MSDS 5043 - Assignment 7

Olivia Samples, Lipscomb University

10/24/2019

Question 1: Exercise 8.3

(a) $\hat{y} = -80.41 + 0.44x_1 - 3.33x_2 - 0.01x_3 + 1.15x_4 + 0.05x_5 - 8.40x_6$, where x_1 = gestation, x_2 = parity, x_3 = age, x_4 = height, x_5 = weight, and x_6 = smoke.

(b) According to the model, the slopes are interpreted as follows:
Gestation- As the length of pregnancy increases by one day, the baby's weight will increase by 0.44 ounces.

Age- As the mother's age in years increases by a year, the baby's weight decreases by 0.01 ounces.

(c) There is a difference here because other factors are determining the baby's weight that allow us to measure each coefficient more accurately.

(d)

```
actual <- 120

model <- -80.41 + 0.44*284 - 3.33*0 - 0.01*27 + 1.15*62 + 0.05*100 -8.40*0

residual <- actual - model
residual
```

```
## [1] -0.58
```

And so, the residual for the first observation in the data set in reference to our model is -.58.

(e) We have the following formula for R^2 and adjusted R^2.

$R^2 = 1 - \frac{Var(e_i)}{Var(y_i)}$

$R^2_{adj} = 1 - \frac{Var(e_i)}{Var(y_i)} * \frac{n-1}{n-k-1}$

Now we will use our given variables to solve:

```
#given
vare <- 249.28
vary <- 332.57
n <- 1236
k <- 6

#calculate R^2
r2 <- 1 - (vare/vary)
r2
```

```
## [1] 0.2504435
```

```
#calculate R^2 adjusted
r2adj <- 1 - (vare/vary) * ((n-1)/(n-k-1))
r2adj
```

```
## [1] 0.2467842
```

Question 2: Exercise 8.5

(a) We will need the coefficient of gender, a calculated t-score for degrees of freedom = 54, and the standard error of gender.

```
#coefficient of gender
b4 <- -0.08

#t-score
t <- qt(.05, 54, lower.tail = FALSE)

#standard error
se <- 0.12

#confidence interval
lower <- b4 - t*se
upper <- b4 + t*se
c(lower, upper)
```

```
## [1] -0.2808278  0.1208278
```

In other words, we are 95% confident that the true gender coefficient falls within (-0.2808278, 0.1208278).

(b) Yes, because each of the variables' p-values are relatively high, meaning they are not very statistically significant. This can also mean that the coefficient could be equal to zero, taking no effect on the students GPA. In other words, I would expect the remaining variables' 95% confidence interval to include zero because their corresponding p-values are greater than 0.05.

Question 3: Exercise 8.8

The model with the largest adjusted R^2 determines this. In this case, when we remove the learner status, the model has the highest adjusted R^2 of all the models. In other worsds, we should remove the learner status variable from the model first.

Question 4: Exercise 8.10

We should add the variable that is statistically significant and has the highest adjusted R^2 value. In this case, Ethnicity has a low p-value (< 0.05) and a high adjusted R^2 value, meaning that it is statistically significant and it should be the first variable added to the model.

Question 5

Many college courses conclude by giving students the opportunity to evaluate the course and the instructor anonymously. However, the use of these student evaluations as an indicator of course quality and teaching effectiveness is often criticized because these measures may reflect the influence of non-teaching related characteristics, such as the physical appearance of the instructor. The article titled, "Beauty in the classroom: instructors' pulchritude and putative pedagogical productivity" (Hamermesh and Parker, 2005) found that instructors who are viewed to be better looking receive higher instructional ratings

The data were gathered from end of semester student evaluations for a large sample of professors from the University of Texas at Austin. In addition, six students rated the professors' physical appearance. ‡ The result is a data frame where each row contains a different course and columns represent variables about the courses and professors.

```
download.file ( "http://www.openintro.org/stat/data/evals.RData" , destfile =
"evals.RData" )
load ( "evals.RData" )
```

