{b_2}$
2. for parallel lines,  $\frac{a_1}{a_2} = \frac{b_1}{b_2} \neq \frac{c_1}{c_2}$
3. for coincident lines,  $\frac{a_1}{a_2} = \frac{b_1}{b_2} = \frac{c_1}{c_2}$

# Inverse matrix

- The inverse of an  $n$  by  $n$  matrix is another  $n$  by  $n$  matrix. The inverse of  $A$  is written  $A^{-1}$  (and pronounced “ $A$  inverse”).
- The fundamental property is simple: If you multiply by  $A$  and then multiply by  $A^{-1}$ , you are back where you started:

**Inverse matrix**      If  $b = Ax$  then  $A^{-1}b = x$

- Thus  $A^{-1}Ax = x$ . The matrix  $A^{-1}$  times  $A$  is the identity matrix. ***Not all matrices have inverses. An inverse is impossible when  $Ax$  is zero and  $x$  is nonzero.*** Then  $A^{-1}$  would have to get back from  $Ax = 0$  to  $x$ . No matrix can multiply that zero vector  $Ax$  and produce a nonzero vector  $x$ .
- Our goals are to define the inverse matrix and compute it and use it, when  $A^{-1}$  exists—and then to understand which matrices don’t have inverses.

## Properties : Inverse matrix

**1K** The **inverse** of  $A$  is a matrix  $B$  such that  $BA = I$  and  $AB = I$ . There is at most one such  $B$ , and it is denoted by  $A^{-1}$ :

$$A^{-1}A = I \quad \text{and} \quad AA^{-1} = I. \quad (1)$$

**Note 1.** *The inverse exists if and only if elimination produces  $n$  pivots* (row exchanges allowed). Elimination solves  $Ax = b$  without explicitly finding  $A^{-1}$ .

**Note 2.** The matrix  $A$  cannot have two different inverses, Suppose  $BA = I$  and also  $AC = I$ . Then  $B = C$ , according to this “proof by parentheses”:

$$B(AC) = (BA)C \quad \text{gives} \quad BI = IC \quad \text{which is} \quad B = C. \quad (2)$$

This shows that a *left-inverse*  $B$  (multiplying from the left) and a *right-inverse*  $C$  (multiplying  $A$  from the right to give  $AC = I$ ) must be the *same matrix*.

**Note 3.** If  $A$  is invertible, the one and only solution to  $Ax = b$  is  $x = A^{-1}b$ :

$$\textbf{Multiply} \quad Ax = b \quad \textbf{by} \quad A^{-1}. \quad \textbf{Then} \quad x = A^{-1}Ax = A^{-1}b.$$

**Note 4.** (Important) *Suppose there is a nonzero vector  $x$  such that  $Ax = 0$ . Then  $A$  cannot have an inverse.* To repeat: No matrix can bring 0 back to  $x$ .

If  $A$  is invertible, then  $Ax = 0$  can only have the zero solution  $x = 0$ .

## Properties : Inverse matrix

**Note 5.** A 2 by 2 matrix is invertible if and only if  $ad - bc$  is not zero:

$$\text{2 by 2 inverse} \quad \begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}. \quad (3)$$

This number  $ad - bc$  is the *determinant* of  $A$ . A matrix is invertible if its determinant is not zero (Chapter 4). In **MATLAB**, the invertibility test is *to find  $n$  nonzero pivots*. Elimination produces those pivots before the determinant appears.

**Note 6.** A diagonal matrix has an inverse provided no diagonal entries are zero:

$$\text{If } A = \begin{bmatrix} d_1 & & \\ & \ddots & \\ & & d_n \end{bmatrix} \text{ then } A^{-1} = \begin{bmatrix} 1/d_1 & & \\ & \ddots & \\ & & 1/d_n \end{bmatrix} \text{ and } AA^{-1} = I.$$

When two matrices are involved, not much can be done about the inverse of  $A + B$ . The sum might or might not be invertible. Instead, it is the inverse of their *product*  $AB$  which is the key formula in matrix computations. Ordinary numbers are the same:  $(a + b)^{-1}$  is hard to simplify, while  $1/ab$  splits into  $1/a$  times  $1/b$ . But for matrices *the order of multiplication must be correct*—if  $ABx = y$  then  $Bx = A^{-1}y$  and  $x = B^{-1}A^{-1}y$ . **The inverses come in reverse order.**

# Properties : Inverse matrix

**1L** A product  $AB$  of invertible matrices is inverted by  $B^{-1}A^{-1}$ :

$$\text{Inverse of } AB \quad (AB)^{-1} = B^{-1}A^{-1}. \quad (4)$$

**Proof.** To show that  $B^{-1}A^{-1}$  is the inverse of  $AB$ , we multiply them and use the associative law to remove parentheses. Notice how  $B$  sits next to  $B^{-1}$ :

$$(AB)(B^{-1}A^{-1}) = ABB^{-1}A^{-1} = AIA^{-1} = AA^{-1} = I$$

$$(B^{-1}A^{-1})(AB) = B^{-1}A^{-1}AB = B^{-1}IB = B^{-1}B = I.$$

A similar rule holds with three or more matrices:

$$\text{Inverse of } ABC \quad (ABC)^{-1} = C^{-1}B^{-1}A^{-1}.$$

when the elimination matrices  $E, F, G$  were inverted to come back from  $U$  to  $A$ . In the forward direction,  $GFEA$  was  $U$ . In the backward direction,  $L = E^{-1}F^{-1}G^{-1}$  was the product of the inverses. *Since  $G$  came last,  $G^{-1}$  comes first.* Please check that  $A^{-1}$  would be  $U^{-1}GFE$ .

$$\begin{aligned} & [A|b] \\ &= [GFEA|GFEB]; \end{aligned}$$

$$\square \quad \begin{aligned} & U = GFEA; \\ & U^{-1} = A^{-1}(GFE)^{-1} \end{aligned}$$

$$A^{-1} = U^{-1}(GFE)$$

# Calculation of $A^{-1}$ : The Gauss-Jordan Method

- Given the  $n \times n$  matrix  $A$ :
  1. Adjoin the  $n \times n$  identity matrix  $I$  to obtain the **augmented matrix**  $[A | I]$ .
  2. Use a sequence of **row operations** to **reduce**  $[A | I]$  to the form  $[I | B]$  if possible.
- Then the matrix  $B$  is the **inverse** of  $A$ .

## Example

- Find the inverse of the matrix  $A = \begin{bmatrix} 2 & 1 & 1 \\ 3 & 2 & 1 \\ 2 & 1 & 2 \end{bmatrix}$

### Solution

- We form the **augmented matrix**

$$\left[ \begin{array}{ccc|ccc} 2 & 1 & 1 & 1 & 0 & 0 \\ 3 & 2 & 1 & 0 & 1 & 0 \\ 2 & 1 & 2 & 0 & 0 & 1 \end{array} \right]$$



## Example

- Find the inverse of the matrix  $A = \begin{bmatrix} 2 & 1 & 1 \\ 3 & 2 & 1 \\ 2 & 1 & 2 \end{bmatrix}$

### Solution

- And use the **Gauss-Jordan elimination method** to **reduce it** to the form  $[I | B]$ :

$$\left[ \begin{array}{ccc|ccc} 2 & 1 & 1 & 1 & 0 & 0 \\ 3 & 2 & 1 & 0 & 1 & 0 \\ 2 & 1 & 2 & 0 & 0 & 1 \end{array} \right] \xrightarrow{R_1 - R_2} \left[ \begin{array}{ccc|ccc} -1 & -1 & 0 & 1 & -1 & 0 \\ 3 & 2 & 1 & 0 & 1 & 0 \\ 2 & 1 & 2 & 0 & 0 & 1 \end{array} \right]$$

$$\left[ \begin{array}{ccc|ccc} 1 & 0 & 1 & 2 & -1 & 0 \\ 0 & 1 & -1 & -3 & 2 & 0 \\ 0 & 0 & 1 & -1 & 0 & 1 \end{array} \right] \xrightarrow{\begin{array}{l} R_1 + R_2 \\ -R_2 \\ R_3 - R_2 \end{array}} \left[ \begin{array}{ccc|ccc} 1 & 1 & 0 & -1 & 1 & 0 \\ 0 & -1 & 1 & 3 & -2 & 0 \\ 0 & -1 & 2 & 2 & -2 & 1 \end{array} \right] \xrightarrow{\begin{array}{l} -R_1 \\ R_2 + 3R_3 \\ R_3 + 2R_1 \end{array}}$$

## Example

- Find the inverse of the matrix  $A = \begin{bmatrix} 2 & 1 & 1 \\ 3 & 2 & 1 \\ 2 & 1 & 2 \end{bmatrix}$

### Solution

- And use the **Gauss-Jordan elimination method** to reduce it to the form  $[I | B]$ :

$$\begin{array}{c} \left[ \begin{array}{ccc|ccc} 1 & 0 & 1 & 2 & -1 & 0 \\ 0 & 1 & -1 & -3 & 2 & 0 \\ 0 & 0 & 1 & -1 & 0 & 1 \end{array} \right] \xrightarrow{\substack{R_1 - R_3 \\ R_2 + R_3}} \left[ \begin{array}{ccc|ccc} 1 & 0 & 0 & 3 & -1 & -1 \\ 0 & 1 & 0 & -4 & 2 & 1 \\ 0 & 0 & 1 & -1 & 0 & 1 \end{array} \right] \\ \text{Previous step} \qquad \qquad \underbrace{\hspace{10em}}_{I_n} \qquad \underbrace{\hspace{10em}}_B \end{array}$$

$$B = A^{-1} = \begin{bmatrix} 3 & -1 & -1 \\ -4 & 2 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

# Finding the inverse of a square matrix using LU decomposition

The inverse  $[B]$  of a square matrix  $[A]$  is defined as

How can LU Decomposition be used to find the inverse?

Methods for LU-Decomp:

Doolittle decomposition, *Crout decomposition*,  
Cholesky decomposition, Full/partial pivots,  
Cormen (recursive)

# Example: Inverse of a Matrix

Find the inverse of a square matrix  $[A]$

$$[A] = \begin{bmatrix} 25 & 5 & 1 \\ 64 & 8 & 1 \\ 144 & 12 & 1 \end{bmatrix}$$

Using the decomposition procedure, the  $[L]$  and  $[U]$  matrices are found to be

$$[A] = [L][U] = \begin{bmatrix} 1 & 0 & 0 \\ 2.56 & 1 & 0 \\ 5.76 & 3.5 & 1 \end{bmatrix} \begin{bmatrix} 25 & 5 & 1 \\ 0 & -4.8 & -1.56 \\ 0 & 0 & 0.7 \end{bmatrix}$$

# Example: Inverse of a Matrix

Solving for the each column of  $[B]$  requires two steps

1) Solve  $[L][Z] = [C]$  for  $[Z]$

2) Solve  $[U][X] = [Z]$  for  $[X]$

$$\text{Step 1: } [L][Z] = [C] \rightarrow \begin{bmatrix} 1 & 0 & 0 \\ 2.56 & 1 & 0 \\ 5.76 & 3.5 & 1 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

This generates the equations:

$$z_1 = 1$$
$$2.56z_1 + z_2 = 0$$
$$5.76z_1 + 3.5z_2 + z_3 = 0$$

# Example: Inverse of a Matrix

Solving for  $[Z]$

$$z_1 = 1$$

$$z_2 = 0 - 2.56z_1$$

$$= 0 - 2.56(1)$$

$$= -2.56$$

$$z_3 = 0 - 5.76z_1 - 3.5z_2$$

$$= 0 - 5.76(1) - 3.5(-2.56)$$

$$= 3.2$$

$$[Z] = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} = \text{[Blue rounded rectangle]}$$

