Multiple linear regression

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.

```r
load("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.
`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.

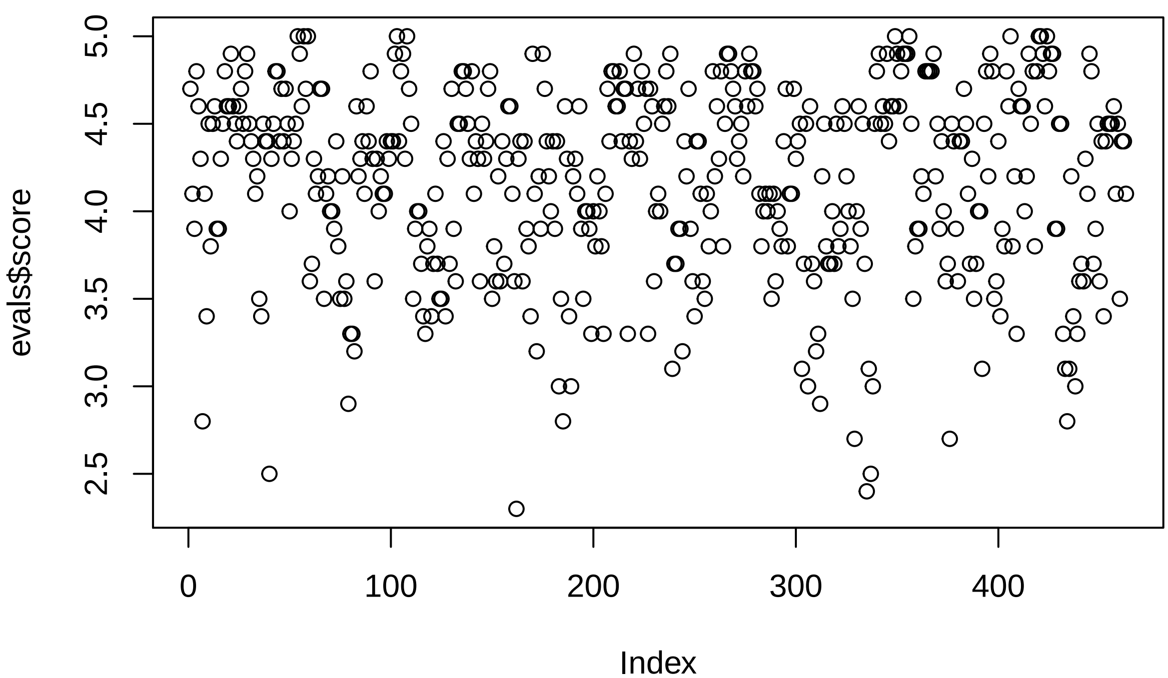
Exploring the data

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.

This is an observational study because there is no treatment being tested.

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?

