

Highlights of Section 2.1 Matrix Operations

An $m \times n$ **matrix** A is a rectangular array of data with m rows, each of which has n columns. The (i,j) th entry of A , denoted a_{ij} or A_{ij} or $A(i,j)$, is the number in row i and column j of A .

The **diagonal entries** of A are $a_{11}, a_{22}, a_{33}, \dots$; they form the **main diagonal** of A .

A **diagonal matrix** is a square ($n \times n$) matrix whose nondiagonal entries are all 0.

An $m \times n$ matrix all of whose entries are 0 is called a **zero matrix** and written as 0 .

Each column of A is a vector in \mathbb{R}^m ; we can write the matrix A as $A = [\mathbf{a}_1 \ \mathbf{a}_2 \ \dots \ \mathbf{a}_n]$ where \mathbf{a}_j is the j th column.

Matrix Addition and Scalar Multiplication

Matrix Equality: $A = B$ if both matrices are of the same size and all the corresponding entries are equal; that is, $a_{ij} = b_{ij}$ for all i and j

Matrix Addition: If A and B are $m \times n$ matrices, then the **sum** $A + B$ is the $m \times n$ matrix whose columns are the sums of the corresponding columns of A and B . We have $(A + B)_{ij} = A_{ij} + B_{ij}$ for all i and j .

Scalar Multiplication: If r is a scalar and A is a matrix, then the **scalar multiple** rA is the matrix whose columns are r times the columns of A . We have $(rA)_{ij} = r A_{ij}$ for all i and j .

Theorem 1: Let A, B , and C be matrices of the same size, and let r and s be scalars.

$A + B = B + A$	$r(A + B) = rA + rB$
$(A + B) + C = A + (B + C)$	$(r + s)A = rA + sA$
$A + 0 = A$	$r(sA) = (rs)A$

Matrix Multiplication

Definition: If A is an $m \times n$ matrix and B is an $n \times p$ matrix with columns $\mathbf{b}_1 \ \mathbf{b}_2 \ \dots \ \mathbf{b}_p$, then the **product** AB is the $m \times p$ matrix whose columns are $A\mathbf{b}_1, A\mathbf{b}_2, \dots, A\mathbf{b}_p$; that is $AB = A[\mathbf{b}_1 \ \mathbf{b}_2 \ \dots \ \mathbf{b}_p] = [A\mathbf{b}_1 \ A\mathbf{b}_2 \ \dots \ A\mathbf{b}_p]$.

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

Theorem 2: Let A be an $m \times n$ matrix, and let B and C have sizes for which the sums and products are defined.

$A(BC) = (AB)C$	Associative Law of Matrix Multiplication
$A(B + C) = AB + AC$	Left Distributive Law
$(B + C)A = BA + CA$	Right Distributive Law
$r(AB) = (rA)B = A(rB)$	
$I_m A = A = A I_n$	Identity for Matrix Multiplication

WARNING: IN GENERAL $AB \neq BA$

Row-Column Rule for Computing AB

If the product AB is defined, then the entry in row i and column j of AB is the sum of the products of the corresponding entries from row i of A and column j of B :

$$(AB)_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + a_{i3}b_{3j} + \dots + a_{in}b_{nj} = \sum_{k=1}^n a_{ik}b_{kj}$$

Powers of a Matrix

Definition: If A is a square matrix and k is a positive integer, then A^k is the product of k copies of A

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

We define A^0 to be the identity matrix I .

Transpose of a Matrix

Definition: The **transpose** of a $m \times n$ matrix A , denoted A^T , is the $n \times m$ matrix whose columns are formed from the corresponding rows of A ; that is, the entry in row i and column j of A^T is the entry in column j and row i of A .

Theorem 3: Let A and B denote matrices whose sizes are appropriate for the following sums and products

$(A^T)^T = A$	For any scalar r , $(rA)^T = r A^T$
$(A + B)^T = A^T + B^T$	$(AB)^T = B^T A^T$

The transpose of a product of a matrices is the product of their transposes in **reverse** order.