

This time: regression, ANOVA

Next time: regression, ANOVA

Read: LN pp. L-(269) → L-(282)

Today: LN p. L-(248) →

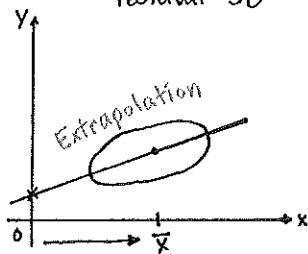
Math fact: ① $E_{IID}(\hat{\beta}_1) = \beta_1$

② $SE_{IID}(\hat{\beta}_1) = \frac{S_{Y|X}}{S_x \sqrt{n-1}}$

note: $y|x$ "given" - how variable y is after you take x into account

where: $S_{Y|X} = S_y \sqrt{1-r^2} \cdot \sqrt{\frac{n-1}{n-2}}$
 interesting part ← boring (close to 1)

residual SD = "root mean squared error" rmse (JMP uses this name)



- need to extrapolate to create line to find x at zero
 - the further away from middle of data, the less secure
- so large extrapolation = large uncertainty

Warning: risky to extrapolate regression predictions outside the observed range of x

$$Y_i = \underbrace{(\beta_0 + \beta_1 x_i)}_{\text{"truth": (hoping the values fit a straight line)}} + e_i$$

← from normal curve w/mean 0 & SD $\sigma_{Y|X}$
 ← "error" (vary from the mean)

$$Y_i \text{ (observed } y) = (\hat{\beta}_0 + \hat{\beta}_1 x_i) \text{ (predicted)} + \hat{e}_i \text{ (residual)}$$

$$\hat{\sigma}_{Y|X} = \sqrt{\frac{1}{n-2} \sum_{i=1}^n \hat{e}_i^2}$$

squared error mean squared error root mean squared error

$\hat{\sigma}_{Y|X}$ represents the typical amount by which you expect y & \hat{y} to differ

2 ways to tell if regression is useful:

$$v(y) = s^2_y = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$$

$$y = \hat{y} + \hat{e} \quad \text{so} \quad v(y) = v(\hat{y} + \hat{e})$$

math fact: $v(\hat{y} + \hat{e}) = v(\hat{y}) + v(\hat{e})$

$$v(\hat{y}) = r^2 v(y)$$

$$v(\hat{e}) = (1-r^2) v(y)$$

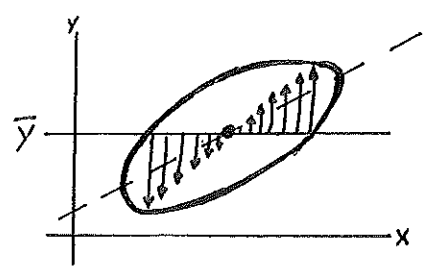
$$\text{so } r^2 = \frac{v(\hat{y})}{v(y)}$$

% of variance in y is "associated with" the regression of y on x, called the coefficient of determination.

we want r^2 to be big

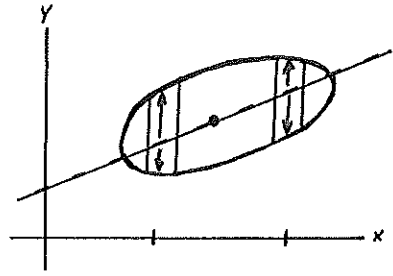
case 1: ignoring x (or if you don't have x)

$\hat{y} = \bar{y}$
& $SE(\hat{y}) = S_y$



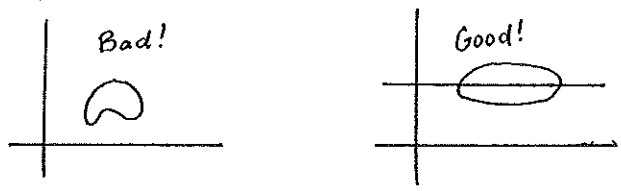
case 2: use x to predict y:

$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$
 $SE(\hat{y}) = \frac{S_y \cdot \sqrt{1-r^2}}{\text{residual}}$



first case looks impressive (can be 76%), but second is much better

Residual plot:



don't want trends

multiple linear regression model: more than 1 variable

Unit 7: One-way Analysis of Variance

For the tree study: weight diff. is practsig!

4 independent variables, need 4 model diagrams instead of 2

the assumption of all equal σ 's is bad