

# Linear Algebra

## Vectors

- A **column vector** is a list of numbers stored vertically. The **dimension** of a column vector is the number of values in the vector.  $W$  is a 3-dimensional column vector and  $V$  is a 5-dimensional column vector:

$$W = \begin{pmatrix} 3 \\ -1 \\ 0 \end{pmatrix} \quad V = \begin{pmatrix} -1 \\ 0 \\ 4 \\ 2 \\ -5 \end{pmatrix}.$$

Subscripts are used to denote single elements of the vector. For example,  $W_2 = -1$ ,  $V_4 = 2$ .

- A **row vector** is a list of numbers stored horizontally. The dimension of a row vector is the number of values in the vector.  $U$  is a 4-dimensional row vector and  $T$  is a 2-dimensional row-vector:

$$U = ( 2 \quad -4 \quad 0 \quad 0 ).$$

$$T = ( 4 \quad 3 ).$$

Elements are accessed by subscript:  $U_3 = 0$ ,  $T_1 = 4$ .

- The term **vector** is used to refer to either a row vector or a column vector in situations where it doesn't matter whether the values are stored in a column or in a row.

- Two vectors with a common dimension can be added or subtracted:

$$\begin{pmatrix} 2 & -4 & 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 1 & 1 & -3 \end{pmatrix} = \begin{pmatrix} 2 & -3 & 1 & -3 \end{pmatrix}.$$

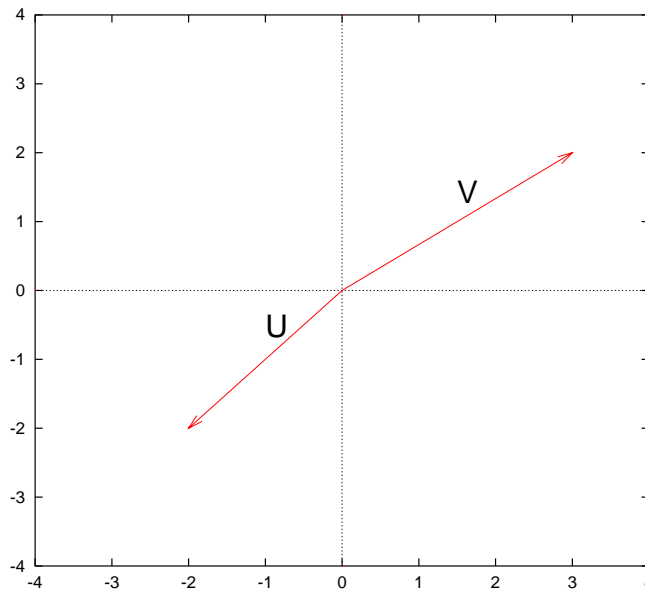
Any vector can be multiplied by a scalar coefficient:

$$2 \begin{pmatrix} 3 \\ -1 \\ 0 \end{pmatrix} = \begin{pmatrix} 6 \\ -2 \\ 0 \end{pmatrix}.$$

Combining addition and scalar multiplication gives a **linear combination**:

$$3 \begin{pmatrix} 4 & 3 \end{pmatrix} - 2 \begin{pmatrix} 1 & -1 \end{pmatrix} = \begin{pmatrix} 10 & 11 \end{pmatrix}.$$

- Geometrically, a vector  $V$  can be viewed as a line segment in  $d$ -dimensional space with its tail at the origin and its head at the point  $V$ .



$V$  is the vector  $(3,2)$ , and  $U$  is the vector  $(-2,-2)$ .

- The **scalar product** (also called the **dot product** or **inner product**) is formed from two vectors  $V$  and  $W$  having the same dimension. The scalar product is a single number (a “scalar”), and is notated  $V \cdot W$  or  $\langle V, W \rangle$ . The definition of the scalar product is

