Lab 8

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April 3, 2016

Grading the professor

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. (Daniel S. Hamermesh, Amy Parker, Beauty in the classroom: instructors pulchritude and putative pedagogical productivity, *Economics of Education Review*, Volume 24, Issue 4, August 2005, Pages 369-376, ISSN 0272-7757, 10.1016/j.econedurev.2004.07.013. http://www.sciencedirect.com/science/article/pii/S0272775704001165.)

In this lab we will analyze the data from this study in order to learn what goes into a positive professor evaluation.

The data

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. (This is aslightly modified version of the original data set that was released as part of the replication data for *Data Analysis Using Regression and Multilevel/Hierarchical Models* (Gelman and Hill, 2007).) The result is a data frame where each row contains a different course and columns represent variables about the courses and professors.

```
load("~/R/win-library/3.2/IS606/labs/lab8/more/evals.RData")
```

variable	description
`score`	average professor evaluation score: (1) very unsatisfactory - (5) excellent.
`rank`	rank of professor: teaching, tenure track, tenured.
`ethnicity`	ethnicity of professor: not minority, minority.
`gender`	gender of professor: female, male.
`language`	language of school where professor received education: english or non-english.
`age`	age of professor.
`cls_perc_eval`	percent of students in class who completed evaluation.
`cls_did_eval`	number of students in class who completed evaluation.
`cls_students`	total number of students in class.
`cls_level`	class level: lower, upper.
`cls_profs`	number of professors teaching sections in course in sample: single, multiple.
`cls_credits`	number of credits of class: one credit (lab, PE, etc.), multi credit.
`bty_f1lower`	beauty rating of professor from lower level female: (1) lowest - (10) highest.
`bty_f1upper`	beauty rating of professor from upper level female: (1) lowest - (10) highest.
`bty_f2upper`	beauty rating of professor from second upper level female: (1) lowest - (10) highest.
`bty_m1lower`	beauty rating of professor from lower level male: (1) lowest - (10) highest.
`bty_m1upper`	beauty rating of professor from upper level male: (1) lowest - (10) highest.
`bty_m2upper`	beauty rating of professor from second upper level male: (1) lowest - (10) highest.

variable	description
`bty_avg`	average beauty rating of professor.
`pic_outfit`	outfit of professor in picture: not formal, formal.
`pic_color`	color of professor's picture: color, black & white.

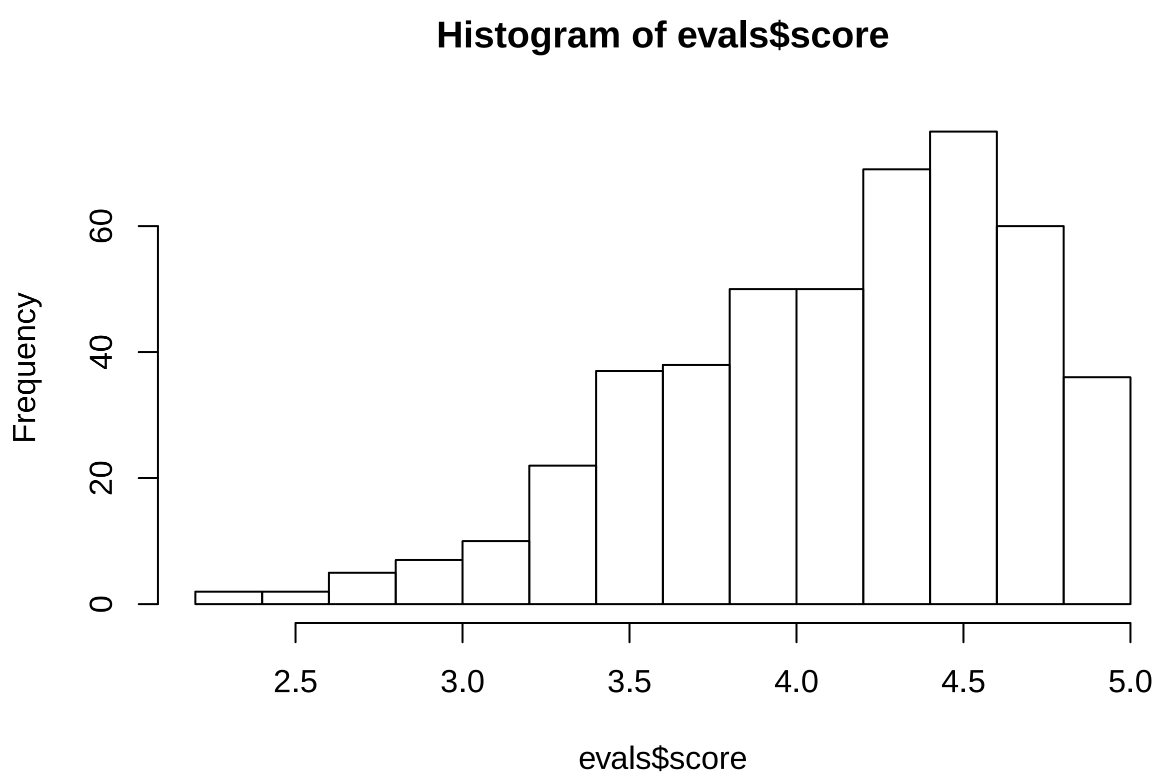
Exploring the data

1. Is this an observational study or an experiment? The original research question posed in the paper is whether beauty leads directly to the differences in course evaluations. Given the study design, is it possible to answer this question as it is phrased? If not, rephrase the question.

- I would say that this is an experiment. We are not just going our an watching people to get our data, the participants are filling out a survey. I don't think we can answer the question as is with the data. I would word it as "Does professor attractivness have an effect on ratings."

2. Describe the distribution of `score`. Is the distribution skewed? What does that tell you about how students rate courses? Is this what you expected to see? Why, or why not?

```
hist(evals$score)
```