# Example: Inverse of a Matrix

Solving  $[U][X] = [Z]$  for  $[X]$

$$\begin{bmatrix} 25 & 5 & 1 \\ 0 & -4.8 & -1.56 \\ 0 & 0 & 0.7 \end{bmatrix} \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \end{bmatrix} = \begin{bmatrix} 1 \\ -2.56 \\ 3.2 \end{bmatrix}$$

$$25b_{11} + 5b_{21} + b_{31} = 1$$

$$-4.8b_{21} - 1.56b_{31} = -2.56$$

$$0.7b_{31} = 3.2$$

# Example: Inverse of a Matrix

Using Backward Substitution

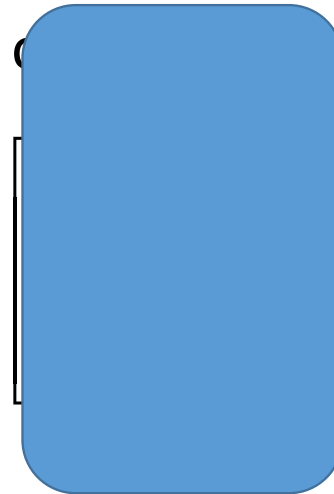
$$b_{31} = \frac{3.2}{0.7} = 4.571$$

$$\begin{aligned} b_{21} &= \frac{-2.56 + 1.560b_{31}}{-4.8} \\ &= \frac{-2.56 + 1.560(4.571)}{-4.8} = -0.9524 \end{aligned}$$

$$\begin{aligned} b_{11} &= \frac{1 - 5b_{21} - b_{31}}{25} \\ &= \frac{1 - 5(-0.9524) - 4.571}{25} = 0.04762 \end{aligned}$$

So the first column of the inverse of

$$\begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \end{bmatrix} =$$





# Example: Inverse of a Matrix

Repeating for the second and third columns of the inverse

Second Column

$$\begin{bmatrix} 25 & 5 & 1 \\ 64 & 8 & 1 \\ 144 & 12 & 1 \end{bmatrix} \begin{bmatrix} b_{12} \\ b_{22} \\ b_{32} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} b_{12} \\ b_{22} \\ b_{32} \end{bmatrix} = \begin{bmatrix} \phantom{0} \\ \phantom{0} \\ \phantom{0} \end{bmatrix}$$

Third Column

$$\begin{bmatrix} 25 & 5 & 1 \\ 64 & 8 & 1 \\ 144 & 12 & 1 \end{bmatrix} \begin{bmatrix} b_{13} \\ b_{23} \\ b_{33} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} b_{13} \\ b_{23} \\ b_{33} \end{bmatrix} = \begin{bmatrix} \phantom{0} \\ \phantom{0} \\ \phantom{0} \end{bmatrix}$$

# Example: Inverse of a Matrix

The inverse of  $[A]$  is

$$[A]^{-1} = \begin{bmatrix} 0.04762 & -0.08333 & 0.03571 \\ -0.9524 & 1.417 & -0.4643 \\ 4.571 & -5.000 & 1.429 \end{bmatrix}$$

To check your work do the following operation

$$[A][A]^{-1} = [I] = [A]^{-1}[A]$$

## Pseudo Inverse Matrix

If the columns of a matrix  $A$  are linearly independent, so  $A^T \cdot A$  is invertible and we obtain with the following formula the pseudo inverse:

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

Here  $A^+$  is a left inverse of  $A$ , what means:  $A^+ \cdot A = E$ .

However, if the rows of the matrix are linearly independent, we obtain the pseudo inverse with the formula:

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

This is a right inverse of  $A$ , what means:  $A \cdot A^+ = E$ .

If both the columns and the rows of the matrix are linearly independent, then the matrix is invertible and the pseudo inverse is equal to the inverse of the matrix.

$$\begin{array}{l} Ax = b \\ (A^T A)x = A^T b \end{array} \Rightarrow \left| \begin{array}{c} x \\ \hline (A^T A)^{-1} A^T b \end{array} \right|$$

$$\begin{array}{l} Ax = b = (AA^T)(AA^T)^{-1} b \\ \Rightarrow Ax = A[A^T(AA^T)^{-1}] b \\ \Rightarrow x = A^T(AA^T)^{-1} b \end{array}$$

The Moore-Penrose pseudo inverse is a generalization of the matrix inverse when the matrix may not be invertible. If  $A$  is invertible, then the Moore-Penrose pseudo inverse is equal to the matrix inverse. However, the Moore-Penrose pseudo inverse is defined even when  $A$  is not invertible.

More formally, the Moore-Penrose pseudo inverse,  $A^+$ , of an  $m$ -by- $n$  matrix is defined by the unique  $n$ -by- $m$  matrix satisfying the following four criteria (we are only considering the case where  $A$  consists of real numbers).

1.  $AA^+A = A$

2.  $A^+AA^+ = A^+$

3.  $(AA^+)' = AA^+$

4.  $(A^+A)' = A^+A$

If  $A$  is an  $m \times n$  matrix where  $m > n$  and  $A$  is of full rank ( $= n$ ), then

$$A^+ = (A'A)^{-1}A'$$

and the solution of  $Ax = b$  is  $x = A^+b$ . In this case, the solution is not exact. It finds the solution that is closest in the least squares sense.

# Eigenvalues and Eigenvectors

CS6015- LARP;

CS5691 - PRML

CS6464;

Ack: Linear Algebra and Its Applications , Gilbert Strang

## The Solution of $Ax = \lambda x$

- $Ax = \lambda x$  is a nonlinear equation;  $\lambda$  multiplies  $x$ . If we could discover  $\lambda$ , then the equation for  $x$  would be **linear**.
- We could write  $\lambda Ix$  in place of  $\lambda x$ , and bring this term over to the left side:

$$(A - \lambda I)x = 0$$

*The vector  $x$  is in the nullspace of  $A - \lambda I$ .*

*The number  $\lambda$  is chosen so that  $A - \lambda I$  has a nullspace.*

- We want a **nonzero** eigenvector  $x$ . The vector  $x = 0$  always satisfies  $Ax = \lambda x$ , but it is useless.
- To be of any use, the nullspace of  $A - \lambda I$  must contain vectors other than zero.
- In short,  **$A - \lambda I$  must be singular.**

## The Solution of $Ax = \lambda x$

**5A** The number  $\lambda$  is an eigenvalue of  $A$  if and only if  $A - \lambda I$  is singular:

$$\det(A - \lambda I) = 0. \quad (10)$$

This is the characteristic equation. Each  $\lambda$  is associated with eigenvectors  $x$ :

$$(A - \lambda I)x = 0 \quad \text{or} \quad Ax = \lambda x. \quad (11)$$

## The Solution of $Ax = \lambda x$

- Example:

$$A = \begin{bmatrix} 4 & -5 \\ 2 & -3 \end{bmatrix} \quad \text{we shift } A \text{ by } \lambda I \text{ to make it singular:}$$

**Subtract  $\lambda I$**       $A - \lambda I = \begin{bmatrix} 4 - \lambda & -5 \\ 2 & -3 - \lambda \end{bmatrix}$

**Determinant**      $|A - \lambda I| = (4 - \lambda)(-3 - \lambda) + 10$      or      $\lambda^2 - \lambda - 2$

- This is the **characteristic polynomial**.
- Its **roots**, where the **determinant is zero**, are the **eigenvalues**.

$$\lambda^2 - \lambda - 2 = (\lambda + 1)(\lambda - 2)$$



## The Solution of $Ax = \lambda x$

**Eigenvalues**  $\lambda = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} = \frac{1 \pm \sqrt{9}}{2} = -1 \text{ and } 2.$

- There are two eigen values, because a quadratic has two roots.
- The values  $\lambda = -1$  and  $\lambda = 2$  lead to a solution of  $Ax = \lambda x$  or  $(A - \lambda I)x = 0$ .

$$\lambda_1 = -1 : \quad (A - \lambda_1 I)x = \begin{bmatrix} 5 & -5 \\ 2 & -2 \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

The solution (the first eigenvector) is any nonzero multiple of  $x_1$ :

**Eigenvector for  $\lambda_1$**   $x_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$

## The Solution of $Ax = \lambda x$

The solution (the first eigenvector) is any nonzero multiple of  $x_1$ :

$$\text{Eigenvector for } \lambda_1 \quad x_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

The computation for  $\lambda_2$  is done separately:

$$\lambda_2 = 2: \quad (A - \lambda_2 I)x = \begin{bmatrix} 2 & -5 \\ 2 & -5 \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

The second eigenvector is any nonzero multiple of  $x_2$ :

$$\text{Eigenvector for } \lambda_2 \quad x_2 = \begin{bmatrix} 5 \\ 2 \end{bmatrix}.$$

## The Solution of $Ax = \lambda x$

- The steps in solving  $Ax = \lambda x$ :
  - 1. Compute the determinant of  $A - \lambda I$ .** With  $\lambda$  subtracted along the diagonal, this determinant is a polynomial of degree  $n$ . It starts with  $(-\lambda)^n$ .
  - 2. Find the roots of this polynomial.** The  $n$  roots are the eigenvalues of  $A$ .
  - 3. For each eigenvalue solve the equation  $(A - \lambda I)x = 0$ .** Since the determinant is zero, there are solutions other than  $x = 0$ . Those are the eigenvectors.

## The Solution of $Ax = \lambda x$ (Recap)

- The key equation was  $Ax = \lambda x$ .
- Most vectors  $x$  will not satisfy such an equation.
- They **change direction** when multiplied by  $A$ , so that  $Ax$  is not a multiple of  $x$ .
- ***This means that only certain special numbers are eigenvalues, and only certain special vectors  $x$  are eigenvectors.***

**Example 3.** The eigenvalues are on the main diagonal when  $A$  is triangular.

$$\det(A - \lambda I) = \begin{vmatrix} 1 - \lambda & 4 & 5 \\ 0 & \frac{3}{4} - \lambda & 6 \\ 0 & 0 & \frac{1}{2} - \lambda \end{vmatrix} = (1 - \lambda)\left(\frac{3}{4} - \lambda\right)\left(\frac{1}{2} - \lambda\right)$$

- The determinant is just the product of the diagonal entries.
- It is zero if  $\lambda = 1, \lambda = \frac{3}{4},$  or  $\lambda = \frac{1}{2}$
- The eigenvalues were already sitting along the main diagonal.

**5B** The *sum* of the  $n$  eigenvalues equals the sum of the  $n$  diagonal entries:

$$\text{Trace of } A = \lambda_1 + \cdots + \lambda_n = a_{11} + \cdots + a_{nn}. \quad (15)$$

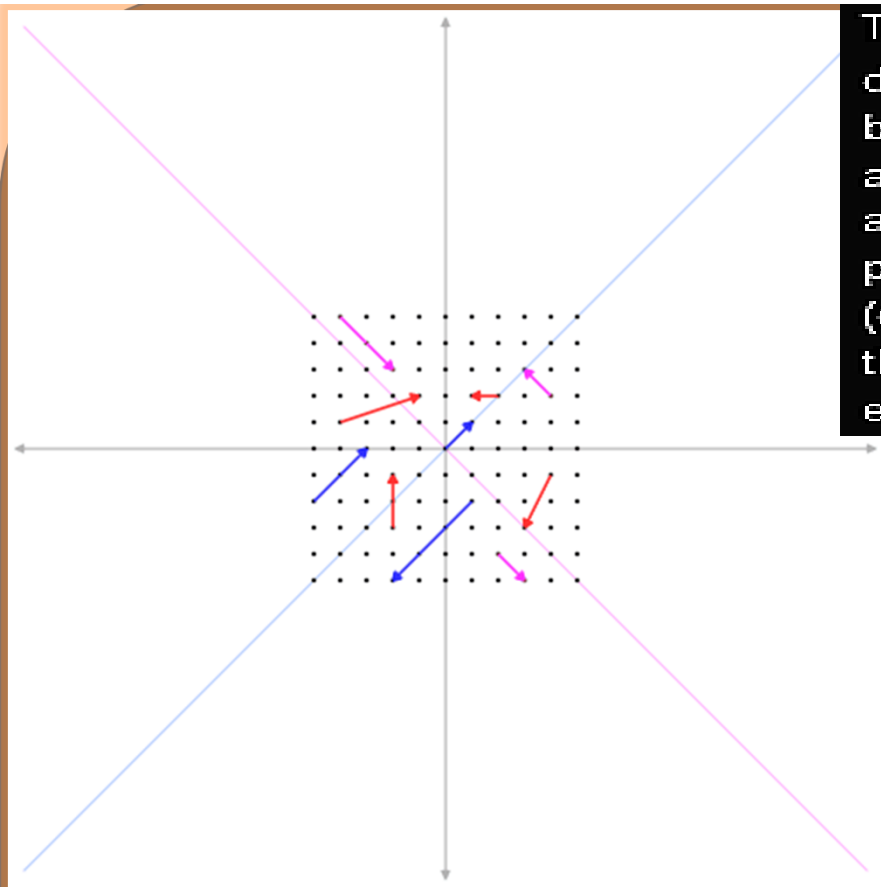
Furthermore, the *product* of the  $n$  eigenvalues equals the *determinant* of  $A$ .

