

# Lecture 1 – Multivariate linear models

AI in Genetics

*ZOO6927 / BOT6935 / ZOO4926*

# Vectors, matrices, and tensors

**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

$$\text{Dim}(A) = 4 \times 2$$

## Matrix Elements (entries of matrix)

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

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

**Vector:** An  $n \times 1$  matrix.

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

$y_i = i^{th}$  element

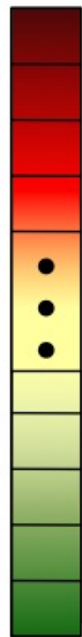
1-indexed vs 0-indexed:

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

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

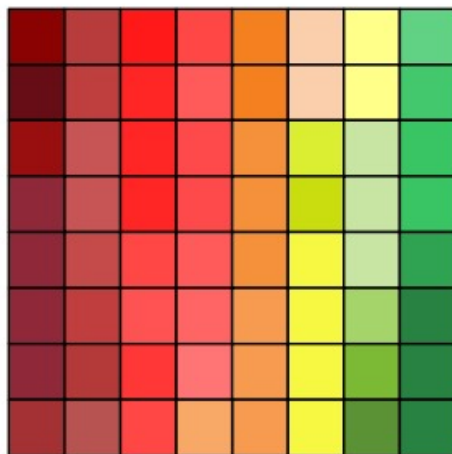
# Tensor: High-dimensional array

**Vector**



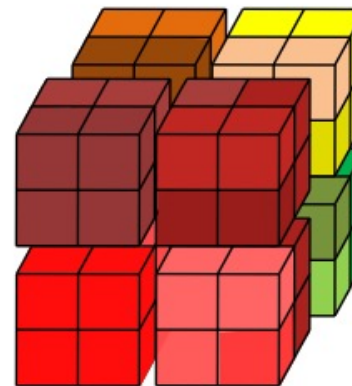
$\mathbb{R}^{64}$

**Matrix**



$\mathbb{R}^{8 \times 8}$

**Tensor**



$\mathbb{R}^{4 \times 4 \times 4}$

# Basic matrix algebra

# Scalar Multiplication

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

then for any scalar 'k'

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

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



# Matrix Addition is element-wise

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

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

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

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

# Matrix transpose

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

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

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

$$V = \begin{bmatrix} a \\ b \\ c \end{bmatrix} \rightarrow V^T = \begin{bmatrix} a & b & c \end{bmatrix}$$

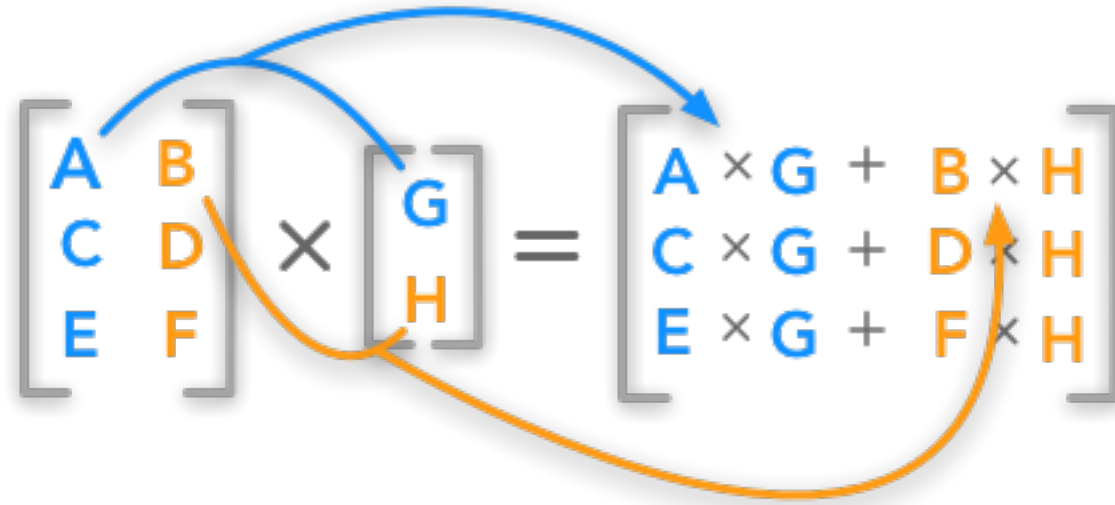
# Vector-Vector Product

“Inner product” or “dot product”

