

# Math 189: Matrix Algebra

## I. Multivariate Data

### Matrix Formulation

In multivariate analysis, we are interested in jointly analyzing multiple dependent variables.

- These variables can be represented using matrices and vectors.
- The benefits of matrix form:
  1. Simplicity in notation
  2. Expressing important formulas in readable format

### Example 1: Multivariate Data of Infant Death

Data records several variables for a baby at birth:

1. Baby Weight (**bwt**): in ounces
2. Gestation (**gestation**): in days

Rows are babies, columns are variables

```
baby <- read.table("C:\\Users\\neide\\Documents\\GitHub\\ma189\\Data\\babies.dat",header=TRUE)
head(baby[,c(1,2)])
```

```
##    bwt gestation
## 1 120         284
## 2 113         282
## 3 128         279
## 4 123         999
## 5 108         282
## 6 136         286
```

Notice anything weird?!

*Source:* The Child Health and Development Studies (CHDS) data are presented in *Stat Labs: Mathematical Statistics Through Applications* by Deborah Nolan and Terry Speed (Springer).

### Math Notation

Let  $\underline{x} = [x_1, x_2]'$  denote the column vector of **bwt** and **gestation**.

$$\underline{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \text{bwt} \\ \text{gestation} \end{bmatrix}.$$

So  $\underline{x} \in \mathbb{R}^2$ .

There are  $n = 1236$  babies. Let  $\underline{x}_i$  for  $1 \leq i \leq 1236$  denote both variables for baby  $i$ , i.e.,

$$\underline{x}_1 = \begin{bmatrix} 120 \\ 284 \end{bmatrix}, \quad \underline{x}_2 = \begin{bmatrix} 113 \\ 282 \end{bmatrix}, \quad \underline{x}_3 = \begin{bmatrix} 128 \\ 279 \end{bmatrix}, \quad \dots$$

This is called the **record** for the  $i$ th baby (or unit). Let  $i$  index baby, and  $j = 1, 2$  index variable. Then  $x_{i,j}$  is **bwt** ( $j = 1$ ) or **gestation** ( $j = 2$ ) for baby  $i$ . Gestation for the fourth baby is  $x_{4,2} = 999$ .

A data matrix consists of all **records** as row vectors:

$$\begin{bmatrix} \underline{x}'_1 \\ \underline{x}'_2 \\ \underline{x}'_3 \end{bmatrix} = \begin{bmatrix} 120 & 284 \\ 113 & 282 \\ 128 & 279 \end{bmatrix}.$$

```
x <- baby[1:3,1:2]
x
```

```
##    bwt gestation
## 1 120         284
## 2 113         282
## 3 128         279
```

Each row is information for one baby; each column is all measurements (across babies) of either **bwt** or **gestation**

## Definition of Matrix and Vector

A matrix is a two-dimensional array of numbers, symbols, or expressions, arranged in rows and columns.

- A vector is a matrix with either one row or one column.
- The dimension of a matrix is two numbers: number of rows (units) and number of columns (units). Dimension of baby is 1236, 7 and dimension of submatrix  $x$  is 3, 2.
- A square matrix is one for which the numbers of rows and number of columns are equal, e.g.

```
x <- baby[1:2,1:2]
dim(x)
```

```
## [1] 2 2
```

## Notations of Matrix and Vector

- Usually in this course we only consider matrices and vectors whose entries are real numbers.
- A real-valued **matrix**  $\mathbf{M}$  of dimension  $n \times m$  is denoted  $\mathbf{M} \in \mathbb{R}^{n \times m}$ .
- A real **vector**  $\underline{v}$  of length  $n$  is denoted  $\underline{v} \in \mathbb{R}^n$ .
- A row vector can be written  $\underline{v} \in \mathbb{R}^{1 \times n}$ , and a column vector can be written  $\underline{v} \in \mathbb{R}^{n \times 1}$ .
- A **scalar** is a real number, or a vector of length 1, or a  $1 \times 1$  dimensional matrix.

```
x <- as.matrix(baby[1:3,1:2])
x
```

```
##    bwt gestation
## 1 120         284
## 2 113         282
## 3 128         279
```

```
x[,1]
```

```
##    1    2    3
## 120 113 128
```

```
x[,1,drop=FALSE]
```

```
##    bwt
## 1 120
## 2 113
## 3 128
```

```
x[1,1]
```

```
## [1] 120
```

```
x[1,1,drop=FALSE]
```

```
##    bwt
## 1 120
```