For a 2 by 2 matrix, the trace and determinant tell us everything:

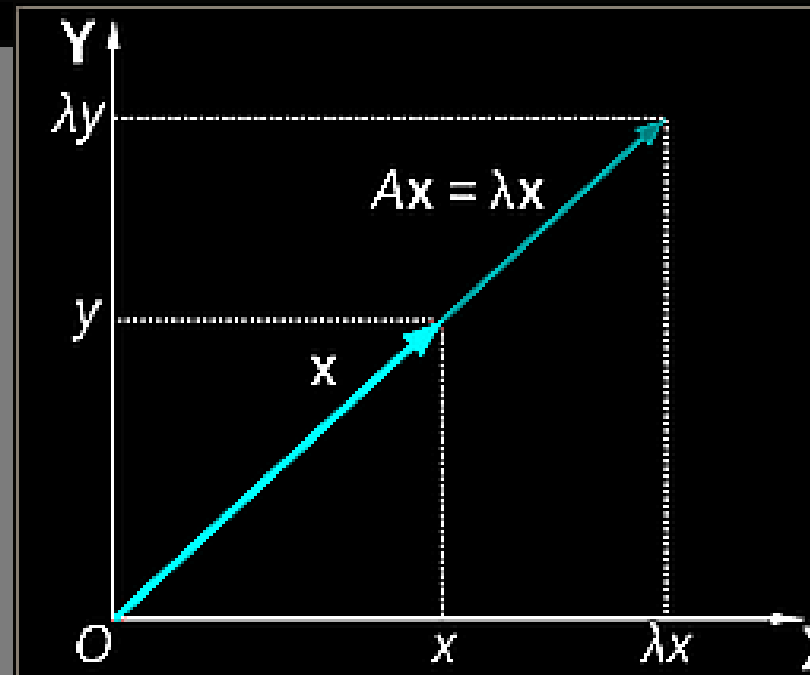
$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \text{ has trace } a + d, \text{ and determinant } ad - bc$$

$$\det(A - \lambda I) = \det \begin{vmatrix} a - \lambda & b \\ c & d - \lambda \end{vmatrix} = \lambda^2 \text{ [redacted]}$$

The eigenvalues are  $\lambda =$  [redacted]



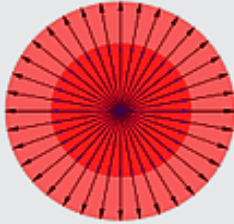
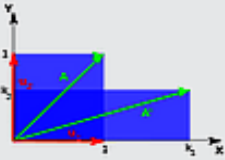
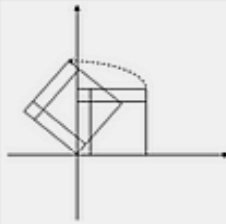
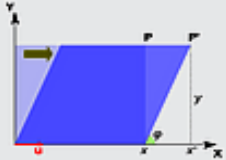
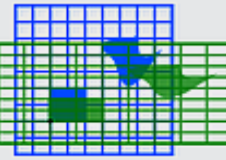
The transformation matrix  $A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$  preserves the direction of purple vectors parallel to  $v_{\lambda=1} = [1 \ -1]^T$  and blue vectors parallel to  $v_{\lambda=3} = [1 \ 1]^T$ . The red vectors are not parallel to either eigenvector, so, their directions are changed by the transformation. The lengths of the purple vectors are unchanged after the transformation (due to their eigenvalue of 1), while blue vectors are three times the length of the original (due to their eigenvalue of 3).



Matrix  $A$  acts by stretching the vector  $x$ , not changing its direction, so  $x$  is an eigenvector of  $A$ .

<https://www.geogebra.org/m/KuMAuEnd>

### Eigenvalues of geometric transformations

	Scaling	Unequal scaling	Rotation	Horizontal shear	Hyperbolic rotation
<b>Illustration</b>					
<b>Matrix</b>	$\begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix}$	$\begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix}$	$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$	$\begin{bmatrix} 1 & k \\ 0 & 1 \end{bmatrix}$	$\begin{bmatrix} \cosh \varphi & \sinh \varphi \\ \sinh \varphi & \cosh \varphi \end{bmatrix}$
<b>Characteristic polynomial</b>	$(\lambda - k)^2$	$(\lambda - k_1)(\lambda - k_2)$	$\lambda^2 - 2 \cos(\theta)\lambda + 1$	$(\lambda - 1)^2$	$\lambda^2 - 2 \cosh(\varphi)\lambda + 1$
<b>Eigenvalues, <math>\lambda_i</math></b>	$\lambda_1 = \lambda_2 = k$	$\lambda_1 = k_1$ $\lambda_2 = k_2$	$\lambda_1 = e^{i\theta}$ $= \cos \theta + i \sin \theta$ $\lambda_2 = e^{-i\theta}$ $= \cos \theta - i \sin \theta$	$\lambda_1 = \lambda_2 = 1$	$\lambda_1 = e^\varphi$ $= \cosh \varphi + \sinh \varphi$ $\lambda_2 = e^{-\varphi}$ $= \cosh \varphi - \sinh \varphi$
<b>Algebraic mult., <math>\mu_i = \mu(\lambda_i)</math></b>	$\mu_1 = 2$	$\mu_1 = 1$ $\mu_2 = 1$	$\mu_1 = 1$ $\mu_2 = 1$	$\mu_1 = 2$	$\mu_1 = 1$ $\mu_2 = 1$
<b>Geometric mult., <math>\gamma_i = \gamma(\lambda_i)</math></b>	$\gamma_1 = 2$	$\gamma_1 = 1$ $\gamma_2 = 1$	$\gamma_1 = 1$ $\gamma_2 = 1$	$\gamma_1 = 1$	$\gamma_1 = 1$ $\gamma_2 = 1$
<b>Eigenvectors</b>	All nonzero vectors	$\mathbf{u}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ $\mathbf{u}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$	$\mathbf{u}_1 = \begin{bmatrix} 1 \\ -i \end{bmatrix}$ $\mathbf{u}_2 = \begin{bmatrix} 1 \\ +i \end{bmatrix}$	$\mathbf{u}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\mathbf{u}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $\mathbf{u}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$



Matrix Type	Eigendecomposition Properties
Square Symmetric	<b>Eigenvalues:</b> always real, nonnegative <b>Eigenvectors:</b> always orthogonal
Square Asymmetric	<b>Eigenvalues:</b> can be complex <b>Eigenvectors:</b> don't necessarily exist
Non-square	Eigendecomposition not possible

## Singular Value Decomposition

$A = U\Sigma V^T$  is known as the “**SVD**” or the ***singular value decomposition***.

The SVD is closely associated with the eigenvalue-eigenvector factorization  $Q\Lambda Q^T$  of a positive definite matrix.

Any  $m \times n$  matrix  $A$  can be factored into

$$A = U\Sigma V^T = (\text{orthogonal})(\text{diagonal})(\text{orthogonal}).$$

The columns of  $U$  ( $m \times m$ ) are ***eigenvectors of  $AA^T$*** , and the columns of  $V$  ( $n \times n$ ) are ***eigenvectors of  $A^T A$*** .

The  $r$  singular values on the diagonal of  $\Sigma$  ( $m \times n$ ) are the ***square roots of the nonzero eigenvalues*** of both  $AA^T$  and  $A^T A$ .

See next few slides for variants →

**Strang - Sec. 6.3 - PP 367**

**Singular Value Decomposition:** Any  $m$  by  $n$  matrix  $A$  can be factored into

$$A = U\Sigma V^T = (\text{orthogonal})(\text{diagonal})(\text{orthogonal}).$$

The columns of  $U$  ( $m$  by  $m$ ) are eigenvectors of  $AA^T$ , and the columns of  $V$  ( $n$  by  $n$ ) are eigenvectors of  $A^T A$ . The  $r$  singular values on the diagonal of  $\Sigma$  ( $m$  by  $n$ ) are the square roots of the nonzero eigenvalues of both  $AA^T$  and  $A^T A$ .

Given the  $N \times p$  data matrix  $\mathbf{X}$ , let

**Hastie - Sec. 18.3.5 - PP 659**

$$\mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^T \quad (18.12)$$

$$= \mathbf{R}\mathbf{V}^T \quad (18.13)$$

be the singular-value decomposition (SVD) of  $\mathbf{X}$ ; that is,  $\mathbf{V}$  is  $p \times N$  with orthonormal columns,  $\mathbf{U}$  is  $N \times N$  orthogonal, and  $\mathbf{D}$  a diagonal matrix with elements  $d_1 \geq d_2 \geq \dots \geq d_N \geq 0$ . The matrix  $\mathbf{R}$  is  $N \times N$ , with rows  $r_i^T$ .

Stack the (centered) observations into the rows of an  $N \times p$  matrix  $\mathbf{X}$ . We construct the *singular value decomposition* of  $\mathbf{X}$ :

**Sec. 14.5 – PP 535**

$$\mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^T. \quad (14.54)$$

This is a standard decomposition in numerical analysis, and many algorithms exist for its computation (Golub and Van Loan, 1983, for example). Here  $\mathbf{U}$  is an  $N \times p$  orthogonal matrix ( $\mathbf{U}^T\mathbf{U} = \mathbf{I}_p$ ) whose columns  $\mathbf{u}_j$  are called the *left singular vectors*;  $\mathbf{V}$  is a  $p \times p$  orthogonal matrix ( $\mathbf{V}^T\mathbf{V} = \mathbf{I}_p$ ) with columns  $\mathbf{v}_j$  called the *right singular vectors*, and  $\mathbf{D}$  is a  $p \times p$  diagonal matrix, with diagonal elements  $d_1 \geq d_2 \geq \dots \geq d_p \geq 0$  known as the *sin-*

Here  $\mathbf{U}$  and  $\mathbf{V}$  are  $N \times p$  and  $p \times p$  orthogonal matrices, with the columns of  $\mathbf{U}$  spanning the column space of  $\mathbf{X}$ , and the columns of  $\mathbf{V}$  spanning the row space.  $\mathbf{D}$  is a  $p \times p$  diagonal matrix, with diagonal entries  $d_1 \geq d_2 \geq \dots \geq d_p \geq 0$  called the singular values of  $\mathbf{X}$ . If one or more values  $d_j = 0$ ,  $\mathbf{X}$  is singular.

