

WEEK 7 (23 FEB 2012)

35%

READ: ① GUJARATI CH 1-4 + CH.5 (S.1-5.8)

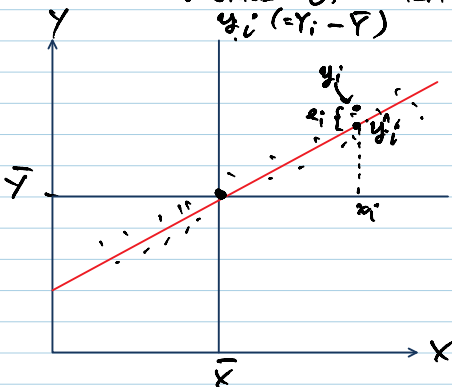
② TOPICS IN LECTURE NOTE

3 MAIN QUESTIONS [. PROOF
INTERPRETATION

DEY: • EXERCISES ON EACH CHAPTER
• (WHY?)

THE COEFFICIENT OF DETERMINATION (R^2)

= DEGREE OF EXPLANATORY POWER.



FROM $y_i = \hat{y}_i + r_i$
 $y_i^2 = \hat{y}_i^2 + r_i^2 + 2\hat{y}_i r_i$
 $\sum y_i^2 = \sum \hat{y}_i^2 + \sum r_i^2 + 2\sum \hat{y}_i r_i$
 (The last two terms are circled in red, with a note 'SEPARATE')

AND $\hat{y}_i = \hat{b} x_i$
 $\sum \hat{y}_i r_i = \sum \hat{b} x_i r_i = \hat{b} \sum x_i r_i = 0$

$\sum y_i^2 = \sum \hat{y}_i^2 + \sum r_i^2$

$\sum (y_i - \bar{y})^2$: TOTAL SUM OF SQUARES (TSS)

$\sum \hat{y}_i^2$: EXPLAINED SUM OF SQUARES (ESS)

$\sum r_i^2$: RESIDUAL SUM OF SQUARE (RSS)

$TSS = ESS + RSS$

DEFINE $R^2 = \frac{ESS}{TSS} = \frac{\text{EXPLAINED SUM OF SQUARE}}{\text{TOTAL SUM OF SQUARE}}$

(TO SEE HOW MUCH VARIATION IN Y COULD BE EXPLAINED BY X)

FROM $TSS = ESS + RSS$,

DIVIDE THROUGH OUT W/ TSS :

$\frac{TSS}{TSS} = \frac{ESS}{TSS} + \frac{RSS}{TSS}$
 $1 = R^2 + \frac{\sum r_i^2}{\sum y_i^2}$

$$1 = R^2 + \frac{RSS}{TSS} = R^2 + \frac{\sum e_i^2}{\sum y_i^2}$$

SO $R^2 = \frac{\sum \hat{y}_i^2}{\sum y_i^2} = 1 - \frac{\sum e_i^2}{\sum y_i^2}$

• $R^2 = 1$ (MAX. VALUE) WHEN $\sum e_i^2 = 0$ (each error = 0)

SO WE CALL "PERFECT FIT"

• $R^2 = 0$ (MIN. VALUE) WHEN ERROR TERM EQUALS TO VARIATION AROUND y_i , i.e.,

IMPLIES THAT THE REGRESSION LINE CANNOT EXPLAIN ANY VARIATION IN Y . $\sum e_i^2 = \sum y_i^2$

R^2 : MEASURES THE GOODNESS OF FIT.

FOR EXAMPLE : $R^2 = 0.8 \Rightarrow 80\%$ VARIATION IN Y CAN BE EXPLAINED BY THE REGRESSION LINE.

THE GREATER R^2 IS, THE HIGHER DEGREE OF EXPLANATORY POWER OF THE REGRESSION LINE.

REMEMBER THAT WE EARLIER DISCUSSED ABOUT r : CORRELATION COEFFICIENT

WHICH MEASURES THE ASSOCIATION BETWEEN ANY TWO VARIABLES.

ADJUSTED- R^2

FROM $b^1 = \frac{\sum x_i y_i}{\sum x_i^2} \times \frac{\sqrt{\frac{\sum y_i^2}{n}}}{\sqrt{\frac{\sum x_i^2}{n}}}$

$= \sqrt{\sum x_i^2} \cdot \sqrt{\sum y_i^2}$

$$= \frac{\sum x_i y_i}{\sqrt{\sum x_i^2} \sqrt{\sum y_i^2}} \cdot \frac{\sqrt{\frac{\sum y_i^2}{n}}}{\sqrt{\frac{\sum x_i^2}{n}}}$$

$$= \frac{\sum x_i y_i}{\sqrt{\sum x_i^2} \sqrt{\sum y_i^2}} \cdot \frac{S_y}{S_x} = r \cdot \frac{S_y}{S_x}$$

$$\therefore r = b^1 \frac{S_x}{S_y} \Rightarrow r^2 = b^2 \cdot \frac{S_x^2}{S_y^2}$$

$$= b^2 \cdot \frac{\sum x_i^2}{\sum y_i^2}$$

$$= \frac{\sum b^2 x_i^2}{\sum y_i^2} = \frac{\sum (b^1 x_i)^2}{\sum y_i^2} = \frac{\sum \hat{y}_i^2}{\sum y_i^2} = R^2$$