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

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

# Matrix-vector multiplication

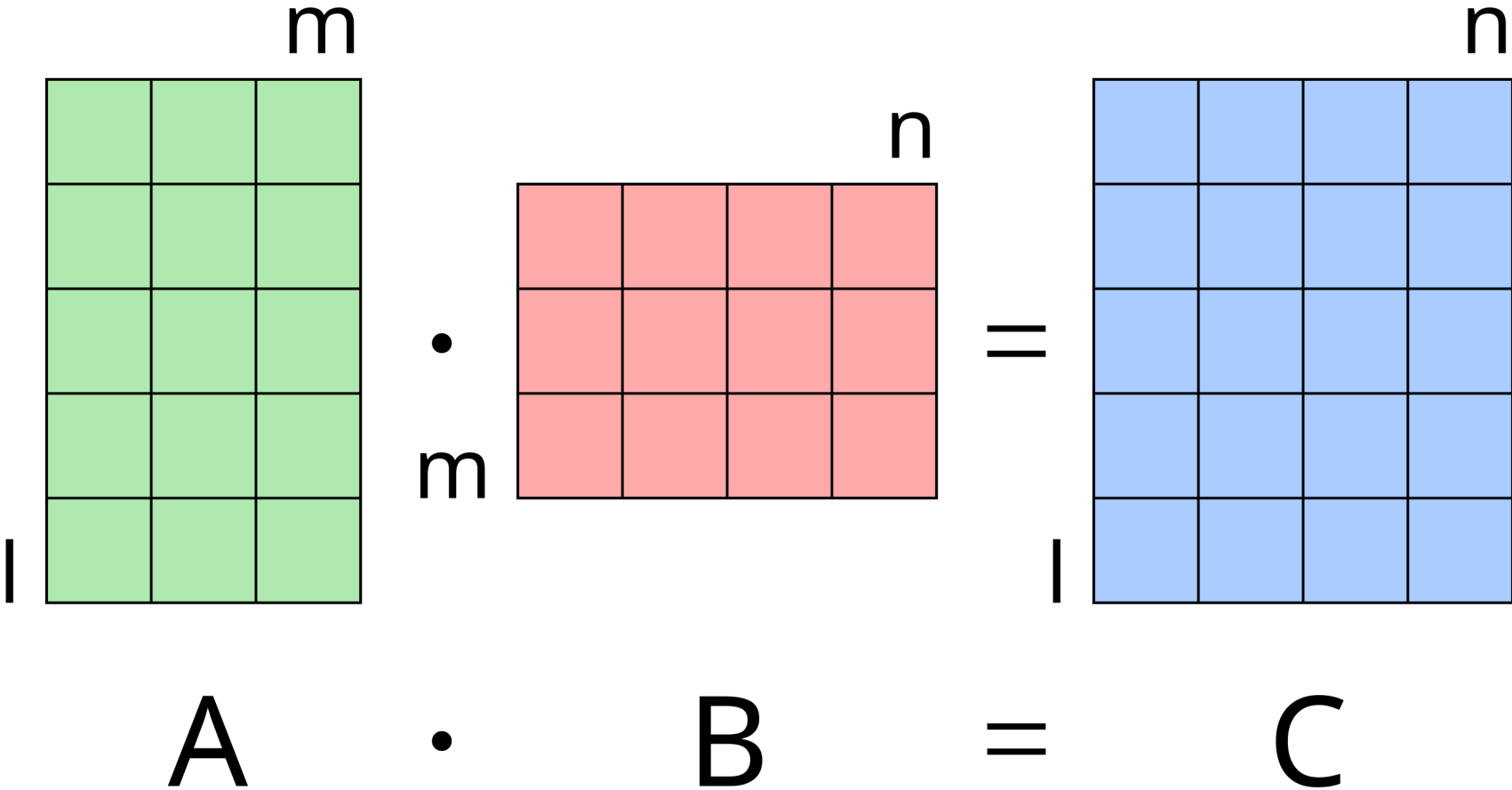


$$\begin{bmatrix} 1 & 3 \\ 4 & 0 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 5 \end{bmatrix} =$$

# Example

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

# Matrix-Matrix Product





# Matrix-Matrix Product

$$\begin{array}{c} A \quad B \quad C \\ \begin{array}{|c|c|c|} \hline \text{red} & \text{green} & \text{blue} \\ \hline \text{red} & \text{green} & \text{blue} \\ \hline \text{red} & \text{green} & \text{blue} \\ \hline \end{array} \times \begin{array}{|c|c|c|} \hline a & d & g \\ \hline b & e & h \\ \hline c & f & i \\ \hline \end{array} = \begin{array}{|c|c|c|} \hline \text{light pink} & \text{pink} & \text{dark purple} \\ \hline \text{light pink} & \text{pink} & \text{dark purple} \\ \hline \text{light pink} & \text{pink} & \text{dark purple} \\ \hline \end{array} \\ \begin{array}{|c|} \hline \text{light pink} \\ \hline \text{light pink} \\ \hline \text{light pink} \\ \hline \end{array} = \begin{array}{|c|} \hline a \\ \hline b \\ \hline c \\ \hline \end{array} \begin{array}{|c|} \hline \text{red} \\ \hline \text{red} \\ \hline \text{red} \\ \hline \end{array} + \begin{array}{|c|} \hline b \\ \hline e \\ \hline f \\ \hline \end{array} \begin{array}{|c|} \hline \text{green} \\ \hline \text{green} \\ \hline \text{green} \\ \hline \end{array} + \begin{array}{|c|} \hline c \\ \hline \text{blue} \\ \hline \text{blue} \\ \hline \end{array} \\ \begin{array}{|c|} \hline \text{pink} \\ \hline \text{pink} \\ \hline \text{pink} \\ \hline \end{array} = \begin{array}{|c|} \hline d \\ \hline e \\ \hline f \\ \hline \end{array} \begin{array}{|c|} \hline \text{red} \\ \hline \text{red} \\ \hline \text{red} \\ \hline \end{array} + \begin{array}{|c|} \hline e \\ \hline \text{green} \\ \hline \text{green} \\ \hline \end{array} + \begin{array}{|c|} \hline f \\ \hline \text{blue} \\ \hline \text{blue} \\ \hline \end{array} \\ \begin{array}{|c|} \hline \text{dark purple} \\ \hline \text{dark purple} \\ \hline \text{dark purple} \\ \hline \end{array} = \begin{array}{|c|} \hline g \\ \hline h \\ \hline i \\ \hline \end{array} \begin{array}{|c|} \hline \text{red} \\ \hline \text{red} \\ \hline \text{red} \\ \hline \end{array} + \begin{array}{|c|} \hline h \\ \hline \text{green} \\ \hline \text{green} \\ \hline \end{array} + \begin{array}{|c|} \hline i \\ \hline \text{blue} \\ \hline \text{blue} \\ \hline \end{array}\end{array}$$

The  $i$ -th column of the matrix  $\mathbf{C}$  is obtained by multiplying  $\mathbf{A}$  with the  $i$  column of  $\mathbf{B}$