Let's run the model...

```
m_full <- lm ( score ~ rank + ethnicity + gender + language + age + cls_perc_eval
+ cls_students + cls_level + cls_profs + cls_credits + bty_avg
+ pic_outfit + pic_color , data = evals )
summary ( m_full )
```

```
##
## Call:
## lm(formula = score ~ rank + ethnicity + gender + language + age +
##     cls_perc_eval + cls_students + cls_level + cls_profs + cls_credits +
##     bty_avg + pic_outfit + pic_color, data = evals)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.77397 -0.32432  0.09067  0.35183  0.95036
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           4.0952141  0.2905277  14.096  < 2e-16 ***
## ranktenure track     -0.1475932  0.0820671  -1.798  0.07278 .
## ranktenured          -0.0973378  0.0663296  -1.467  0.14295
## ethnicitynot minority  0.1234929  0.0786273   1.571  0.11698
## gendermale            0.2109481  0.0518230   4.071 5.54e-05 ***
## languagenon-english  -0.2298112  0.1113754  -2.063  0.03965 *
## age                  -0.0090072  0.0031359  -2.872  0.00427 **
## cls_perc_eval         0.0053272  0.0015393   3.461  0.00059 ***
## cls_students          0.0004546  0.0003774   1.205  0.22896
## cls_levelupper        0.0605140  0.0575617   1.051  0.29369
## cls_profssingle      -0.0146619  0.0519885  -0.282  0.77806
## cls_creditsone credit  0.5020432  0.1159388   4.330 1.84e-05 ***
## bty_avg               0.0400333  0.0175064   2.287  0.02267 *
## pic_outfitnot formal -0.1126817  0.0738800  -1.525  0.12792
## pic_colorcolor       -0.2172630  0.0715021  -3.039  0.00252 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.498 on 448 degrees of freedom
## Multiple R-squared:  0.1871, Adjusted R-squared:  0.1617
## F-statistic: 7.366 on 14 and 448 DF,  p-value: 6.552e-14
```

5.1 (20 points)