$$V \cdot W = \sum_i V_i W_i.$$

For example, if  $V = (3, 1, -1)$  and  $W = (-1, 0, 1)$ ,

$$V \cdot W = 3 \cdot -1 + 1 \cdot 0 + -1 \cdot 1 = -4.$$

If  $U = (4, -1, 0, 4)$  and  $T = (0, -1, -1, 2)$ ,

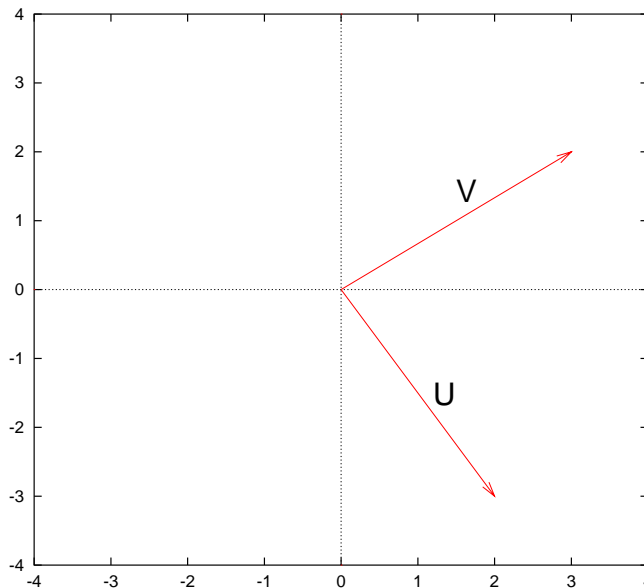
$$U \cdot T = 4 \cdot 0 + -1 \cdot -1 + 0 \cdot -1 + 4 \cdot 2 = 9.$$

- If two  $d$ -dimensional vectors  $U$  and  $V$  have inner product 0,  $\langle U, V \rangle = 0$ , then  $U$  and  $V$  are **orthogonal**, or **perpendicular**.

Viewing 2-dimensional vectors as points in the plane,

$$V = \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} \quad U = \begin{pmatrix} x_2 \\ y_2 \end{pmatrix},$$

then  $\langle V, U \rangle = 0$  when  $V$  and  $U$  are perpendicular in the geometric sense (the angle between them is  $\pi/2$  radians).



$V$  is the vector  $(3,2)$ , and  $U$  is the vector  $(2,-3)$ .

- A **linear combination** of  $d$ -dimensional vectors  $V_1, V_2, \dots, V_m$  is an expression of the form

$$c_1V_1 + c_2V_2 + \dots + c_mV_m,$$

where  $c_1, \dots, c_m$  are scalars called **coefficients**. For example, if

$$V_1 = \begin{pmatrix} 4 \\ -1 \\ 2 \end{pmatrix}, \quad V_2 = \begin{pmatrix} 2 \\ 0 \\ 0 \end{pmatrix}, \quad V_3 = \begin{pmatrix} -1 \\ 1 \\ -1 \end{pmatrix},$$

and  $c_1 = 2, c_2 = -1, c_3 = 3$ , then  $c_1V_1 + c_2V_2 + c_3V_3$  is

$$\begin{pmatrix} 3 \\ 1 \\ 1 \end{pmatrix}.$$

- A set of  $d$ -dimensional vectors  $V_1, \dots, V_m$  are **linearly dependent** if there exist scalars  $c_1, \dots, c_m$ , not all of which are zero, such that the linear combination  $c_1V_1 + \dots + c_mV_m$  is zero. For example,

$$V_1 = \begin{pmatrix} 3 \\ 1 \\ -3 \\ 2 \end{pmatrix}, \quad V_2 = \begin{pmatrix} 0 \\ 1 \\ -1 \\ 2 \end{pmatrix}, \quad V_3 = \begin{pmatrix} -6 \\ 1 \\ 3 \\ 2 \end{pmatrix},$$

are linearly dependent, since if  $c_1 = -2, c_2 = 3$ , and  $c_3 = -1$ , then  $c_1V_1 + c_2V_2 + c_3V_3 = 0$ .

- A set of  $d$ -dimensional vectors  $V_1, \dots, V_m$  are **linearly independent** if they are not linearly dependent. That is, whenever  $c_1V_1 + \dots + c_mV_m = 0$ , then  $c_1 = \dots = c_m = 0$ . For example, suppose

$$V_1 = \begin{pmatrix} 3 \\ 0 \\ -3 \\ 2 \end{pmatrix}, \quad V_2 = \begin{pmatrix} 5 \\ 0 \\ -1 \\ 2 \end{pmatrix}, \quad V_3 = \begin{pmatrix} -6 \\ -2 \\ 3 \\ 2 \end{pmatrix},$$

and  $c_1V_1 + c_2V_2 + c_3V_3 = 0$ . The linear combination can be written

$$\begin{pmatrix} 3c_1 + 5c_2 - 6c_3 \\ -2c_3 \\ -3c_1 - c_2 + 3c_3 \\ 2c_1 + 2c_2 + 2c_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}.$$

From the second line,  $c_3 = 0$ , and from the final line  $c_2 = -c_1$ . From the third line,  $c_2 = -3c_1$ , so we conclude  $c_1 = c_2 = 0$ , hence  $V_1, V_2, V_3$  are linearly independent.