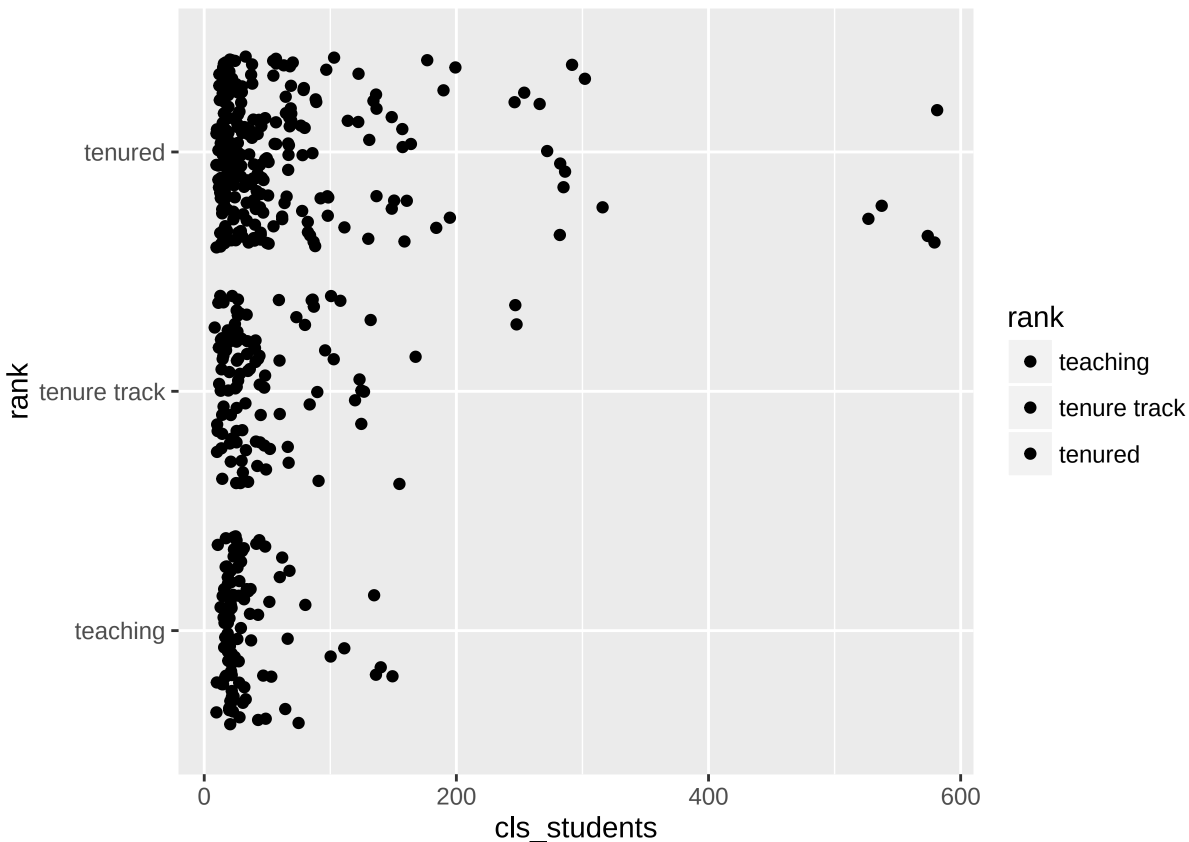
- The score data is heavily skewed to the left. It shows that students tend to rate their course pretty high. This is not a surprise to me, because when I was filling out my teach evaluations, I pretty much gave them a high rating, because I didn't want to get the prof in trouble for a bad rating, or I just didn't care and gave all 5's.

3. Excluding `score`, select two other variables and describe their relationship using an appropriate visualization (scatterplot, side-by-side boxplots, or mosaic plot).

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.2.4
```

```
ggplot(evals, aes(x=cls_students, y=rank, fill = rank)) + geom_jitter()
```

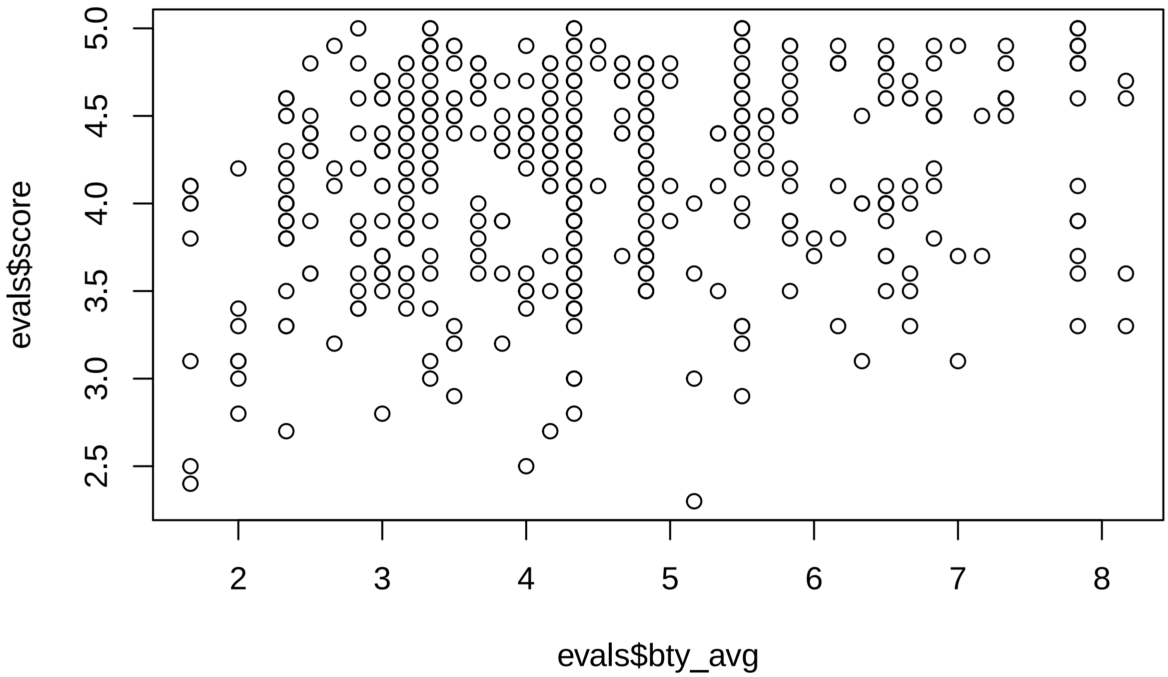


- I choose the rank of the professor and the amount of students they have in class. You can see by the jitter plot that a tenured teacher has more sutdents then the other two, followed by the tenure trac professors and the normal teachers last. It shows that the more experienced the prof, the more students they get in their classes.

Simple linear regression

The fundamental phenomenon suggested by the study is that better looking teachers are evaluated more favorably. Let's create a scatterplot to see if this appears to be the case:

```
plot(evals$score ~ evals$bty_avg)
```

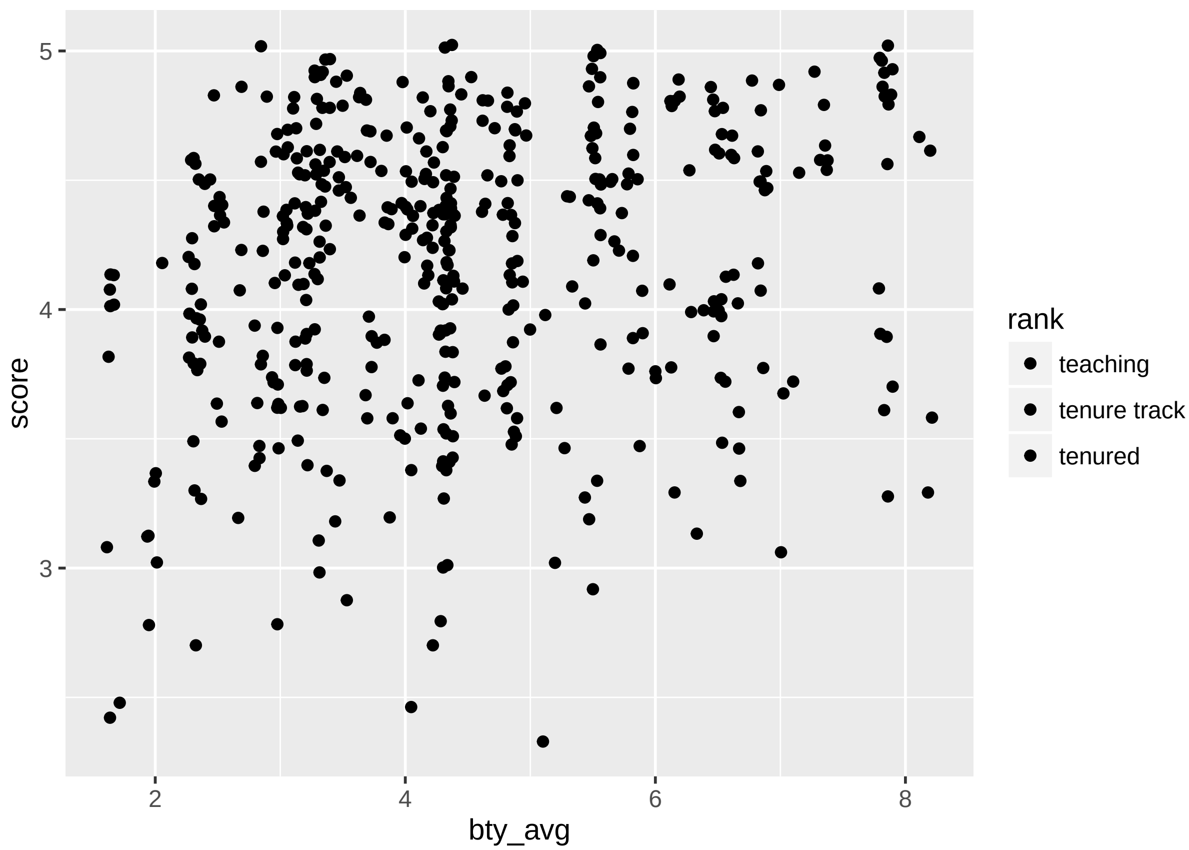


Before we draw conclusions about the trend, compare the number of observations in the data frame with the approximate number of points on the scatterplot. Is anything awry?

- There appears to be less plots on the scatter plot then the number of observations

4. Replot the scatterplot, but this time use the function `jitter()` on the y- or the x-coordinate. (Use `?jitter` to learn more.) What was misleading about the initial scatterplot?

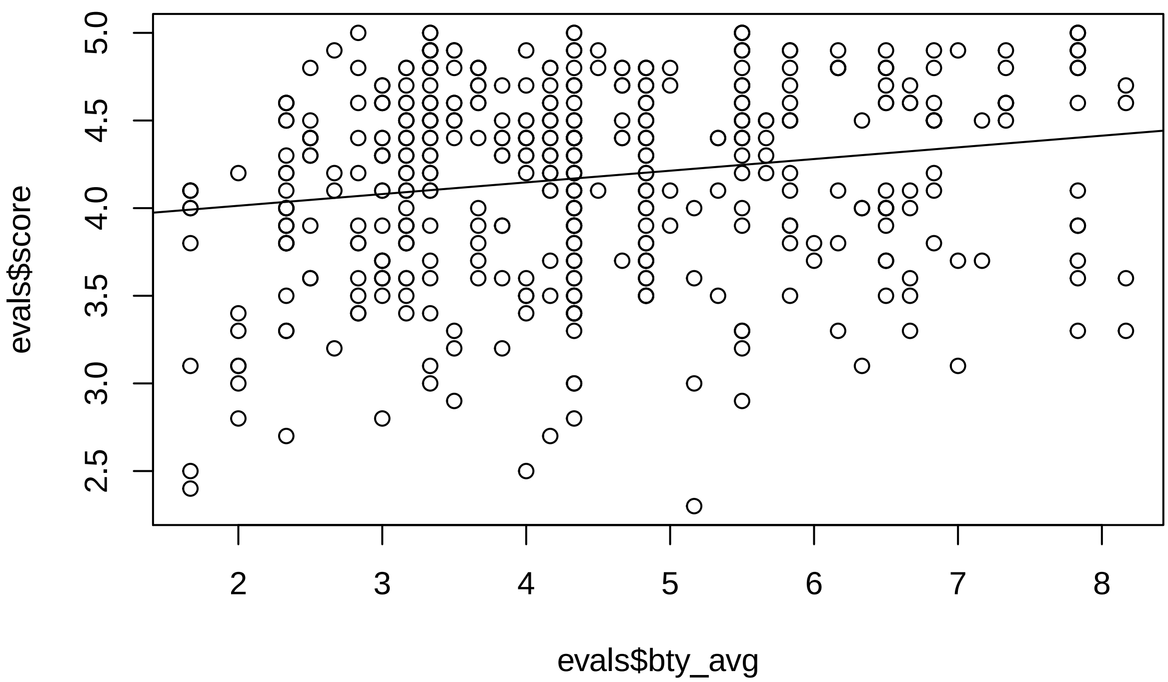
```
ggplot(evals, aes(x=bty_avg, y=score, fill = rank)) + geom_jitter()
```



- There was less points then the number of observations. I didn't show the full spread of the data.

5. Let's see if the apparent trend in the plot is something more than natural variation. Fit a linear model called `m_bty` to predict average professor score by average beauty rating and add the line to your plot using `abline(m_bty)`. Write out the equation for the linear model and interpret the slope. Is average beauty score a statistically significa nt predictor? Does it appear to be a practically significant predictor?