Using backward-selection and p-value as the selection criterion, determine the best model. You do not need to show all steps in your answer, just the output for the final model. Also, write out the linear model for predicting score based on the final model you settle on.

```
step(m_full, direction = "backward", test = "F")
```

```
## Start:  AIC=-630.9
## score ~ rank + ethnicity + gender + language + age + cls_perc_eval +
##     cls_students + cls_level + cls_profs + cls_credits + bty_avg +
##     pic_outfit + pic_color
##
##                 Df Sum of Sq    RSS     AIC F value    Pr(>F)
```

```
## - cls_profs      1    0.0197 111.11 -632.82  0.0795 0.7780566
## - cls_level      1    0.2740 111.36 -631.76  1.1052 0.2936925
## - cls_students   1    0.3599 111.44 -631.40  1.4513 0.2289607
## - rank           2    0.8930 111.98 -631.19  1.8007 0.1663804
## <none>                       111.08 -630.90
## - pic_outfit     1    0.5768 111.66 -630.50  2.3262 0.1279153
## - ethnicity      1    0.6117 111.70 -630.36  2.4668 0.1169791
## - language       1    1.0557 112.14 -628.52  4.2576 0.0396509 *
## - bty_avg        1    1.2967 112.38 -627.53  5.2294 0.0226744 *
## - age            1    2.0456 113.13 -624.45  8.2499 0.0042688 **
## - pic_color      1    2.2893 113.37 -623.46  9.2328 0.0025162 **
## - cls_perc_eval  1    2.9698 114.06 -620.69 11.9769 0.0005903 ***
## - gender         1    4.1085 115.19 -616.09 16.5694 5.544e-05 ***
## - cls_credits    1    4.6495 115.73 -613.92 18.7510 1.839e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Step:  AIC=-632.82
## score ~ rank + ethnicity + gender + language + age + cls_perc_eval +
##     cls_students + cls_level + cls_credits + bty_avg + pic_outfit +
##     pic_color
##
##                 Df Sum of Sq    RSS     AIC F value    Pr(>F)
## - cls_level      1    0.2752 111.38 -633.67  1.1121 0.2922000
## - cls_students   1    0.3893 111.49 -633.20  1.5733 0.2103843
## - rank           2    0.8939 112.00 -633.11  1.8063 0.1654529
## <none>                       111.11 -632.82
## - pic_outfit     1    0.5574 111.66 -632.50  2.2527 0.1340803
## - ethnicity      1    0.6728 111.78 -632.02  2.7191 0.0998556 .
## - language       1    1.0442 112.15 -630.49  4.2199 0.0405303 *
## - bty_avg        1    1.2872 112.39 -629.49  5.2018 0.0230315 *
## - age            1    2.0422 113.15 -626.39  8.2529 0.0042616 **
## - pic_color      1    2.3457 113.45 -625.15  9.4795 0.0022052 **
## - cls_perc_eval  1    2.9502 114.06 -622.69 11.9224 0.0006072 ***
## - gender         1    4.0895 115.19 -618.08 16.5265 5.665e-05 ***
## - cls_credits    1    4.7999 115.90 -615.24 19.3974 1.329e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Step:  AIC=-633.67
## score ~ rank + ethnicity + gender + language + age + cls_perc_eval +
##     cls_students + cls_credits + bty_avg + pic_outfit + pic_color
##
##                 Df Sum of Sq    RSS     AIC F value    Pr(>F)
## - cls_students   1    0.2459 111.63 -634.65  0.9934 0.3194514
## - rank           2    0.8140 112.19 -634.30  1.6443 0.1943109
## <none>                       111.38 -633.67
## - pic_outfit     1    0.6618 112.04 -632.93  2.6736 0.1027219
## - ethnicity      1    0.8698 112.25 -632.07  3.5142 0.0614914 .
## - language       1    0.9015 112.28 -631.94  3.6423 0.0569659 .
## - bty_avg        1    1.3694 112.75 -630.02  5.5329 0.0190925 *
## - age            1    1.9342 113.31 -627.70  7.8147 0.0054040 **
## - pic_color      1    2.0777 113.46 -627.12  8.3942 0.0039478 **
## - cls_perc_eval  1    3.0290 114.41 -623.25 12.2380 0.0005148 ***
```

```
## - gender         1    3.8989 115.28 -619.74 15.7525 8.400e-05 ***
## - cls_credits    1    4.5296 115.91 -617.22 18.3006 2.306e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Step:  AIC=-634.65
## score ~ rank + ethnicity + gender + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_outfit + pic_color
##
##                 Df Sum of Sq    RSS     AIC F value    Pr(>F)
## - rank           2    0.7892 112.42 -635.39  1.5943 0.2041875
## <none>                       111.63 -634.65
## - ethnicity      1    0.8832 112.51 -633.00  3.5683 0.0595353 .
## - pic_outfit     1    0.9700 112.60 -632.65  3.9191 0.0483466 *
## - language       1    1.0338 112.66 -632.38  4.1769 0.0415580 *
## - bty_avg        1    1.5783 113.20 -630.15  6.3770 0.0119026 *
## - pic_color      1    1.9477 113.57 -628.64  7.8693 0.0052456 **
## - age            1    2.1163 113.74 -627.96  8.5504 0.0036285 **
## - cls_perc_eval  1    2.7922 114.42 -625.21 11.2814 0.0008493 ***
## - gender         1    4.0945 115.72 -619.97 16.5430 5.613e-05 ***
## - cls_credits    1    4.5163 116.14 -618.29 18.2472 2.368e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Step:  AIC=-635.39
## score ~ ethnicity + gender + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_outfit + pic_color
##
##                 Df Sum of Sq    RSS     AIC F value    Pr(>F)
## <none>                       112.42 -635.39
## - pic_outfit     1    0.7141 113.13 -634.46  2.8775 0.0905102 .
## - ethnicity      1    1.1790 113.59 -632.56  4.7508 0.0297983 *
## - language       1    1.3403 113.75 -631.90  5.4010 0.0205673 *
## - age            1    1.6847 114.10 -630.50  6.7888 0.0094749 **
## - pic_color      1    1.7841 114.20 -630.10  7.1895 0.0076009 **
## - bty_avg        1    1.8553 114.27 -629.81  7.4762 0.0064972 **
## - cls_perc_eval  1    2.9147 115.33 -625.54 11.7455 0.0006655 ***
## - gender         1    4.0577 116.47 -620.97 16.3513 6.184e-05 ***
## - cls_credits    1    6.1208 118.54 -612.84 24.6649 9.681e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Call:
## lm(formula = score ~ ethnicity + gender + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_outfit + pic_color, data = evals)
##
## Coefficients:
##          (Intercept)  ethnicitynot minority            gendermale
##             3.907030               0.163818              0.202597
##   languagenon-english                    age         cls_perc_eval
##            -0.246683              -0.006925              0.004942
## cls_creditsone credit                bty_avg   pic_outfitnot formal
##             0.517205               0.046732             -0.113939
```

```
##        pic_colorcolor
##             -0.180870
```

