Lesson 3: Afghan Schools (continued)

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Notation

Notation	Definition
i	group
j	observation
$y_{i,j}$	the response for the j^{th} observation from the i^{th}
	group
$ar{y}$	overall sample mean
$ar{y}_i$	sample mean of the i^{th} group
$\stackrel{\cdot}{n}$	total sample size
n_i	group size of the i^{th} group

Background

Recall that in Lesson 2 we analyzed a data set of 1394 school children in northwestern Afghanistan. Researchers grouped 31 villages into 11 equally sized village groups based on political and cultural alliances. Five of these village groups were then randomly assigned to establish a village based school.

```
library(tidyverse)
afghan = read_csv("https://raw.githubusercontent.com/jkstarling/MA376/main/afghan_school.csv")
```

Single Mean Model

A general single mean statistical model for predicting outcomes is:

$$y_{ij} = \mu + \epsilon_{ij}$$

 $\epsilon_{ij} \sim \text{iid } F(0, \sigma)$

For the Afghan Schools experiment, the fitted single mean model and the standard error of the residuals (SD of the response) are:

Predicted test score = $\hat{y}_i = 73.24$ points; SE of residuals = 11.14 points.

```
single.model = lm(test_score~1, data = afghan)
summary(single.model)
```

```
##
## Call:
## lm(formula = test_score ~ 1, data = afghan)
##
## Residuals:
## Min 1Q Median 3Q Max
## -16.244 -9.244 -1.244 7.756 23.756
##
```

Sum of squares total (SSTotal), Sum of squared error (SSError), and Standard Error of Residuals (SE)

The SSError (SSE) is the sum of the squared prediction errors (residuals) for a particular model.

$$SSError = \sum_{\rm all~obs} ({\rm observed~value~-~predicted~value})^2 = \sum_{\rm all~obs} residuals^2$$

The SSTotal (SST) represents the sum of squared difference between the observed values and the overall mean. Note that in the case of the single mean model, SSE = SST.

$$SSTotal = \sum_{\text{all observation}} (\text{observed value - overall mean})^2$$

The Standard Error of the residuals (SE) is an estimate of the standard deviation of the residuals $\epsilon_{i,j}$. In general, the formula for SE is the square root of the SSE divided by the degrees of freedom of our model (to get an unbiased estimate of σ^2 . The standard error of our residuals is one way to estimate how appropriate the model is for our data by comparing the SEs for different models.

$$SE = \sqrt{\frac{SSE}{degreesoffreedom}}$$

1) Calculate SSE for the single-means model and name it SSTotal.

```
ybar <- mean(afghan$test_score)
SSTotal <- sum( ( afghan$test_score - ybar)^2 )
SSTotal</pre>
```

[1] 172961.1

2) Calculate the standard error of the residuals and name it SE.single. How many degrees of freedom do we have with the single-means model?

```
n <- length(afghan$test_score)
dof.1 <- n - 1
SE.single <- sqrt(SSTotal/dof.1)
SE.single</pre>
```

[1] 11.14291

Multiple (Separate) Means Model

A general statistical model for predicting outcomes depending on which treatment group the experimental unit is assigned to is:

$$y_{ij} = \mu_i + \epsilon_{ij}$$
$$\epsilon_{ij} \sim \text{iid } F(0, \sigma)$$

For the Afghan Schools experiment, the fitted multiple means model and the standard error of the residuals are:

 $\text{Predicted Score} = \hat{y}_i = \left\{ \begin{array}{ll} 70.003 \text{ points,} & \text{if traditional school (Control)} \\ 76.485 \text{ points,} & \text{if village school (Treatment)} \end{array} \right.$

3) Recreate the multiple-means model in R that we did last class:

```
multi.model <- afghan %>% lm(test_score ~ 0 + as.factor(treatment), data = .)
summary(multi.model)
```

```
##
## Call:
## lm(formula = test_score ~ 0 + as.factor(treatment), data = .)
##
## Residuals:
##
       Min
                1Q Median
                                3Q
                                       Max
## -19.485 -9.003 -1.485
                             7.997
                                    26.997
##
## Coefficients:
##
                         Estimate Std. Error t value Pr(>|t|)
## as.factor(treatment)0
                           70.003
                                       0.404
                                               173.3
                                                        <2e-16 ***
## as.factor(treatment)1
                           76.485
                                       0.404
                                               189.3
                                                        <2e-16 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.66 on 1392 degrees of freedom
## Multiple R-squared: 0.9793, Adjusted R-squared: 0.9793
## F-statistic: 3.294e+04 on 2 and 1392 DF, p-value: < 2.2e-16
```

Effects Model

This section in our book also proposes another model (see p. 47). This model incorporates the **effect** of each treatment, where the **effect** is the difference of the mean response in the mean of each treatment group from the overall mean response. We can calculate the effect for each group by subtracting the overall mean from each group mean.

This model can be represented by:

$$y_{ij} = \mu + \alpha_i + \epsilon_{ij}$$
$$\alpha_i = \mu_1 - \mu$$
$$\epsilon_{ij} \sim \text{iid } F(0, \sigma)$$

How is this different than the multiple means model?

