

Ans: $\theta = (X^T X)^{-1} X^T Y$

let a be a non-zero vector.

~~$$a^T (X^T X) a$$~~

$$\Rightarrow a^T (X^T X) a$$

$$\Rightarrow (Xa)^T (Xa)$$

$$\Rightarrow \|Xa\|^2 \geq 0$$

$X^T X$ is semi-positive definite.

It is because:

$b^T M b \geq 0$; \forall then M is semi-positive definite.

Now let $X_{m \times n}$.

Now $Xa = 0$; only when X is linearly independent ~~when~~ a is non-zero vector.

~~Now as given X is linearly independent,~~

so, $\|Xa\| \geq 0$, when columns of X is independent.

Claim: Every positive definite ~~matrix~~ matrix is invertible.

From the above claim, $X^T X$ is invertible as it is positive definite.

~~Thus, proving that columns of X~~

Thus, $X^T X$ is invertible when columns of X are linearly independent.

Ans:

$$\hat{y} = X\hat{\theta}$$

$$y = X\theta + \varepsilon$$

$$y - \hat{y} = \hat{\varepsilon}$$

From question:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N-M}$$

$$= \frac{E[\hat{\varepsilon}^T \hat{\varepsilon}]}{N-M}$$

$$\hat{\varepsilon} = y - \hat{y}$$

$$= y - X\hat{\theta}$$

$$= y - X(X^T X)^{-1} X^T y ; \theta = (X^T X)^{-1} X^T y$$

$$= [I - X(X^T X)^{-1} X^T] y$$

$$\text{let } I - X(X^T X)^{-1} X^T = P$$

$$\hat{\varepsilon} = P y$$

$$= [I - X(X^T X)^{-1} X^T] (X\theta + \varepsilon)$$

$$= X\theta + \varepsilon - X(X^T X)^{-1} X^T X\theta +$$

$$X(X^T X)^{-1} X^T \varepsilon$$

$$= [I - X(X^T X)^{-1} X^T] \varepsilon$$

$$\hat{\varepsilon} = P \varepsilon$$

$$E[\hat{\varepsilon}^T \hat{\varepsilon}] = (P \varepsilon)^T (P \varepsilon)$$

$$= \varepsilon^T P^T P \varepsilon$$

$$P = [I - X(X^T X)^{-1} X^T] [I - X(X^T X)^{-1} X^T]$$

$$= P$$

~~$$E[\hat{\epsilon}^T \hat{\epsilon}] = \epsilon^T P \epsilon$$~~

$$E[\hat{\epsilon}^T \hat{\epsilon}] = E[\epsilon^T P \epsilon]$$

$$= E[\text{tr}(\epsilon^T P \epsilon)] \quad (1)$$

~~$$\text{tr}(\epsilon^T P \epsilon) = \epsilon^T P \epsilon = \text{tr}(\epsilon \epsilon^T P)$$~~

P is semi positive definite matrix:

$$\text{tr}(X^T A X) = X^T A X = \text{tr}(A X X^T)$$

from (1):

$$E[\hat{\epsilon}^T \hat{\epsilon}] = E[\epsilon^T P \epsilon] \quad , \text{ as } P \text{ is semi positive definite}$$

$$= E[\text{tr}(\epsilon^T M \epsilon)]$$

$$= E[\text{tr}(M \epsilon \epsilon^T)]$$

$$= [\text{tr}(M)] \cdot E[\epsilon \epsilon^T]$$

$$\text{tr}(M) = \text{tr}[I_{N \times N}] - \text{tr}[X(X^T X)^{-1} X^T]$$

$$\text{tr}[X(X^T X)^{-1} X^T] = \text{tr}[(X^T X)^{-1} X X^T]$$

$$= \text{tr}(I_{M \times M})$$

$$= M$$

$$\text{tr}(M) = N - M.$$

$$E[\hat{\varepsilon}^T \hat{\varepsilon}] = \cancel{(N-M)} (N-M) E[\varepsilon \varepsilon^T]$$

$$\cancel{E[\hat{\varepsilon}^T \hat{\varepsilon}]} E[\varepsilon \varepsilon^T] = \sigma^2 I$$

$$\cancel{E[\hat{\varepsilon}^T \hat{\varepsilon}]} E[\hat{\varepsilon}^2] = \sigma^2$$

Hence proved.

Ans 3: So, the 5 points from X:

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 3 \\ 1 & 4 \end{bmatrix}$$

$$Y = \begin{bmatrix} 2 \\ 1 \\ 2 \\ 3 \\ 2 \end{bmatrix}$$

So, the best fit is when

$$J = [2 - (\theta_1 + \theta_2)]^2 + [1 - (\theta_1 + 2\theta_2)]^2 + [2 - (\theta_1 + 3\theta_2)]^2 + [3 - (\theta_1 + 3\theta_2)]^2 + [2 - (\theta_1 + 4\theta_2)]^2$$

$$\begin{aligned} &= (4 + 1 + 4 + 9 + 4) - 2[2(\theta_1 + \theta_2)] \\ &\quad - 2[2(\theta_1 + 2\theta_2)] - 2[2(\theta_1 + 3\theta_2)] \\ &\quad - 2[3(\theta_1 + 3\theta_2)] - 2[2(\theta_1 + 4\theta_2)] \\ &\quad + (\theta_1 + \theta_2)^2 + (\theta_1 + 2\theta_2)^2 \\ &\quad + (\theta_1 + 3\theta_2)^2 + (\theta_1 + 3\theta_2)^2 \\ &\quad + (\theta_1 + 4\theta_2)^2 \end{aligned}$$

$$\frac{dJ}{d\theta} = 0$$

We will choose that θ that gives us best fit.

