#### 2.1 Matrix Operations

### **Matrix Notation:**

Two ways to denote  $m \times n$  matrix *A*:

In terms of the *columns* of A:

$$A = \left[ \begin{array}{ccc} \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_n \end{array} \right]$$

In terms of the *entries* of *A*:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{m1} & \cdots & a_{mj} & \cdots & a_{mn} \end{bmatrix}$$

Main diagonal entries:\_\_\_\_\_

Zero matrix:

$$0 = \begin{bmatrix} 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}$$

#### **THEOREM 1**

Let *A*, *B*, and *C* be matrices of the same size, and let *r* and *s* be scalars. Then

a. 
$$A + B = B + A$$
  
b.  $(A + B) + C = A + (B + C)$   
c.  $A + 0 = A$   
d.  $r(A + B) = rA + rB$   
e.  $(r + s)A = rA + sA$   
f.  $r(sA) = (rs)A$ 

**Matrix Multiplication** 

Multiplying *B* and **x** transforms **x** into the vector *B***x**. In turn, if we multiply *A* and *B***x**, we transform *B***x** into  $A(B\mathbf{x})$ . So  $A(B\mathbf{x})$  is the composition of two mappings.

Define the product *AB* so that  $A(B\mathbf{x}) = (AB)\mathbf{x}$ .

Suppose *A* is  $m \times n$  and *B* is  $n \times p$  where

$$B = \begin{bmatrix} \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_p \end{bmatrix} \text{ and } \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}$$

Then

$$B\mathbf{x} = x_1\mathbf{b}_1 + x_2\mathbf{b}_2 + \dots + x_p\mathbf{b}_p$$

#### and

$$A(B\mathbf{x}) = A(x_1\mathbf{b}_1 + x_2\mathbf{b}_2 + \cdots + x_p\mathbf{b}_p)$$

$$= A(x_1\mathbf{b}_1) + A(x_2\mathbf{b}_2) + \dots + A(x_p\mathbf{b}_p)$$
$$= x_1A\mathbf{b}_1 + x_2A\mathbf{b}_2 + \dots + x_pA\mathbf{b}_p = \begin{bmatrix} A\mathbf{b}_1 & A\mathbf{b}_2 & \dots & A\mathbf{b}_p \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}.$$

Therefore,

$$A(B\mathbf{X}) = \begin{bmatrix} A\mathbf{b}_1 & A\mathbf{b}_2 & \cdots & A\mathbf{b}_p \end{bmatrix} \mathbf{X}.$$

and by defining

$$AB = \begin{bmatrix} A\mathbf{b}_1 & A\mathbf{b}_2 & \cdots & A\mathbf{b}_p \end{bmatrix}$$

we have  $A(B\mathbf{x}) = (AB)\mathbf{x}$ .

**EXAMPLE:** Compute *AB* where  $A = \begin{bmatrix} 4 & -2 \\ 3 & -5 \\ 0 & 1 \end{bmatrix}$  and

$$B = \begin{bmatrix} 2 & -3 \\ 6 & -7 \end{bmatrix}.$$

Solution:

$$A\mathbf{b}_{1} = \begin{bmatrix} 4 & -2 \\ 3 & -5 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 6 \end{bmatrix}, \qquad A\mathbf{b}_{2} = \begin{bmatrix} 4 & -2 \\ 3 & -5 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} -3 \\ -7 \end{bmatrix}$$
$$= \begin{bmatrix} -4 \\ -24 \\ 6 \end{bmatrix} \qquad = \begin{bmatrix} 2 \\ 26 \\ -7 \end{bmatrix}$$

$$\Rightarrow AB = \begin{bmatrix} -4 & 2 \\ -24 & 26 \\ 6 & -7 \end{bmatrix}$$

Note that  $A\mathbf{b}_1$  is a linear combination of the columns of A and  $A\mathbf{b}_2$  is a linear combination of the columns of A.

Each column of AB is a linear combination of the columns of A using weights from the corresponding columns of B.

**EXAMPLE:** If *A* is  $4 \times 3$  and *B* is  $3 \times 2$ , then what are the sizes of *AB* and *BA*?

Solution:

which is \_\_\_\_\_\_.

If A is  $m \times n$  and B is  $n \times p$ , then AB is  $m \times p$ .

## Row-Column Rule for Computing AB (alternate method)

The definition

$$AB = \begin{bmatrix} A\mathbf{b}_1 & A\mathbf{b}_2 & \cdots & A\mathbf{b}_p \end{bmatrix}$$

is good for theoretical work.

When A and B have small sizes, the following method is more efficient when working by hand.

If AB is defined, let  $(AB)_{ij}$  denote the entry in the ith row and jth column of AB. Then



**EXAMPLE** 
$$A = \begin{bmatrix} 2 & 3 & 6 \\ -1 & 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 2 & -3 \\ 0 & 1 \\ 4 & -7 \end{bmatrix}$$
. Compute

*AB*, if it is defined.

