

Lecture 11: Vectors, matrices, and tensors

Lecturer: Jie Fu

EEL 3850

Vector: An n x 1 matrix.



$$y = \begin{bmatrix} 460 \\ 232 \\ 315 \\ 178 \end{bmatrix}$$

 $y_i = i^{th}$ element

1-indexed vs 0-indexed:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} \qquad y = \begin{bmatrix} y_0 \\ y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

Matrix: Rectangular array of numbers:



$$A = \begin{bmatrix} 1402 & 191 \\ 1371 & 821 \\ 949 & 1437 \\ 147 & 1448 \end{bmatrix}$$

Dimension of matrix: number of rows x number of columns

$$Dim(A) = 4 \times 2$$

Matrix Elements (entries of matrix)

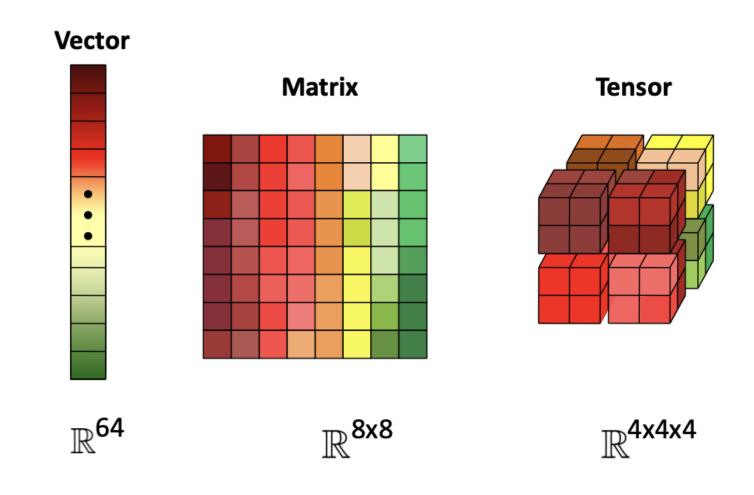


$$A = \begin{bmatrix} 1402 & 191 \\ 1371 & 821 \\ 949 & 1437 \\ 147 & 1448 \end{bmatrix}$$

$$A_{ij} = ij, j \text{ entry}$$
 in the i^{th} row, j^{th} column.

Tensor: High-dimensional array







Basic algebra



Transposing a column vector results in a row vector, and vice versa

$$\left[egin{array}{c} \mathsf{a} \ \mathsf{b} \ \mathsf{c} \end{array}
ight] \qquad o \ oldsymbol{\mathcal{V}}^T =$$

Vector-Vector Product



"Inner product" or "dot product"
$$\langle \mathbf{x}, \mathbf{y} \rangle \triangleq \mathbf{x}^{\top} \mathbf{y} = \sum_{i=1}^{n} x_i y_i$$
.

$$\left\langle \begin{bmatrix} a \\ b \\ c \end{bmatrix}, \begin{bmatrix} e \\ f \\ g \end{bmatrix} \right\rangle = \begin{bmatrix} a & b & c \end{bmatrix} \cdot \begin{bmatrix} e \\ f \\ g \end{bmatrix} = a \cdot e + b \cdot f + c \cdot g$$

$$\begin{bmatrix} 2 \\ 7 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 8 \\ 2 \\ 8 \end{bmatrix} = 2 \cdot 8 + 7 \cdot 2 + 1 \cdot 8 = 38$$
Dot product

Usages of inner products



0.1 L2-norm: the intuitive notion of length of the vector

The L_2 norm (also known as the Euclidean norm) of a vector $\mathbf{x} \in \mathbb{R}^n$ is defined as:

$$\|\mathbf{x}\|_2 = \sqrt{\sum_{i=1}^n x_i^2}$$

0.2 Squared error computation

The squared error between a sample $\{x_1, x_2, \dots, x_n\}$ and its mean is given by:

$$SE = \sum_{i=1}^{n} (x_i - \mu_x)^2 = |\vec{x} - \mu_x \mathbf{1}|^2.$$

Geometric interpretation of inner product



An alternative expression using vector norms and the angle θ between the two vectors is:

$$\mathbf{a} \cdot \mathbf{b} = \|\mathbf{a}\| \|\mathbf{b}\| \cos \theta$$

where:

- $\|\mathbf{a}\| = \sqrt{\sum_{i=1}^n a_i^2}$ is the norm of \mathbf{a} .
- $\|\mathbf{b}\| = \sqrt{\sum_{i=1}^{n} b_i^2}$ is the norm of **b**.
- θ is the angle between the two vectors.

Usage of inner product

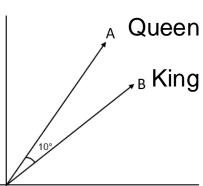


0.1 Cosine Similarity: measure the similarity between two vectors

Given two vectors $\mathbf{a}, \mathbf{b} \in \mathbb{R}^n$, the cosine similarity is the cosine of the angle between the vectors, and can be computed as:

cosine similarity =
$$\frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$

This is commonly used in text mining and natural language processing (NLP) to measure the similarity between document embeddings.