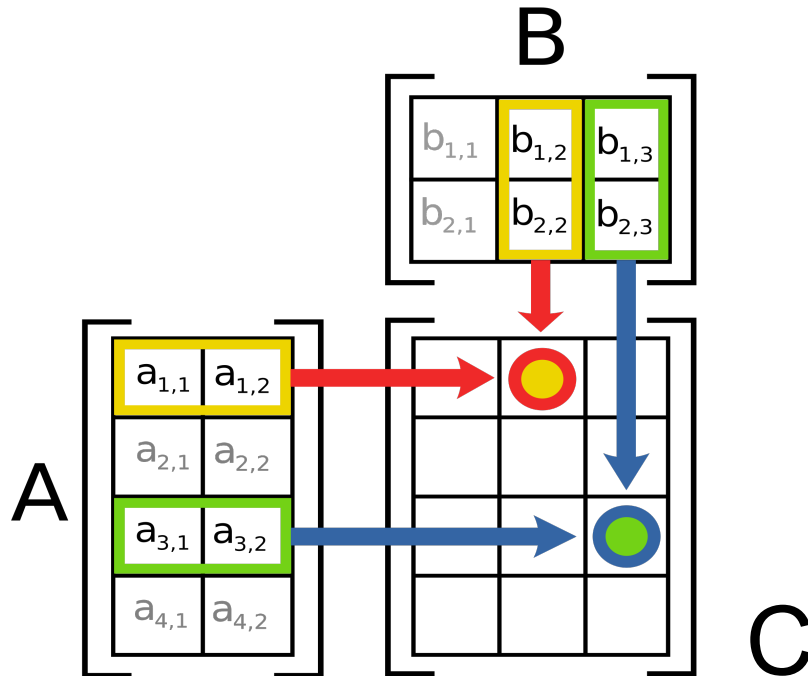
# Example

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

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

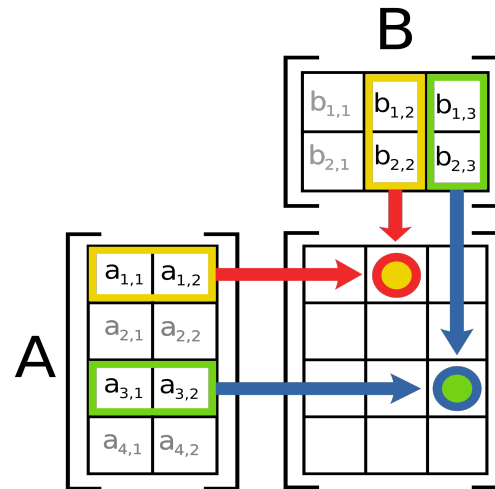
$$\begin{bmatrix} 1 & 3 \\ 2 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} =$$

$$\mathbf{C} = \mathbf{AB} = \begin{bmatrix} \text{---} & \mathbf{a}_1^\top & \text{---} \\ \text{---} & \mathbf{a}_2^\top & \text{---} \\ & \vdots & \\ \text{---} & \mathbf{a}_m^\top & \text{---} \end{bmatrix} \begin{bmatrix} | & | & \cdots & | \\ \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_p \\ | & | & & | \end{bmatrix} = \begin{bmatrix} \mathbf{a}_1^\top \mathbf{b}_1 & \mathbf{a}_1^\top \mathbf{b}_2 & \cdots & \mathbf{a}_1^\top \mathbf{b}_p \\ \mathbf{a}_2^\top \mathbf{b}_1 & \mathbf{a}_2^\top \mathbf{b}_2 & \cdots & \mathbf{a}_2^\top \mathbf{b}_p \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{a}_m^\top \mathbf{b}_1 & \mathbf{a}_m^\top \mathbf{b}_2 & \cdots & \mathbf{a}_m^\top \mathbf{b}_p \end{bmatrix}$$



The  $i, j$ -th element of the matrix  $\mathbf{C}$  is the dot product of the  $i$ -th row of  $\mathbf{A}$  with the  $j$ -th column of  $\mathbf{B}$

