Linear Regression

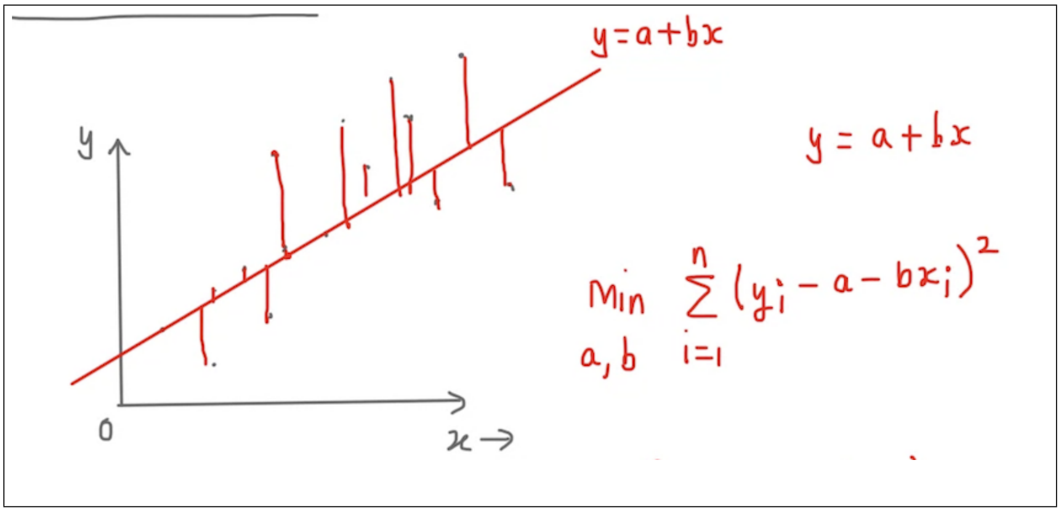

Figure 1: The Best fit line

$\min_{a,b} \sum_{i=1}^{n} (y_i - a - bx_i)^2$

Differentiating w.r.t a we get,

$-2 \sum_{i=1}^{n} (y_i - a - bx_i) = 0$

Differentiating w.r.t b we get,

$-2 \sum_{i=1}^{n} (y_i - a - bx_i)x_i = 0$

Rewriting the above equations;

$$na + b\sum x_i = \sum y_i$$
$$a\sum x_i + b\sum x_i^2 = \sum x_i y_i$$

or,

$$\frac{\sum x_i}{n} \times [na + b\sum x_i = \sum y_i] \qquad \ldots(1)$$
$$a\sum x_i + b\sum x_i^2 = \sum x_i y_i \qquad \ldots(2)$$

From 1 we get;

$$a\sum x_i + \frac{b\left(\sum x_i\right)^2}{n} = \frac{\sum x_i \sum y_i}{n} \qquad \ldots(3)$$

Subtracting 3 from 2 we get;

$$b\left(\sum x_i^2 - \frac{(\sum x_i)^2}{n}\right) = \sum x_i y_i - \frac{\sum x_i \sum y_i}{n}$$

$$\implies \text{Slope of the best fit line, } b = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x_i^2 - \left(\sum x_i\right)^2}$$

So,

$$\begin{aligned} b &= \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x_i^2 - \left(\sum x_i\right)^2} \\ &= \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} \\ &= \frac{\sum (X_i - \bar{X})Y_i}{\sum (X_i - \bar{X})^2}, \qquad \text{where } \bar{X} = \frac{\sum x_i}{n} \text{ and } \bar{Y} = \frac{\sum y_i}{n} \end{aligned}$$