Using the singular value decomposition we can write the least squares fitted vector as

$$\begin{aligned} \mathbf{X}\hat{\boldsymbol{\beta}}^{\text{ls}} &= \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} \\ &= \mathbf{U}\mathbf{U}^T\mathbf{y}, \end{aligned} \quad (3.46)$$

## Singular Value Decomposition

### *Remark 1.*

- For positive definite matrices,  $\Sigma$  is  $\Lambda$  and  $U\Sigma V^T$  is identical to  $Q\Lambda Q^T$ .
- For other symmetric matrices, any negative eigenvalues in  $\Lambda$  become positive in  $\Sigma$ .
- For complex matrices,  $\Sigma$  remains real but  $U$  and  $V$  become *unitary* (the complex version of orthogonal).

### *Remark 2.*

$U$  and  $V$  give orthonormal bases for all four fundamental subspaces:

first	$r$	columns of $U$ :	<b>column space</b> of $A$
last	$m - r$	columns of $U$ :	<b>left nullspace</b> of $A$
first	$r$	columns of $V$ :	<b>row space</b> of $A$
last	$n - r$	columns of $V$ :	<b>nullspace</b> of $A$

## Singular Value Decomposition

### **Remark 3.**

Eigenvectors of  $AA^T$  and  $A^T A$  must go into the columns of  $U$  and  $V$ :

$$AA^T = (U\Sigma V^T)(V\Sigma^T U^T) = U\Sigma\Sigma^T U^T \quad \text{and, similarly,} \quad A^T A = V\Sigma^T \Sigma V^T.$$

- $U$  must be the eigenvector matrix for  $AA^T$ .
- The eigenvalue matrix in the middle is  $\Sigma\Sigma^T$  — which is  $m \times m$  with  $\sigma_1^2, \dots, \sigma_r^2$  on the diagonal.
- From the  $A^T A = V\Sigma^T \Sigma V^T$ , the  $V$  matrix must be the eigenvector matrix for  $A^T A$ .

## SVD – the theorem (Src; WIKI ++)

Suppose  $M$  is an **m-by-n** matrix whose entries come from the field  $K$ , which is either the field of real numbers or the field of complex numbers. Then there exists a factorization of the form

$$M = U\Sigma V^*$$

where,  **$U$  is an m-by-m** unitary matrix, the matrix  **$\Sigma$  is m-by-n** with nonnegative numbers on the diagonal and zeros off the diagonal, and  **$V^*$**  denotes the conjugate transpose of  **$V$ , an n-by-n** unitary matrix over  $K$ . Such a factorization is called a singular-value decomposition of  $M$ .

The matrix  $V$  thus contains a set of orthonormal "input" or "analysing" basis vector directions for  $M$ .

The matrix  $U$  contains a set of orthonormal "output" basis vector directions for  $M$ . The matrix  $\Sigma$  contains the singular values, which can be thought of as scalar "gain controls" by which each corresponding input is multiplied to give a corresponding output.

A common convention is to order the values  $\Sigma_{i,i}$  in non-increasing fashion. In this case, the diagonal matrix  $\Sigma$  is uniquely determined by  $M$  (though the matrices  $U$  and  $V$  are not).

For  $p = \min(m,n)$  -  **$U$  is m-by-p,  $\Sigma$  is p-by-p, and  $V$  is n-by-p.**



A timeline of major singular value decomposition developments.

Erichson, N. B., Voronin, S., **Brunton, S. L.**, & Kutz, J. N. (2019). Randomized Matrix  
 The columns of  $U$  ( $m \times m$ ) are **eigenvectors of  $AA^T$** , and the columns of  $V$  ( $n \times n$ ) are **eigenvectors of  $A^T A$**

Given a real matrix  $A \in \mathbb{R}^{m \times n}$  with  $m \geq n$ , the singular value decomposition takes the form

$$A = U \Sigma V^T.$$

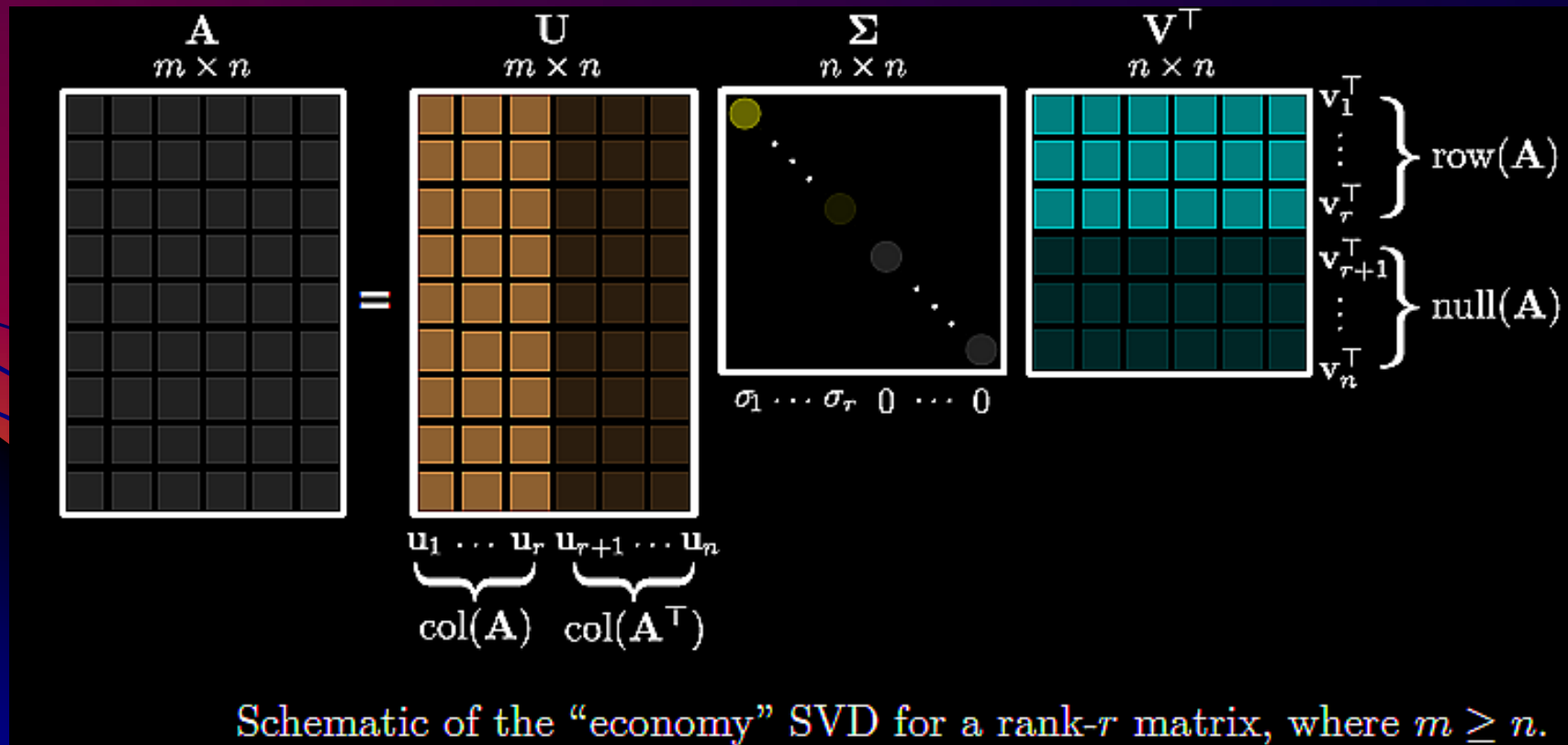
The matrices  $U = [u_1, \dots, u_m] \in \mathbb{R}^{m \times m}$  and  $V = [v_1, \dots, v_n] \in \mathbb{R}^{n \times n}$  are orthonormal so that  $U^T U = I$  and  $V^T V = I$ . The left singular vectors in  $U$  provide a basis for the range (column space), and the right singular vectors in  $V$  provide a basis for the domain (row space) of the matrix  $A$ . The rectangular diagonal matrix  $\Sigma \in \mathbb{R}^{m \times n}$  contains the corresponding non-negative singular values  $\sigma_1 \geq \dots \geq \sigma_n \geq 0$ , describing the spectrum of the data.



The so called “economy” or “thin” SVD computes only the left singular vectors and singular values corresponding to the number (i.e.,  $n$ ) of right singular vectors

$$A = U\Sigma V = [u_1, \dots, u_n] \text{diag}(\sigma_1, \dots, \sigma_n) [v_1, \dots, v_n]^T.$$

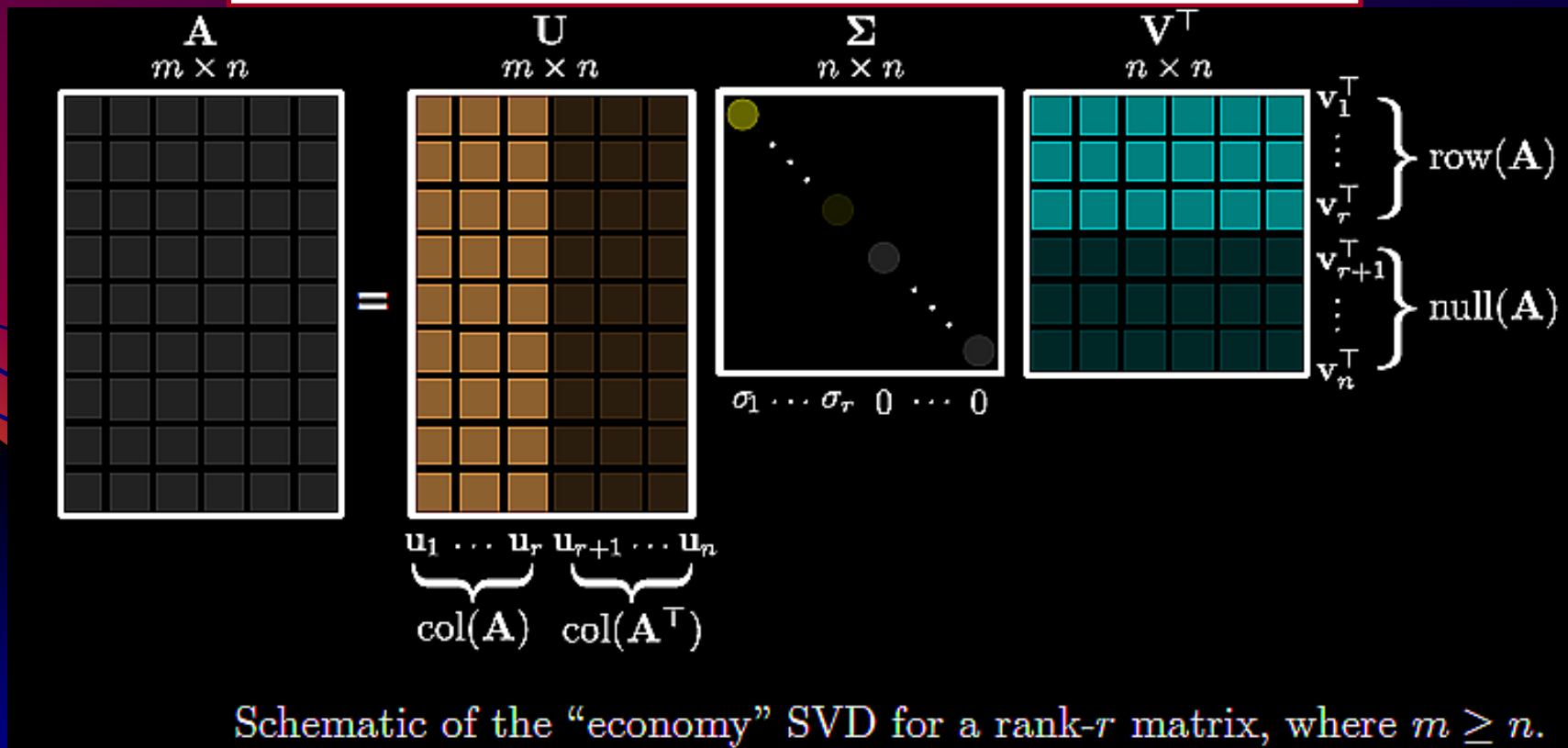
**If the number of right singular vectors is small (i.e.  $n \ll m$ ), this is a more compact factorization than the full SVD.**