- It is a fact that any set of  $m > d$   $d$ -dimensional vectors must be linearly dependent. For example, there can never be a set of 4 linearly independent vectors having dimension 3.

## Matrices

- A  $m \times n$  matrix  $A$  is a  $m \times n$  array of numbers, where  $M_{ij}$  refers to the value in the  $i^{\text{th}}$  row and  $j^{\text{th}}$  column. For example, the following is a  $2 \times 3$  matrix

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

where  $A_{12} = 3$ ,  $A_{22} = 0$ , etc.  
The following is a  $3 \times 2$  matrix

$$B = \begin{pmatrix} 1 & -2 \\ -1 & 3 \\ 2 & 0 \end{pmatrix},$$

where  $B_{11} = 1$ ,  $B_{32} = 0$ , etc.

- Matrices of the same shape can be added and subtracted:

$$\begin{pmatrix} 4 & 3 & 0 \\ -1 & 0 & -2 \end{pmatrix} + \begin{pmatrix} 0 & -2 & 3 \\ 4 & 4 & -1 \end{pmatrix} = \begin{pmatrix} 4 & 1 & 3 \\ 3 & 4 & -3 \end{pmatrix},$$

Any matrix can be multiplied by a scalar:

$$3 \begin{pmatrix} 4 & 3 & 0 \\ -1 & 0 & -2 \end{pmatrix} = \begin{pmatrix} 12 & 9 & 0 \\ -3 & 0 & -6 \end{pmatrix},$$

We can form linear combinations of matrices:

$$2 \begin{pmatrix} 2 & 2 & -1 \\ 0 & 0 & 4 \end{pmatrix} - 3 \begin{pmatrix} 1 & 2 & 0 \\ -1 & 2 & -3 \end{pmatrix} = \begin{pmatrix} 1 & -2 & -2 \\ 3 & -6 & 17 \end{pmatrix}.$$

- A  $n$ -dimensional column vector is also a  $n \times 1$  matrix. A  $n$ -dimensional row vector is also a  $1 \times n$  matrix.
- The **transpose** of an  $m \times n$  matrix  $A$ , written  $A'$ , is an  $n \times m$  matrix where  $A'_{ij} = A_{ji}$ . For example,

$$\begin{pmatrix} 4 & 3 & 0 \\ -1 & 0 & -2 \end{pmatrix}' = \begin{pmatrix} 4 & -1 \\ 3 & 0 \\ 0 & -2 \end{pmatrix},$$

A matrix  $A$  is **symmetric** if  $A = A'$ . For example,

$$S = \begin{pmatrix} 4 & 3 \\ 3 & 5 \end{pmatrix}$$

is symmetric, while

$$T = \begin{pmatrix} 4 & 3 \\ 6 & 5 \end{pmatrix}$$

is not.

- If  $A$  is a  $m \times n$  matrix and  $V$  is a  $n$ -dimensional column vector, we can form the **matrix vector product**  $W = AV$ , where  $W_i$  is the dot product of  $V$  with row  $i$  of  $A$ . For example,

$$\begin{pmatrix} 2 & -1 \\ 1 & 4 \end{pmatrix} \begin{pmatrix} 3 \\ -1 \end{pmatrix} = \begin{pmatrix} 3 \cdot 2 + -1 \cdot -1 \\ 3 \cdot 1 + -1 \cdot 4 \end{pmatrix} = \begin{pmatrix} 7 \\ -1 \end{pmatrix}.$$

- The **nullspace** of  $M$ , written  $\text{Null}(M)$ , is the set of all vectors  $V$  such that  $MV = 0$ . For example, if

$$\begin{pmatrix} 2 & -1 & 4 \\ 0 & 1 & 2 \end{pmatrix}$$

then

$$V = \begin{pmatrix} 3 \\ 2 \\ -1 \end{pmatrix}$$

is in  $\text{Null}(M)$ .

