

①

QDA 2023.03.16

$y_t$

↑  
OBSERVED

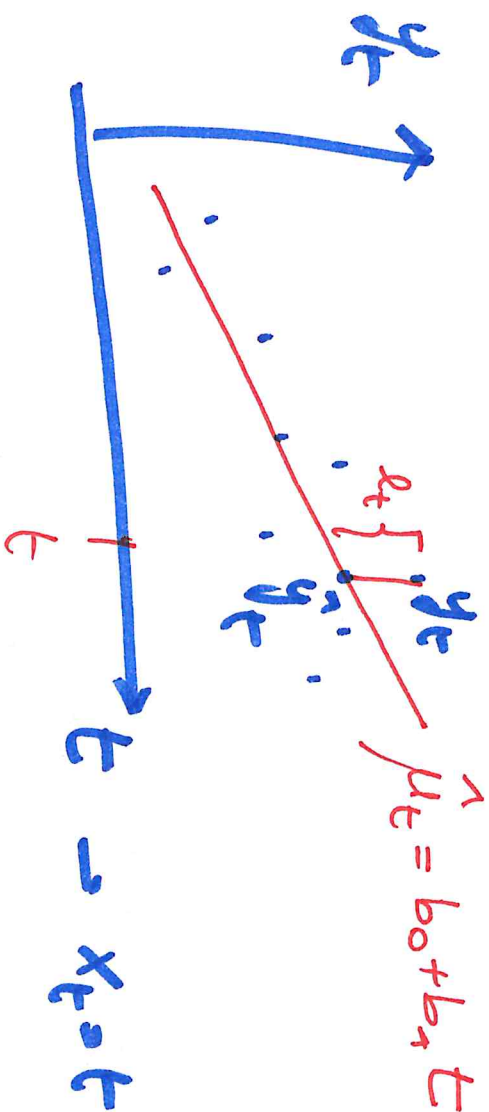
$$Y_t = \beta_0 + \beta_1 x_t$$

$$\hat{y}_t = b_0 + b_1 x_t$$

"PREDICTION", / ESTIMATE  
 $t \neq 1, \dots, T$

$$\rightarrow (y_t - \hat{y}_t) = e_t$$

↑  
error



$$\left\{ \begin{array}{l} \frac{\partial SSE}{\partial \beta_0} \Big|_{\beta_0 = b_0} = 0 \quad (1) \rightarrow b_0 \\ \frac{\partial SSE}{\partial \beta_1} \Big|_{\beta_1 = b_1} = 0 \quad (2) \rightarrow b_1 \end{array} \right. \quad \begin{array}{l} \text{NORMAL} \\ \text{EQUATIONS} \end{array}$$

$$(1) \quad \sum_t (y_t - b_0 - b_1 x_t) = \sum_t (y_t - \underbrace{b_0 + b_1 x_t}_{\hat{y}_t = \bar{y}_t}) = \sum_t e_t \quad \boxed{\sum_t e_t = 0}$$

$$(2) \quad \sum_t x_t (y_t - b_0 - b_1 x_t) = \sum_t x_t \cdot e_t = 0 \quad \boxed{\sum_t x_t \cdot e_t = 0}$$

