Section 3. Simple Regression – OLS Estimators

- 1. Last time: Lines, Population Linear Regression PARAMETER S
- 2. Estimators of β_0, β_1^{t} cere bo and by
- 3. Least Squares Estimators
- 4. OLS Assumptions

RANDOM VARIABUES

1. Review: Lines, Clouds and Pop. Linear Regression

- e.g. Demand for Coffee, Global warming, CA test scores and student-teacher ratios
- Decide which parameters in population we care about (β_0, β_1)
 - just like we did with $\boldsymbol{\mu}$
- Draw a sample and estimate parameters
 just like we did with μ
- Construct CI for parameters, test hypotheses, make predictions.
 - just like..

Coffee Example (with a line)



What's the slope of the line? About how many cups would you sell at \$1?

Global Warming Example







2. Estimators of β_0, β_1

- Decide which parameters in population we care about (β_0, β_1) - we chose Pop. Linear Regression
- Draw a sample and estimate parameters
- Which estimates to use?
- We'd like something with nice properties:

 - unbiased, $E(b_i) = \beta_i$ consistent, $b_i \stackrel{p}{\rightarrow} \beta_i$ efficient, $V(b_i)$ is smallest
 - with an approximately normal distribution. $b_{i} \stackrel{\wedge}{\sim} N(\beta_{i}, \gamma(b_{i}))'_{i} = \frac{b_{i} - \beta_{i}}{\sqrt{\hat{\gamma}(b_{i})}} \stackrel{\wedge}{\sim} N(\alpha_{i})$

3. The Ordinary Least Squares (OLS) Estimators

- Try b₀ and b₁ that minimize the sum of e_i^2 in $\sum_{i=1}^{n} e_i^2$ Find b₀, b₁ that minimize Ξe_i^2 where $e_i = Y_i - (b_0 + b_1 x)$
- Why this one? Well, it's analogous to what we asked for in the population.
- And it seems like a nice property in the sample.
- Deriving formulae for OLS estimators.. (S&W p. 143)

$$\begin{aligned} \mathcal{Q} \neq 0. \text{ C. } & \underline{z}_{2:=0}, \underline{z}_{2:=0}, \underline{z}_{2:=0}, \text{ new solve for } b_{1}, b_{1} \\ & = \underbrace{1}_{N} \sum_{i=0}^{N} \underbrace{1}_{N} \underbrace{1}_{i} \underbrace{1}_{N} \underbrace{1}_{N$$

Formula for OLS estimators

The OLS Estimator, Predicted Values, and Residuals

The OLS estimators of the slope β_1 and the intercept β_0 are:

$$\hat{\beta}_{1} = \frac{\sum_{i=1}^{n} (X_{i} - \overline{X})(Y_{i} - \overline{Y})}{\sum_{i=1}^{n} (X_{i} - \overline{X})^{2}} = \frac{s_{XY}}{s_{X}^{2}}$$

$$\hat{\beta}_{0} = \overline{Y} - \hat{\beta}_{1}\overline{X}.$$
(4.8)
(4.9)

The OLS predicted values \hat{Y}_i and residuals \hat{u}_i are:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i, \ i = 1, \dots, n$$
 (4.10)

$$\hat{u}_i = Y_i - \hat{Y}_i, \ i = 1, \dots, n.$$
 (4.11)

The estimated intercept $(\hat{\beta}_0)$, slope $(\hat{\beta}_1)$, and residual (\hat{u}_i) are computed from a sample of *n* observations of X_i and Y_i , i = 1, ..., n. These are estimates of the unknown true population intercept (β_0) , slope (β_1) , and error term (u_i) .



The Least Squares Assumptions

$$Y_i = \beta_0 + \beta_1 X_i + u_i, i = 1, ..., n$$
, where:

- 1. The error term u_i has conditional mean zero given X_i , that is, $E(u_i | X_i) = 0$;
- 2. (X_i, Y_i) , i = 1, ..., n are independent and identically distributed (i.i.d.) draws from their joint distribution; and
- 3. (X_i, u_i) have nonzero finite fourth moments.

Next time..

- Confidence intervals for β_0 and β_1
- Examples