The angle between vector A and B is 10 deg.

Cos(10) = 0.9848...

The angles could be said to be 98% similar



Projection

 To "project" a vector u onto v (basically, rotate a vector and place it on a second vector);

$$proj_{v}u = \left(\frac{u \cdot v}{\|v\|^{2}}\right)v$$

$$Proj_{v}\vec{u}$$

Cauchy-Schwarz inequality



Cauchy-Schwarz Inequality:

For any two vectors $\mathbf{a}, \mathbf{b} \in \mathbb{R}^n$, the inner product satisfies:

$$|\mathbf{a} \cdot \mathbf{b}| \le ||\mathbf{a}|| ||\mathbf{b}||$$

In component form, for vectors $\mathbf{a} = (a_1, a_2, \dots, a_n)$ and $\mathbf{b} = (b_1, b_2, \dots, b_n)$:

$$\left| \sum_{i=1}^n a_i b_i \right| \le \sqrt{\sum_{i=1}^n a_i^2} \cdot \sqrt{\sum_{i=1}^n b_i^2}$$

Scalar Multiplication



If A =
$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}_{m \times n}$$

then for any scaler 'k'

$$kA = \begin{bmatrix} ka_{11} & ka_{12} & \dots & ka_{1n} \\ ka_{21} & ka_{22} & \dots & ka_{2n} \\ \vdots & \vdots & & \vdots \\ ka_{m1} & ka_{m2} & \dots & ka_{mn} \end{bmatrix}_{m \times n}$$

$$\begin{vmatrix} 1 & 0 \\ 2 & 5 \\ 3 & 1 \end{vmatrix} =$$

Matrix Addition is element-wise



$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_{11} & \mathbf{a}_{12} & \mathbf{a}_{13} \\ \mathbf{a}_{21} & \mathbf{a}_{22} & \mathbf{a}_{23} \\ \mathbf{a}_{31} & \mathbf{a}_{32} & \mathbf{a}_{33} \end{bmatrix} \text{ and } \mathbf{B} = \begin{bmatrix} \mathbf{b}_{11} & \mathbf{b}_{12} & \mathbf{b}_{13} \\ \mathbf{b}_{21} & \mathbf{b}_{22} & \mathbf{b}_{23} \\ \mathbf{b}_{31} & \mathbf{b}_{32} & \mathbf{b}_{33} \end{bmatrix}$$

$$\mathbf{A} + \mathbf{B} = \begin{bmatrix} \mathbf{a}_{11} + \mathbf{b}_{11} & \mathbf{a}_{12} + \mathbf{b}_{12} & \mathbf{a}_{13} + \mathbf{b}_{13} \\ \mathbf{a}_{21} + \mathbf{b}_{21} & \mathbf{a}_{22} + \mathbf{b}_{22} & \mathbf{a}_{23} + \mathbf{b}_{23} \\ \mathbf{a}_{31} + \mathbf{b}_{31} & \mathbf{a}_{32} + \mathbf{b}_{32} & \mathbf{a}_{33} + \mathbf{b}_{33} \end{bmatrix}$$



$$\begin{bmatrix} 1 & 0 \\ 2 & 5 \\ 3 & 1 \end{bmatrix} + \begin{bmatrix} 4 & 0.5 \\ 2 & 5 \\ 0 & 1 \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 0 \\ 2 & 5 \\ 3 & 1 \end{bmatrix} + \begin{bmatrix} 4 & 0.5 \\ 2 & 5 \end{bmatrix} =$$

Matrix transpose



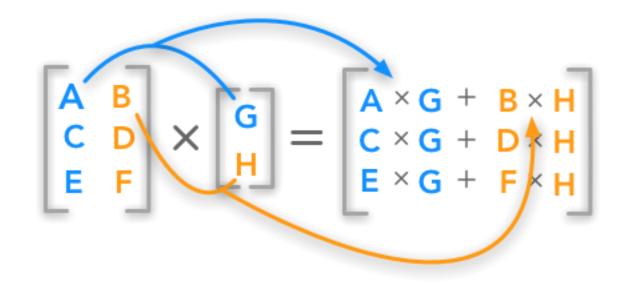
$$A = \begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix}_{2 \times 3}$$