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## TEST 1

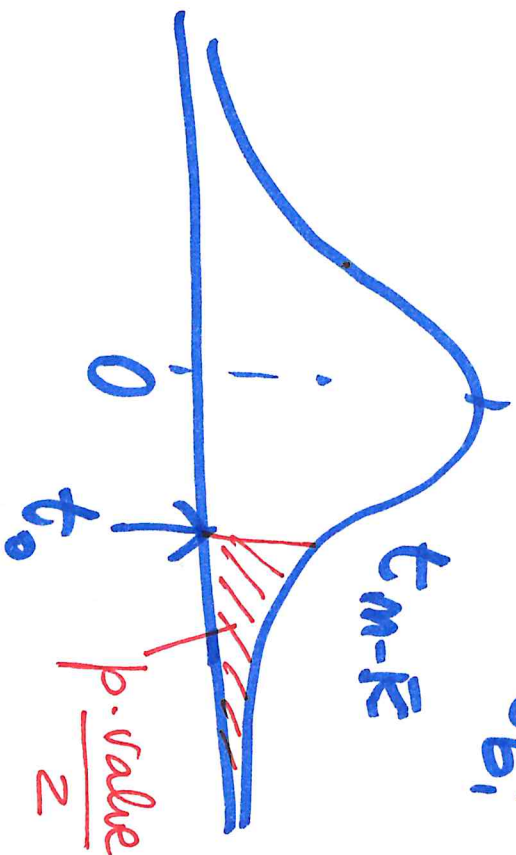
$$H_0: \beta_i = 0$$

$$H_1: \beta_i \neq 0$$

for a given

TEST STATISTIC  $\sim \beta_i = 0$

$$t_0 = \frac{b_i - 0}{\hat{\sigma}_{b_i}} \sim t_{n-k}$$



$\Rightarrow$

p-value  $> \alpha$   
we cannot reject

$$H_0: \beta_i = 0$$

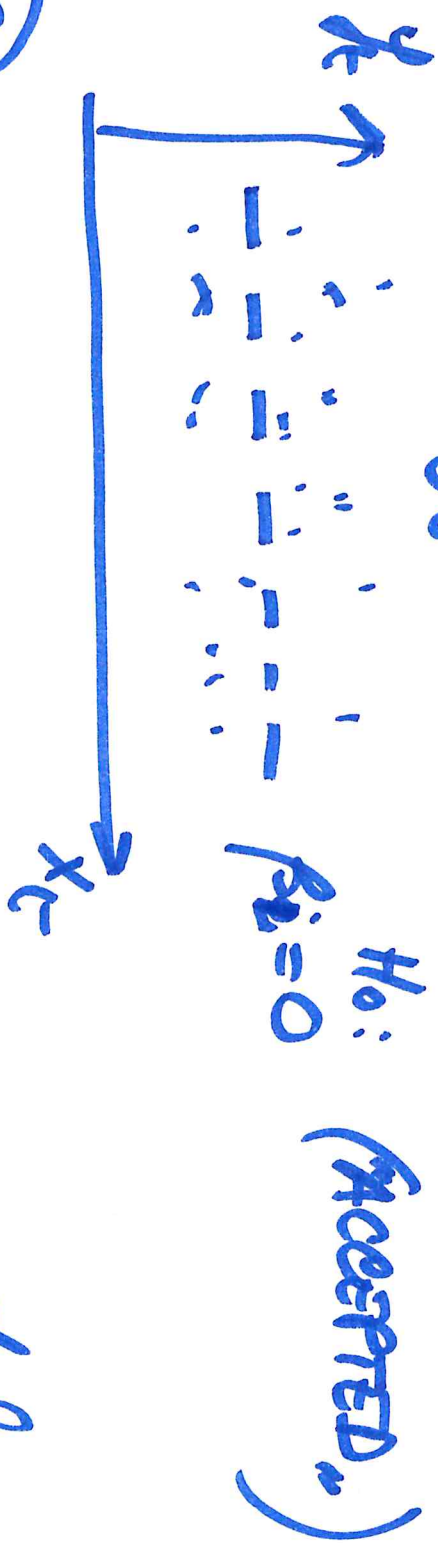
$p+1 \rightarrow$  intercept  $\beta_0$   
 $\downarrow$   
# regressors

