

# Matrices

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We can address the elements (or entries) in a matrix by specifying the row and the column of that entry (always in that order). If we say the  $ij$ -entry, we mean the entry in row  $i$  and column  $j$ . For example, an  $n \times k$  matrix with unspecified entries would look like

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nk} \end{pmatrix}$$

Thus, the  $ij$ -entry is  $a_{ij}$  and this is sometimes abbreviated  $A = (a_{ij})$ .



In fact, if we state that  $B$  and  $C$  are matrices and talk about  $b_{ij}$  or  $c_{ij}$ , we will understand that  $b_{ij}$  are entries of  $B$  and  $c_{ij}$  are entries of  $C$ .

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The above illustrates a convention our book uses: If a matrix is specified, the corresponding bold lower case letter with a subscript represents the corresponding column of the matrix. If there is an arrow over the letter, that represents the corresponding row. Finally, we can represent a matrix as a list of column vectors or a stack of row vectors as follows

$$A = (\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_k), \text{ or } \begin{pmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_k \end{pmatrix}, \quad B = \begin{pmatrix} \vec{\mathbf{b}}_1 \\ \vec{\mathbf{b}}_2 \\ \vdots \\ \vec{\mathbf{b}}_n \end{pmatrix}$$

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Note: you cannot add matrices that are different sizes. If  $A$  is  $n \times k$  then you can add  $A + B$  only if  $B$  is also  $n \times k$

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Note that the result is a number, or it can be viewed as a  $1 \times 1$  matrix.

Next case: an  $n \times k$  matrix times a  $k \times 1$  column vector. In this case each row of the first matrix is multiplied by the column vector.



$$\text{So: } A\mathbf{b} = \begin{pmatrix} \vec{\mathbf{a}}_1 \\ \vec{\mathbf{a}}_2 \\ \vdots \\ \vec{\mathbf{a}}_n \end{pmatrix} \mathbf{b} = \begin{pmatrix} \vec{\mathbf{a}}_1 \mathbf{b} \\ \vec{\mathbf{a}}_2 \mathbf{b} \\ \vdots \\ \vec{\mathbf{a}}_n \mathbf{b} \end{pmatrix}$$

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$$\text{If } A \text{ is } n \times k \text{ and } B \text{ is } k \times m \text{ then: } \mathbf{AB} = \left( \mathbf{Ab}_1 \quad \mathbf{Ab}_2 \quad \cdots \quad \mathbf{Ab}_m \right)$$

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$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{kn} \end{pmatrix}, \quad \mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{pmatrix} \quad \text{and} \quad \mathbf{b} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix}$$

## Some special cases.

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Then the equation  $A\mathbf{x} = \mathbf{b}$  is the same as

$$A\mathbf{x} = \begin{pmatrix} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1k}x_k \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2k}x_k \\ \vdots \\ a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nk}x_k \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix} = \mathbf{b}$$

Equating the positions in  $A\mathbf{x}$  to the corresponding positions in  $\mathbf{b}$  gives us a system of equations.



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Equating the positions in  $Ax$  to the corresponding positions in  $\mathbf{b}$  gives us a system of equations.

Another special case is confusing at first: a column vector times a row vector. This can always be done: as it is an  $n \times 1$  times a  $1 \times k$ . The rows of the first have length 1 as do the columns of the second. The result will be  $n \times k$ :

$$\mathbf{a}\vec{\mathbf{b}} = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} \begin{pmatrix} b_1 & b_2 & \cdots & b_k \end{pmatrix} = \begin{pmatrix} a_1b_1 & a_1b_2 & \cdots & a_1b_k \\ a_2b_1 & a_2b_2 & \cdots & a_2b_k \\ \vdots & \vdots & \ddots & \vdots \\ a_nb_1 & a_nb_2 & \cdots & a_nb_k \end{pmatrix}$$

This is sometimes called the *outer product* of  $\mathbf{a}$  and  $\vec{\mathbf{b}}$ .