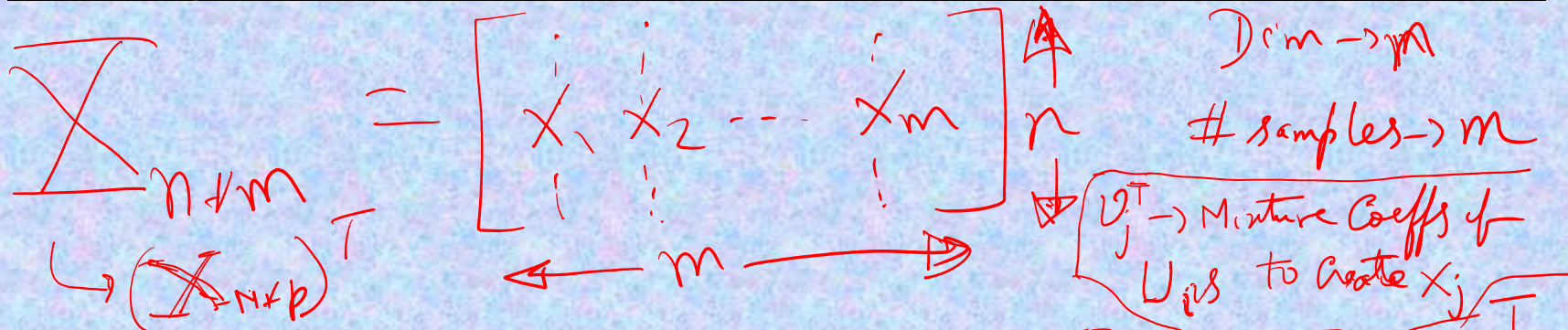
Low-rank matrices feature a rank ( $r$ ) that is smaller than the dimension of the matrix. For a matrix  $A$  of size  $m \times n$ , the rank  $r$  is the number of non-zero rows.

For a rank- $r$  matrix  $A$ , the SVD decomposition  $A = U \Sigma V^T$  reveals the column space and the row space of  $A$ .

first	$r$	columns of $U$ :	<b>column space</b> of $A$
last	$m - r$	columns of $U$ :	<b>left nullspace</b> of $A$
first	$r$	columns of $V$ :	<b>row space</b> of $A$
last	$n - r$	columns of $V$ :	<b>nullspace</b> of $A$



$$U \Sigma V^T = \begin{bmatrix} | & | & & | \\ u_1 & u_2 & \dots & u_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_m \\ \hline & & & & 0 \end{bmatrix} \begin{bmatrix} v_1 & v_2 & \dots & v_m \end{bmatrix}^T$$



$$= \begin{bmatrix} | & | & & | \\ u_1 & u_2 & \dots & u_n \\ | & | & & | \end{bmatrix}_{n \times n} \begin{bmatrix} \sigma_1 & & & 0 \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_m \\ \hline & & & & 0 \end{bmatrix}_{n \times m} \begin{bmatrix} v_1 & v_2 & \dots & v_m \\ \vdots & \vdots & & \vdots \end{bmatrix}_{m \times m}^T$$

$v_i \in \mathbb{R}^m; u_i, x_i \in \mathbb{R}^n$   
 $U^T U = U U^T = I_{n \times n}$  ||  
 L.S.V.

$V^T V = V V^T = I_{m \times m}$   
 R.S.V.

**In practical applications matrices are often contaminated by errors, and the effective rank of a matrix can be smaller than its exact rank  $r$ .**

**In this case, the matrix can be well approximated by including only those singular vectors which correspond to singular values of a significant magnitude. Hence, it is often desirable to compute a reduced version of the SVD, as:**

$$A_k := U_k \Sigma_k V_k = [u_1, \dots, u_k] \text{diag}(\sigma_1, \dots, \sigma_k) [v_1, \dots, v_k]^T,$$

where  $k$  denotes the desired target rank of the approximation. In other words, this reduced form of the SVD allows one to express  $A$  approximately by the sum of  $k$  rank-one matrices

$$A_k \approx \sum_{i=1}^k \sigma_i u_i v_i^T.$$

Choosing an optimal target rank  $k$  is highly dependent on the task.

**For massive datasets, however, the truncated/reduced SVD is costly to compute. The cost to compute the full SVD of an  $m \times n$  matrix is of the order  $O(mn^2)$ , from which the first  $k$  components can then be extracted to form  $A_k$ .**

**$k$  should be chosen close to the effective rank – data representation Applcn.; while chosen much smaller ( $\ll r$ ) for dimension reduction (PCA).**

$$\begin{array}{|c|} \hline A \\ \hline n \times d \\ \hline \end{array} = \begin{array}{|c|} \hline U \\ \hline n \times r \\ \hline \end{array} \begin{array}{|c|} \hline D \\ \hline r \times r \\ \hline \end{array} \begin{array}{|c|} \hline V^T \\ \hline r \times d \\ \hline \end{array}$$

B.Tech, CSE\_ IIT Madras (1997);  
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Miller Research Fellow,  
UC Berkeley (2001-02);  
CMU; Berkeley

The SVD decomposition of an  $n \times d$  matrix.

*Theorem 1.5 Let  $A$  be an  $n \times d$  matrix with right singular vectors  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_r$ , left singular vectors  $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r$ , and corresponding singular values  $\sigma_1, \sigma_2, \dots, \sigma_r$ . Then*

$$A = \sum_{i=1}^r \sigma_i \mathbf{u}_i \mathbf{v}_i^T.$$

$$U^T U = I_{r \times r} \Leftrightarrow U U^T$$

$$V V^T \Leftrightarrow I_{r \times r} = V^T V$$

$$\mathbf{A} = \mathbf{U} \mathbf{S} \mathbf{V}^T \text{ and } \mathbf{A}^T = \mathbf{V} \mathbf{S} \mathbf{U}^T$$

$$\mathbf{A}^T \mathbf{A} = \mathbf{V} \mathbf{S} \mathbf{U}^T \mathbf{U} \mathbf{S} \mathbf{V}^T = \mathbf{V} \mathbf{S}^2 \mathbf{V}^T$$

$$\mathbf{A}^T \mathbf{A} \mathbf{V} = \mathbf{V} \mathbf{S}^2; \quad \mathbf{V}^T \mathbf{A}^T \mathbf{A} \mathbf{V} = \mathbf{S}^2;$$

$$\mathbf{A} \cdot \mathbf{A}^T = ??$$

The diagonal entries  $\sigma_i = \Sigma_{ii}$  of  $\Sigma$  are uniquely determined by  $\mathbf{M}$  and are known as the **singular values** of  $\mathbf{M}$ . The number of non-zero singular values is equal to the **rank** of  $\mathbf{M}$ . The columns of  $\mathbf{U}$  and the columns of  $\mathbf{V}$  are called left-singular vectors and right-singular vectors of  $\mathbf{M}$ , respectively. They form two sets of **orthonormal bases**  $\mathbf{u}_1, \dots, \mathbf{u}_m$  and  $\mathbf{v}_1, \dots, \mathbf{v}_n$ , and if they are sorted so that the singular values  $\sigma_i$  with value zero are all in the highest-numbered columns (or rows), the singular value decomposition can be written as  $\mathbf{M} = \sum_{i=1}^r \sigma_i \mathbf{u}_i \mathbf{v}_i^*$ , where  $r \leq \min\{m, n\}$  is the rank of  $\mathbf{M}$ .

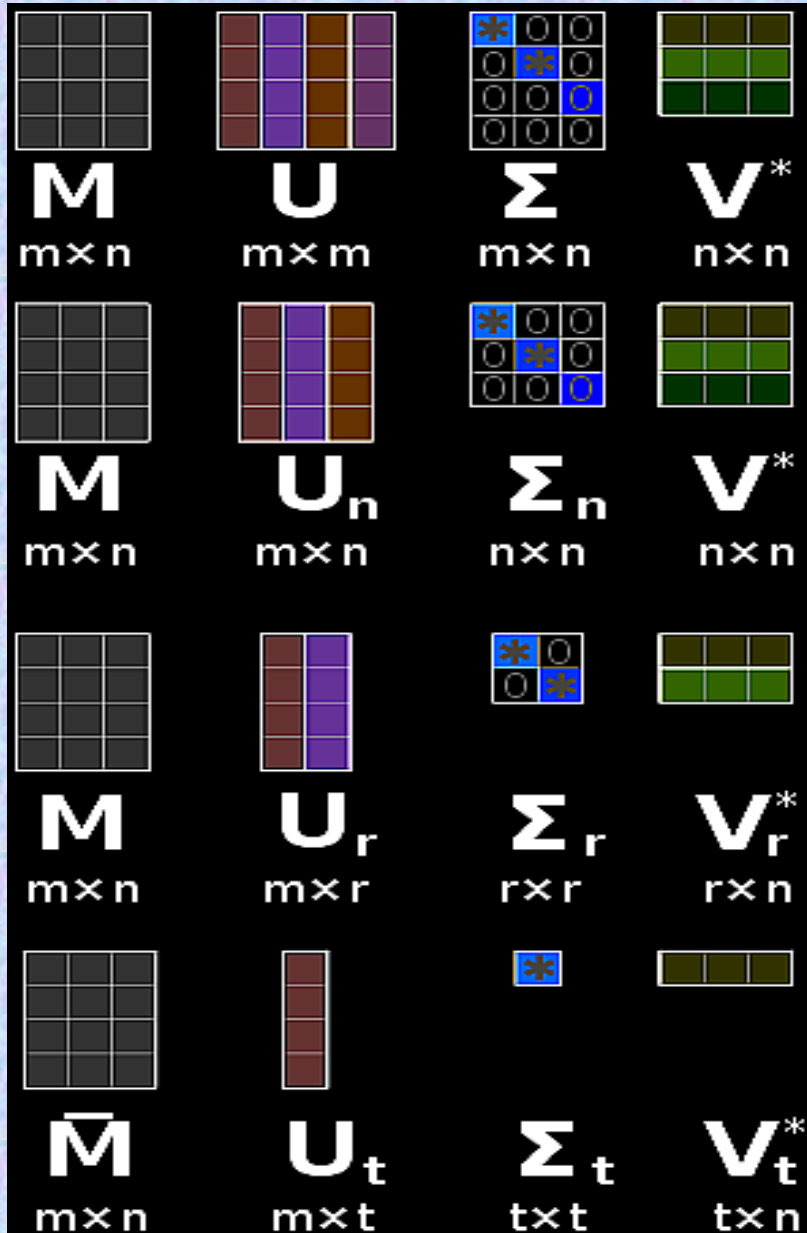
The term sometimes refers to the **compact SVD**, a similar decomposition  $\mathbf{M} = \mathbf{U}\Sigma\mathbf{V}^*$  in which  $\Sigma$  is square diagonal of size  $r \times r$ , where  $r \leq \min\{m, n\}$  is the rank of  $\mathbf{M}$ , and has only the non-zero singular values. In this variant,  $\mathbf{U}$  is an  $m \times r$  **semi-unitary matrix** and  $\mathbf{V}$  is an  $n \times r$  **semi-unitary matrix**, such that  $\mathbf{U}^*\mathbf{U} = \mathbf{V}^*\mathbf{V} = \mathbf{I}_r$ .