ex:  $Y_t = \beta_0 + \beta_1 x_t \rightarrow Y_t = \beta_0 + 0 x_t$

④

$\Rightarrow X_t$  is not supposed to influence

$y_t$ 's



$R^2$

consider regression model important

$R^2 \approx 80\% \rightarrow$  let's care

$R^2 = 30\% \rightarrow$  given model NOT REVENUE



⑤

$$H_0: \beta_1 = \beta_2 = \dots \beta_K = \dots \beta_{K-1} = 0$$

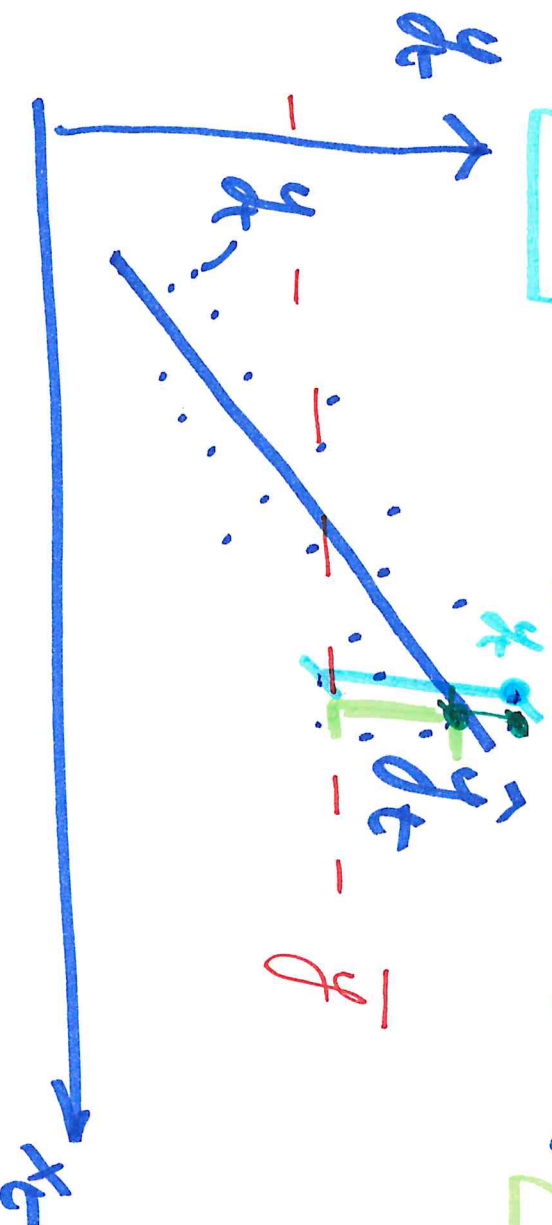
$$H_1: \beta_j \neq 0 \text{ for at least one } j \text{ in } 1 \dots p$$

$$\rightarrow Y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_{K-1} x_{p-1,t}$$

$p = K-1$

$$\sum_t (y_t - \bar{y})^2 = \sum_t (y_t - \hat{y}_t)^2 + \sum_t (\hat{y}_t - \bar{y})^2$$

$K = p+1$



$$\sum_t (y_t - \bar{y})^2 = \sum_t (\overbrace{y_t - \bar{y}}^{(y_t - \bar{y})} + \overbrace{\bar{y} - \bar{y}}^{(\bar{y} - \bar{y})})^2 = \quad (6)$$

$$= \sum_t [(y_t - \bar{y}) + (\bar{y} - \bar{y})]^2 =$$

$$= \sum_t (y_t - \bar{y})^2 + \sum_t (\bar{y} - \bar{y})^2 + 2 \sum_t \underbrace{(y_t - \bar{y})(\bar{y} - \bar{y})}_{\cancel{2ab}}$$

(\*)

$$\sum_t e_t \cdot (y_t - \bar{y}) =$$

$$= \sum_t e_t y_t - \sum_t e_t \cdot \bar{y} = \sum_t e_t y_t - \underbrace{\sum_t e_t}_{=0} \bar{y}$$

$$= \sum_t e_t (b_0 + b_1 x_t) = \underbrace{\sum_t e_t \cdot b_0}_{=0} + b_1 \underbrace{\sum_t e_t x_t}_{=0}$$

