Simple Linear Regression: A Simple Application and How We Make Inference

BIOS 6611

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Week 7

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Refresher

Recall, we are learning about the Simple Linear Regression (SLR) model:

$$
Y_i = \beta_0 + \beta_1 X_{1i} + \epsilon_i
$$

where $i=1,\ldots,n$ indexes the data pairs $(Y_i,X_i).$

A simple linear regression model has a single explanatory variable (X_1) . (Linear regression models that are not simple can have more than one explanatory variable.)

The assumptions are Existence, Linearity, Independent, Homoscedasticity, and Normality of the error term.

[Inference for Least Squares Estimators](#page-4-0)

Inference for Least Squares Estimators

Under the assumptions, we have

$$
\epsilon_i \sim N(0, \sigma_e^2)
$$

$$
Y_i | X_i \sim N(\mu_{Y|X}, \sigma_{Y|X}^2)
$$

where $\mu_{Y|X}$ is allowed to change (linearly) with the explanatory variable. That is,

$$
\mu_{Y|X} = \beta_0 + \beta_1 X
$$

Therefore, if we assume normality of errors, then the least squares estimators $\hat{\beta}_0$ and $\hat{\beta}_1$ are normally distributed, since $\hat{\beta}_0$ and $\hat{\beta}_1$ will be functions of independent normally distributed random variables (See Corollary 4.6.10 in Casella & Berger).

Inference for Least Squares Estimators (cont.)

Alternatively, if we cannot assume normality of the error terms:

- **1** If we have a large sample size, asymptotic normality may be assumed for the estimators (CLT!)
- **2** If we don't have a large sample size and errors are not normally distributed, bootstrap or Monte Carlo methods may be appropriate.

[Testing for Significant Associations](#page-7-0)

Testing for Significant Associations

Say we want to test if there is a *linear* association between the explanatory (X) and response (Y) variables. This would be equivalent to testing if the slope is zero in the SLR model. Thus, we test the hypothesis:

$$
H_0: \beta_1 = 0 \quad \text{vs.} \quad H_A: \beta_1 \neq 0
$$

To perform this test, we use the fact that the ratio of the estimate to its standard errors, called the t-statistic, follows a t-distribution with $n-2$ degrees of freedom:

$$
t=\frac{\hat{\beta_1}}{SE(\hat{\beta_1})}\sim t_{n-2}
$$

 $(n-2)$ degrees of freedom because we estimate both the intercept and the predictor beta coefficients)

Testing for Significant Associations (cont.)

95% CI for the slope coefficient:

$$
\hat{\beta_1} \pm t_{n-2, 1-\alpha/2}\mathsf{SE}(\hat{\beta_1})
$$

If we fail to reject H_0 , it generally means one of three things:

- **1** There is no association
- **2** There is no *linear* association
- **³** We've made a Type II error

[Example Regression Code and Output for FEV](#page-10-0) [Data](#page-10-0)

R code

```
# Load in FEV dataset
fev <- read.csv("FEV_rosner.csv")
```
*# Fit SLR FEV = B0 + B1*Age + E* fev_slr \leftarrow lm(fev \sim age, data=fev) summary(fev_slr)

R code (cont.)

```
##
## Call:
## lm(formula = few ~ age, data = few)##
## Residuals:
## Min 1Q Median 3Q Max
## -1.57539 -0.34567 -0.04989 0.32124 2.12786
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.431648 0.077895 5.541 4.36e-08 ***
## age 0.222041 0.007518 29.533 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5675 on 652 degrees of freedom
## Multiple R-squared: 0.5722, Adjusted R-squared: 0.5716
## F-statistic: 872.2 on 1 and 652 DF, p-value: < 2.2e-16
```
SAS code

```
SAS Code:
proc reg data=fev;
    model fev = age;run:
```



```
Q: What is the regression equation?
A:
```

$$
\hat{\text{FEV}} = 0.432 + 0.222 \times \text{Age}
$$

Q: What is the interpretation of the slope parameter?

A: For every 1 year increase in age between the ages of 3 and 19, the FEV increases on average by 0.222 liters. (Note: restricted to observed range of age values, no extrapolation!)

Q: What is the interpretation of the intercept? A: When age is 0 years, average FEV is 0.432 liters. (Note: not scientifically meaningful and also extrapolating outside the range of age values)

Q: Is there a significant linear relationship between age and FEV? A: Yes.

$$
t = \frac{0.22204}{0.00752} = 29.53 \sim t_{654-2}
$$

\n
$$
\Rightarrow p < 0.0001
$$

Thus, we reject H_0 : $\beta_1 = 0$, and conclude there is a significant linear relationship between age and FEV.

Q: Calculate the 95% CI for age. Interpret. A:

> $0.22204 \pm t_{652.0.975} \times 0.007518$ $= 1.963609 \times 0.007518$ = (0*.*207*,* 0*.*237)

We are 95% confident that FEV increases between 0.207 and 0.237 liters on average for every 1-year increase in age (between the ages of 3 and 19).

Q: What is the predicted FEV for an 11-year old child? A: $F\hat{E}V = 0.432 + 0.222(11) = 2.874$ liters

Q: What is the predicted difference in FEV for 16-year old children versus 11-year old children? A^{\cdot}

$$
E(FEV|Age = 16) - E(FEV|Age = 11) = [\beta_0 + \beta_1 16] - [\beta_0 + \beta_1 11] = \beta_1 (16 - 11) = 5\beta_1
$$

Based on the estimate from our regression model we predict the difference between a 16- and 11-year old child to be $5\hat{\beta}_1 = 5(0.22204) = 1.1102$ liters.

Q: What is the 95% CI around this predicted difference? A:

$$
5\hat{\beta}_1 \pm t_{652,0.975} SE(5\hat{\beta}_1)
$$

5(0.22204) \pm 1.96 × 5 × 0.00752
 $=$ (1.037, 1.184) liters

We are 95% confident that FEV increases between 1.037 and 1.184 liters on average from ages 11 to 16 (or any other 5 year age difference between 3 and 19 years).