**1: Full SVD,**

**2: Thin SVD (remove columns of U not corresponding to rows of V\*),**

**3: Compact SVD (remove vanishing singular values and corresponding columns/rows in U and V\*),**

**4: Truncated SVD (keep only largest t singular values and corresponding columns/rows in U and V\*)**



$A : m \times n$  matrix of rank  $r$

eigenvectors

$$AA^T \longrightarrow \underbrace{u_1, u_2, u_3, \dots, u_r, \dots, u_m}_{\text{span column space of } A} \quad \underbrace{\quad}_{\text{span left nullspace of } A: N(A^T)}$$

$$A^T A \longrightarrow \underbrace{v_1, v_2, v_3, \dots, v_r, \dots, v_n}_{\text{span row space of } A} \quad \underbrace{\quad}_{\text{span nullspace of } A: N(A)}$$

$$\begin{array}{c} \begin{matrix} & \mathbf{A} & & & \mathbf{U} & & \mathbf{S} & & \mathbf{V}^T \\ \begin{pmatrix} x_{11} & x_{12} & & x_{1n} \\ & & \ddots & \\ & & & \\ x_{m1} & & & x_{mn} \end{pmatrix} & = & \begin{pmatrix} u_{11} & & & u_{m1} \\ & & \ddots & \\ & & & \\ u_{1m} & & & u_{mm} \end{pmatrix} & \begin{pmatrix} \sigma_1 & & & 0 \\ & \ddots & & \\ & & \sigma_r & \\ 0 & & & \dots & 0 \end{pmatrix} & \begin{pmatrix} v_{11} & & & v_{1n} \\ & & \ddots & \\ & & & \\ v_{n1} & & & v_{nn} \end{pmatrix} \end{matrix} \\ \\ \begin{matrix} & \mathbf{A} & & & \mathbf{V} & & \mathbf{U} & & \mathbf{S} \\ \begin{pmatrix} x_{11} & x_{12} & & x_{1n} \\ & & \ddots & \\ & & & \\ x_{m1} & & & x_{mn} \end{pmatrix} & \begin{pmatrix} v_{11} & & & v_{r1} \\ & & \ddots & \\ & & & \\ v_{1n} & & & v_{rn} \end{pmatrix} & = & \begin{pmatrix} u_{11} & & & u_{r1} \\ & & \ddots & \\ & & & \\ u_{1m} & & & u_{rm} \end{pmatrix} & \begin{pmatrix} \sigma_1 & & & 0 \\ & \ddots & & \\ & & & \\ 0 & & & \sigma_r \end{pmatrix} \end{matrix} \\ \\ \begin{matrix} m \times n & & n \times r & & m \times r & & r \times r \end{matrix} \end{array}$$



## Singular Value Decomposition

### *Example 1.*

This  $A$  has only one column: rank  $r = 1$ . Then  $\Sigma$  has only  $\sigma_1 = 3$ :

$$\mathbf{SVD} \quad A = \begin{bmatrix} -1 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} -\frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \\ \frac{2}{3} & \frac{2}{3} & -\frac{1}{3} \end{bmatrix} \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 \end{bmatrix} = U_{3 \times 3} \Sigma_{3 \times 1} V_{1 \times 1}^T$$

$A^T A$  is 1 by 1, whereas  $AA^T$  is 3 by 3. They both have eigenvalue 9 (whose square root is the 3 in  $\Sigma$ ). The two zero eigenvalues of  $AA^T$  leave some freedom for the eigenvectors in columns 2 and 3 of  $U$ . We kept that matrix orthogonal.

## Singular Value Decomposition

### *Example 2.*

Now A has rank 2, and  $AA^T = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$  with  $\lambda = 3$  and 1:

$$\begin{bmatrix} -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} = U\Sigma V^T = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & -2 & 1 \\ -1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{matrix} /\sqrt{6} \\ / \sqrt{2} \\ / \sqrt{3} \end{matrix}$$

Notice  $\sqrt{3}$  and  $\sqrt{1}$ . The columns of U are *left singular vectors* (unit eigenvectors of  $AA^T$ ).

The columns of V are *right singular vectors* (unit eigenvectors of  $A^T A$ ).

In general, the best rank- $r$  approximation to  $A$  is given by

$$\tilde{A} = \begin{bmatrix} \vdots & \vdots & \dots & \vdots \\ \mathbf{u}_1 & \mathbf{u}_2 & \dots & \mathbf{u}_r \\ \vdots & \vdots & \dots & \vdots \end{bmatrix}_{m \times r} \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & \sigma_r \end{bmatrix}_{r \times r} \begin{bmatrix} \vdots & \vdots & \dots & \vdots \\ \mathbf{v}_1 & \mathbf{v}_2 & \dots & \mathbf{v}_r \\ \vdots & \vdots & \dots & \vdots \end{bmatrix}_{r \times n}^T$$

$$= \sigma_1 \mathbf{u}_1 \mathbf{v}_1^T + \sigma_2 \mathbf{u}_2 \mathbf{v}_2^T + \dots + \sigma_r \mathbf{u}_r \mathbf{v}_r^T$$

and it can be shown that

$$\|A - \tilde{A}\|_F = \sqrt{\sigma_{r+1}^2 + \sigma_{r+2}^2 + \dots + \sigma_n^2} \quad (2)$$

The MATLAB command

```
[U, S, V] = svd(A)
```

returns the SVD decomposition of the matrix  $A$ , that is, it returns matrices  $U$ ,  $S$  and  $V$  such that  $A = USV^T$ .

**Example**

The SVD of the following matrix  $A$  is:

$$A = \begin{bmatrix} -2 & 8 & 20 \\ 14 & 19 & 10 \\ 2 & -2 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 30 & 0 & 0 \\ 0 & 15 & 0 \\ 0 & 0 & 3 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

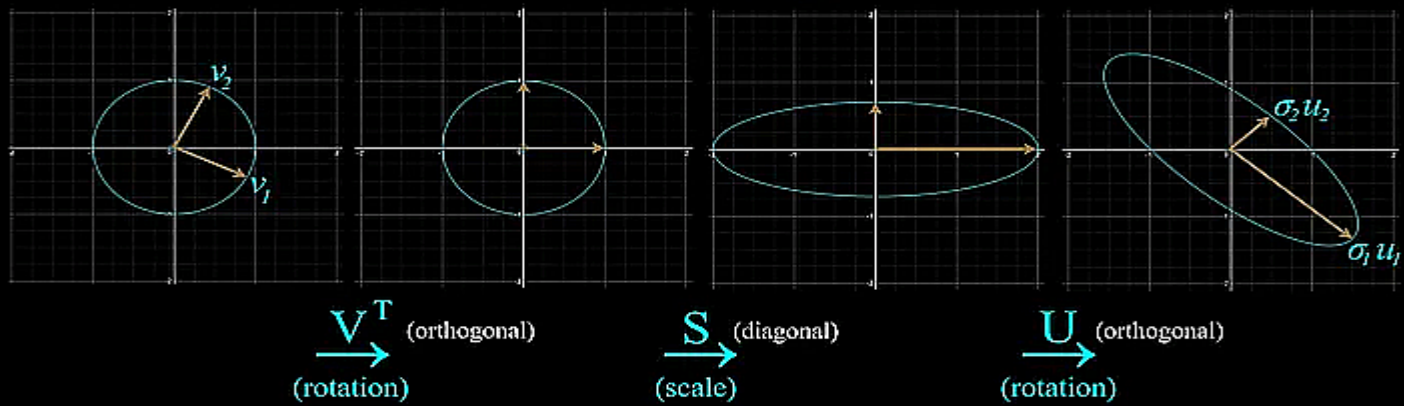
- (a) Enter the matrix  $A$  and compute  $U$ ,  $S$  and  $V$  using the `svd` command. Verify that  $A = USV^T$ .

**Answer:**

```
>> A=[-2,8,20;14,19,10;2, -2, 1];
>> [U,S,V]=svd(A)
U =
 0.6000  -0.8000  0.0000
 0.8000   0.6000  0.0000
 0.0000  -0.0000  1.0000
S =
30.0000   0   0
 0  15.0000   0
 0   0   3.0000
V =
 0.3333  0.6667  0.6667
 0.6667  0.3333 -0.6667
 0.6667 -0.6667  0.3333
```

We can easily verify that  $U*S*V'$  returns the matrix  $A$ .

$$Ax = USV^T x$$



Let  $A = \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix}$ . Then

$$AA^T = \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 3 \\ -1 & 1 \\ 3 & 1 \end{bmatrix} = \begin{bmatrix} 11 & 5 \\ 5 & 11 \end{bmatrix}.$$

$$A^T A = \begin{bmatrix} 1 & 3 \\ -1 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 & 3 \\ 3 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 10 & 2 & 6 \\ 2 & 2 & -2 \\ 6 & -2 & 10 \end{bmatrix}$$

$$\begin{aligned} &= \det(xI - AA^T) = \begin{vmatrix} x - 11 & -5 \\ -5 & x - 11 \end{vmatrix} \\ &= (x - 11)^2 - 25 \\ &= x^2 - 22x + 121 - 25 \\ &= x^2 - 22x + 96 \\ &= (x - 16)(x - 6). \end{aligned}$$

$$\begin{bmatrix} 1 & 4 \\ 2 & 8 \end{bmatrix} = \left( \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix} \right) \begin{bmatrix} \bullet \\ \bullet \\ \bullet \end{bmatrix} \left( \frac{1}{\sqrt{17}} \begin{bmatrix} 1 & -4 \\ 4 & 1 \end{bmatrix} \right)$$

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

$$= \left( \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \right) \begin{bmatrix} 4 & 0 & 0 \\ 0 & \sqrt{6} & 0 \end{bmatrix} \left( \frac{1}{\sqrt{6}} \begin{bmatrix} \sqrt{3} & 0 & \sqrt{3} \\ -\sqrt{2} & -\sqrt{2} & \sqrt{2} \\ -1 & 2 & 1 \end{bmatrix} \right)$$

$$V = \frac{1}{\sqrt{6}} \begin{bmatrix} \sqrt{3} & -\sqrt{2} & -1 \\ 0 & -\sqrt{2} & 2 \\ \sqrt{3} & \sqrt{2} & 1 \end{bmatrix}$$

$$\Sigma = \begin{bmatrix} 4 & 0 & 0 \\ 0 & \sqrt{6} & 0 \end{bmatrix},$$

$$A = \begin{pmatrix} 3 & 2 & 2 \\ 2 & 3 & -2 \end{pmatrix}$$

$$A = USV^T = \begin{pmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{pmatrix} \begin{pmatrix} 5 & 0 & 0 \\ 0 & 3 & 0 \end{pmatrix} \begin{pmatrix} 1/\sqrt{2} & 1/\sqrt{2} & 0 \\ 1/\sqrt{18} & -1/\sqrt{18} & 4/\sqrt{18} \\ 2/3 & -2/3 & -1/3 \end{pmatrix}$$

$$A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad (\text{singular, inverse does not exist})$$

$$A = U\Sigma V^T = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

$$A^+ = V\Sigma^+U^T = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1/2 & 0 \\ 0 & 0 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

$n = 5$ :

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 & 2 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 & 0 \end{pmatrix}$$

As seen here, the SVD is given by  $A = U\tilde{S}V^T$ , with

$$U = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & -1 \\ 1 & 0 & 0 & 0 \end{pmatrix}, \tilde{S} = \begin{pmatrix} 4 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & \sqrt{5} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}, V^T = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ \sqrt{0.2} & 0 & 0 & 0 & \sqrt{0.8} \\ 0 & 0 & 0 & 1 & 0 \\ -\sqrt{0.8} & 0 & 0 & 0 & \sqrt{0.2} \end{pmatrix}.$$