Solution: Since A is  $2 \times 3$  and B is  $3 \times 2$ , then AB is defined and AB is \_\_\_\_\_×\_\_\_\_.

$$AB = \begin{bmatrix} 2 & 3 & 6 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & -3 \\ 0 & 1 \\ 4 & -7 \end{bmatrix} = \begin{bmatrix} 28 & \bullet \\ \bullet & \bullet \end{bmatrix}$$
$$\begin{bmatrix} 2 & 3 & 6 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & -3 \\ 0 & 1 \\ 4 & -7 \end{bmatrix} = \begin{bmatrix} 28 & -45 \\ \bullet & \bullet \end{bmatrix}$$
$$\begin{bmatrix} 2 & 3 & 6 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & -3 \\ 0 & 1 \\ 4 & -7 \end{bmatrix} = \begin{bmatrix} 28 & -45 \\ 2 & \bullet \end{bmatrix}$$
$$\begin{bmatrix} 2 & 3 & 6 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & -3 \\ 0 & 1 \\ 4 & -7 \end{bmatrix} = \begin{bmatrix} 28 & -45 \\ 2 & \bullet \end{bmatrix}$$
$$\begin{bmatrix} 2 & 3 & 6 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & -3 \\ 0 & 1 \\ 4 & -7 \end{bmatrix} = \begin{bmatrix} 28 & -45 \\ 2 & -4 \end{bmatrix}$$
So  $AB = \begin{bmatrix} 28 & -45 \\ 2 & -4 \end{bmatrix}$ .

# **THEOREM 2**

Let A be  $m \times n$  and let B and C have sizes for which the indicated sums and products are defined.

a. $A(BC) = (AB)C$	(associative law of multiplication)
b. A(B+C) = AB + AC	(left - distributive law)
C. (B+C)A = BA + CA	(right-distributive law)
d. $r(AB) = (rA)B = A(rB)$	
for any scalar r	
e. $I_m A = A = A I_n$	(identity for matrix multiplication)

## WARNINGS

Properties above are analogous to properties of real numbers. But **NOT ALL** real number properties correspond to matrix properties.

1. It is not the case that *AB* always equal *BA*. (see Example 7, page 114) 2. Even if AB = AC, then *B* may not equal *C*. (see Exercise 10, page 116) 3. It is possible for AB = 0 even if  $A \neq 0$  and  $B \neq 0$ . (see Exercise 12, page 116) Powers of A

$$A^k = \underbrace{A \cdots A}_k$$

EXAMPLE:  

$$\begin{bmatrix} 1 & 0 \\ 3 & 2 \end{bmatrix}^3 = \begin{bmatrix} 1 & 0 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 3 & 2 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 21 & 8 \end{bmatrix}$$

If A is  $m \times n$ , the **transpose** of A is the  $n \times m$  matrix, denoted by  $A^{T}$ , whose columns are formed from the corresponding rows of Α.

#### **EXAMPLE:**

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 \\ 6 & 7 & 8 & 9 & 8 \\ 7 & 6 & 5 & 4 & 3 \end{bmatrix} \implies A^{T} = \begin{bmatrix} 1 & 6 & 7 \\ 2 & 7 & 6 \\ 3 & 8 & 5 \\ 4 & 9 & 4 \\ 5 & 8 & 3 \end{bmatrix}$$

**EXAMPLE:** Let 
$$A = \begin{bmatrix} 1 & 2 & 0 \\ 3 & 0 & 1 \end{bmatrix}$$
,  $B = \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ -2 & 4 \end{bmatrix}$ . Compute  $AB$ ,  $(AB)^{T}$ ,  $A^{T}B^{T}$  and  $B^{T}A^{T}$ .

Solution:

$$AB = \begin{bmatrix} 1 & 2 & 0 \\ 3 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ -2 & 4 \end{bmatrix} = \begin{bmatrix} & & \\ & \end{bmatrix}$$
$$(AB)^{T} = \begin{bmatrix} & & \\ & & \end{bmatrix}$$

$$A^{T}B^{T} = \begin{bmatrix} 1 & 3 \\ 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -2 \\ 2 & 1 & 4 \end{bmatrix} = \begin{bmatrix} 7 & 3 & 10 \\ 2 & 0 & -4 \\ 2 & 1 & 4 \end{bmatrix}$$
$$B^{T}A^{T} = \begin{bmatrix} 1 & 0 & -2 \\ 2 & 1 & 4 \end{bmatrix} \begin{bmatrix} 1 & 3 \\ 2 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -1 \end{bmatrix}$$

### **THEOREM 3**

Let *A* and *B* denote matrices whose sizes are appropriate for the following sums and products.

a. 
$$(A^T)^T = A$$
 (I.e., the transpose of  $A^T$  is A)

b. 
$$(A + B)^T = A^T + B^T$$

- c. For any scalar *r*,  $(rA)^T = rA^T$
- d.  $(AB)^T = B^T A^T$  (I.e. the transpose of a product of matrices equals the product of their transposes in reverse order.)

**EXAMPLE:** Prove that  $(ABC)^T =$ \_\_\_\_\_.

Solution: By Theorem 3d,

$$(ABC)^{T} = ((AB)C)^{T} = C^{T} ( )^{T}$$
$$= C^{T} ( ) = \underline{\qquad}.$$