## Transpose of a Matrix

- Definition: flip the rows and columns by interchanging row and column index. Denoted by  $\mathbf{M}'$ .
- If  $\mathbf{M}_{i,j}$  is row  $i$ , column  $j$  of matrix  $\mathbf{M}$ , then  $\mathbf{M}'_{i,j} = \mathbf{M}_{j,i}$ , so that now  $i$  is the column index, and  $j$  is the row index.

```
x
```

```
##    bwt gestation
## 1 120          284
## 2 113          282
## 3 128          279
```

```
t(x)
```

```
##           1    2    3
## bwt       120 113 128
## gestation 284 282 279
```

## Symmetric Matrices

- Definition: A square matrix  $\mathbf{M}$  is symmetric if  $\mathbf{M}' = \mathbf{M}$ .
- Hence  $\mathbf{M}_{i,j} = \mathbf{M}_{j,i}$ .

```
m <- t(x) %*% x
m
```

```
##           bwt gestation
## bwt       43553  101658
## gestation 101658  238021
```

- Important examples of symmetric matrices in multivariate statistics include the variance-covariance matrix and the correlation matrix.

## Linear Combination of Two Matrices

- Two matrices may be added if and only if they have the same dimensions. To add two matrices, add the corresponding elements.

```
y <- as.matrix(baby[5:7,1:2])
y
```

```
##    bwt gestation
## 5 108          282
## 6 136          286
## 7 138          244
```

```
x+y
```

```
##    bwt gestation
## 1 228          566
## 2 249          568
## 3 266          523
```

- If  $\mathbf{A}$  and  $\mathbf{B}$  are two  $n \times m$  dimensional matrices,  $\alpha$  and  $\beta$  are two scalars, then  $\mathbf{C} = \alpha \mathbf{A} + \beta \mathbf{B} \in \mathbb{R}^{n \times m}$ . A scalar multiplies each entry of the matrix, i.e.,

$$\mathbf{C}_{i,j} = \alpha \mathbf{A}_{i,j} + \beta \mathbf{B}_{i,j}.$$

```
2*x + 3*y
```

```
##    bwt gestation
## 1 564          1414
## 2 634          1422
## 3 670          1290
```

## Multiplication of Two Matrices

- The **dot product** of two vectors  $\underline{x}$  and  $\underline{y}$  is the sum of the product of their entries:  $\underline{x} \cdot \underline{y} = \sum_{i=1}^n x_i y_i$ .

```
sum(x[,1]*x[,2])
```

```
## [1] 101658
```

```
t(x[,1,drop=FALSE]) %*% x[,2,drop=FALSE]
```

```
##    gestation
## bwt      101658
```

- We multiply matrices by taking dot products of row and column vectors:  $\mathbf{C} = \mathbf{A} \mathbf{B}$  is defined if number of columns in  $\mathbf{A}$  equals the number of rows in  $\mathbf{B}$ . Then

$$\mathbf{C}_{i,j} = \mathbf{A}_{i,-} \cdot \mathbf{B}_{-,j} = \sum_{k=1}^p \mathbf{A}_{i,k} \mathbf{B}_{k,j}.$$

Here  $\mathbf{A} \in \mathbb{R}^{n \times p}$ ,  $\mathbf{B} \in \mathbb{R}^{p \times m}$ , and  $\mathbf{C} \in \mathbb{R}^{n \times m}$ .

```
x %*% t(y)
```

```
##          5          6          7
## 1 93048 97544 85856
## 2 91728 96020 84402
## 3 92502 97202 85740
```

```
sum(x[1,]*t(y)[,3])
```

```
## [1] 85856
```

## Identity Matrix

- Definition: An identity matrix  $\mathbf{I}$  is a square matrix that has ones on its diagonal (from upper left to bottom right) and has zeros elsewhere.

```
eye <- diag(2)
eye
```

```
##      [,1] [,2]
## [1,]    1    0
## [2,]    0    1
```

- When multiplying any square matrix, it leaves the matrix unchanged:  $\mathbf{I}\mathbf{A} = \mathbf{A}$ .

```
z <- as.matrix(baby[1:2,1:2])
z
```

```
##      bwt gestation
## 1 120          284
## 2 113          282
```

```
eye %**% z
```

```
##      bwt gestation
## [1,] 120          284
## [2,] 113          282
```