```
m_bty <- lm(score ~ bty_avg, data=evals)
plot(x=evals$bty_avg, y=evals$score)
abline(m_bty)
```




```r
summary(m_bty)
```

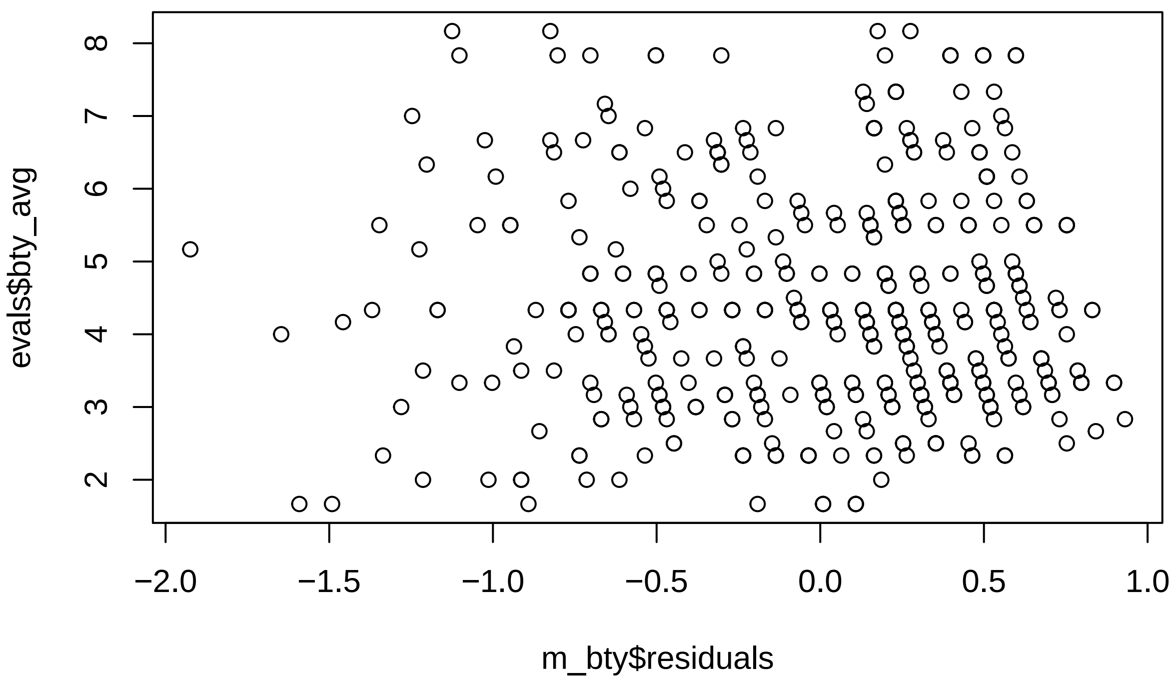
```
##
## Call:
## lm(formula = score ~ bty_avg, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.9246 -0.3690  0.1420  0.3977  0.9309
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.88034    0.07614   50.96  < 2e-16 ***
## bty_avg      0.06664    0.01629    4.09 5.08e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5348 on 461 degrees of freedom
## Multiple R-squared:  0.03502,    Adjusted R-squared:  0.03293
## F-statistic: 16.73 on 1 and 461 DF,  p-value: 5.083e-05
```

$$\hat{y} = 3.88034 + 0.06664 * bty_avg$$

- The slope is telling us that for every 1 more beauty point the teach has, they will get .06664 more of a rating. The R^2 value of the graph is only .03502. That is not a very good correlation so I would say that this is not a good predictor.

6. Use residual plots to evaluate whether the conditions of least squares regression are reasonable. Provide plots and comments for each one (see the Simple Regression Lab for a reminder of how to make these).

```
plot(x=m_bty$residuals, y=evals$bty_avg)
abline(h = 0, lty = 3)
```



- The residuals are not evenly spread out

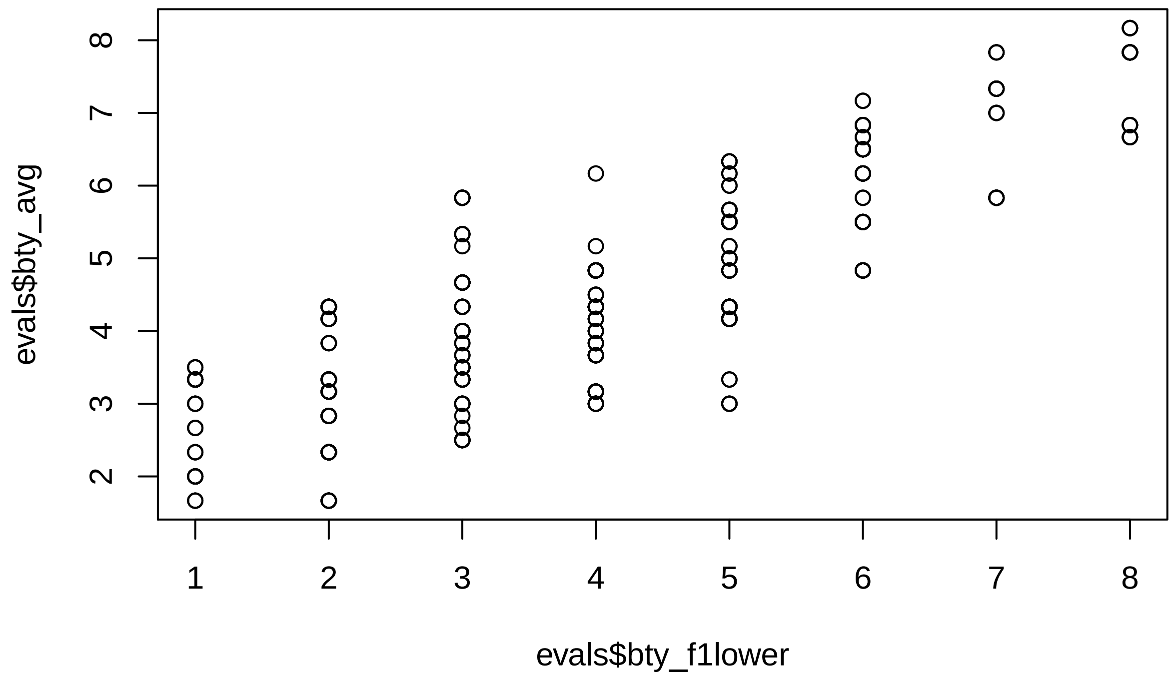
```
hist(m_bty$residuals)
```

- The residauls do not look normal. They are skewed to the right. I would not use a linear plot to predict this graph.

Multiple linear regression

The data set contains several variables on the beauty score of the professor: individual ratings from each of the six students who were asked to score the physical appearance of the professors and the average of these six scores. Let's take a look at the relationship between one of these scores and the average beauty score.

