

$Y = X\beta + \varepsilon$ is our model β is the unknown we want to estimate

$\hat{\beta}_{OLS}$ is the estimator

the locus is there now

$\hookrightarrow (X'X)^{-1}X'Y$ solution to the problem of the least squares

$(X'X)\beta = X'Y$ is a NORMAL EQUATION
 $k \times k \quad (k \times 1) \quad (k \times 1)$

$\hat{\beta} = (X'X)^{-1}X'Y$ \rightarrow these are all variables that i already know

forget about the error term for now

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & \dots & x_{1k} \\ \vdots & \vdots & & \vdots \\ 1 & x_{N1} & \dots & x_{Nk} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}$$

\rightarrow it is a system of equations, one for each "individual"

N equations, k variables unknown, and $k \ll N$

into vector β

it is a system $Ax = b$
 A has to be square and has to have full rank, hence X isn't square
 there is no solution, for this reason there is an error term

$X'X\beta = X'Y$
 $(N \times k)(k \times k) \quad (N \times 1)$
 we multiply by X' to make the matrix square

\downarrow
 and we get the same equation of before

the OLS estimator is what makes the closest possible the left hand side and the right hand side of
 $Y = X\beta$ (pseudo-solution)

$$y = \beta_0 + \beta_1 x + \epsilon$$

UNVARIATE D.V. IN THIS CASE

we follow expectation

$$\bullet \beta_0 = E(y) - \beta_1 E(x)$$

$$\bullet \beta_1 = \frac{\text{Cov}(x, y)}{\text{Var}(x)}$$

these are the parameters but they have one interpretation

these parameters are unknown

$$i = \begin{bmatrix} 1 \\ \vdots \\ i \end{bmatrix}_{N \times 1} \quad x = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}_{N \times 1}$$

$$X = \begin{bmatrix} i & x \end{bmatrix}_{(N \times 2)}$$

↓
iota, vector of ones
(N x 1)

little x

$$\text{we have to compute } X'X = \begin{bmatrix} i' & x' \\ x' & \sum x_i^2 \end{bmatrix}_{(2 \times N)(N \times 2)} \begin{bmatrix} 1 \\ x \end{bmatrix}$$

the output is going to be a 2x2

$$\begin{bmatrix} i'i = N & i'x = \sum_{i=1}^N x_i \\ \sum_{i=1}^N x_i & \sum_{i=1}^N x_i^2 \end{bmatrix}$$

the matrix is symmetric

$$= \begin{bmatrix} N & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix}$$

$$\begin{matrix} & \text{2xN} & \text{N x 1} \\ \text{2xN} & X'Y & \end{matrix} \rightarrow \text{2x1 is the dimension}$$

$$X'Y = \begin{bmatrix} i' & x' \end{bmatrix} \begin{bmatrix} y \\ \end{bmatrix} = \begin{bmatrix} i'y = \sum_{i=1}^N y_i \\ \sum_{i=1}^N x_i y_i \end{bmatrix}$$

$$\text{NORMAL EQUATION } \frac{(X'X)}{N} \beta = \frac{X'Y}{N} \quad \text{divide both members by N}$$

$$\frac{X'X}{N} = \begin{bmatrix} 1 & \bar{x} \\ \bar{x} & (\bar{x}^2) \end{bmatrix}$$

↘ variance for the second moment

$$\frac{X'Y}{N} = \begin{bmatrix} \bar{y} \\ \bar{xy} \end{bmatrix} \quad \bar{xy} = \frac{1}{N} \sum_{i=1}^N x_i y_i$$

$$\hat{\beta} = \left(\frac{X'X}{N} \right)^{-1} \left(\frac{X'Y}{N} \right)$$

$$\left(\frac{X'X}{N} \right)^{-1} = \frac{1}{(\bar{x}^2) - (\bar{x})^2} \begin{pmatrix} (\bar{x}^2) & -\bar{x} \\ -\bar{x} & 1 \end{pmatrix}$$

because β is a column vector $\begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}$

↓
sample variance
VAR(x)

and it is the determinant of the matrix

↘ formula for the inverse of a 2x2 matrix

$$\hat{\beta}_1 = \frac{1}{\text{var}(x)} \begin{pmatrix} -\bar{x} & 1 \end{pmatrix} \begin{pmatrix} \bar{y} \\ \bar{xy} \end{pmatrix} \rightarrow \text{because this equation is for } \beta_0$$

$$\hat{\beta}_1 = \frac{-\bar{x}\bar{y} + \bar{xy}}{\text{var}(x)} \quad \text{SAMPLE COVARIANCE} = \hat{COV}(x, y)$$

$$\hat{\beta}_1 = \frac{\hat{COV}(x, y)}{\text{var}(x)}$$

what about $\hat{\beta}_0 \rightarrow \begin{pmatrix} 1 & \bar{x} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} = \bar{y}$ ← this is the normal equation

$\hat{\beta}_0 + \bar{x} \hat{\beta}_1 = \bar{y}$ ← the second equation has been already solved

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

MATLAB PART

sqrrt (Figure 2) is to give the equation the same variance that we want it to take

select the line and select F9 to run a single line

GEOMETRY OF OLS

we look at some algebraic properties of the OLS

$$\hat{\beta} = (X'X)^{-1}X'y$$

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

are the fitted values, that lie on the fitted line

$\hat{e} \rightarrow$ residuals

are the values predicted by the model

the error term is a stochastic variable that cannot be observed

the error is different from ϵ , we do not know the true beta, we only can know the residuals

$$\hat{e} = y - X\hat{\beta}$$

$$\hat{y} = X(X'X)^{-1}X'y =$$

$(N \times K) \quad (K \times K) \quad (K \times N)$

$N \times N$ is the result we call it P_X

$$P_X y$$

projection matrix

other important matrix is Residual maker matrix

$$\hat{e} = y - \hat{y} = y - P_X y = (I - P_X)y = M_X y$$

M_X is the residual maker matrix

$$E \left[\underset{(L \times 1)}{\tilde{x}_i} (y_i - \tilde{x}_i' \beta) \right] = \underset{(L \times 1)}{0}$$

$$\beta$$

$$J(\beta) = \underset{1 \times L}{\tilde{\mu}(\beta)'} \underset{L \times L}{W} \underset{L \times 1}{\tilde{\mu}(\beta)}$$

$$\frac{\partial J(\beta)}{\partial \beta} = 2 \frac{\partial \tilde{\mu}(\beta)'}{\partial \beta} W \tilde{\mu}(\beta)$$

$$2 \underset{(L \times 1)}{(L \times L)} L \times L L \times 1$$

$$\beta$$