

# Homework Assignment 1 - MGSC 695

Lakshya Agarwal

January 9, 2024

## 1 Problem 1

### 1.1 Part 1

The dimensions of each matrix are as follows:

- $Y$  is a  $n \times 1$  matrix
- $X$  is a  $n \times (k+1)$  matrix
- $\beta$  is a  $(k+1) \times 1$  matrix
- $\epsilon$  is a  $n \times 1$  matrix

Therefore, the dimensions of Equation (1) are as follows:

$$X_{n \times (k+1)} \beta_{(k+1) \times 1} + \epsilon_{n \times 1} = Y_{n \times 1}$$

It is clear that the left-hand side of the above equation results in a  $n \times 1$  matrix, which is the same as the dimensions of  $Y$ . Therefore, the dimensions of the matrices on both sides of Equation (1) match.

### 1.2 Part 2

$$\begin{aligned} Y &= X\beta + \epsilon \\ \epsilon &= Y - X\beta \\ \epsilon &= \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} - \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \dots & x_{nk} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_k \end{bmatrix} \end{aligned}$$

The  $i^{th}$  element of the  $\epsilon$  matrix is given by:

$$\epsilon_{ij} = y_i - \sum_{l=0}^{(k+1)} x_{il}\beta_l$$

Then, the sum of squared residuals is given by:

$$\sum_{i=1}^n \epsilon_{ij}^2 = \sum_{i=1}^n \left( y_i - \sum_{l=0}^{(k+1)} x_{il}\beta_l \right)^2$$

In matrix notation, this can be written as:

$$\begin{aligned} MSE &= \epsilon^T \epsilon \\ &= (Y - X\beta)^T (Y - X\beta) \end{aligned}$$

Here,  $\epsilon^T \epsilon$  is a dot product of two vectors, and therefore, it is a scalar value.

### 1.3 Part 3

To calculate the partial derivative of the sum of squared residuals with respect to  $\beta$ , we first expand the matrix multiplication in the above equation:

$$\begin{aligned}MSE &= (Y^T - \beta^T X^T)(Y - X\beta) \\&= Y^T Y - Y^T X \beta - \beta^T X^T Y + \beta^T X^T X \beta\end{aligned}$$

Since  $Y^T X \beta$  is a scalar, it is equal to its transpose. Therefore,  $Y^T X \beta = \beta^T X^T Y$ .

$$MSE = Y^T Y - 2\beta^T X^T Y + \beta^T X^T X \beta$$

Then, the partial derivative of the sum of squared residuals with respect to  $\beta$  is given by:

$$\frac{\partial MSE}{\partial \beta} = -2X^T Y + 2X^T X \beta$$

Setting the above equation to zero, we get:

$$\begin{aligned}-2X^T Y + 2X^T X \beta^* &= 0 \\X^T Y &= X^T X \beta^* \\(X^T X) \beta^* &= X^T Y\end{aligned}$$

### 1.4 Part 4

Since  $X^T X$  is a square matrix of size  $(k+1)$ , it is invertible. Therefore, we can multiply both sides of the above equation by  $(X^T X)^{-1}$  to get:

$$(X^T X)^{-1}(X^T X) \beta^* = (X^T X)^{-1} X^T Y$$

Since  $A^{-1}A = I$ , where  $I$  is the identity matrix, we get:

$$\begin{aligned}I \beta^* &= (X^T X)^{-1} X^T Y \\ \beta^* &= (X^T X)^{-1} (X^T Y)\end{aligned}$$

## 2 Problem 2

Using the `advertising.csv` dataset, the parameter estimates obtained from Equation (2) and using the `scikit-learn` library are as follows:

$$\begin{aligned}\text{Matrix algebra : } & [2.939 \ 0.046 \ 0.189 \ -0.001] \\ \text{scikit-learn : } & [2.939 \ 0.046 \ 0.189 \ -0.001]\end{aligned}$$

The parameter estimates obtained from the procedures are the same. Please run the attached `python` script to verify the results.