

## More on Matrix Multiplication

**Definition:** Let  $B$  be an  $m \times n$  matrix with rows  $\vec{b}_1^T, \dots, \vec{b}_m^T$ , and let  $A$  be an  $n \times p$  matrix with columns  $\vec{a}_1, \dots, \vec{a}_p$ . Then we define  $BA$  to be the matrix whose  $ij$ -th entry is

$$(BA)_{ij} = \vec{b}_i \cdot \vec{a}_j$$

Taking a closer look at the calculation  $\vec{b}_i \cdot \vec{a}_j$ :

$$\vec{b}_i \cdot \vec{a}_j = \begin{bmatrix} b_{i1} \\ b_{i2} \\ \vdots \\ b_{in} \end{bmatrix} \cdot \begin{bmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{nj} \end{bmatrix} = b_{i1}a_{1j} + b_{i2}a_{2j} + \dots + b_{in}a_{nj}$$

We can rewrite this dot product using summation notation:  $b_{i1}a_{1j} + b_{i2}a_{2j} + \dots + b_{in}a_{nj} = \sum_{k=1}^n b_{ik}a_{kj}$

This will give us a new definition for  $BA$ .

**Definition:** Let  $B$  be an  $m \times n$  matrix and let  $A$  be an  $n \times p$  matrix. Then the  $ij$ -th entry of  $BA$  is

$$(BA)_{ij} = \sum_{k=1}^n b_{ik}a_{kj} = \sum_{k=1}^n (B)_{ik}(A)_{kj}$$

## More on Matrix Multiplication

### Theorem 3.1.3

If  $A, B$ , and  $C$  are matrices of the correct size so that the required products are defined, and  $t \in \mathbb{R}$ , then

1.  $A(B + C) = AB + AC$
2.  $t(AB) = (tA)B = A(tB)$
3.  $A(BC) = (AB)C$
4.  $(AB)^T = B^T A^T$

### Proof

1. Suppose  $A, B$ , and  $C$  are matrices such that  $A(B + C)$  is defined, and let  $D = B + C$ .

Then  $(D)_{ij} = d_{ij} = b_{ij} + c_{ij}$ .

$$\begin{aligned} (A(B + C))_{ij} &= (AD)_{ij} \\ &= \sum_k a_{ik}d_{kj} \\ &= \sum_k a_{ik}(b_{kj} + c_{kj}) \\ &= \sum_k (a_{ik}b_{kj} + a_{ik}c_{kj}) \\ &= \sum_k a_{ik}b_{kj} + \sum_k a_{ik}c_{kj} \\ &= (AB)_{ij} + (AC)_{ij} = (AB + AC)_{ij} \end{aligned}$$

We see that  $(A(B + C))_{ij} = (AB + AC)_{ij}$  for all  $i, j$ , and thus  $A(B + C) = AB + AC$ .  $\square$

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### Proof

4. Let  $A$  be an  $m \times n$  matrix and let  $B$  be an  $n \times p$  matrix.

Note that  $(B^T)_{ik} = (B)_{ki}$  and  $(A^T)_{kj} = (A)_{jk}$ .

$$\begin{aligned}(B^T A^T)_{ij} &= \sum_{k=1}^n (B^T)_{ik} (A^T)_{kj} \\ &= \sum_{k=1}^n (B)_{ki} (A)_{jk} \\ &= \sum_{k=1}^n (A)_{jk} (B)_{ki} \\ &= (AB)_{ji}\end{aligned}$$

So, we've seen that  $(B^T A^T)_{ij} = (AB)_{ji}$  for all  $i$  and  $j$ , which means that  $B^T A^T = (AB)^T$ .  $\square$

## More on Matrix Multiplication

### Notes about Matrix Multiplication Properties:

- Matrix multiplication is not commutative. That is, in general,  $AB \neq BA$ .
- $BA$  may not even be defined even if  $AB$  is. Even if both  $AB$  and  $BA$  are defined they might not even be the same size.
- Sometimes  $AB = BA$ , so  $AB \neq BA$  is not always true.
- The cancellation law does not hold. That is, if  $AB = AC$ , this does not necessarily mean that  $B = C$ .

#### Example

Let  $A = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix}$ ,  $B = \begin{bmatrix} 4 & 8 \\ -1 & 3 \end{bmatrix}$ , and  $C = \begin{bmatrix} -5 & 5 \\ 8 & 6 \end{bmatrix}$ .

Then:

$$AB = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} 4 & 8 \\ -1 & 3 \end{bmatrix} = \begin{bmatrix} 3 & 11 \\ 6 & 22 \end{bmatrix}$$

and

$$AC = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} -5 & 5 \\ 8 & 6 \end{bmatrix} = \begin{bmatrix} 3 & 11 \\ 6 & 22 \end{bmatrix} = AB$$

Even though  $B$  does not equal  $C$ , we still have  $AB = AC$ .

- Matrix division cannot be defined.
- Only the properties listed in Theorem 3.1.4. are the properties you can use regarding matrix multiplication.

## More on Matrix Multiplication

### Theorem 3.1.4

If  $A$  and  $B$  are  $m \times n$  matrices such that  $A\vec{x} = B\vec{x}$  for every  $\vec{x} \in \mathbb{R}^n$ , then  $A = B$ .

### Proof

The key fact here is that  $A\vec{x} = B\vec{x}$  **for all**  $\vec{x}$ , not just any one in particular.

Recall that  $\vec{e}_j$  is the  $j$ -th standard basis vector (that is, it is a vector that has a 1 in the  $j$ -th component, and all other components are zeros), then  $A\vec{e}_j = B\vec{e}_j$  for all  $1 \leq j \leq n$ . But what is  $A\vec{e}_j$ ?

Well, first of all, note that it is an  $n \times 1$  matrix, so we need only look at  $(A\vec{e}_j)_{i1}$ .

Using our summation definition, we see that  $(A\vec{e}_j)_{i1} = \sum_{k=1}^n (A)_{ik}(\vec{e}_j)_{k1}$ , but since  $(\vec{e}_j)_{k1}$  is zero for  $k \neq j$  (and equals 1

when  $k = j$ ), we see that  $(A\vec{e}_j)_{i1} = (A)_{ij}$  for all  $i$ .

This means that  $A\vec{e}_j$  is the  $j$ -th column of  $A$ .

Similarly,  $B\vec{e}_j$  is the  $j$ -th column of  $B$ .

We have  $A\vec{e}_j = B\vec{e}_j$ , so this means that the  $j$ -th column of  $A$  is the same as the  $j$ -th column of  $B$ . Since this is true for every  $j$ , we see that  $A = B$ .  $\square$

**Note:** The fact that  $A\vec{e}_j$  is the  $j$ -th column of  $A$  is actually quite useful. More specifically, the fact that if we line up all the products  $A\vec{e}_1 \ A\vec{e}_2 \ \dots \ A\vec{e}_n$ , then we get another copy of  $A$ . We use this fact to define a very special matrix.

## More on Matrix Multiplication

**Definition:** The  $n \times n$  matrix  $I_n = \text{diag}(1, 1, \dots, 1)$  is called the identity matrix. That is, the identity matrix is a diagonal matrix, with all the diagonal entries equal to 1.

### Examples

$$I_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \text{ and } I_5 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

**Note:** Often we simply use  $I$  to denote an identity matrix, with the expectation that the size of  $I$  can be determined from context.

### Theorem 3.1.5

If  $A$  is any  $m \times n$  matrix, then  $I_m A = A = A I_n$ .