***A*** and ***B*** must have conforming dimensions!



$$\text{Dim}(A) = m \times n$$

$$\text{Dim}(B) = n \times p$$

$$\text{Dim}(AB) = m \times p$$

$$\mathbf{C} = \mathbf{AB} = \left[ \begin{array}{c|c|c|c} | & | & & | \\ \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_n \\ | & | & & | \end{array} \right] \left[ \begin{array}{c|c|c} \text{---} & \mathbf{b}_1^\top & \text{---} \\ \text{---} & \mathbf{b}_2^\top & \text{---} \\ & \vdots & \\ \text{---} & \mathbf{b}_n^\top & \text{---} \end{array} \right] = \sum_{i=1}^n \mathbf{a}_i \mathbf{b}_i^\top .$$

\*The matrix  $\mathbf{C}$  is the sum of outer product of  $i$ -th column of A and  $i$ -th row of B

# Back to the simple linear regression example

House sizes:

Size in feet <sup>2</sup> (x)	Price (\$) in 1000's (y)
2104	460
1416	232
1534	315
852	178
...	...

Hypothesis:

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

Parameters:

$$\theta_0, \theta_1$$

Cost Function (MSE):

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

Goal: minimize  $J(\theta_0, \theta_1)$   
 $\theta_0, \theta_1$

House sizes:

Size in feet <sup>2</sup> (x)	Price (\$) in 1000's (y)
2104	460
1416	232
1534	315
852	178
...	...

Hypothesis:

$$h_{\theta}(x) = -40 + 0.25x$$

Use matrix-vector multiplication:

$$\begin{bmatrix} 1 & 2104 \\ 1 & 1416 \\ 1 & 1534 \\ 1 & 852 \end{bmatrix} \cdot \begin{bmatrix} -40 \\ 0.25 \end{bmatrix} = \begin{bmatrix} 486.0 \\ 314.0 \\ 343.5 \\ 173.0 \end{bmatrix}$$

$$X \quad \theta \quad \hat{y}$$

## House sizes:

Size in feet <sup>2</sup> (x)	Price (\$) in 1000's (y)
2104	460
1416	232
1534	315
852	178
...	...

## Model prediction

$$\begin{bmatrix} 1 & 2104 \\ 1 & 1416 \\ 1 & 1534 \\ 1 & 852 \end{bmatrix} \cdot \begin{bmatrix} -40 \\ 0.25 \end{bmatrix} = \begin{bmatrix} 486.0 \\ 314.0 \\ 343.5 \\ 173.0 \end{bmatrix}$$

$X \qquad \theta \qquad \hat{\mathbf{y}}$

## Cost

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$$J(\theta) = \frac{1}{2m} (\hat{\mathbf{y}} - \mathbf{y})^T (\hat{\mathbf{y}} - \mathbf{y}) = \frac{1}{2m} (\mathbf{X}\theta - \mathbf{y})^T (\mathbf{X}\theta - \mathbf{y})$$



## Model prediction

$$\begin{bmatrix} 1 & 2104 \\ 1 & 1416 \\ 1 & 1534 \\ 1 & 852 \end{bmatrix} \cdot \begin{bmatrix} -40 \\ 0.25 \end{bmatrix} = \begin{bmatrix} 486.0 \\ 314.0 \\ 343.5 \\ 173.0 \end{bmatrix}$$