4) Calculate the effects for both treatments.

```
gp0 <- afghan %>% filter(treatment=="0")
gp1 <- afghan %>% filter(treatment=="1")
gp0.mean <- mean(gp0$test_score)
gp1.mean <- mean(gp1$test_score)
eff0 <- gp0.mean - ybar
eff1 <- gp1.mean - ybar
print(c(eff0, eff1))</pre>
```

```
## [1] -3.241033 3.241033
```

5) Create this model in R and assign it to eff.model. What do we notice about the values we see in the summary output?

```
afghan <- afghan %>% mutate(treatment1 = as.factor(treatment))
contrasts(afghan$treatment1) = contr.sum
eff.model <- afghan %>% lm(test_score~treatment1, data = .)
summary(eff.model)
```

```
##
## lm(formula = test_score ~ treatment1, data = .)
##
## Residuals:
               1Q Median
      Min
                               3Q
                                      Max
## -19.485 -9.003 -1.485
                            7.997 26.997
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 73.2439
                           0.2856 256.42
                                            <2e-16 ***
```

```
## treatment11 -3.2410    0.2856 -11.35    <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.66 on 1392 degrees of freedom
## Multiple R-squared: 0.08466,    Adjusted R-squared: 0.084
## F-statistic: 128.7 on 1 and 1392 DF, p-value: < 2.2e-16</pre>
```

We should get the result: (check the values for contrasts in the afghan dataframe)

$$\text{Predicted Test Score} = \hat{y}_i = 73.24 + \left\{ \begin{array}{ll} -3.24, \text{ points,} & \text{if traditional school (Control)} \\ 3.24, \text{ points,} & \text{if village school (Treatment)} \end{array} \right.$$

To see what this model is fitting, consider the model:

$$y_{ij} = \mu + \alpha_i \, x_{ij} + \epsilon_{ij}$$

 $x_{ij} = 1$ if observation j is from a government school, -1 if observation j is from a village school

$$\epsilon_{ij} \sim \text{iid } F(0,\sigma)$$

Alternative (base R model)

If we had created a model using only the linear model where the **treatment** is a categorical variable, we will get the following model:

$$y_{ij} = \mu + \beta \, x_{ij} + \epsilon_{ij}$$

$$x_{ij} = 1 \text{ if observation } j \text{ is from a village school, 0 otherwise}$$

$$\epsilon_{ij} \sim \text{iid } F(0,\sigma)$$

7) Create a model with treatment as a categorical variable and assign it to base.model. What is μ ?

```
base.model <- afghan %>% lm(test_score~as.factor(treatment), data = .)
summary(base.model)
```

```
##
## lm(formula = test_score ~ as.factor(treatment), data = .)
##
## Residuals:
      Min
                1Q Median
                                3Q
                                       Max
## -19.485 -9.003 -1.485
                            7.997
                                    26.997
##
## Coefficients:
##
                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                         70.0029
                                      0.4040
                                              173.29
                                                       <2e-16 ***
## as.factor(treatment)1
                         6.4821
                                      0.5713
                                               11.35
                                                       <2e-16 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 10.66 on 1392 degrees of freedom
## Multiple R-squared: 0.08466,
                                    Adjusted R-squared: 0.084
## F-statistic: 128.7 on 1 and 1392 DF, p-value: < 2.2e-16
```

8) Calculate and verify that the SE for the multiple means model is 10.66 points. Name the output SE.multi. What is the degrees of freedom for this model? What does this mean in relation to the two models?*

```
SSE0 <- sum((gp0$test_score - gp0.mean)^2)
SSE1 <- sum((gp1$test_score - gp1.mean)^2)
SSError <- SSE0 + SSE1

dof.2 <- n - 2
SE.multi <- sqrt(SSError / dof.2)
SE.multi</pre>
```

[1] 10.66463

Sum of squares model (SSModel).

The SSModel measures the variation in the group means from the overall mean. This is also referred to as the sum of squares for the treatment.

$$SSModel = \sum_{\text{all observation}} (\text{group mean - overall mean})^2 = \sum_{allgroups} (\text{group size}) \times (effect)^2$$

9) Calculate SSModel. Hint use fitted values from the multiple means model.

```
#summing across observations
SSModel <- sum((multi.model$fitted.values - ybar)^2)

# or...
SSModel <- length(gp0$test_score) * eff0^2 + length(gp1$jerib_cnt) * eff1^2
SSModel</pre>
```

[1] 14642.99

10) Verify your sum of squares calculations by ensuring the SSTotal = SSError + SSModel below.

SSTotal == SSError + SSModel

[1] TRUE

To summarize these calculations:

$$SSTotal = SSModel + SSError,$$

and given degrees of freedom (df) for a sum of squares calculation is the number of data points minus the number of parameters we need to estimate, i.e.,

$$df(SSTotal) = df(SSModel) + df(SSError)$$

Degrees of freedom represents the number of independent values in a sum.

Note: these output (SST, SSM, SSE and their df) are given in what is known as an ANOVA (analysis of variance) table. More on this will come later in the course.

Coefficient of Determination (R^2)

The **coefficient of determination**, R^2 , is the proportion of the total variation in the response variable which is explained by the explanatory variable(s) in the model. Note that $0 < R^2 < 1$. Larger values of R^2 indicate that more of the variation in the response is explained by the explanatory variable(s).

$$R^2 = \frac{\text{SSModel}}{\text{SSTotal}} = 1 - \frac{\text{SSError}}{\text{SSTotal}}$$

11) Calculate the R^2 for the multiple means model.

rsquared <- SSModel / SSTotal rsquared

[1] 0.08466059

1-(SSError/SSTotal)

[1] 0.08466059

Note: We should NOT use the Rsquared value from the model without the intercept (separate means models).

References

Burde, Dana, and Leigh L Linden. "Bringing Education to Afghan Girls: A Randomized Controlled Trial of Village-Based Schools." American Economic Journal: Applied Economics 5, no. 3 (July 2013): 27–40. https://doi.org/10.1257/app.5.3.27.