```r
plot(evals$bty_avg ~ evals$bty_f1lower)
```

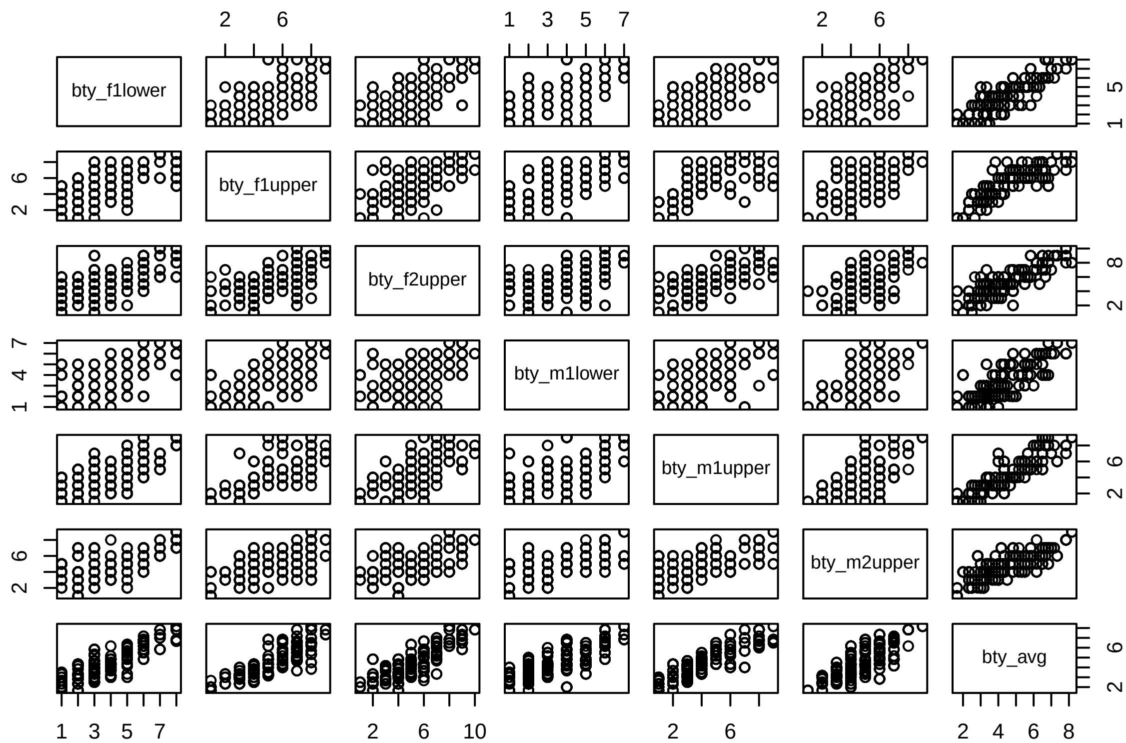



```r
cor(evals$bty_avg, evals$bty_f1lower)
```

```
## [1] 0.8439112
```

As expected the relationship is quite strong - after all, the average score is calculated using the individual scores. We can actually take a look at the relationships between all beauty variables (columns 13 through 19) using the following command:

```r
plot(evals[,13:19])
```



These variables are collinear (correlated), and adding more than one of these variables to the model would not add much value to the model. In this application and with these highly-correlated predictors, it is reasonable to use the average beauty score as the single representative of these variables.

In order to see if beauty is still a significant predictor of professor score after we've accounted for the gender of the professor, we can add the gender term into the model.

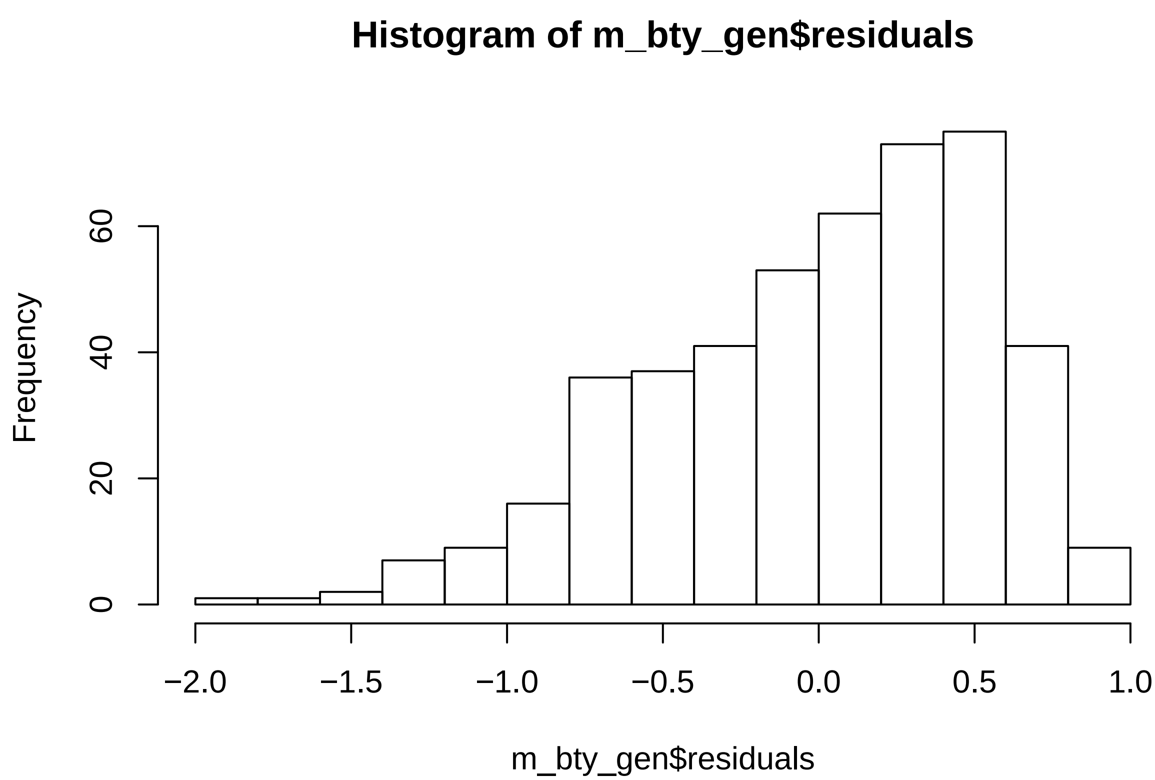
```
m_bty_gen <- lm(score ~ bty_avg + gender, data = evals)
summary(m_bty_gen)
```

```
##
## Call:
## lm(formula = score ~ bty_avg + gender, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8305 -0.3625  0.1055  0.4213  0.9314
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.74734    0.08466  44.266  < 2e-16 ***
## bty_avg      0.07416    0.01625   4.563 6.48e-06 ***
## gendermale   0.17239    0.05022   3.433 0.000652 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