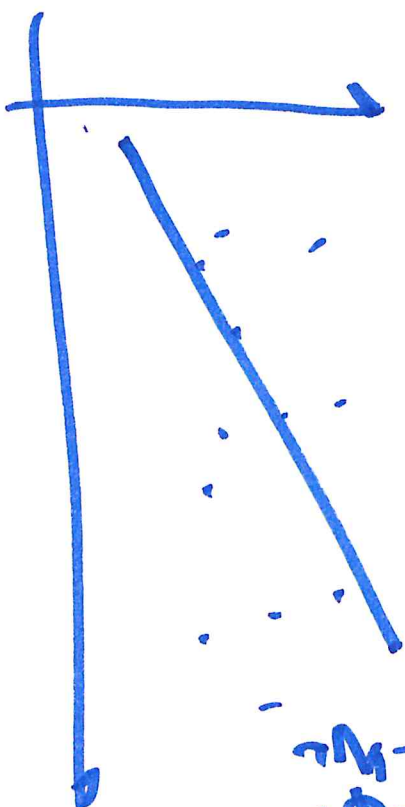
(2)

$$\sum_e (y_e - \bar{y})^2 = \sum_e (y_e - \hat{y}_e)^2 + \sum_e (\hat{y}_e - \bar{y})^2$$