$X \qquad \theta \qquad \hat{\mathbf{y}}$

Goal: minimize  $J(\theta_0, \theta_1)$   
 $\theta_0, \theta_1$

## Solution

### Cost

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

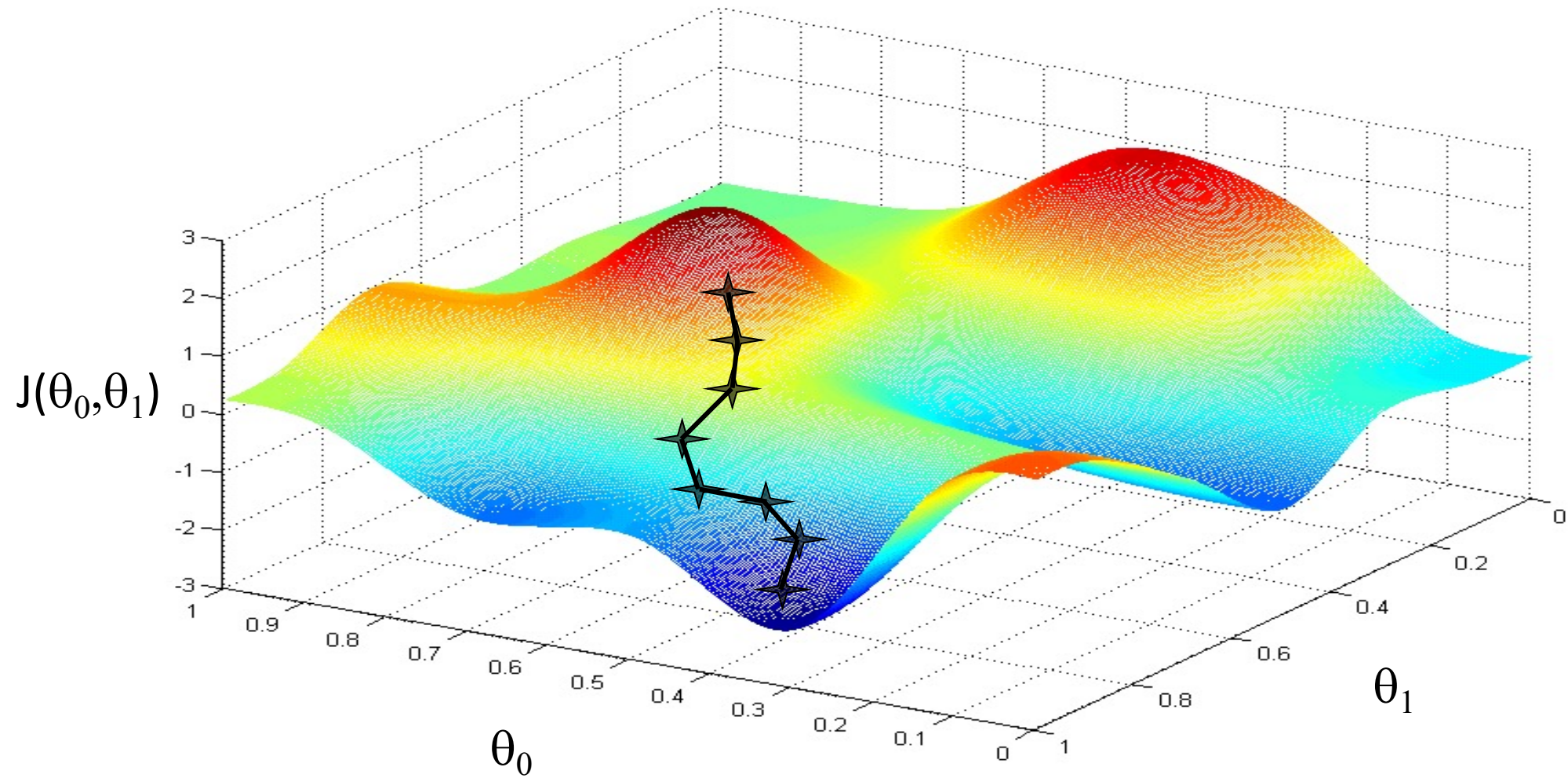
$$J(\boldsymbol{\theta}) = \frac{1}{2m} (\hat{\mathbf{y}} - \mathbf{y})^T (\hat{\mathbf{y}} - \mathbf{y}) = \frac{1}{2m} (\mathbf{X}\boldsymbol{\theta} - \mathbf{y})^T (\mathbf{X}\boldsymbol{\theta} - \mathbf{y})$$

$$\hat{\boldsymbol{\theta}} = \mathbf{argmin}_{\boldsymbol{\theta}} (\mathbf{X}\boldsymbol{\theta} - \mathbf{y})^T (\mathbf{X}\boldsymbol{\theta} - \mathbf{y})$$