SO

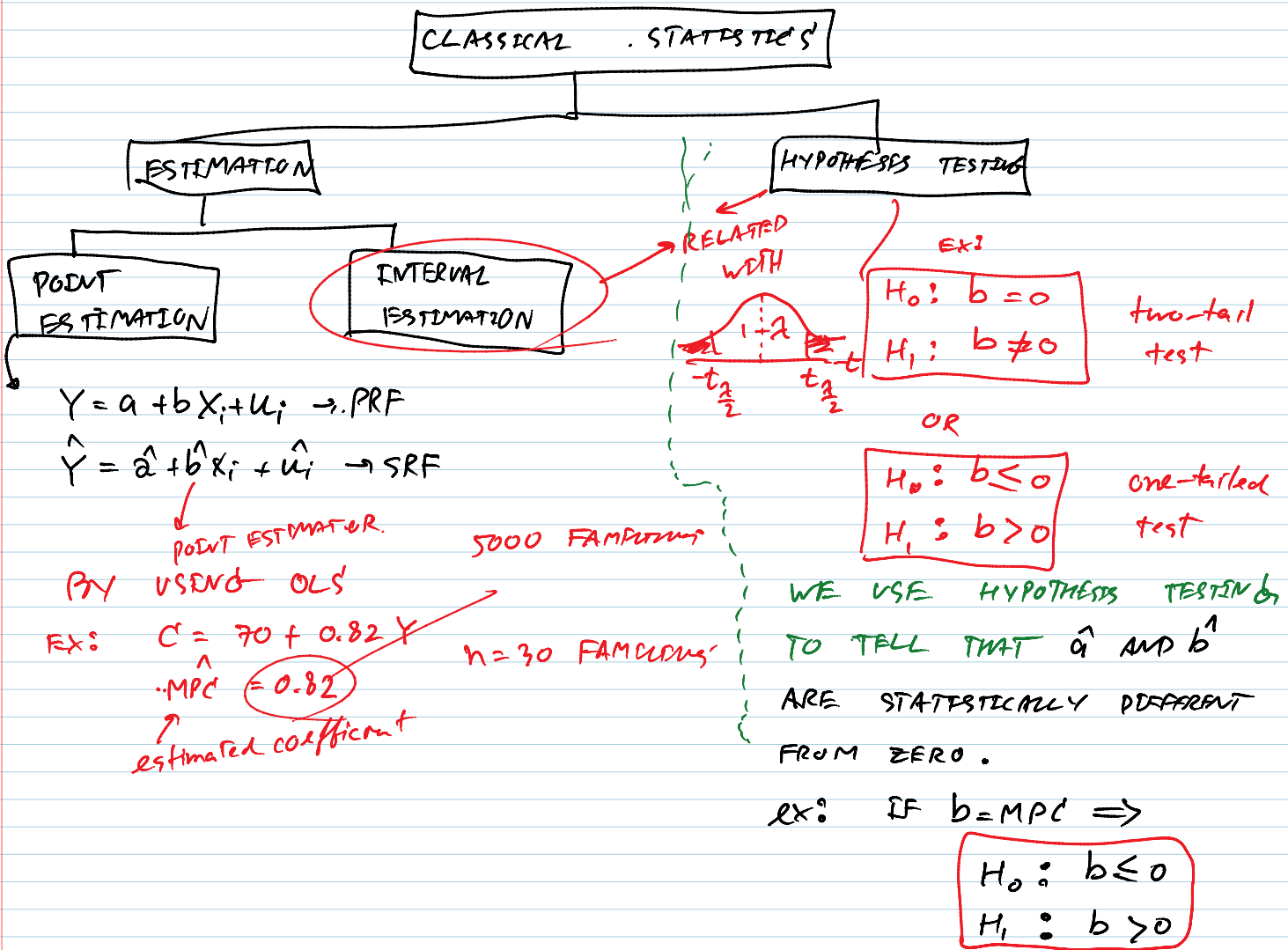
$r^2 = R^2$

TRUE ONLY IN SIMPLE

So, $r^2 = R^2$ $\sum y_i^2$ $\sum y_i^2$ $\sum y_i^2$
 TRUE ONLY IN SIMPLE

INTERVAL ESTIMATION AND HYPOTHESES TESTING [CHAPTER 5]
 REGRESSION. (TWO-VARIABLE REGRESSION)

BIG PICTURE ?



FROM MODEL: $Y_i = a + bX_i + U_i$

YOU GET $\hat{a} = \bar{Y} - \hat{b}\bar{X}$

$\hat{b} = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} = \frac{\sum_{i=1}^n k y_i}{\sum_{i=1}^n k}$ AND

IF WE ASSUME THAT $U_i \sim N(0, \sigma_u^2)$

" THIS IS NORMALITY ASSUMPTION

OF U_i (READ CH. 4)

$$U_i \sim N(0, \sigma_u^2) \Rightarrow \text{MEAN: } E(U_i) = 0$$

$$\text{VARIANCE: } E(U_i - E(U_i))^2 = E(U_i)^2 \\ = \sigma_u^2$$

$$\text{COVARIANCE: } E(U_i - E(U_i))(U_j - E(U_j)) \\ = E(U_i U_j) = 0$$

QUESTION : WHY DO YOU NEED NORMALITY ASSUMPTION OF U_i ?

(EXAMPLE QUESTION YOU MIGHT SEE IN THE MIDTERM)

So, U_i IS iid $N(0, 1)$ WHERE

iid = independently and identically distributed