$$SS_T = SSE + SSR$$

degrees  
of  
freedom

$$n-1 = n-K-1$$



$$\bar{y} = \frac{\sum y_i}{n}$$

⑧

$$H_0: \beta_1 = \dots = \beta_p = 0$$

$H_1: \neq$  at least one

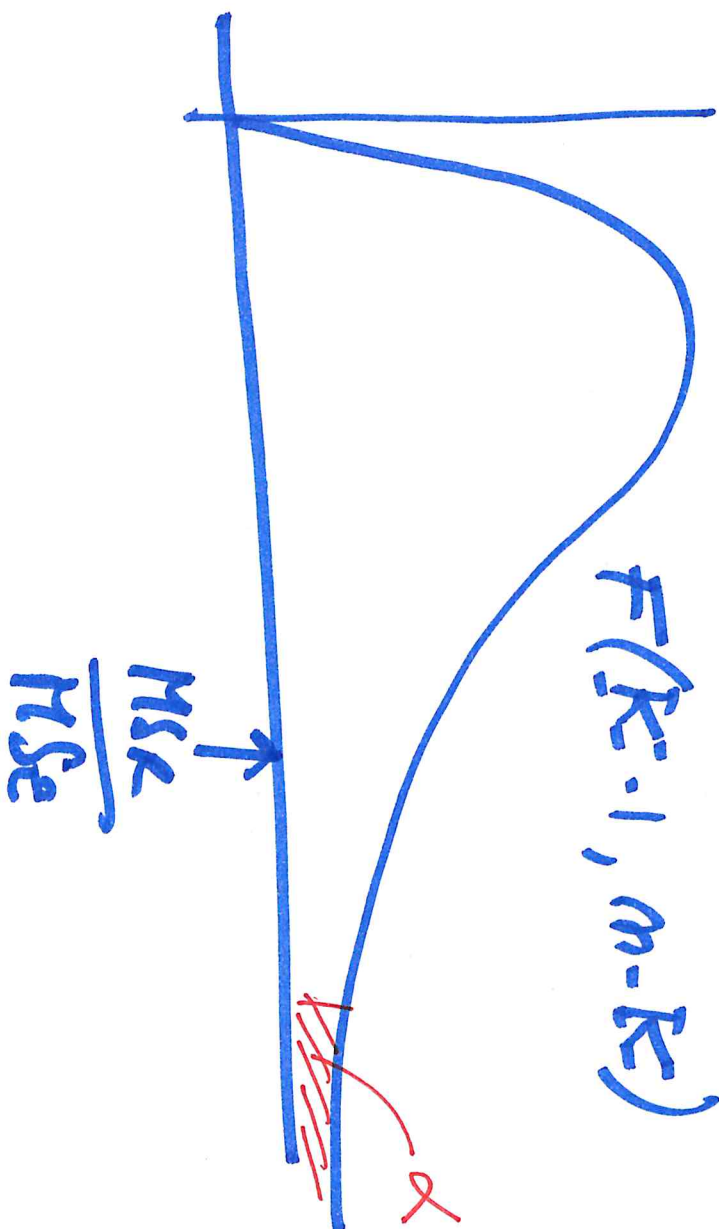
If  $H_0$  is true  $\rightarrow$

$$\frac{MSE}{MSE} \sim F(k-1, n-k)$$

$$\frac{SS_R}{df_R} = \frac{SS_R}{k-1}$$

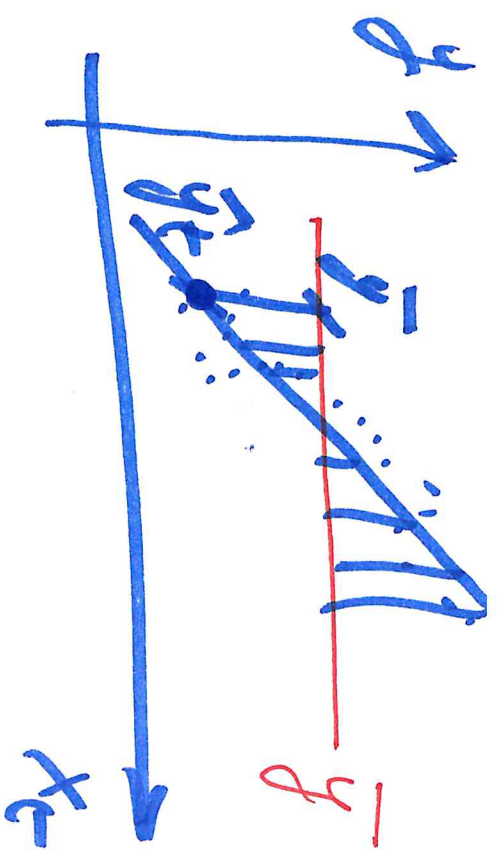
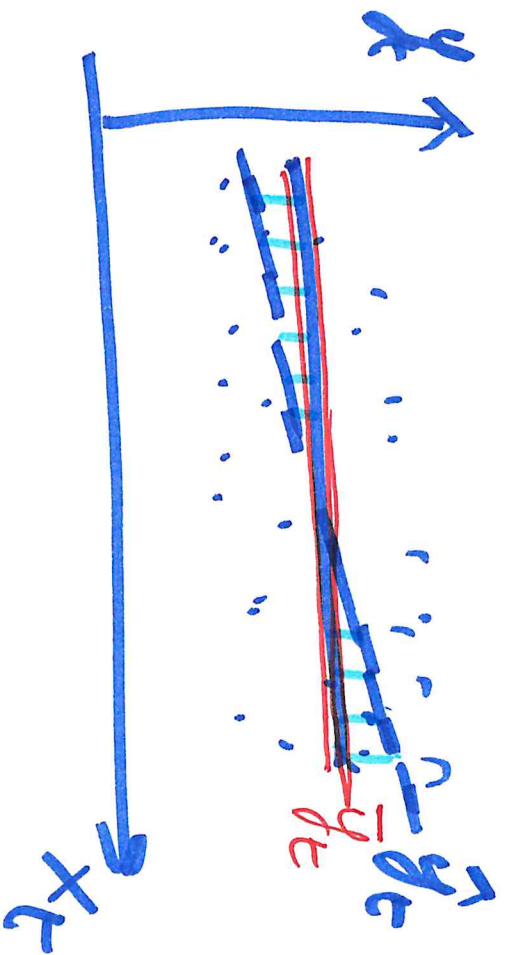
$$\frac{SS_E}{df_E} = \frac{SS_E}{n-k}$$

