PSTAT 126 - Assignment 2 Fall 2022

Kayla Katakis

Note: Submit both your Rmd and generated pdf file to Canvas. Use the same indentation level as Solution markers to write your solutions. Improper indentation will break your document.

library(alr4)
library(ggplot2)
data(UN11)

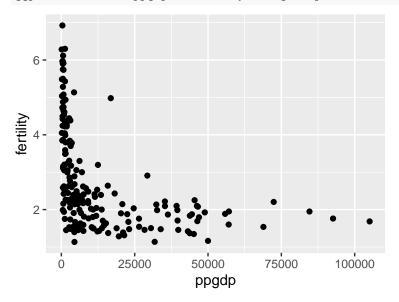
- 1. The data set UN11 in the alr4 package contains several variables, including ppgdp, the gross national product per person in U.S. dollars, and fertility, the birth rate per 1000 females, from the year 2009. The data are for 199 localities, and we will study the regression of fertility on ppgdp.
- (a) Identify the predictor and response.

Solution: The predictor is ppgdp, and the response is fertility.

(b) Draw the scatterplot of fertility against ppgdp and describe the relationship between these two variables. Is the trend linear?

Solution: The trend is not linear, it appears to be negatively exponential. As fertility increases, ppgdp decreases dramatically.

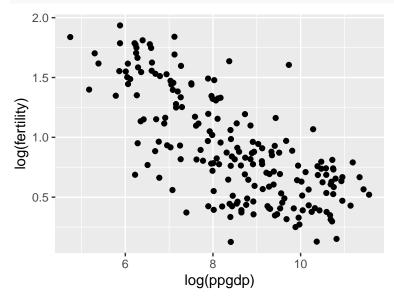
ggplot(UN11, aes(ppgdp, fertility)) + geom_point()



(c) Replace both variables by their natural logarithms and draw another scatterplot. Does the simple linear regression model seem plausible for a summary of this graph?

Solution: The simple linear regression model definitely seems more plausible, as taking the natural log of each variable resulyts in a more linear relationship with a clearer slope and intercept.

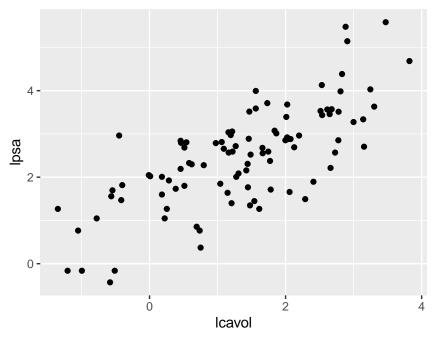
ggplot(UN11, aes(log(ppgdp),log(fertility))) + geom_point()



- 2. The data set prostate in the faraway package is from a study of 97 men with prostate cancer. Interest is in predicting lpsa (log prostate specific antigen) with lcavol (log cancer volume). You may not use the function lm for this question.
- (a) Draw a scatterplot does a simple linear regression model seem reasonable?

Solution: A simple linear regression model seems reasonable; there is a clear positive linear relationship

```
data("prostate", package = "faraway")
View(prostate)
ggplot(prostate, aes(lcavol, lpsa)) + geom_point()
```



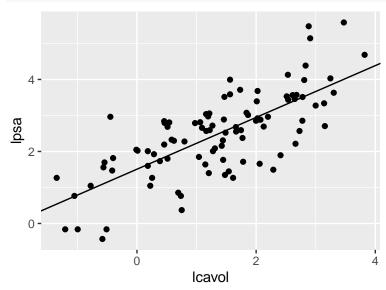
(b) Compute the values $\bar{x}, \bar{y}, S_{xx}, S_{yy}$ and S_{xy} . Compute the ordinary least squares estimates of the intercept and slope for the simple linear regression model, and draw the fitted line on your plot from part a).

Solution:

```
xbar = mean(prostate$lcavol)
ybar = mean(prostate$lpsa)
sxx = sum((prostate$lcavol - xbar)**2)
syy = sum((prostate$lpsa - ybar)**2)
sxy = sum((prostate$lcavol - xbar)*(prostate$lpsa - ybar))

OLS_b1 = sxy/sxx
OLS_b0 = ybar - OLS_b1*xbar

ggplot(prostate, aes(lcavol, lpsa)) + geom_point()+ geom_abline(aes(intercept=OLS_b0, slope = OLS_b1))
```



(c) Compute $\hat{\sigma}^2$ and find the estimated standard errors of $\hat{\beta}_0$ and $\hat{\beta}_1$. Also find the estimated covariance between $\hat{\beta}_0$ and $\hat{\beta}_1$.