The matrix is rank  $r = 3$ . A rank-two approximation is given by zeroing out the smallest singular value, which produces

$$\begin{aligned} \hat{A}_2 &= \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & -1 \\ 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 4 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ \sqrt{0.2} & 0 & 0 & 0 & \sqrt{0.8} \\ 0 & 0 & 0 & 1 & 0 \\ -\sqrt{0.8} & 0 & 0 & 0 & \sqrt{0.2} \end{pmatrix} \\ &= \begin{pmatrix} 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 4 & 0 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix} \\ &= \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 & 0 \end{pmatrix}. \end{aligned}$$

$$\begin{matrix} & R & & U & & \Sigma & & V^T \\ \begin{bmatrix} 5 & 5 & 0 & 0 & 1 \\ 4 & 5 & 1 & 1 & 0 \\ 5 & 4 & 1 & 1 & 0 \\ 0 & 0 & 4 & 4 & 4 \\ 0 & 0 & 5 & 5 & 5 \\ 1 & 1 & 4 & 4 & 4 \end{bmatrix} & \approx & \begin{bmatrix} -0,27 & 0,55 & -0,78 & 0 \\ -0,29 & 0,47 & 0,44 & -0,71 \\ -0,29 & 0,47 & 0,44 & 0,71 \\ -0,45 & -0,29 & -0,01 & 0 \\ -0,56 & -0,36 & -0,02 & 0 \\ -0,50 & -0,18 & -0,05 & 0 \end{bmatrix} & \begin{bmatrix} 13,74 & 0 & 0 & 0 \\ 0 & 10,88 & 0 & 0 \\ 0 & 0 & 1,36 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} & \begin{bmatrix} -0,32 & -0,32 & -0,52 & -0,52 & -0,5 \\ 0,63 & 0,63 & -0,25 & -0,25 & -0,29 \\ -0,02 & -0,02 & 0,41 & 0,41 & -0,82 \\ 0,71 & -0,71 & 0 & 0 & 0 \end{bmatrix}
 \end{matrix}$$

$$\begin{matrix} \begin{bmatrix} 5 & 5 & 0 & 0 & 1 \\ 4 & 5 & 1 & 1 & 0 \\ 5 & 4 & 1 & 1 & 0 \\ 0 & 0 & 4 & 4 & 4 \\ 0 & 0 & 5 & 5 & 5 \\ 1 & 1 & 4 & 4 & 4 \end{bmatrix} & \approx & \begin{bmatrix} -0,27 & 0,55 \\ -0,29 & 0,47 \\ -0,29 & 0,47 \\ -0,45 & -0,29 \\ -0,56 & -0,36 \\ -0,50 & -0,18 \end{bmatrix} & \begin{bmatrix} 13,74 & 0 \\ 0 & 10,88 \end{bmatrix} & \begin{bmatrix} -0,32 & -0,32 & -0,52 & -0,52 & -0,5 \\ 0,63 & 0,63 & -0,25 & -0,25 & -0,29 \end{bmatrix}
 \end{matrix}$$

$$\begin{matrix} \begin{bmatrix} 4,95 & 4,95 & 0,43 & 0,43 & 0,11 \\ 4,49 & 4,49 & 0,79 & 0,79 & 0,50 \\ 4,49 & 4,49 & 0,79 & 0,79 & 0,50 \\ -0,00 & -0,00 & 4,00 & 4,00 & 4,00 \\ -0,00 & -0,00 & 4,98 & 4,98 & 4,98 \\ 0,96 & 0,96 & 4,06 & 4,06 & 4,00 \end{bmatrix} & = & \begin{bmatrix} -0,27 & 0,55 \\ -0,29 & 0,47 \\ -0,29 & 0,47 \\ -0,45 & -0,29 \\ -0,56 & -0,36 \\ -0,50 & -0,18 \end{bmatrix} & \begin{bmatrix} 13,74 & 0 \\ 0 & 10,88 \end{bmatrix} & \begin{bmatrix} -0,32 & -0,32 & -0,52 & -0,52 & -0,5 \\ 0,63 & 0,63 & -0,25 & -0,25 & -0,29 \end{bmatrix}
 \end{matrix}$$

<b>X:</b>	<b>U</b>	<b><math>\Sigma</math></b>	<b><math>V^T</math></b>
[ 0 1 2 ] [-1 0 3 ] [-2 -3 0 ]	[-0.5976 0. 0.8018] [-0.7171 0.4472 -0.5345] [ 0.3586 0.8944 0.2673]	[3.7417 0. 0.] [ 0. 3.7417 0.] [ 0. 0. 0.]	[[-0. -0.4472 -0.8944] [-0.5976 -0.7171 0.3586] [ 0.8018 -0.5345 0.2673]]
[ 0 1 2 ] [-1 1 3 ] [-2 -3 0 ]	[ 0.5167 0.1746 0.8382] [ 0.6713 0.5251 -0.5232] [-0.5314 0.833 0.1541]	[4.1449 0. 0.] [ 0. 3.4265 0.] [ 0. 0. 0.2816]	[0.0945 0.6713 0.7352] [-0.6394 -0.5251 0.5616] [ 0.763 -0.5232 0.3796]]
[0 1.01 2 ] [-1 0 3 ] [-2 -3 0 ]	[-0.5238 -0.2893 0.8012] [-0.4091 -0.7395 -0.5345] [ 0.7472 -0.6078 0.269 ]	[3.7455 0. 0.] [ 0. 3.7405 0.] [ 0. 0. 0.0043]	[-0.2897 -0.7397 -0.6074] [ 0.5227 0.4093 -0.7478] [-0.8018 0.5341 -0.268 ]]
[ 0 1 2 ] [0 1.5 3 ] [0 0 0 ]	[-0.5547 0.8321 0. ] [-0.8321 -0.5547 0. ] [ 0. 0. 1. ]	[ 4.0311 0. 0.] [ 0. 0. 0.] [ 0. 0. 0.]	[ 0. -0.4472 -0.8944] [-0. 0.8944 -0.4472] [ 1. 0. 0. ]



X:	U	$\Sigma$	$V^T$
[40 -10 110]	[-0.2673 0.9561 0.1204]	[439.5452 0. 0.]	[-0.3405 0.0851 -0.9364]
80 -20 220]	[-0.5345 -0.0431 -0.8441]	[ 0. 0. 0.]	[-0.9379 0.0396 0.3447]
120 -30 330]	[-0.8018 -0.29 0.5226]	[ 0. 0. 0.]	[-0.0664 -0.9956 -0.0664]
[ 0 0 0]	[ 0. 0.8944 0.4472]	[8.3666 0. 0.]	[-0.2673 -0.5345 -0.8018]
[-1 -2 -3]	[ 0.4472 -0.4 0.8 ]	[ 0. 0. 0.]	[ 0. -0.8321 0.5547]
[-2 -4 -6]	[ 0.8944 0.2 -0.4 ]	[ 0. 0. 0.]	[ 0.9636 -0.1482 -0.2224]

X:	U	$\Sigma$	$V^T$
$\begin{bmatrix} 0 & 0 & -3 & 0 \\ -\sqrt{2} & \frac{4\sqrt{3}}{3} & 0 & 0 \\ -\sqrt{2} & -\frac{4\sqrt{3}}{3} & 0 & 0 \\ 0 & \frac{4\sqrt{3}}{3} & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ \frac{1}{\sqrt{3}} & 0 & \frac{-1}{\sqrt{2}} & 0 & \frac{-1}{\sqrt{6}} \\ \frac{-1}{\sqrt{3}} & 0 & \frac{-1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & 0 & 0 & 0 & \frac{2}{\sqrt{6}} \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$	$\begin{bmatrix} 4 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

## Applications of Singular Value Decomposition

### *Image Processing.*

- Suppose a satellite takes a picture, and wants to send it to Earth.
- The picture may contain  $1000 \times 1000$  “pixels” —a million little squares, each with a definite color.
- We can code the colors, and send back 1,000,000 numbers.
- It is ***better to find the essential information inside the  $1000 \times 1000$  matrix***, and send only that.

In SVD some  $\sigma$ 's are significant and others are extremely small.

If we keep 20 and throw away 980, then we send only the corresponding 20 columns of  $U$  and  $V$ .

The other 980 columns are multiplied in  $U\Sigma V^T$  by the small  $\sigma$ 's that are being ignored. ***If only 20 terms are kept, we send 20 times 2000 numbers instead of a million (25 to 1 compression).***

The **conjugate transpose**, also known as the **Hermitian transpose**, of an  $m \times n$  complex matrix  $A$  is an  $n \times m$  matrix obtained by transposing  $A$  and applying complex conjugate on each entry (the complex conjugate of  $a + ib$  being  $a - ib$ , for real numbers  $a$  and  $b$ )

$$\left(\mathbf{AA}^T\right)^T = \left(\mathbf{A}^T\right)^T \mathbf{A}^T = \mathbf{AA}^T. \qquad \mathbf{A}^H = \left(\overline{\mathbf{A}}\right)^T = \overline{\mathbf{A}^T}$$

A **matrix is full row rank** when each of the rows of the matrix are linearly independent and full column rank when each of the columns of the matrix are linearly independent.

For a **square matrix** these two concepts are equivalent and we say the matrix is **full rank if all rows and columns are linearly independent**. A square matrix is full rank if and only if its determinant is nonzero.

For a **non-square matrix** with  $m$  rows and  $n$  columns, it will always be the case that either the rows or columns (whichever is larger in number) are linearly dependent. Hence when we say that a non-square matrix is full rank, we mean that the row and column rank are as high as possible, given the shape of the matrix. So, if there are **more rows than columns ( $m > n$ )**, then the matrix is full rank if the matrix is full column rank.

The **rank of  $A$  equals the number of non-zero singular values**, which is the same as the number of non-zero diagonal elements **in  $\Sigma$**  in the singular value decomposition  $A = U \Sigma V^*$

If  $A$  is a matrix over the real numbers then the rank of  $A$  and the rank of its corresponding Gram matrix are equal. Thus, for real matrices

$$\text{rank}(A^T A) = \text{rank}(A A^T) = \text{rank}(A) = \text{rank}(A^T).$$

suppose  $A$  is an  $n \times m$  matrix and  $n \neq m$ . It must be that  $\text{rank}(A^\dagger) = \text{rank}(A) \leq \min(n, m) < \max(n, m)$ .

Using the fact that  $\text{rank}(AB) \leq \text{rank}(A)$  for any  $A, B$  for which the product is defined, we have that:

$$\text{rank}(A A^\dagger) \leq \text{rank}(A) < \max(n, m)$$

$$\text{rank}(A^\dagger A) \leq \text{rank}(A^\dagger) < \max(n, m).$$

But it must be the case that the dimensions of  $A A^\dagger$  or  $A^\dagger A$  is  $\max(n, m)$ . Therefore at least one of them does not have full rank. For square matrices, not having full rank is equivalent to being singular.

## Example 1

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

$$C = AA^T = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix} = \begin{bmatrix} 14 & 32 \\ 32 & 77 \end{bmatrix}$$

$$D = A^T A = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} = \begin{bmatrix} 17 & 22 & 27 \\ 22 & 29 & 36 \\ 27 & 36 & 45 \end{bmatrix}$$

$$\text{rank}(A) = \text{rank}(A^T) = \text{rank}(C) = \text{rank}(D) = 2$$

## Example 2

$$A = \begin{bmatrix} 3 & 6 & 1 & 1 & 7 \\ 1 & 2 & 2 & 3 & 1 \\ 2 & 4 & 5 & 8 & 4 \\ 0 & 0 & 1 & 2 & 2 \end{bmatrix} \quad A^T = \begin{bmatrix} 3 & 1 & 2 & 0 \\ 6 & 2 & 4 & 0 \\ 1 & 2 & 5 & 1 \\ 1 & 3 & 8 & 2 \\ 7 & 1 & 4 & 2 \end{bmatrix}$$

$$C = AA^T = \begin{bmatrix} 96 & 27 & 71 & 17 \\ 27 & 19 & 48 & 10 \\ 71 & 48 & 125 & 29 \\ 17 & 10 & 29 & 9 \end{bmatrix} \quad D = A^T A = \begin{bmatrix} 14 & 28 & 15 & 22 & 30 \\ 28 & 56 & 30 & 44 & 60 \\ 15 & 30 & 31 & 49 & 31 \\ 22 & 44 & 49 & 78 & 46 \\ 30 & 60 & 31 & 46 & 70 \end{bmatrix}$$

$$\text{rank}(A) = \text{rank}(A^T) = \text{rank}(C) = \text{rank}(D) = 3$$



## Definition [ edit ]

Throughout this article, boldfaced unsubscripted  $\mathbf{X}$  and  $\mathbf{Y}$  are used to refer to random vectors, and unboldfaced subscripted  $X_i$  and  $Y_i$  are used to refer to scalar random variables.

