

Let  $A$  be  $(1 \times 2)$  and  $B$  be  $(2 \times 1)$ .  $A$  is a row vector and  $B$  is a column vector.  $C = AB$ . Multiplication is to do element by element multiplication, then sum the result.

$$A = \begin{pmatrix} a_{11} & a_{12} \end{pmatrix}, \quad B = \begin{pmatrix} b_{11} \\ b_{21} \end{pmatrix},$$

$$\begin{aligned} C &= AB = \begin{pmatrix} a_{11} & a_{12} \end{pmatrix} \begin{pmatrix} b_{11} \\ b_{21} \end{pmatrix} \\ &= (a_{11}b_{11} + a_{12}b_{21}) = C, \text{ (a scalar).} \end{aligned}$$

$$\begin{aligned} BA &= \begin{pmatrix} b_{11} \\ b_{21} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \end{pmatrix} \\ &= \begin{pmatrix} b_{11}a_{11} & b_{11}a_{12} \\ b_{21}a_{11} & b_{21}a_{12} \end{pmatrix} = D \text{ (a matrix)} \end{aligned}$$

Next, let's do it with actual matrices: Let

$$A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}, \quad B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}.$$

$C = AB$ , is formed by  $c_{ij} = \sum a_{ij}b_{ji}$ . The  $i, j$  element of  $C$  is formed from multiplying row  $i$  of  $A$  and column  $j$  of  $B$ .

$$\begin{aligned} C &= AB = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \\ &= \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} \\ b_{11}a_{31} + b_{21}a_{32} & a_{31}b_{12} + a_{32}b_{22} \end{pmatrix} \end{aligned}$$

**note:** Even if  $A$  and  $B$  are both square matrices, the order matters.  $AB \neq BA$ .

- **Determinant of a  $(2 \times 2)$  matrix.** Subtract the product of the off-diagonal elements from the product of the diagonal elements.

$$\text{Let } A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}. \quad |A| = \det(A) = ad - bc.$$

Note: You can only get a determinant from **square** matrices. Calculating the determinant by hand from anything bigger than a  $(2 \times 2)$  is beyond the scope of this class. But that's okay because we'll be doing it by computer.

- **Matrix Inverse.** The inverse can only be computed for **square** matrices. It is the matrix when multiplied by itself gives the identity matrix. If  $A^{-1}A = AA^{-1} = I$ , then  $A^{-1}$  is the inverse of  $A$ . To get the inverse of a  $(2 \times 2)$  matrix  $A$  (defined above), switch positions of the diagonal elements, multiply the off diagonal elements by  $-1$ , then divide everything by the determinant of  $A$ .

$$A^{-1} = \frac{1}{ad-bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}. \text{ Let's check:}$$

$$\frac{1}{ad-bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix} \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} \frac{ad}{ad-bc} - \frac{bc}{ad-bc} & 0 \\ 0 & \frac{ad}{ad-bc} - \frac{bc}{ad-bc} \end{pmatrix} = I$$

Again, computing the inverse of anything bigger than a  $(2 \times 2)$  matrix by hand is beyond the scope of this class. We just ask the computer to do it.

Sometimes the inverse doesn't exist. This happens if there is a (linear) dependence across rows or columns. If

$$A = \begin{pmatrix} a & 2a \\ b & 2b \end{pmatrix}$$

then

$$|A| = 2ab - 2ab = 0$$

and  $1/|A|$  doesn't exist.

### 8.3 Why Matrix Algebra?

Well, one thing is we can write regression in matrix form. Begin with

$$y_t = \alpha + \beta x_t + \epsilon_t$$

stack the dependent variable observations in a column vector and independent variables Independent variables: constant (a vector of 1s) and  $x_t$

$$\underbrace{\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{pmatrix}}_y = \underbrace{\begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_T \end{pmatrix}}_X \underbrace{\begin{pmatrix} \alpha \\ \beta \end{pmatrix}}_b + \underbrace{\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_T \end{pmatrix}}_\epsilon$$

$$y = Xb + \epsilon$$

Multiply through by  $X'$

$$\begin{aligned} X'y &= X'Xb + X'\epsilon \\ X'Xb &= X'(y - \epsilon) \\ b &= (X'X)^{-1} X'y - (X'X)^{-1} X'\epsilon \end{aligned}$$

Least squares forces the residuals  $\hat{\epsilon}$  to be uncorrelated with the regressors.  $X'\hat{\epsilon} = 0$ . Hence, in matrix form, the least squares formula is

$$\hat{b} = (X'X)^{-1} X'y$$