$$\# \frac{dJ}{dA_0} = 0$$

$$\begin{aligned} & 22 - 4[A_1 + A_2] - 2[A_1 + 2A_2] - 4[A_1 + 3A_2] \\ & - 6[A_1 + 4A_2] - 4[A_1 + 5A_2] + (A_1^2 + 2A_1A_2 + A_2^2) \\ & + (A_1^2 + 4A_1A_2 + 4A_2^2) + 2(A_1^2 + 6A_1A_2 + 9A_2^2) \\ & + (A_1^2 + 8A_1A_2 + 16A_2^2) = 0 \end{aligned}$$

$$\# \frac{dJ}{dA_1} = 0$$

$$\begin{aligned} & -4 - 2 - 4 - 6 - 4 + 2A_1 + 2A_2 \\ & + 2A_1 + 4A_2 + 4A_1 + 12A_2 + 2A_1 + 8A_2 = 0 \end{aligned}$$

$$\Rightarrow -20 + 10A_1 + 26A_2 = 0$$

$$\Rightarrow 5A_1 + 13A_2 = 10$$

$$\# \frac{dJ}{dA_2} = 0$$

$$\Rightarrow -4 - 4 - 12 - 18 - 6 + 2A_1 + 2A_2$$

$$+ 4A_1 + 8A_2 + 12A_1 + 36A_2 +$$

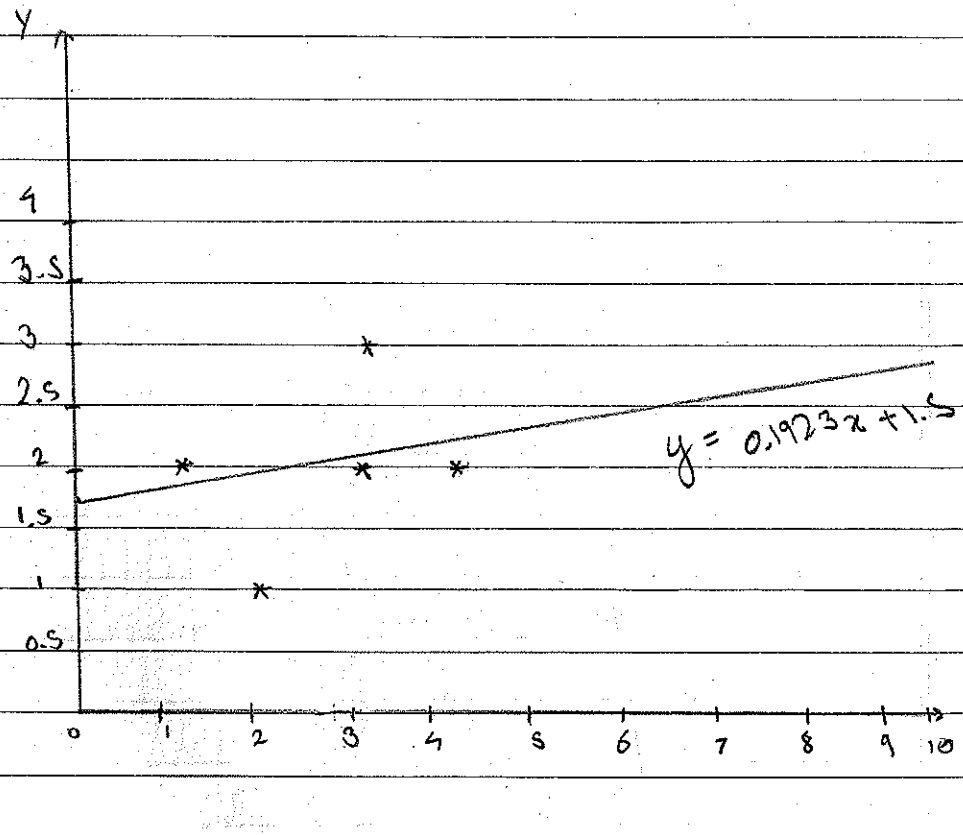
$$8A_1 + 32A_2 = 0$$

$$\Rightarrow -54 + 26A_1 + 78A_2 = 0$$

$$\Rightarrow 13A_1 + 49A_2 = 27$$

$$\theta_0, \theta_1 = 1.5$$

$$\theta_2 = 0.1923$$



Plot with $\theta_0 = (X^T X)^{-1} X^T Y$ also gives same θ .
 Plot attached in report (drawn from ~~matlab~~ matlab).