and since, $a + b\bar{X} = \bar{Y}$ we get,

$$a = \bar{Y} - b\bar{X}$$

Linear Regression Model

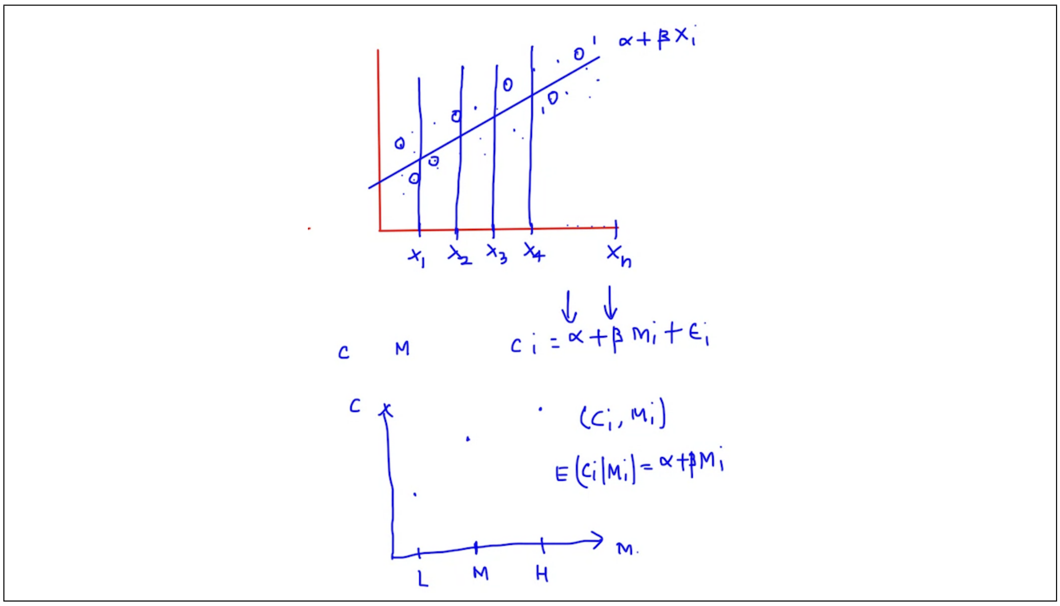

Figure 2: Linear Regression Model

There are some unknown parameters that we want to estimate just like in estimation.

$E(Y_i|X_i) = \alpha + \beta X_i$

Now we have the following assumptions about our model;

- $Y_i = \alpha + \beta X_i + \epsilon_i \qquad \dots (A_1)$

  where ϵ_i is a random variable.

  So we are trying to estimate α and β for which we will draw some points from around the line(population) $(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)$ and then using those points we will try to estimate the line.

- Now if we fix X_i's and then for each X_i we draw a value of Y_i then $E(\epsilon_i) = 0 \quad \forall i \qquad \dots (A_2)$

  and if we do not fix X_i's then $E(\epsilon_i|X_i) = 0 \quad \forall X_i$

- $E(\epsilon_i^2) = \sigma^2 \quad \forall i. \qquad \dots (A_3)$
- $E(\epsilon_i \epsilon_j) = 0 \quad \forall i \neq j \qquad \dots (A_4)$

or we can have a much stronger assumption rather than all the last three above, i.e.,

ϵ_i's $\overset{iid}{\sim} \mathcal{N}(0, \sigma^2). \qquad \dots (A_5)$

So now,

$$\hat{\beta}_{\text{OLS}} = \frac{\sum_{i=1}^n (X_i - \bar{X}) Y_i}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

and

$$\hat{\alpha}_{\text{OLS}} = \bar{Y} - \hat{\beta}_{\text{OLS}} \bar{X}$$

Now under assumptions A_1, A_2, A_3, A_4 and specifically A_1, A_2;

$$\begin{aligned}
E\left(\hat{\beta}_{OLS}\right) &= E\left(\frac{\sum \left(X_i - \bar{X}\right)\left(\alpha + \beta X_i + \epsilon_i\right)}{\sum \left(X_i - \bar{X}\right)^2}\right) \\
&= E\left(\frac{\alpha \sum \left(X_i - \bar{X}\right)}{\sum \left(X_i - \bar{X}\right)^2} + \frac{\beta \sum \left(X_i - \bar{X}\right) X_i}{\sum \left(X_i - \bar{X}\right)^2} + \frac{\sum \left(X_i - \bar{X}\right) \epsilon_i}{\sum \left(X_i - \bar{X}\right)^2}\right) \\
&= E\left(\beta + \frac{\sum \left(X_i - \bar{X}\right) \epsilon_i}{\sum \left(X_i - \bar{X}\right)^2}\right) = \beta \qquad \text{since } \frac{\sum (X_i - \bar{X}) X_i}{\sum (X_i - \bar{X})^2} = 1 \text{ and } \frac{\alpha \sum (X_i - \bar{X})}{\sum (X_i - \bar{X})^2} = 0
\end{aligned}$$

