# STATS 2107

# Statistical Modelling and Inference II Solutions

# Workshop 3: Confidence intervals and hypothesis testing

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# Confidence intervals for Simple Linear Regression Estimates

#### The model

For data  $(x_1, Y_1), (x_2, Y_2), \dots, (x_n, Y_n), x_i, Y_i \in \mathbb{R}$ , consider the simple linear regression model

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \,,$$

where  $\varepsilon_i \overset{i.i.d.}{\sim} N(0, \sigma^2)$ 

#### The model estimates

Recall that the estimates for  $\beta_0$  and  $\beta_1$  are given by

$$\hat{\beta}_1 = \frac{S_{XY}}{S_{XX}}$$

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{x}$$

where

$$S_{XY} = \sum_{i=1}^{n} (x_i - \bar{x})(Y_i - \bar{Y})$$
$$S_{XX} = \sum_{i=1}^{n} (x_i - \bar{x})^2$$

# The distribution of $\hat{\beta}_1$

What is the distribution of  $\hat{\beta}_1$ ?

- 1. Recall  $\hat{\beta}_1 = \sum_{i=1}^n a_i Y_i$ 2. Each  $Y_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$
- 3. The sum of normals is normal

Hence  $\hat{\beta}_1$  follows a normal distribution.

## The parameters

- 1. From last workshop,  $\hat{\beta}_1$  is unbiased for  $\beta_1$ , so  $E\left[\hat{\beta}_1\right] = \beta_1$
- 2. The variance is given by:

$$\operatorname{Var}\left(\hat{\beta}_{1}\right) = \frac{\sigma^{2}}{S_{XX}}$$

So 
$$\hat{\beta}_1 \sim N\left(\beta_1, \frac{\sigma^2}{S_{XX}}\right)$$
.

#### A confidence interval for $\beta_1$

If  $\sigma^2$  is known, a symmetric  $(1-\alpha) \times 100\%$  confidence interval for  $\beta_1$  is given by

$$\hat{\beta}_1 \pm z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{S_{XX}}} \,.$$

PROOF:

#### Your turn

#### What to do

1. Show that  $\hat{\beta}_0 \sim N\left(\beta_0, \sigma^2\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{XX}}\right)\right)$ .

#### **Solutions:**

Recall from last workshop that  $\hat{\beta}_0$  is the BLUE for  $\beta_0$ , that is,  $\beta_0$  is linear and unbiased. You also showed that

$$\operatorname{Var}\left(\hat{\beta}_{0}\right) = \sigma^{2}\left(\frac{1}{n} + \frac{\bar{x}^{2}}{S_{XX}}\right).$$

Hence, since the  $Y_i$  are normal,  $\hat{\beta}_0 \sim N\left(\beta_0, \sigma^2\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{XX}}\right)\right)$ .

2. Find a  $(1 - \alpha) \times 100\%$  confidence interval for  $\beta_0$ .

#### **Solutions:**

Using part 1, a  $(1 - \alpha) \times 100\%$  confidence interval for  $\beta_0$  is

$$\hat{\beta}_0 \pm z_{\frac{\alpha}{2}} \, \sigma \sqrt{\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{XX}}\right)}$$

# Hypothesis testing for Simple Linear Regression Estimates

#### What do we need

Recall we need the following 4 things for a hypothesis test:

- 1. A null hypothesis
- 2. An alternative hypothesis
- 3. A test statistic
- 4. A critical region.

#### Some hypotheses

Let's suppose we are doing inference on  $\beta_1$ . Then, if we know  $\sigma^2$ , we can do a simple Z-test. Our hypothesis looks like:

$$H_0: \beta_1 = \tilde{\beta}_1 \quad \text{vs} \quad H_a: \beta_1 \neq \tilde{\beta}_1$$

where  $\tilde{\beta}_1$  is a fixed value.

#### A test statistic

Our test statistic will be of the form:

 $\frac{\text{Best Guess} - \text{Null hypothesis}}{SE}$ 

So

$$Z = \frac{\hat{\beta}_1 - \tilde{\beta}_1}{\sigma / \sqrt{S_{XX}}}$$

#### Critical region

Since  $Z \sim N(0,1)$  under the null hypothesis, our critical region at the  $\alpha$ -level of significance is

$$C_{\alpha} = \left\{ z : |z| > z_{\frac{\alpha}{2}} \right\} .$$

#### Putting this together

We test the hypothesis

$$H_0: \beta_1 = \tilde{\beta}_1 \quad \text{vs} \quad H_a: \beta_1 \neq \tilde{\beta}_1$$

with the test statistic

$$Z = \frac{\hat{\beta}_1 - \tilde{\beta}_1}{\sigma / \sqrt{S_{XX}}}$$

and critical region

$$C_{\alpha} = \left\{ z : |z| > z_{\frac{\alpha}{2}} \right\} .$$

# Your turn

#### What to do

1. Describe an hypothesis test for  $\beta_0$  assuming  $\sigma^2$  is known.

#### **Solutions:**

We test the hypothesis

$$H_0: \beta_0 = \tilde{\beta}_0 \quad \text{vs} \quad H_a: \beta_0 \neq \tilde{\beta}_0$$

with the test statistic

$$Z = \frac{\hat{\beta}_0 - \tilde{\beta}_0}{\sigma \sqrt{\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{XX}}\right)}}$$

and critical region

$$C_{\alpha} = \left\{ z : |z| > z_{\frac{\alpha}{2}} \right\} .$$

# A practical example

#### Some data

Let's look at the FVC dataset.

and the model

$$FVC_i = \beta_0 + \beta_1 Height_i + \varepsilon_i$$
.