The zero vector is always in  $\text{Null}(M)$ , and if the columns of  $M$  are linearly independent, the zero vector is the only vector in  $\text{Null}(M)$ . But if the columns of  $M$  are linearly dependent, there will be infinitely many nonzero vectors in  $\text{Null}(M)$ .

A square ( $m \times m$ ) matrix with nullspace containing only the zero vector is **nonsingular**, otherwise it is **singular**. Equivalently, a square matrix is nonsingular if and only if its columns are linearly independent.

- If  $A$  is a  $m \times n$  matrix and  $B$  is a  $n \times r$  matrix, we can form the **matrix matrix product**  $C = AB$ , where  $C$  is a  $m \times r$  matrix whose elements are defined as:  $C_{ij}$  is the dot product of row  $i$  of  $A$  with column  $j$  of  $B$ . For example,

$$\begin{pmatrix} 2 & -1 & 1 \\ 1 & 0 & 4 \end{pmatrix} \begin{pmatrix} 3 & -1 \\ 1 & 0 \\ 2 & -1 \end{pmatrix} = \begin{pmatrix} 7 & -3 \\ 11 & -5 \end{pmatrix},$$

where, for example,  $11 = 1 \cdot 3 + 0 \cdot 1 + 4 \cdot 2$ .

Rectangular matrices can only be multiplied if the number of columns in the first matrix is equal to the number of rows in the second matrix (i.e.  $AB$  can be formed only if  $A$  is  $m \times n$  and  $B$  is  $n \times r$ ).

For square matrices, the products  $AB$  and  $BA$  can both be formed. However it is important to note that they are different:

$$\begin{pmatrix} 2 & -1 \\ 1 & 4 \end{pmatrix} \begin{pmatrix} 3 & -1 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} 5 & -2 \\ 7 & -1 \end{pmatrix},$$

$$\begin{pmatrix} 3 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 2 & -1 \\ 1 & 4 \end{pmatrix} = \begin{pmatrix} 5 & -7 \\ 2 & -1 \end{pmatrix}.$$

- For any matrix  $m \times n$  matrix  $A$ , the products  $A'A$  and  $AA'$  can always be formed. The first product is  $n \times n$  and the second product is  $m \times m$ .

The product  $A'A$  is the “column-wise inner product matrix”, since  $(A'A)_{ij}$  is the inner product of the  $i^{\text{th}}$  column of  $A$  with the  $j^{\text{th}}$  column of  $A$ .

The product  $AA'$  is the “row-wise inner product matrix”, since  $(AA')_{ij}$  is the inner product of the  $i^{\text{th}}$  row of  $A$  with the  $j^{\text{th}}$  row of  $A$ .

For example, if

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

then

$$A'A = \begin{pmatrix} 5 & -2 & 6 \\ -2 & 1 & -1 \\ 6 & -1 & 17 \end{pmatrix},$$

and

$$AA' = \begin{pmatrix} 6 & 6 \\ 6 & 17 \end{pmatrix}.$$

Note that both  $A'A$  and  $AA'$  are symmetric.

- The **identity matrix** is a special square ( $n \times n$ ) matrix  $I$ , where  $I_{jj} = 1$  and  $I_{ij} = 0$  if  $i \neq j$ . For example, the  $4 \times 4$  identity matrix is

$$I = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

The identity matrix acts like “1” for matrix multiplication:  $AI = A$  and  $IA = A$  (if  $A$  is  $m \times n$ , the first  $I$  is the  $m \times m$  identity matrix, and the second  $I$  is the  $n \times n$  identity matrix).

- If  $A$  is a square ( $n \times n$ ) matrix with linearly independent columns, then an  $n \times n$  matrix  $A^{-1}$  can be constructed such that  $AA^{-1} = A^{-1}A = I$ , where  $I$  is the  $n \times n$  identity.

For example,

$$A = \begin{pmatrix} 3 & 2 \\ 7 & 1 \end{pmatrix} \quad A^{-1} = \begin{pmatrix} -1/11 & 2/11 \\ 7/11 & -3/11 \end{pmatrix}$$

For a  $2 \times 2$  matrix, the general form of the inverse is

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

where if  $ad = bc$ ,  $A$  is singular and has no inverse.

For  $d > 2$ , the formula for the inverse of a  $d \times d$  matrix is very complicated, but inverses can be easily calculated on a computer.