Now under assumptions A_1, A_2, A_3, A_4;

$$
\begin{aligned}
Var(\hat{\beta}_{\text{OLS}}) &= E(\hat{\beta}_{\text{OLS}} - \beta)^2 \\
&= E\left(\left(\frac{\sum(X_i - \bar{X})\epsilon_i}{\sum(X_i - \bar{X})^2}\right)^2\right) \\
&= \frac{1}{\left(\sum(X_i - \bar{X})^2\right)^2} E\left(\left(\sum(X_i - \bar{X})\epsilon_i\right)^2\right) \\
&= \frac{1}{\left(\sum(X_i - \bar{X})^2\right)^2} E\left(\sum_{i=1}^{n}(X_i - \bar{X})^2 + 2\sum_{i<j}(X_i - \bar{X})(X_j - \bar{X})\epsilon_i\epsilon_j\right) \\
&= \frac{\sum(X_i - \bar{X})^2}{\left(\sum\left(X_i - \bar{X}\right)^2\right)^2} = \frac{\sigma^2}{\sum(X_i - \bar{X})^2}
\end{aligned}
$$

Now if we assume assumption A_5 we can even find the distribution of $\hat{\beta}_{\text{OLS}}$;

$$
\hat{\beta}_{\text{OLS}} = \beta + \frac{\sum(X_i - \bar{X})\epsilon_i}{\sum(X_i - \bar{X})^2} \qquad \text{is } \mathcal{N}\left(\beta, \frac{\sigma^2}{\sum(X_i - \bar{X})^2}\right)
$$

Multiple Linear Regression

Suppose we have n observations; and Assume that x is full rank;

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n\times 1} \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & & \\ \vdots & & \\ x_{m1} & \cdots & x_{nm} \end{bmatrix}_{n\times m} \begin{bmatrix} \beta_1 \\ \vdots \\ \vdots \\ \beta_m \end{bmatrix}_1 + \epsilon_i$$

$$\begin{aligned}
&(y - x\beta)^T_{1\times n} (y - x\beta)_{n\times 1} \\
&= (y^T - \beta^T x^T)(y - x\beta) \\
&= y^T y - y^T x\beta - \beta^T x^T y + \beta^T x^T x\beta \\
&= y^T y - 2\beta^T x^T y + \beta^T x^T x\beta \\
&\text{differentiating w.r.t } \beta^T \text{ we get,} \\
&= -2x^T y + 2x^T x\beta = 0 \\
&= \hat{\beta}_{\text{OLS}} = \left(x^T x\right)^{-1} (x^T y) \\
&E(\hat{\beta}_{\text{OLS}}) = E(\beta + (x^T x)^{-1} x^T \epsilon) = \beta
\end{aligned}$$

and

$$\begin{aligned}
&Var(\hat{\beta}_{\text{OLS}}) = E\left(\hat{\beta}_{\text{OLS}} - \beta\right)^2 \\
&= E\left(\left(x^\top x\right)^{-1} x^\top \epsilon\epsilon^\top x \left(x^\top x\right)^{-1}\right) \\
&= \sigma^2 E\left(\left(x^\top x\right)^{-1} x^\top x \left(x^\top x\right)^{-1}\right) \qquad \text{since} \quad E\left(\epsilon_{n\times 1} - \epsilon^\top_{1\times n}\right) = \sigma^2 I_{n\times n} \\
&= \sigma^2 \left(x^\top x\right)^{-1}
\end{aligned}$$