$$F(k-1, n-k)$$



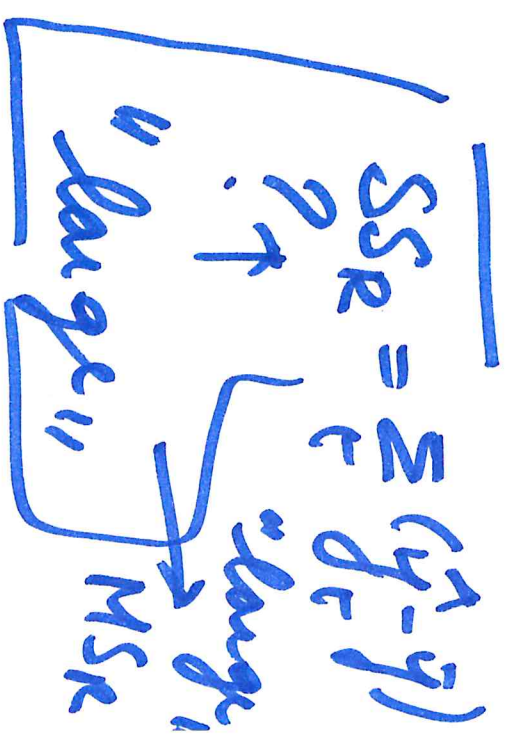
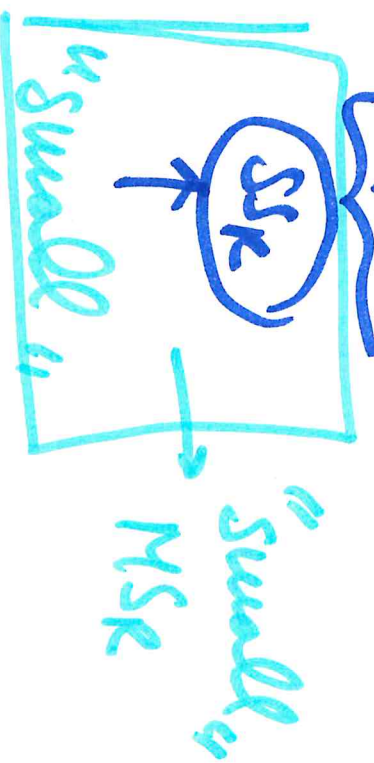