# How to find the solution - calculus

$$\hat{\theta} = (X^T X)^{-1} X^T \mathbf{y}$$

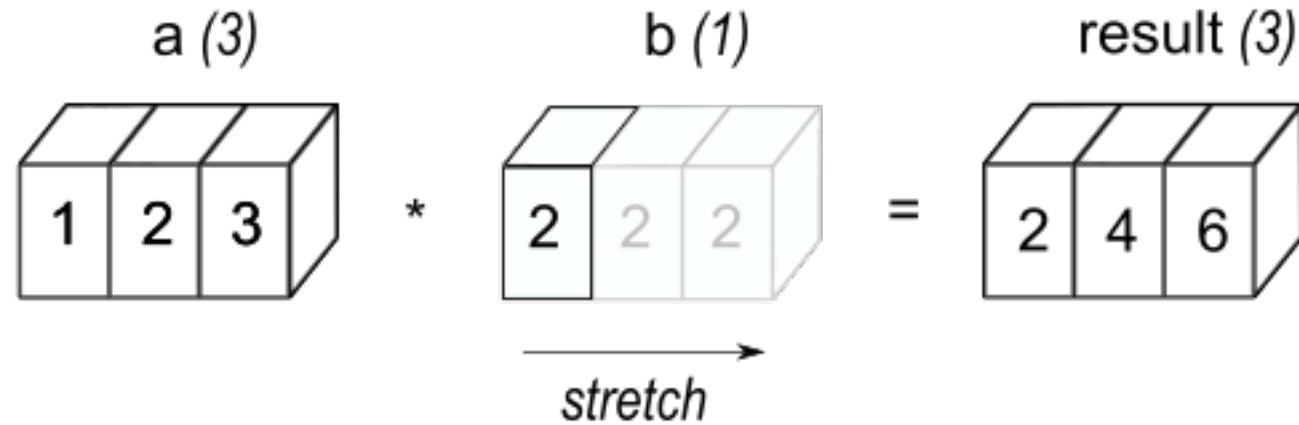
# How to find the solution – gradient descent