#### Hypothesis to test

Let's test the hypothesis (at  $\alpha = 0.05$ ) that

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

What do we need:

- 1. Our best guess  $\hat{\beta}_1$ .
- 2. Our SE, which involves
  - a.  $\sigma^2$
  - b.  $S_{XX}$ .

# Getting $\hat{\beta}_1$

We can calculate this the hard way, or use R. To use R, let's fit the model (using lm) and view the output (using summary).

#### Model output

```
fvc_lm <- lm(FVC ~ Height, data = fvc)
summary(fvc_lm)</pre>
```

```
##
## Call:
## lm(formula = FVC ~ Height, data = fvc)
##
## Residuals:
##
                 1Q
                      Median
                                           Max
## -0.75507 -0.23898 -0.00411 0.21238 0.87589
##
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
                          0.552593 -9.166 1.24e-15 ***
## (Intercept) -5.064961
## Height
               0.052194
                          0.003618 14.426 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.3137 on 125 degrees of freedom
## Multiple R-squared: 0.6248, Adjusted R-squared: 0.6218
```

```
## F-statistic: 208.1 on 1 and 125 DF, p-value: < 2.2e-16
```

# Getting $\hat{\beta}_1$

We can calculate this the hard way, or use R. To use R, let's fit the model (using 1m) and view the output (using summary).

We find  $\hat{\beta}_1 = 0.052194$ .

## Getting $\sigma^2$ (doing a dodgy)

In truth, we don't know  $\sigma^2$  and there are ways to deal with this. For today, we assuming that

$$\sigma^2 \approx s_e^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$
.

PLEASE NOTE: This is dodgy. We are doing this for illustrative purpose.

#### Model output

```
fvc_lm <- lm(FVC ~ Height, data = fvc)</pre>
summary(fvc_lm)
##
## Call:
## lm(formula = FVC ~ Height, data = fvc)
## Residuals:
##
                      Median
                                    3Q
                  1Q
                                            Max
  -0.75507 -0.23898 -0.00411 0.21238
##
  Coefficients:
##
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.064961
                           0.552593
                                    -9.166 1.24e-15 ***
               0.052194
                           0.003618 14.426 < 2e-16 ***
## Height
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.3137 on 125 degrees of freedom
## Multiple R-squared: 0.6248, Adjusted R-squared: 0.6218
## F-statistic: 208.1 on 1 and 125 DF, p-value: < 2.2e-16
```

# Getting $\sigma^2$ (doing a dodgy)

We take  $\sigma^2 = 0.3137^2$ .

### Getting $S_{XX}$

If you consider the data given by  $x_1, x_2, \ldots, x_n$  (Height values), you see that the sample variance of this data (which we denote by  $s_X^2$ ) is such that

$$s_X^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{S_{XX}}{n-1}.$$

# Getting $S_{XX}$

## [1] 7517.512

#### Getting $S_{XX}$

We take  $S_{XX} = 7517.512$ 

#### Putting it together

Using all this, we get the following Z-statistic:

$$z = \frac{0.052194 - 0}{0.3137/\sqrt{7517.512}} = 14.42591.$$

Since z > 1.96, we reject the null hypothesis that  $\beta_1 = 0$ .

#### Your turn

#### What to do

1. Construct a 95% confidence interval for the coefficient of Height in the model  $FVC_i = \beta_0 + \beta_1 Height_i + \varepsilon_i$ .

#### **Solutions:**

From above, we have that a 95% confidence interval will be given by

$$\hat{\beta}_1 \pm 1.96 \frac{\sigma}{\sqrt{S_{XX}}} \,.$$

Thus the 95% confidence interval is given by

$$0.052194 \pm 1.96 \times \frac{0.3137}{\sqrt{7517.512}} \approx (0.0451, 0.0593) \ .$$

2. Test the hypothesis that  $\beta_0 = -5$  at  $\alpha = 0.05$ .

#### **Solutions:**

Let's test the hypothesis (at  $\alpha = 0.05$ ) that

$$H_0: \beta_0 = -5.$$

What do we need:

- 1. Our best guess  $\hat{\beta}_0$ .
- 2. Our SE, which involves
- a.  $\sigma^2$ ,

b. 
$$S_{XX}$$
, c.  $\bar{x}$ .

The only thing we don't have from above is  $\bar{x}$ , which is found with

(xbar <- mean(fvc\$Height))</pre>

## [1] 152.5433

#### **Solutions:**

Putting this together, we get that

$$z = \frac{-5.064961 + 5}{0.3137\sqrt{\left(\frac{1}{127} + \frac{152.5433^2}{7517.512}\right)}} = -0.1175521.$$

Since |z| < 1.96, there is insignificant evidence to reject the null hypothesis are the 5% level.