⑨



$$\sum e_t^2 + \sum (y_t - \hat{y}_t)^2 = SS_T$$

$\underbrace{\hspace{10em}}_{SSE} \quad \underbrace{\hspace{10em}}_{SSR}$

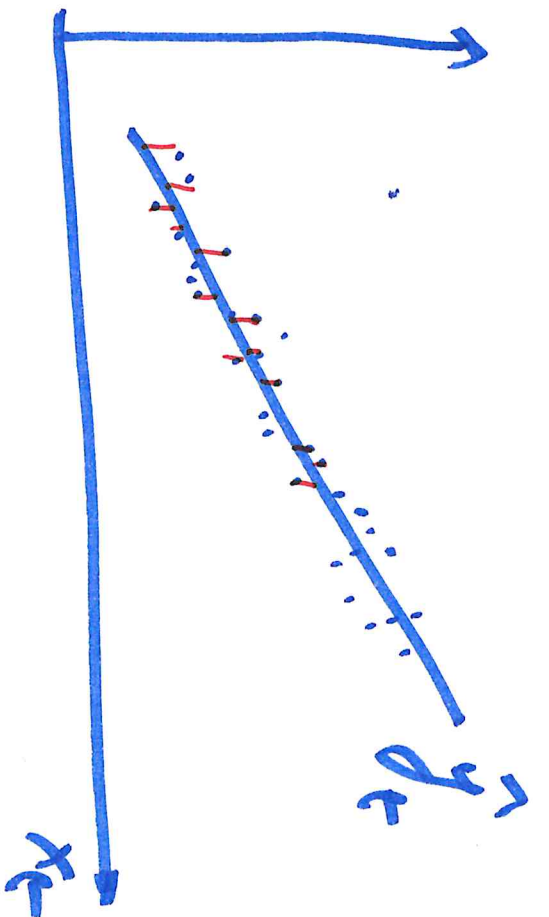


$\beta_1 \approx 0$   
 "ACCEPT"  $H_0$

$\beta_1 \neq 0$   
 REJECT  $H_0$

$$\frac{MSR}{MSE} \sim F$$

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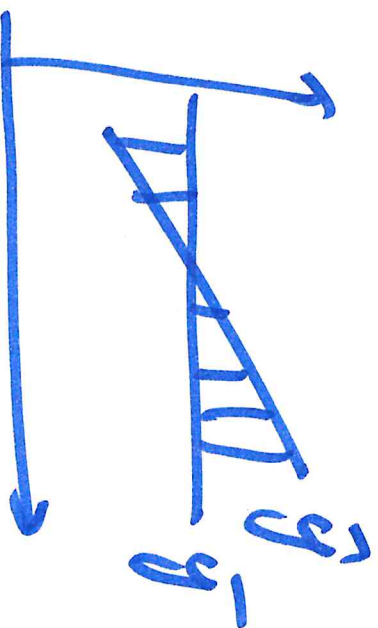
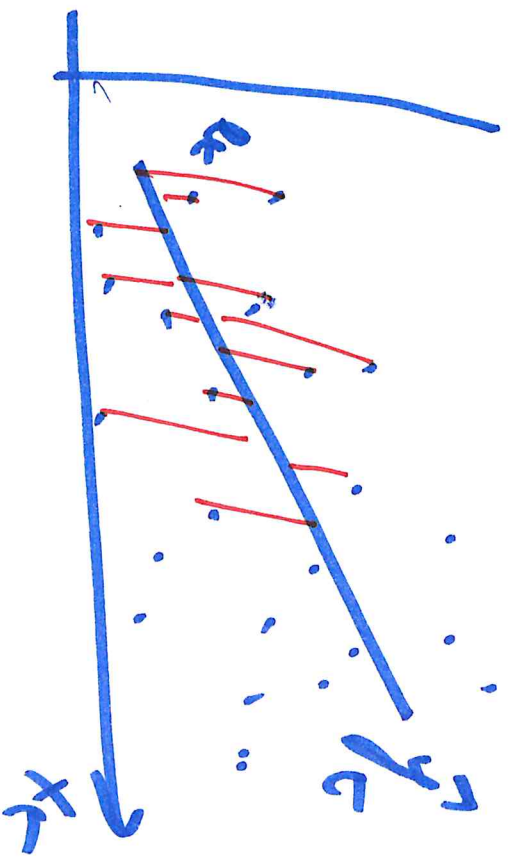
Small MSE