$$A^{T} = \begin{bmatrix} a & d \\ b & e \\ c & f \end{bmatrix}_{3 \times 2}$$

$$(\mathbf{A}^{\top})_{ij} = A_{ji}$$



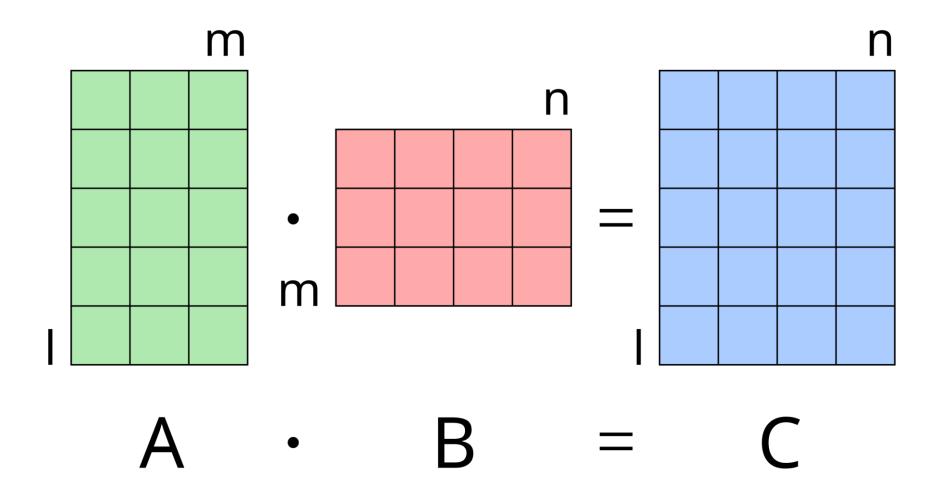




$$\begin{bmatrix} 1 & 3 \\ 4 & 0 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 5 \end{bmatrix} =$$

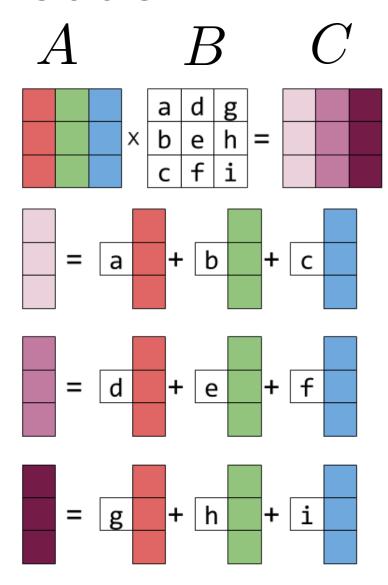
Matrix-Matrix Product





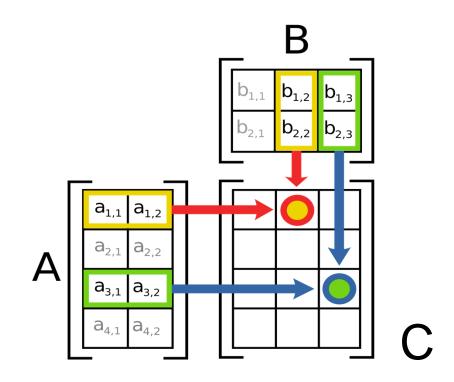
Matrix-Matrix Product





The *i*-th column of the matrix *C* is obtained by multiplying *A* with the *i* column of *B*

$$\mathbf{C} = \mathbf{A}\mathbf{B} = \begin{bmatrix} - & \mathbf{a}_1^\top & - \\ - & \mathbf{a}_2^\top & - \\ & \vdots & \\ - & \mathbf{a}_m^\top & - \end{bmatrix} \begin{bmatrix} \ \mid & \ \mid & \ \mid \\ \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_p \\ \mid & \ \mid & \ \mid \end{bmatrix} = \begin{bmatrix} \mathbf{a}_1^\top \mathbf{b}_1 & \mathbf{a}_1^\top \mathbf{b}_2 & \cdots & \mathbf{a}_1^\top \mathbf{b}_p \\ \mathbf{a}_2^\top \mathbf{b}_1 & \mathbf{a}_2^\top \mathbf{b}_2 & \cdots & \mathbf{a}_2^\top \mathbf{b}_p \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{a}_m^\top \mathbf{b}_1 & \mathbf{a}_m^\top \mathbf{b}_2 & \cdots & \mathbf{a}_m^\top \mathbf{b}_p \end{bmatrix}^{\text{IVERSITY of }} \mathbf{LORIDA}$$



The *i,j*-th element of the matrix **C** is the inner product of the *i*-th row of **A** with the *j*-th column of **B**

Example



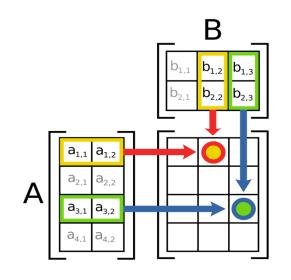
$$\begin{bmatrix} 1 & 3 \\ 2 & 5 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 3 & 2 \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 3 \\ 2 & 5 \end{bmatrix} \begin{bmatrix} 0 \\ 3 \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 3 \\ 2 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} =$$



A and B must have conforming dimensions!



 $Dim(A) = m \times n$ $Dim(B) = n \times p$ $Dim(AB) = m \times p$