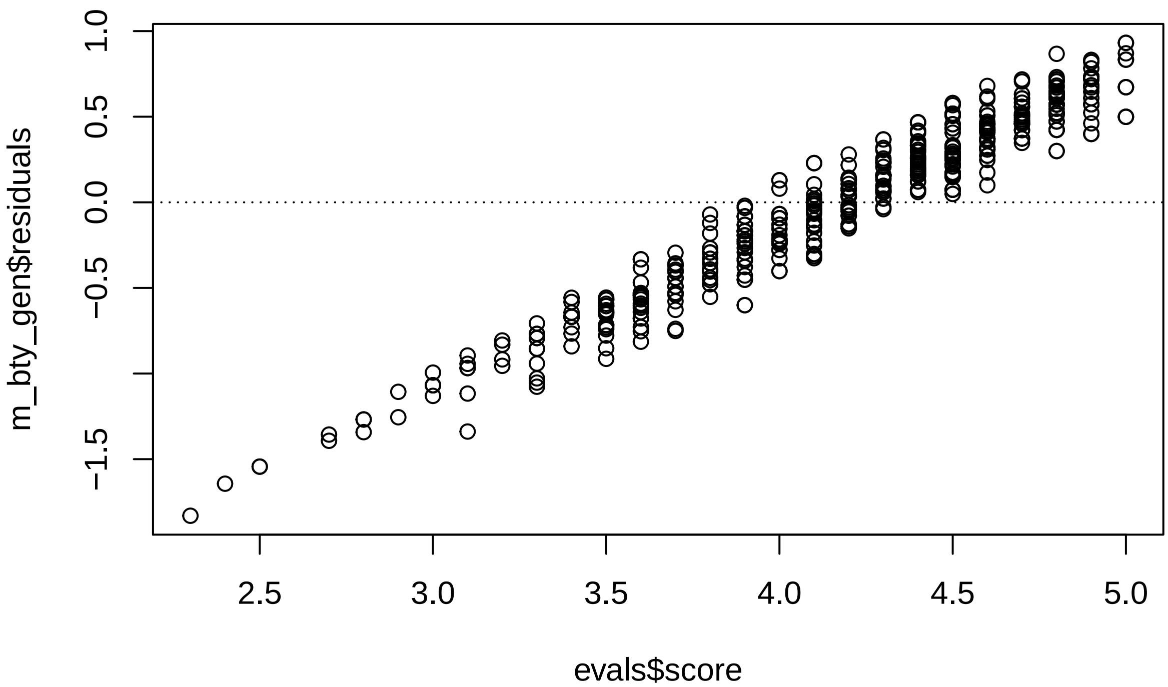
```
## Residual standard error: 0.5287 on 460 degrees of freedom
## Multiple R-squared:  0.05912,    Adjusted R-squared:  0.05503
## F-statistic: 14.45 on 2 and 460 DF,  p-value: 8.177e-07
```

7. P-values and parameter estimates should only be trusted if the conditions for the regression are reasonable. Verify that the conditions for this model are reasonable using diagnostic plots.

```r
hist(m_bty_gen$residuals)
```




```r
plot(evals$score, m_bty_gen$residuals)
abline(h = 0, lty = 3)
```



- The histogram does not appear to be normale to me. I would no use a linear plot for this data.

8. Is `bty_avg` still a significant predictor of `score`? Has the addition of `gender` to the model changed the parameter estimate for `bty_avg`?

- BTY_AVG is not a good pedictor of score, but the addition of the gender did help the correlation. I would still say that it is not a goog predictor, because the residuals are not normal.

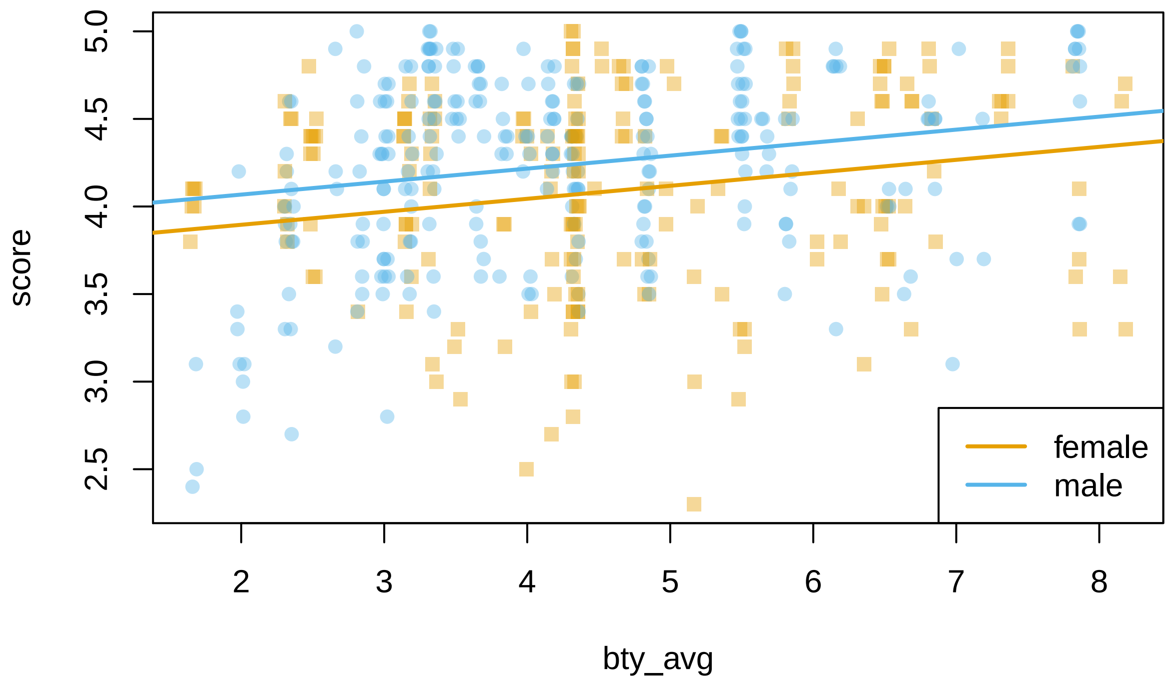
Note that the estimate for `gender` is now called `gendermale`. You'll see this name change whenever you introduce a categorical variable. The reason is that R recodes `gender` from having the values of `female` and `male` to being an indicator variable called `gendermale` that takes a value of 0 for females and a value of 1 for males. (Such variables are often referred to as "dummy" variables.)

As a result, for females, the parameter estimate is multiplied by zero, leaving the intercept and slope form familiar from simple regression.

$$
\begin{aligned}
\widehat{score} &= \hat{\beta}_0 + \hat{\beta}_1 \times bty\_avg + \hat{\beta}_2 \times (0) \\
&= \hat{\beta}_0 + \hat{\beta}_1 \times bty\_avg
\end{aligned}
$$

We can plot this line and the line corresponding to males with the following custom function.

```
multiLines(m_bty_gen)
```




```r
males <- lm(m_bty_gen)
summary(males)
```

```
##
## Call:
## lm(formula = m_bty_gen)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8305 -0.3625  0.1055  0.4213  0.9314
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.74734    0.08466  44.266  < 2e-16 ***
## bty_avg      0.07416    0.01625   4.563 6.48e-06 ***
## gendermale   0.17239    0.05022   3.433 0.000652 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5287 on 460 degrees of freedom
## Multiple R-squared:  0.05912,    Adjusted R-squared:  0.05503
## F-statistic: 14.45 on 2 and 460 DF,  p-value: 8.177e-07
```

9. What is the equation of the line corresponding to males? (*Hint:* For males, the parameter estimate is multiplied by 1.) For two professors who received the same beauty rating, which gender tends to have the higher course evaluation score?

$$\hat{y} = 3.91973 + .17239 * bty_avg$$

- Males will have a higher rating then the females will with the same beauty rating

The decision to call the indicator variable `gendermale` instead of`genderfemale` has no deeper meaning. R simply codes the category that comes first alphabetically as a 0. (You can change the reference level of a categorical variable, which is the level that is coded as a 0, using the`relevel` function. Use `?relevel` to learn more.)