$$\hat{\sigma}_e^2 =$$

$$MSE =$$

$$\frac{SSE}{n-k}$$

large MSE



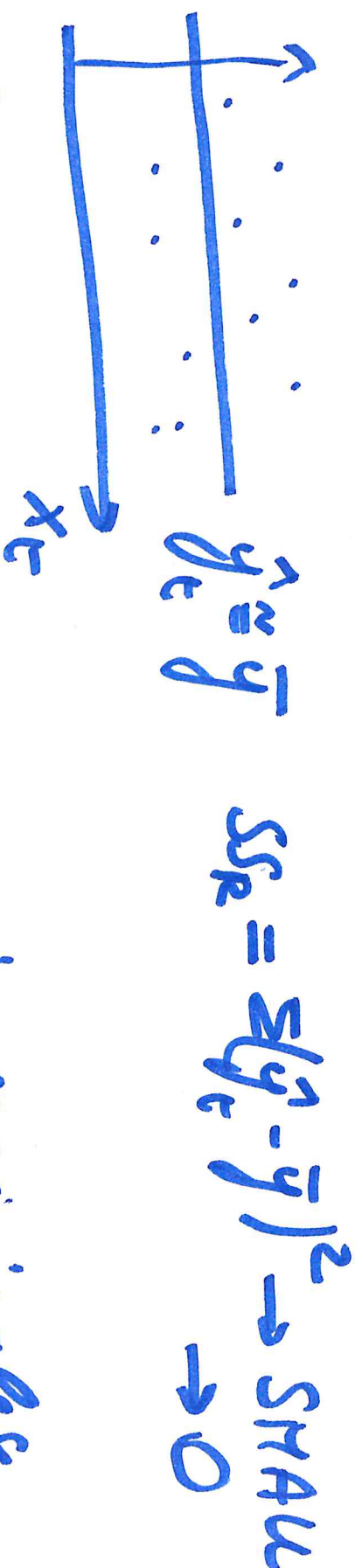
$$SSE = \sum (y_c - \hat{y}_c)^2$$

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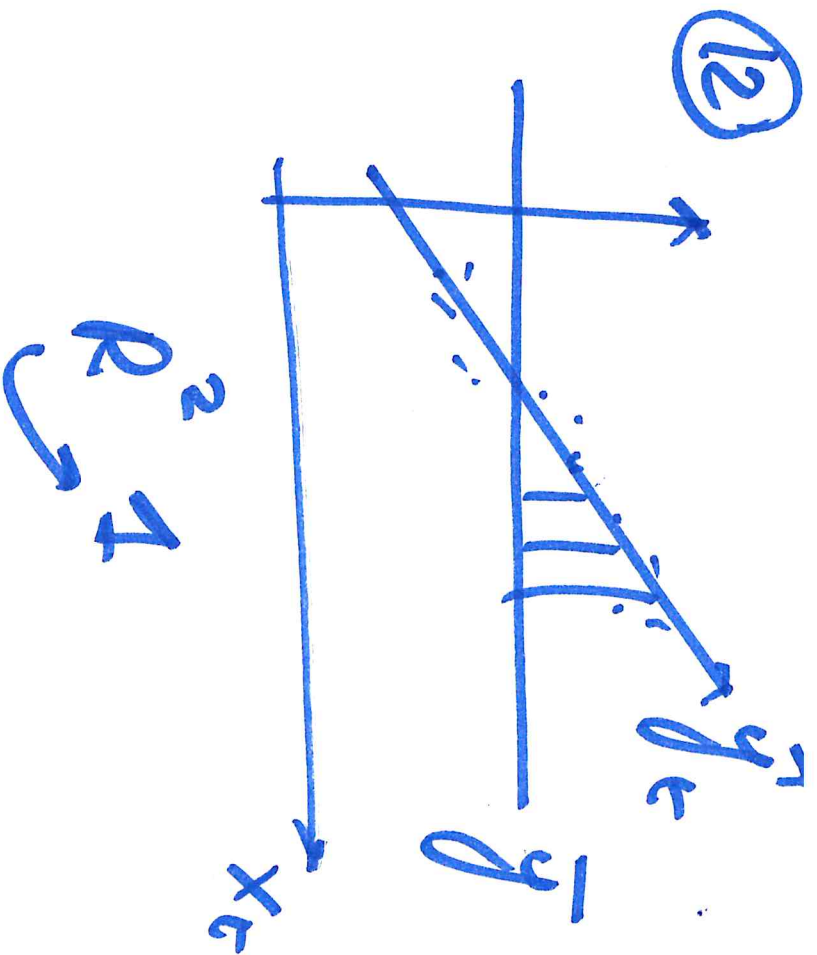
$$R^2 = \frac{SS_R}{SS_T} = \frac{SS_T - SS_E}{SS_T} = 1 - \frac{SS_E}{SS_T}$$

$$SS_T = SS_E + SS_R$$

$$0 \leq R^2 \leq 1$$



$R^2 \rightarrow 0$   $x_t$  the regressor is meaningless  
 → we can assume that the regression model is not to be considered



$SSR = \sum (y_e - \bar{y})^2$  large  
 → regression is  
 meaning for  
 as  $x_c$  is increasing  
 data