

Q1:- The model is given by

$$y_i = \beta x_i + \epsilon_i x_i$$

we can write $\epsilon_i = \frac{y_i - \beta x_i}{x_i}$

The sum of squared errors is given by

$$SSE = \sum_{i=1}^n \epsilon_i^2 = \sum_{i=1}^n \left(\frac{y_i - \beta x_i}{x_i} \right)^2$$

Now, derivative of SSE with respect to β is taken and set to zero.

$$\frac{d SSE}{d \beta} = 0$$

$$\Rightarrow \sum_{i=1}^n \left(\frac{y_i}{x_i} - \beta \right) = 0$$

$$\Rightarrow \sum_{i=1}^n \frac{y_i}{x_i} - n\beta = 0$$

$$\Rightarrow \beta = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{x_i}$$

(a) Least squares estimator: $\beta_{LS} = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{x_i}$

(b) The pdf of ϵ_i is $f(u) = \frac{1}{2\lambda} \exp\left(-\frac{|u|}{\lambda}\right)$, $-\infty < u < \infty$

Now, substituting $u = \frac{y_i - \beta x_i}{x_i}$, the joint likelihood function is given by.

$$L(\beta, \lambda) = \left(\frac{1}{2\lambda} \right)^n \exp\left(- \sum_{i=1}^n \frac{|y_i - \beta x_i|}{\lambda} \right).$$

The log-likelihood function is given by.

$$\ell(\beta, \lambda) = -n \log(2\lambda) - \frac{1}{\lambda} \sum_{i=1}^n \left| \frac{y_i - \beta x_i}{x_i} \right|$$

To find the maximum likelihood estimator of β , the log-likelihood

function is maximized with respect to β .

This is equivalent to minimizing the term $\sum_{i=1}^n \left| \frac{y_i - \beta x_i}{x_i} \right|$.

Let, $t_i = \frac{y_i}{x_i}, i=1, 2, \dots, n$. then ~~we~~ we ~~maximize~~ minimize

$$\sum_{i=1}^n |t_i - \beta|.$$

~~we know that~~ Now the value of β that minimizes the sum of absolute deviations is the sample median of t_i values.

\therefore Maximum likelihood estimator: $\hat{\beta}_{ML} = \text{median}(t_i)_{i=1, \dots, n}$
 $= \text{median}\left(\frac{y_1}{x_1}, \dots, \frac{y_n}{x_n}\right).$