Solution: Note that $E(\hat{\sigma}^2) = \sigma^2$

```
error = prostate$lpsa - (OLS_b0 +OLS_b1*prostate$lcavol)
RSS = sum(error**2)
sigma2hat = (1/nrow(prostate)-2)*RSS

se_b0 = sigma2hat*((1/nrow(prostate))+(xbar**2/sxx))
se_b1 = sigma2hat/sxx
covb0b1 = ((-xbar*sigma2hat)/sxx)
```

(d) Carry out t-tests for the two null hypotheses $\beta_0 = 0$ and $\beta_1 = 0$, reporting the value of the test statistic and a p-value in each case.

Solution: In both cases, where $\beta_0 = 0$ and $\beta_1 = 0$, as seen in the model, the p-values are the same at 2.2e-16.

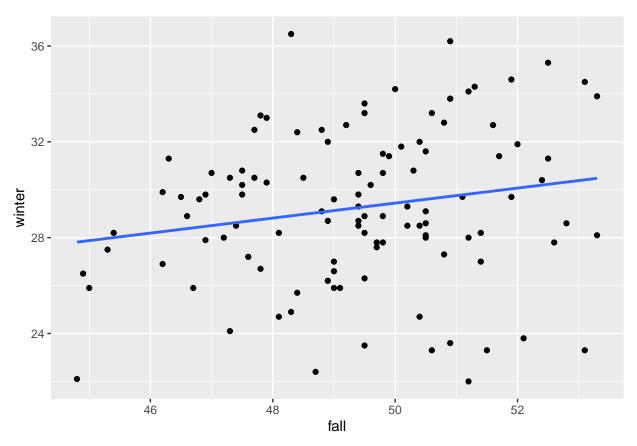
```
model_prostate <- lm(lpsa~lcavol, prostate)
summary(model_prostate)</pre>
```

Call:

```
## lm(formula = lpsa ~ lcavol, data = prostate)
##
## Residuals:
##
                                    3Q
       Min
                  1Q
                      Median
                                            Max
##
   -1.67625 -0.41648
                     0.09859
                              0.50709
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.50730
                           0.12194
                                     12.36
                                             <2e-16 ***
## lcavol
                0.71932
                           0.06819
                                     10.55
                                             <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.7875 on 95 degrees of freedom
## Multiple R-squared: 0.5394, Adjusted R-squared: 0.5346
## F-statistic: 111.3 on 1 and 95 DF, p-value: < 2.2e-16
```

- 3. The data set ftcollinstemp in the alr4 package gives the mean temperature in the fall of each year, defined as September 1 to November 30, and the mean temperature in the following winter, defined as December 1 to the end of February in the following calendar year, in degrees Fahrenheit, for Ft. Collins, CO (Colorado Climate Center, 2012). These data cover the time period from 1900 to 2010. The question of interest is: Does the average fall temperature predict the average winter temperature?
- (a) Use the 1m function in R to fit the regression of the response on the predictor. Draw a scatterplot of the data and add your fitted regression line.

```
Solution:
data("ftcollinstemp", package = 'alr4')
temp_lm <- lm(winter ~ fall, ftcollinstemp)</pre>
summary(temp lm)
##
## Call:
## lm(formula = winter ~ fall, data = ftcollinstemp)
##
## Residuals:
##
       Min
                1Q Median
                                3Q
                                       Max
##
   -7.8186 -1.7837 -0.0873
                           2.1300
                                    7.5896
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 13.7843
                            7.5549
                                     1.825
                                              0.0708 .
## fall
                 0.3132
                            0.1528
                                     2.049
                                             0.0428 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 3.179 on 109 degrees of freedom
## Multiple R-squared: 0.0371, Adjusted R-squared: 0.02826
                  4.2 on 1 and 109 DF, p-value: 0.04284
## F-statistic:
ggplot(ftcollinstemp, aes(fall, winter)) + geom_point() + stat_smooth(method = 'lm', se = FALSE)
## `geom_smooth()` using formula 'y ~ x'
```



(b) Test the null hypothesis that the slope is 0 against a two-sided alternative at $\alpha = 0.01$, and interpret your findings.

Solution: The *p*-value corresponding to β_1 , or the change in rate of winter temperatures as fall temperatures increase, is 0.0428. At $\alpha = 0.01$, this value is not significant, so we fail reject the null hypothesis that the slope is 0, which implies that fall temperatures are not a significant predictor of winter temperatures.

(c) What percentage of the variability in winter is explained by fall?

Solution: The R^2 value given by the model is 0.0371, which implies that approximately 3.7% of the variability in winter temperatures is explained by fall temperatures.