10. Create a new model called `m_bty_rank` with `gender` removed and `rank` added in. How does R appear to handle categorical variables that have more than two levels? Note that the rank variable has three levels: `teaching`, `tenure track`, `tenured`.

```
m_bty_rank <- lm(score ~ bty_avg + rank, data = evals)
summary(m_bty_rank)
```

```
##
## Call:
## lm(formula = score ~ bty_avg + rank, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8713 -0.3642  0.1489  0.4103  0.9525
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       3.98155    0.09078  43.860  < 2e-16 ***
## bty_avg           0.06783    0.01655   4.098 4.92e-05 ***
## ranktenure track -0.16070    0.07395  -2.173   0.0303 *
## ranktenured      -0.12623    0.06266  -2.014   0.0445 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5328 on 459 degrees of freedom
## Multiple R-squared:  0.04652,    Adjusted R-squared:  0.04029
## F-statistic: 7.465 on 3 and 459 DF,  p-value: 6.88e-05
```

- R adds one more row to the summary output.

The interpretation of the coefficients in multiple regression is slightly different from that of simple regression. The estimate for `bty_avg` reflects how much higher a group of professors is expected to score if they have a beauty rating that is one point higher *while holding all other variables constant.* In this case, that translates into considering only professors of the same rank with `bty_avg` scores that are one point apart.

The search for the best model

We will start with a full model that predicts professor score based on rank, ethnicity, gender, language of the university where they got their degree, age, proportion of students that filled out evaluations, class size, course level, number of professors, number of credits, average beauty rating, outfit, and picture color.

11. Which variable would you expect to have the highest p-value in this model? Why? *Hint:* Think about which variable would you expect to not have any association with the professor score.

Let's run the model…

```r
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)
```

- I would think that the highest P value would be if the professor is single or not. That is because most students do not wish to date their teachers. The do not truly care or not if the professor is single or married or anything of that nature.

12. Check your suspicions from the previous exercise. Include the model output in your response.

```r
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
```

13. Interpret the coefficient associated with the ethnicity variable.

```r
m_full$coefficients["ethnicitynot minority"]
```

```
## ethnicitynot minority
##             0.1234929
```

- The coefficient of the ethnicity variable means that the rating of the rating of the professor will increase by .1234929 if the professor is not a minority. That means that non-minority professor have a higher rating than non-minority professors.

14. Drop the variable with the highest p-value and re-fit the model. Did the coefficients and significance of the other explanatory variables change? (One of the things that makes multiple regression interesting is that coefficient estimates depend on the other variables that are included in the model.) If not, what does this say about whether or not the dropped variable was collinear with the other explanatory variables?

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

```
##
## Call:
## lm(formula = score ~ rank + 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
## -1.73681 -0.32734  0.08283  0.35834  0.98639
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            4.2676351  0.2694274  15.840  < 2e-16 ***
## ranktenure track      -0.1660677  0.0813523  -2.041 0.041801 *
## ranktenured           -0.1127978  0.0657022  -1.717 0.086705 .
## gendermale             0.2241744  0.0512176   4.377 1.50e-05 ***
## languagenon-english   -0.2862448  0.1055924  -2.711 0.006968 **
## age                   -0.0092040  0.0031385  -2.933 0.003534 **
## cls_perc_eval          0.0051119  0.0015357   3.329 0.000944 ***
## cls_students           0.0004785  0.0003777   1.267 0.205899
## cls_levelupper         0.0767503  0.0567182   1.353 0.176677
## cls_profssingle       -0.0292174  0.0512393  -0.570 0.568817
## cls_creditsone credit  0.4589918  0.1128358   4.068 5.61e-05 ***
## bty_avg                0.0375980  0.0174661   2.153 0.031880 *
## pic_outfitnot formal  -0.1208610  0.0738165  -1.637 0.102265
## pic_colorcolor        -0.2400696  0.0701264  -3.423 0.000675 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4988 on 449 degrees of freedom
## Multiple R-squared:  0.1826, Adjusted R-squared:  0.159
## F-statistic: 7.717 on 13 and 449 DF,  p-value: 6.792e-14
```

```r
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
```

- The coefficients of the other variables did change a little bit. The P values of the variables also changed. The R squared value actaully went down when the ethnicity variable was dropped. That means that removing that variable actually hurts the correlation with the other variables. That means that the variable should not ber removed.

15. 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.

