

1) Write down SSE for this model

$$\text{model} \rightarrow \hat{y}_i = b_0 + b_1 z_{i1} + b_2 z_{i2}$$

$$\text{residual } (e_i) = (y_i - \hat{y}_i)^2$$

$$\text{SSE } (b_0, b_1, b_2) = \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2})^2$$

2) take partial derivative w.r.t respect to b_0, b_1, b_2

$$e_i = y_i - b_0 - b_1 z_{i1} - b_2 z_{i2}$$

$$\therefore \text{SSE} = \sum_i e_i^2$$

derivative rule

$$\hookrightarrow \frac{d}{dx} (e_i^2) = 2e_i \cdot \frac{de_i}{dx}$$

a. derivative with respect to b_0

$$\begin{aligned} \frac{\partial \text{SSE}}{\partial b_0} &= \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2})(-1) \\ &= -2 \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2}) = -2 \sum_{i=1}^N e_i \end{aligned}$$

b. derivative with respect to b_1

$$\begin{aligned} \frac{\partial \text{SSE}}{\partial b_1} &= \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2})(-z_{i1}) \\ &= -2 \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2}) z_{i1} = -2 \sum_{i=1}^N e_i z_{i1} \end{aligned}$$

c. derivative with respect to b_2

$$\begin{aligned} \frac{\partial \text{SSE}}{\partial b_2} &= \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2})(-z_{i2}) \\ &= -2 \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2}) z_{i2} = -2 \sum_{i=1}^N e_i z_{i2} \end{aligned}$$

3) Verify that avg error = 0 and $e \cdot z = 0$ @ optimum

a avg error is zero

at optimum b_0, b_1, b_2

$$\frac{\partial \text{SSE}}{\partial b_0} = 0 = -2 \sum_i e_i = 0 \Rightarrow \sum_i e_i = 0 \Rightarrow \frac{1}{N} \sum_i e_i = \bar{e} = 0$$

b $e \cdot z = 0$

$$\frac{\partial \text{SSE}}{\partial b_0} = 0 = \sum_i e_i z_{i1} = 0 \quad \& \quad \sum_i e_i z_{i2} = 0$$

$$e \cdot z_j = \sum_i e_i z_{ij} \Rightarrow e \cdot z_1 = 0 \quad \& \quad e \cdot z_2 = 0$$

4) Show that $b^* = y$.

$$\frac{\partial \text{SSE}}{\partial b_0} = -2 \sum_{i=1}^N e_i \rightarrow \text{min} \rightarrow \sum_{i=1}^N e_i = 0$$

$$0 = \sum_{i=1}^N (y_i - b_0 - b_1 z_{i1} - b_2 z_{i2}) = \sum_{i=1}^N y_i - N b_0 - b_1 \sum_{i=1}^N z_{i1} - b_2 \sum_{i=1}^N z_{i2}$$

$$\sum_i z_{i1} = 0 \quad \& \quad \sum_i z_{i2} = 0$$

$$0 = \sum_{i=1}^N y_i = N b_0 \Rightarrow b_0^* = \bar{y}$$

$$e_i = (y_i - \bar{y}) - b_1 z_{i1} - b_2 z_{i2}$$

$$\sum_{i=1}^N e_i z_{i1} = 0 \quad \& \quad \sum_{i=1}^N e_i z_{i2} = 0$$

Substitute e_i
Equations:

$$\sum_{i=1}^N z_{i1} (y_i - \bar{y}) = b_1 \sum_{i=1}^N z_{i1}^2 + b_2 \sum_{i=1}^N z_{i1} z_{i2}$$

$$\sum_{i=1}^N z_{i2} (y_i - \bar{y}) = b_1 \sum_{i=1}^N z_{i1} z_{i2} + b_2 \sum_{i=1}^N z_{i2}^2$$

(b_0 is removed)

5) write eq in form "Ab = c" \Rightarrow normal functions

$$\begin{matrix} A & B \\ \begin{bmatrix} \sum z_{ii}^2 & \sum z_{i1}z_{i2} \\ \sum z_{i1}z_{i2} & \sum z_{ii}^2 \end{bmatrix} & \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \end{matrix} = \begin{bmatrix} \sum z_{ii}(y_i - \bar{y}) \\ \sum z_{i2}(y_i - \bar{y}) \end{bmatrix}$$

(e) Divide by N & substitute $Z_{ij} = x_{ij} - m_j$

$$\frac{1}{N} \left(\begin{bmatrix} \sum z_{ii}^2 & \sum z_{i1}z_{i2} \\ \sum z_{i1}z_{i2} & \sum z_{ii}^2 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \right) = \begin{bmatrix} \sum z_{ii}(y_i - \bar{y}) \\ \sum z_{i2}(y_i - \bar{y}) \end{bmatrix}$$

$$\begin{matrix} A & B & C \\ \begin{bmatrix} \frac{1}{N} \sum (x_{ii} - m_i)^2 & \frac{1}{N} \sum (x_{i1} - m_1)(x_{i2} - m_2) \\ \frac{1}{N} \sum (x_{i1} - m_1)(x_{i2} - m_2) & \frac{1}{N} \sum (x_{i2} - m_2)^2 \end{bmatrix} & \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} & = \begin{bmatrix} \frac{1}{N} \sum (x_{ii} - m_i)(y_i - \bar{y}) \\ \frac{1}{N} \sum (x_{i2} - m_2)(y_i - \bar{y}) \end{bmatrix} \end{matrix}$$

A \rightarrow covariance matrix of predictors

\hookrightarrow its avg products of x deviations

tells us how spread out & correlated predictions are

C \rightarrow covariance between predictor & response

\hookrightarrow avg product of deviations btwn x_i & y

dividing by N gives averages

means that coeff. proportional to how much x_i covaries w/ y
and coeff. $\Rightarrow b = A^{-1}C$