## Matrix Inverse

- Definition: The inverse of a square matrix  $\mathbf{A}$ , if it exists (the inverse of zero does not exist!), is denoted by  $\mathbf{A}^{-1}$ , and satisfies

$$\mathbf{A}^{-1}\mathbf{A} = \mathbf{A}\mathbf{A}^{-1} = \mathbf{I}.$$

```
a <- t(x) %**% x
a_inv <- solve(a)
a_inv
```

```
##              bwt    gestation
## bwt          0.007396631 -0.003159077
## gestation -0.003159077  0.001353433
```

```
a %**% a_inv
```

```
##              bwt    gestation
## bwt          1 2.842171e-14
## gestation    0 1.000000e+00
```

```
a_inv %**% a
```

```
##              bwt    gestation
## bwt          1.000000e+00 1.136868e-13
## gestation 2.842171e-14 1.000000e+00
```

*What is a numerical zero in R?*

- If the inverse exists, we say the matrix is **invertible**.

## Matrix Trace

- Definition: The trace of an  $n \times n$  matrix  $\mathbf{A}$  is the sum of its diagonal elements:

$$\text{tr}\mathbf{A} = \sum_{i=1}^n \mathbf{A}_{i,i}.$$

```
sum(diag(a))
```

```
## [1] 281574
```

- For two matrices  $\mathbf{A} \in \mathbb{R}^{n \times p}$ ,  $\mathbf{B} \in \mathbb{R}^{p \times n}$ ,

$$\text{tr} \mathbf{A} \mathbf{B} = \text{tr} \mathbf{B} \mathbf{A}.$$

```
x
```

```
##    bwt gestation
## 1 120         284
## 2 113         282
## 3 128         279
```

```
z <- t(y)
z
```

```
##           5    6    7
## bwt       108 136 138
## gestation 282 286 244
```

```
sum(diag(x %*% z))
```

```
## [1] 274808
```

```
sum(diag(z %*% x))
```

```
## [1] 274808
```

## Eigenvalues and Eigenvectors

- Given a symmetric matrix  $\mathbf{A}$ , then any scalar  $\lambda$  and vector  $\underline{v}$  such that

$$\mathbf{A} \underline{v} = \lambda \underline{v}$$

are an **eigenvalue** and **eigenvector** (together called an **eigenpair**).

```
eig <- eigen(a)
a %*% eig$vector[,1]
```

```
##           [,1]
## bwt       110594.8
## gestation 258821.1
```

```
eig$values[1] * eig$vector[,1]
```

```
## [1] 110594.8 258821.1
```

. - A  $n \times n$  symmetric matrix has  $n$  real eigenvalues, denoted  $\lambda_1, \dots, \lambda_n$ .

- Fact:  $\text{tr} \mathbf{A} = \sum_{i=1}^n \lambda_i$ .

```
eig$values
```

```
## [1] 281459.6687    114.3313
```

```
sum(eig$values)
```

```
## [1] 281574
```

```
sum(diag(a))
```

```
## [1] 281574
```

- Fact: the determinant is the product of the eigenvalues:  $\det \mathbf{A} = \prod_{i=1}^n \lambda_i$ .

## Positive Definite Matrix

- A symmetric  $n \times n$  dimensional matrix  $\mathbf{A}$  is **positive definite** if  $\underline{v}' \mathbf{A} \underline{v} > 0$  for all non-zero length  $n$  vectors  $\underline{v}$ . Compactly written  $\mathbf{A} > 0$ .

```
v <- rnorm(2)
t(v) %*% a %*% v
```

```
##           [,1]
```

```
## [1,] 12128.92
```

- A symmetric  $n \times n$  dimensional matrix  $\mathbf{A}$  is **positive semi-definite** if  $\underline{v}' \mathbf{A} \underline{v} \geq 0$  for all length  $n$  vectors  $\underline{v}$ . Compactly written  $\mathbf{A} \geq 0$ .
- Fact: a symmetric  $n \times n$  dimensional matrix is **positive definite** if and only if all of its eigenvalues are positive. (Remember, they must be real by symmetry!)
- Fact: a **positive definite** matrix is invertible.