

## Recap

Data  $(y_1, x_1), (y_2, x_2), \dots, (y_n, x_n) \in \mathbb{R}^2$   
 $p=2$

Best fit  $y = b_0 + b_1 x$  where

$$\left. \begin{aligned} \sum y_i &= n b_0 + b_1 \sum x_i \\ \sum x_i y_i &= b_0 \sum x_i + b_1 \sum x_i^2 \end{aligned} \right\} \begin{array}{l} \text{normal} \\ \text{eqns} \end{array}$$

fitted value

$$\hat{y}_i = b_0 + b_1 x_i$$

Residual

$$e_i = y_i - \hat{y}_i$$

sample mean

$$\bar{y} = \frac{1}{n} \sum y_i$$

$$SSTO = \sum (y_i - \bar{y})^2$$

$$SSE = \sum (y_i - \hat{y}_i)^2$$

$$SSR = \sum (\hat{y}_i - \bar{y})^2$$

Defn Coefficient of determination

$$R^2 := \frac{SSR}{SSTO}$$

typically a good fit has  $R^2$  close to 1.

Lemma i)  $\sum e_i = 0$

ii)  $\sum \hat{y}_i e_i = 0$

Proposition i)  $SSTO = SSR + SSE$

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

Proof of Prop (i)  $\Rightarrow$  Prop (ii)

(i) implies  $R^2 = \frac{SSR}{SSTO} = \frac{SSR}{SSR + SSE} = 1 - \frac{SSE}{SSTO}$

But  $0 \leq SSE, SSTO$ . By (i),  $0 \leq SSE \leq SSTO$ .

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

Proof of Prop (i)

$$\begin{aligned} \sum (y_i - \bar{y})^2 &= \sum \left[ (\hat{y}_i - \bar{y}) + (y_i - \hat{y}_i) \right]^2 \\ &= \sum \left\{ (\hat{y}_i - \bar{y})^2 + (y_i - \hat{y}_i)^2 \right\} + 2 \underbrace{\sum (\hat{y}_i - \bar{y})(y_i - \hat{y}_i)}_A \end{aligned}$$

$$A = \sum \hat{y}_i (y_i - \hat{y}_i) - \bar{y} \sum (y_i - \hat{y}_i)$$

$$= \sum \hat{y}_i e_i - \bar{y} \sum e_i$$

$$= 0 \text{ by Lemma 1.}$$

So  $SSTO = SSE + SSR$ .  $\square$

Proof of Lemma (i)

$$\sum e_i = \sum (y_i - b_0 - b_1 x_i)$$

$$= \sum y_i - nb_0 - b_1 \sum x_i$$

$$= 0 \text{ by first normal eqn.}$$

Proof of Lemma (ii) use both

normal eqns.

## Matrix Notation ( $p \geq 2$ )

$$B = (X^t X)^{-1} X^t Y$$

$$Y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \quad X = \begin{pmatrix} 1 & x_{11} & \dots & x_{1,p-1} \\ \vdots & \vdots & \dots & \vdots \\ 1 & x_{n1} & \dots & x_{n,p-1} \end{pmatrix}$$

$$SSTO = Y^t Y - n \bar{y}^2$$

$$SSR = B^t X^t Y - n \bar{y}^2$$

$$SSE = Y^t Y - B^t X^t Y$$

$$R^2 = \frac{SSR}{SSTO}, \quad \text{Again} \quad 0 \leq R^2 \leq 1.$$

## Some statistics (skipping proofs)

Suppose

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_{p-1} x_{i,p-1} + \varepsilon_i$$

where

$$i = 1, 2, \dots, n$$

$x_{i1}, \dots, x_{i,p-1}$  are known constants

$\varepsilon_i$  are independent  $N(0, \sigma^2)$ ,

$\beta_0, \dots, \beta_{p-1}$  parameters.

Def'n  $MSR = \frac{SSR}{p-1}$  regression mean square

$$MSE = \frac{SSE}{n-p}$$
 error mean square

$$F^* = \frac{MSR}{MSE}$$

Theorem If  $\beta_1 = \beta_2 = \dots = \beta_{p-1} = 0$  then  $F^*$  follows an  $F$  distribution with  $p-1$  and  $n-p$  degrees of freedom.

So to choose between the two hypotheses,

$$C_1 : \beta_1 = \beta_2 = \dots = \beta_n = 0$$

$$C_2 : \beta_i \neq 0 \text{ for at least one } i$$

We use :

if  $F^* \leq F(1-\alpha, p-1, n-p)$  then conclude  $C_1$ ,

if  $F^* > F(1-\alpha, p-1, n-p)$  then conclude  $C_2$ ,

to control Type I errors at level  $\alpha$ .

Example using the Skui Cream  
example

$y$  : sales in district

$x_1$  : size of district

$x_2$  : per capita income of district

one can compute:

$$p = 3 \quad B = (X^T X)^{-1} X^T Y = \begin{pmatrix} 3.4526 \\ 0.4960 \\ 0.0092 \end{pmatrix}$$

$n = 15$

$$MSE = \frac{1}{p-1} (Y^T Y - B^T X^T Y) = 26922.4$$

$$MSE = 4.74$$

$$F^* = \frac{MSE}{MSE} = 5680$$

Assuming  $\alpha$  at 0.05 and assuming  
the  $\epsilon_i$  are independent  $N(0, \sigma^2)$ , we

require

$$F(0.95, 2, 12) = 3.89$$

Since  $F^*$  exceeds 3.89 we conclude

$C_2$ : Sales are related to population and income.

But is this relation useful for predictions,

well

$$R^2 = \frac{SSR}{SSTO} = 0.9989$$

So when the independent variables  $x_1$  and  $x_2$  are considered, the variation in sales is "99.9% explained".