We will go one step further by eliminating the pic_outfit variable due to its high p-value. And so our final model is as follows:

```r
fm <- lm(score ~ ethnicity + gender + language + age + cls_perc_eval +
    cls_credits + bty_avg + pic_color, data = evals)
summary(fm)
```

```
##
## Call:
## lm(formula = score ~ ethnicity + gender + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_color, data = evals)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.85320 -0.32394  0.09984  0.37930  0.93610
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           3.771922   0.232053  16.255  < 2e-16 ***
## ethnicitynot minority  0.167872   0.075275   2.230  0.02623 *
## gendermale            0.207112   0.050135   4.131 4.30e-05 ***
## languagenon-english  -0.206178   0.103639  -1.989  0.04726 *
## age                  -0.006046   0.002612  -2.315  0.02108 *
## cls_perc_eval         0.004656   0.001435   3.244  0.00127 **
## cls_creditsone credit  0.505306   0.104119   4.853 1.67e-06 ***
## bty_avg               0.051069   0.016934   3.016  0.00271 **
## pic_colorcolor       -0.190579   0.067351  -2.830  0.00487 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4992 on 454 degrees of freedom
## Multiple R-squared:  0.1722, Adjusted R-squared:  0.1576
## F-statistic:  11.8 on 8 and 454 DF,  p-value: 2.58e-15
```

And so, the final model for predicting the professor rating, $\hat{y}$, can be written like this: $\hat{y} = 3.772 + 0.168x_1 + 0.207x_2 - 0.206x_3 - 0.006x_4 + 0.005x_5 + 0.505x_6 + 0.051x_7 - 0.191x_9$, where x_1 = ethnicity, x_2 = gender, x_3 = non-english language, x_4 = age, x_5 = percentage of class evaluated, x_6 = class credits, x_7 = beauty average, and x_8 = picture color.

5.2 (10 points)

Based on your final model, describe the characteristics of a professor and course at University of Texas at Austin that would be associated with a high evaluation score.

The characteristics of a professor and a course at UT at Austin that would be associated with a high evaluation score according to our model include: non-minority, male, english speaker, young, large majority of class evaluations, one credit class, attractive, and their picture not in color. A professor containing all of these qualities (optimized) would have the best score.

5.3 (10 points)

Would you be comfortable generalizing your conclusions to apply to professors generally (at any university)? Why or why not?

No, because the University of Texas at Austin has its own particular demographic that would not be similar to many colleges in the US and all over the world. Changing universities would also change the significance of each variable in regards to professor ratings.