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

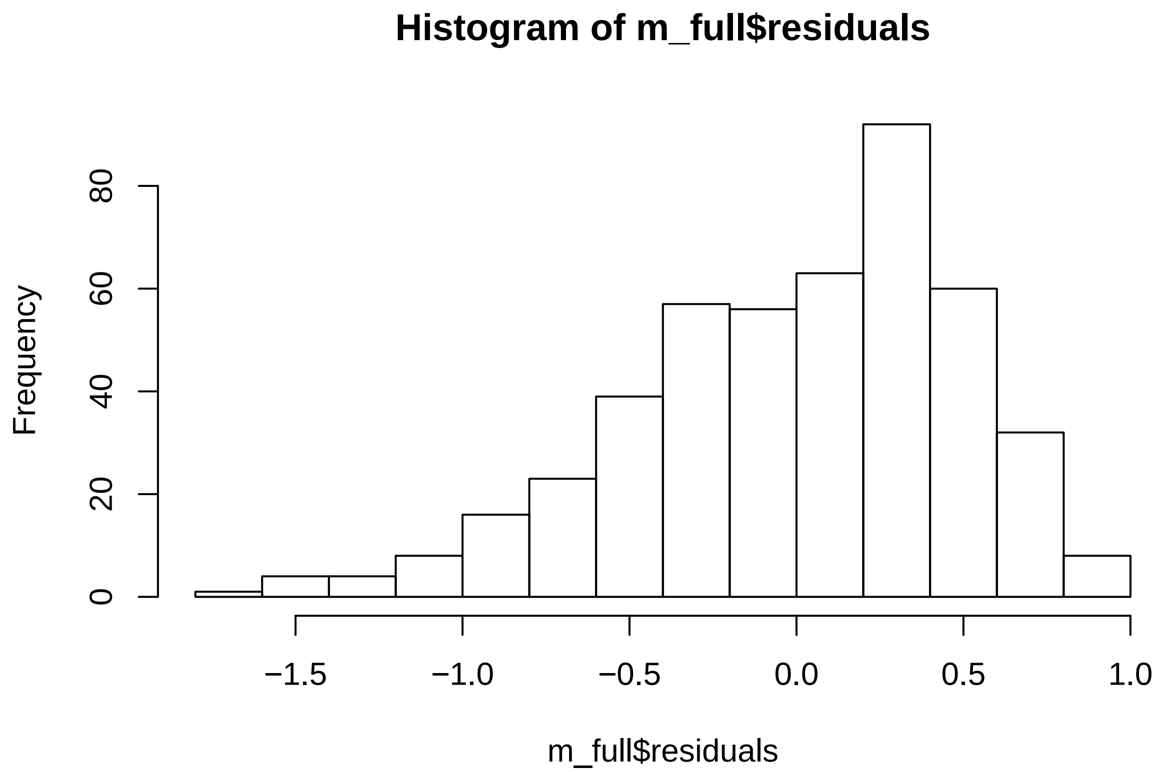
```
##
## Call:
```

```
## lm(formula = score ~ rank + 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
## -1.73681 -0.32734  0.08283  0.35834  0.98639
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            4.2676351  0.2694274  15.840  < 2e-16 ***
## ranktenure track      -0.1660677  0.0813523  -2.041 0.041801 *
## ranktenured           -0.1127978  0.0657022  -1.717 0.086705 .
## gendermale             0.2241744  0.0512176   4.377 1.50e-05 ***
## languagenon-english   -0.2862448  0.1055924  -2.711 0.006968 **
## age                   -0.0092040  0.0031385  -2.933 0.003534 **
## cls_perc_eval          0.0051119  0.0015357   3.329 0.000944 ***
## cls_students           0.0004785  0.0003777   1.267 0.205899
## cls_levelupper         0.0767503  0.0567182   1.353 0.176677
## cls_profssingle       -0.0292174  0.0512393  -0.570 0.568817
## cls_creditsone credit  0.4589918  0.1128358   4.068 5.61e-05 ***
## bty_avg                0.0375980  0.0174661   2.153 0.031880 *
## pic_outfitnot formal  -0.1208610  0.0738165  -1.637 0.102265
## pic_colorcolor        -0.2400696  0.0701264  -3.423 0.000675 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4988 on 449 degrees of freedom
## Multiple R-squared:  0.1826, Adjusted R-squared:  0.159
## F-statistic: 7.717 on 13 and 449 DF,  p-value: 6.792e-14
```

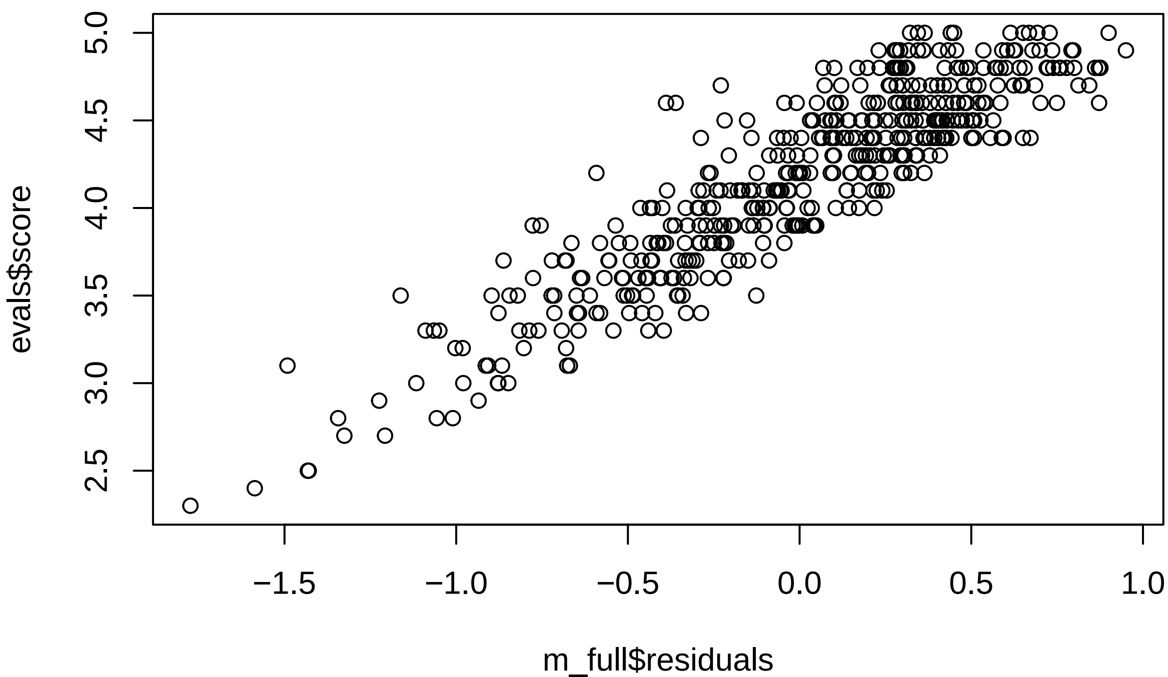
- It appears that they best model is including all of the other variables. If anything gets removed, even the variables that are not significant due to their P values, the R squared value drops dramtically. Therefore, the best model is to compare all of the variables together at once.

16. Verify that the conditions for this model are reasonable using diagnostic plots.

```r
hist(m_full$residuals)
```




```r
plot(evals$score~m_full$residuals)
```



- The residuals are a little bit skewed to the right, but I do not think that it is enough to say that it is not a linear relationship.

17. The original paper describes how these data were gathered by taking a sample of professors from the University of Texas at Austin and including all courses that they have taught. Considering that each row represents a course, could this new information have an impact on any of the conditions of linear regression?

- I think that since it is based off of every course that each of the professor taught, it can have an effect on some of the variables that are in the model. The students variable would be a large one. Some teachers teach one class, while other professors teach multiple classes. The more student that the teacher teaches, the more ratings the professor has. That will have a a huge effect on the rating of the professor. That also goes along with the level of the classes the profs teach. Most lower level classes are taken by all students. most of them feel that the class may not pertain to their major and do not care about the teacher or class. That can also effect the rating.

18. 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 professor that would get the higest rating would be, non tenured, non-mionrity, male teacher who teaches a one credit class and wears a formal, non-colorful outfit.

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

- I would not feel comrofatble genralizing this data to any university. I have done teacher evaluations and I have seen other people do those evaluations. I know that they are not taken seriously 95% of the time. Some of this data is probably not how the students actually feel about the prof. Also, different parts of the USA/World would rate their professor differently. I would not generalize this to other universities.