If the entries in the column vector

$$\mathbf{X} = (X_1, X_2, \dots, X_n)^T$$

are random variables, each with finite variance and expected value, then the covariance matrix  $\mathbf{K}_{\mathbf{X}\mathbf{X}}$  is the matrix whose  $(i, j)$  entry is the covariance<sup>[1]: p. 177</sup>

$$\mathbf{K}_{X_i X_j} = \text{cov}[X_i, X_j] = \mathbf{E}[(X_i - \mathbf{E}[X_i])(X_j - \mathbf{E}[X_j])]$$

where the operator  $\mathbf{E}$  denotes the expected value (mean) of its argument.

## Conflicting nomenclatures and notations [ edit ]

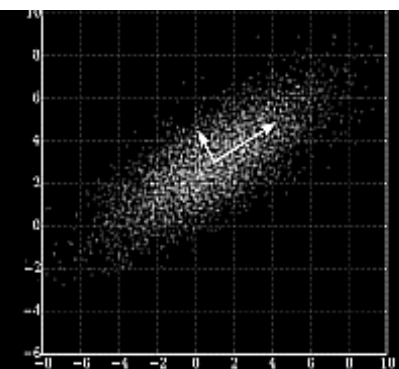
Nomenclatures differ. Some statisticians, following the probabilist William Feller in his two-volume book *An Introduction to Probability Theory and Its Applications*,<sup>[2]</sup> call the matrix  $\mathbf{K}_{\mathbf{X}\mathbf{X}}$  the **variance** of the random vector  $\mathbf{X}$ , because it is the natural generalization to higher dimensions of the 1-dimensional variance. Others call it the **covariance matrix**, because it is the matrix of covariances between the scalar components of the vector  $\mathbf{X}$ .

$$\text{var}(\mathbf{X}) = \text{cov}(\mathbf{X}, \mathbf{X}) = \mathbf{E}[(\mathbf{X} - \mathbf{E}[\mathbf{X}])(\mathbf{X} - \mathbf{E}[\mathbf{X}])^T].$$

Both forms are quite standard, and there is no ambiguity between them. The matrix  $\mathbf{K}_{\mathbf{X}\mathbf{X}}$  is also often called the *variance-covariance matrix*, since the diagonal terms are in fact variances.

By comparison, the notation for the cross-covariance matrix *between* two vectors is

$$\text{cov}(\mathbf{X}, \mathbf{Y}) = \mathbf{K}_{\mathbf{X}\mathbf{Y}} = \mathbf{E}[(\mathbf{X} - \mathbf{E}[\mathbf{X}])(\mathbf{Y} - \mathbf{E}[\mathbf{Y}])^T].$$



Sample points from a bivariate Gaussian distribution with a standard deviation of 3 in roughly the lower left–upper right direction and of 1 in the orthogonal direction. Because the  $x$  and  $y$  components co-vary, the variances of  $x$  and  $y$  do not fully describe the distribution. A  $2 \times 2$  covariance matrix is needed; the directions of the arrows correspond to the eigenvectors of this covariance matrix and their lengths to the square roots of the eigenvalues.



## Basic properties

For  $\mathbf{K}_{\mathbf{X}\mathbf{X}} = \text{var}(\mathbf{X}) = \mathbf{E}[(\mathbf{X} - \mathbf{E}[\mathbf{X}])(\mathbf{X} - \mathbf{E}[\mathbf{X}])^T]$  and  $\mu_{\mathbf{X}} = \mathbf{E}[\mathbf{X}]$ , where  $\mathbf{X} = (X_1, \dots, X_n)^T$  is a  $n$ -dimensional random variable, the following basic properties apply:<sup>[4]</sup>

1.  $\mathbf{K}_{\mathbf{X}\mathbf{X}} = \mathbf{E}(\mathbf{X}\mathbf{X}^T) - \mu_{\mathbf{X}}\mu_{\mathbf{X}}^T$
2.  $\mathbf{K}_{\mathbf{X}\mathbf{X}}$  is positive-semidefinite, i.e.  $\mathbf{a}^T \mathbf{K}_{\mathbf{X}\mathbf{X}} \mathbf{a} \geq 0$  for all  $\mathbf{a} \in \mathbb{R}^n$
3.  $\mathbf{K}_{\mathbf{X}\mathbf{X}}$  is symmetric, i.e.  $\mathbf{K}_{\mathbf{X}\mathbf{X}}^T = \mathbf{K}_{\mathbf{X}\mathbf{X}}$
4. For any constant (i.e. non-random)  $m \times n$  matrix  $\mathbf{A}$  and constant  $m \times 1$  vector  $\mathbf{a}$ , one has  $\text{var}(\mathbf{A}\mathbf{X} + \mathbf{a}) = \mathbf{A} \text{var}(\mathbf{X}) \mathbf{A}^T$
5. If  $\mathbf{Y}$  is another random vector with the same dimension as  $\mathbf{X}$ , then  $\text{var}(\mathbf{X} + \mathbf{Y}) = \text{var}(\mathbf{X}) + \text{cov}(\mathbf{X}, \mathbf{Y}) + \text{cov}(\mathbf{Y}, \mathbf{X}) + \text{var}(\mathbf{Y})$  where  $\text{cov}(\mathbf{X}, \mathbf{Y})$  is the cross-covariance matrix of  $\mathbf{X}$  and  $\mathbf{Y}$ .

For random vectors  $\mathbf{X}$  and  $\mathbf{Y}$ , each containing random elements whose expected value and variance exist, the **cross-covariance matrix** of  $\mathbf{X}$  and  $\mathbf{Y}$  is defined by<sup>[1]: p.336</sup>

$$\mathbf{K}_{\mathbf{X}\mathbf{Y}} = \text{cov}(\mathbf{X}, \mathbf{Y}) \stackrel{\text{def}}{=} \mathbf{E}[(\mathbf{X} - \mu_{\mathbf{X}})(\mathbf{Y} - \mu_{\mathbf{Y}})^T] \quad (\text{Eq.1})$$

where  $\mu_{\mathbf{X}} = \mathbf{E}[\mathbf{X}]$  and  $\mu_{\mathbf{Y}} = \mathbf{E}[\mathbf{Y}]$  are vectors containing the expected values of  $\mathbf{X}$  and  $\mathbf{Y}$ . The vectors  $\mathbf{X}$  and  $\mathbf{Y}$  need not have the same dimension, and either might be a scalar value.

The cross-covariance matrix is the matrix whose  $(i, j)$  entry is the covariance

$$\mathbf{K}_{X_i Y_j} = \text{cov}[X_i, Y_j] = \mathbf{E}[(X_i - \mathbf{E}[X_i])(Y_j - \mathbf{E}[Y_j])]$$

For the cross-covariance matrix, the following basic properties apply:<sup>[2]</sup>

1.  $\text{cov}(\mathbf{X}, \mathbf{Y}) = \mathbf{E}[\mathbf{X}\mathbf{Y}^T] - \mu_{\mathbf{X}}\mu_{\mathbf{Y}}^T$
2.  $\text{cov}(\mathbf{X}, \mathbf{Y}) = \text{cov}(\mathbf{Y}, \mathbf{X})^T$
3.  $\text{cov}(\mathbf{X}_1 + \mathbf{X}_2, \mathbf{Y}) = \text{cov}(\mathbf{X}_1, \mathbf{Y}) + \text{cov}(\mathbf{X}_2, \mathbf{Y})$
4.  $\text{cov}(A\mathbf{X} + \mathbf{a}, B^T\mathbf{Y} + \mathbf{b}) = A \text{cov}(\mathbf{X}, \mathbf{Y}) B$
5. If  $\mathbf{X}$  and  $\mathbf{Y}$  are independent (or somewhat less restrictedly, if every random variable in  $\mathbf{X}$  is uncorrelated with every random variable in  $\mathbf{Y}$ ), then  $\text{cov}(\mathbf{X}, \mathbf{Y}) = \mathbf{0}_{p \times q}$

where  $\mathbf{X}$ ,  $\mathbf{X}_1$  and  $\mathbf{X}_2$  are random  $p \times 1$  vectors,  $\mathbf{Y}$  is a random  $q \times 1$  vector,  $\mathbf{a}$  is a  $q \times 1$  vector,  $\mathbf{b}$  is a  $p \times 1$  vector,  $A$  and  $B$  are  $q \times p$  matrices of constants, and  $\mathbf{0}_{p \times q}$  is a  $p \times q$  matrix of zeroes.

Given a sample consisting of  $n$  independent observations  $x_1, \dots, x_n$  of a  $p$ -dimensional random vector  $X \in \mathbf{R}^{p \times 1}$  (a  $p \times 1$  column-vector), an unbiased estimator of the ( $p \times p$ ) covariance matrix

$$\Sigma = \mathbf{E}[(X - \mathbf{E}[X])(X - \mathbf{E}[X])^T]$$

is the sample covariance matrix

$$\mathbf{Q} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^T,$$

where  $x_i$  is the  $i$ -th observation of the  $p$ -dimensional random vector, and the vector

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

is the sample mean. This is true regardless of the distribution of the random variable  $X$ , provided of course that the theoretical means and covariances exist. The reason

$$\begin{aligned}\text{Var}[bX] &= \mathbb{E}[(bX - \mathbb{E}[bX])(bX - \mathbb{E}[bX])^\top] \\ &= \mathbb{E}[(bX - b\mathbb{E}[X])(bX - b\mathbb{E}[X])^\top]\end{aligned}$$

Which matrices are covariance matrices?

let  $\mathbf{b}$  be a  $(p \times 1)$  real-valued vector, then

$$\text{var}(\mathbf{b}^\top \mathbf{X}) = \mathbf{b}^\top \text{var}(\mathbf{X}) \mathbf{b},$$

which must always be nonnegative, since it is the variance of a real-valued random variable, so a covariance matrix is always a positive-semidefinite matrix.

The above argument can be expanded as follows:

$$\begin{aligned}w^\top \mathbb{E}[(\mathbf{X} - \mathbb{E}[\mathbf{X}])(\mathbf{X} - \mathbb{E}[\mathbf{X}])^\top] w &= \mathbb{E}[w^\top (\mathbf{X} - \mathbb{E}[\mathbf{X}])(\mathbf{X} - \mathbb{E}[\mathbf{X}])^\top w] \\ &= \mathbb{E}[(w^\top (\mathbf{X} - \mathbb{E}[\mathbf{X}]))^2] \geq 0,\end{aligned}$$

where the last inequality follows from the observation that  $w^\top (\mathbf{X} - \mathbb{E}[\mathbf{X}])$  is a scalar.

Conversely, every symmetric positive semi-definite matrix is a covariance matrix. To see this, suppose  $M$  is a  $p \times p$  symmetric positive-semidefinite matrix. From the finite-dimensional case of the spectral theorem, it follows that  $M$  has a nonnegative symmetric square root, which can be denoted by  $M^{1/2}$ . Let  $\mathbf{X}$  be any  $p \times 1$  column vector-valued random variable whose covariance matrix is the  $p \times p$  identity matrix. Then

$$\text{var}(M^{1/2} \mathbf{X}) = M^{1/2} \text{var}(\mathbf{X}) M^{1/2} = M.$$