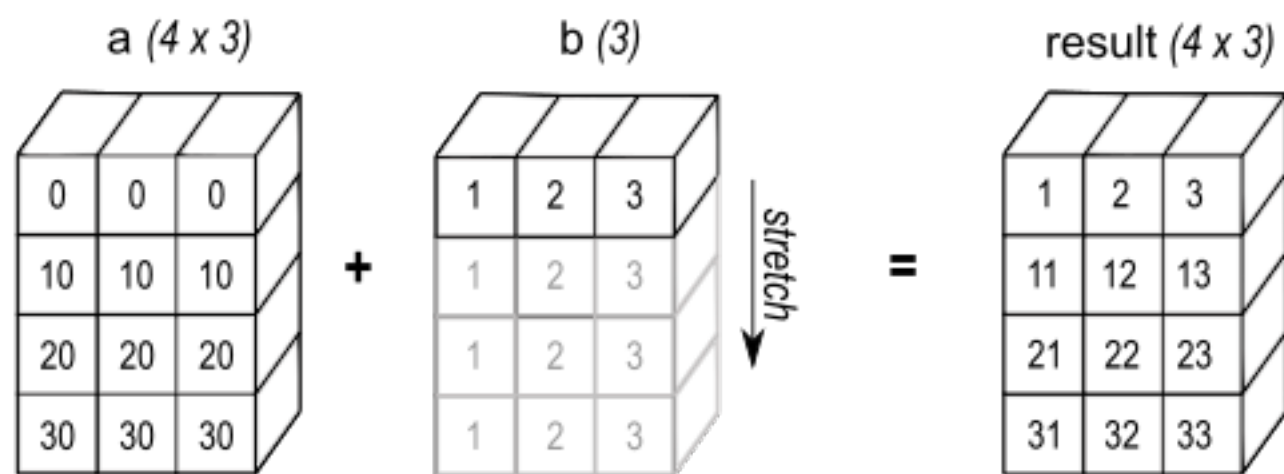


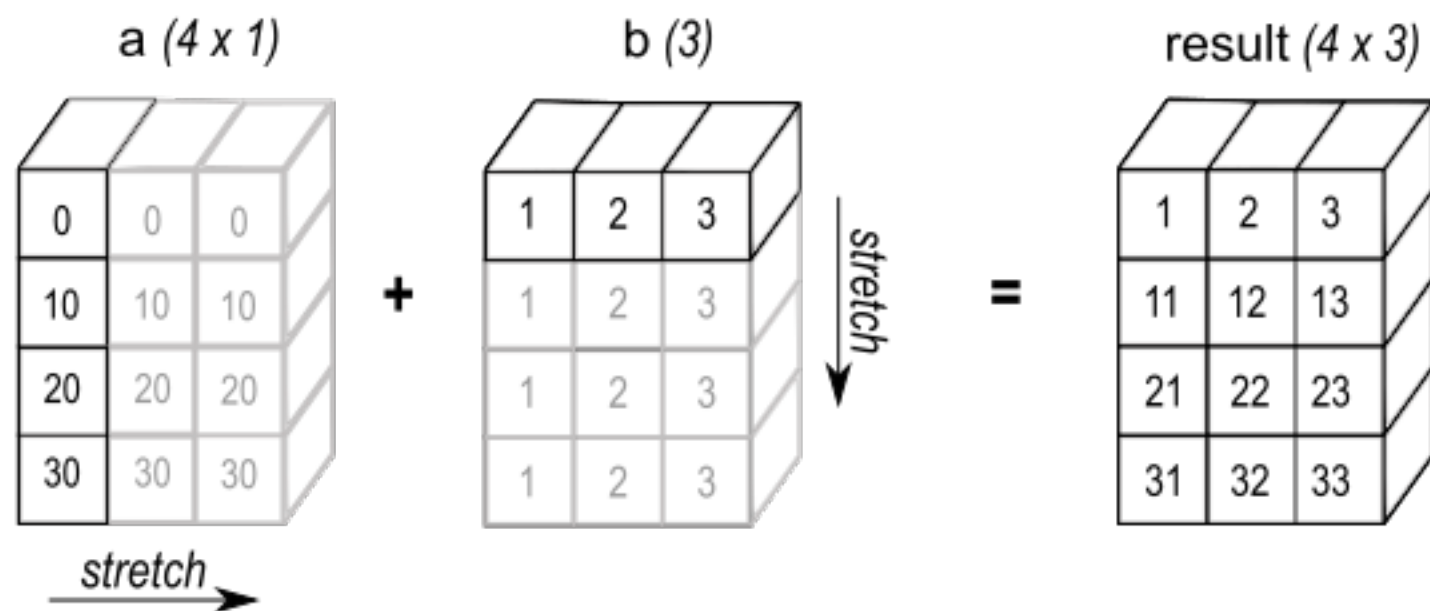
# Broadcasting

- Broadcasting: how NumPy (torch, tensorflow) treats arrays with different shapes during arithmetic operations.
- When performing operations between two arrays, broadcasting automatically expands one or both arrays so they have compatible shapes. This allows element-wise operations without the need for explicitly reshaping arrays.

# Generalized tensor operation: Broadcasting







**Concise Code:** It reduces the need for explicit loops and reshaping, making the code more concise and easier to read.

**Performance:** Broadcasting is implemented in a memory-efficient manner, avoiding unnecessary copies of data.

**Flexibility:** It allows operations on arrays of different shapes without needing them to be exactly the same size.