```
plot(evals$score)
```

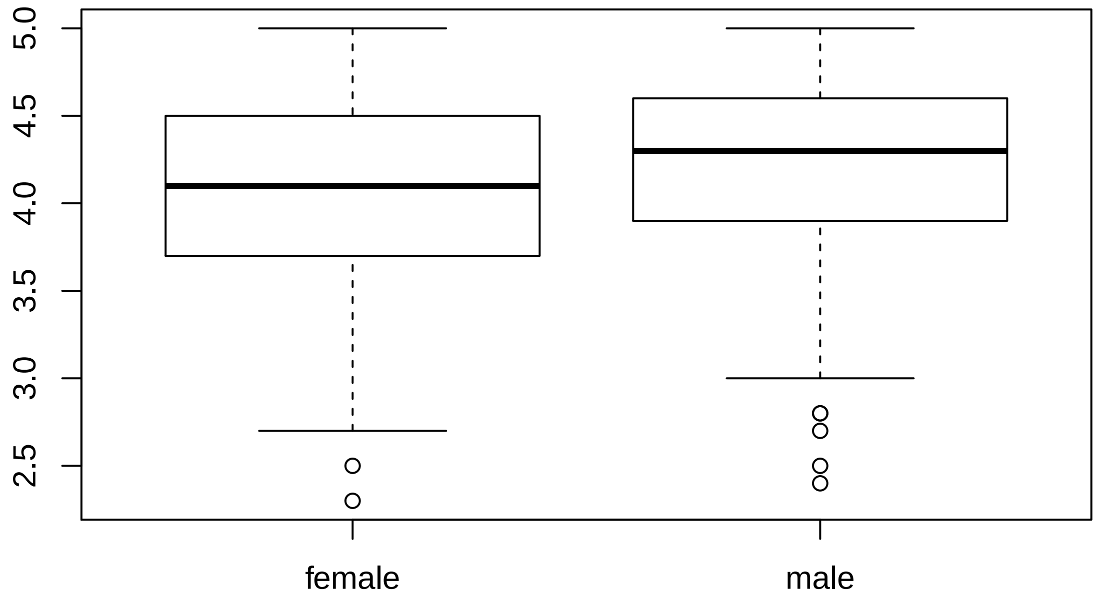


The scores tend to be generally skewed towards the higher end of the ratings spectrum. Other than that it seems evenly distributed

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

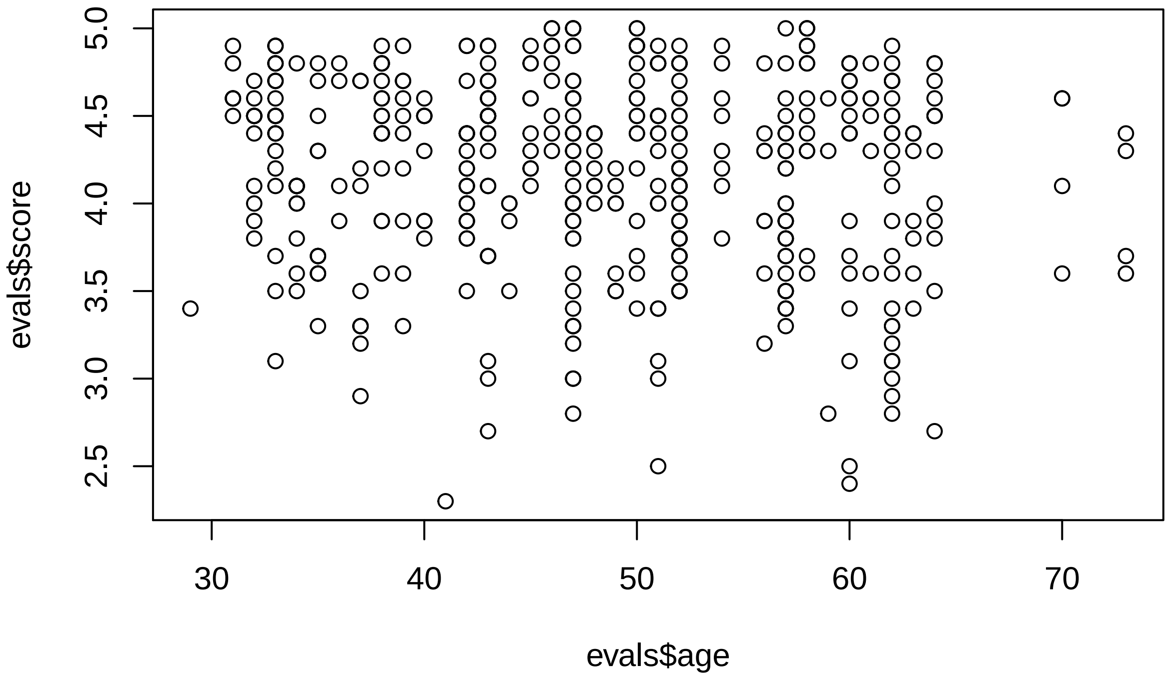
_The below graph seems to show a slight bias towards male teachers

```
plot(evals$gender, evals$score)
```



_There seems to be a slightly negative correlation between professor age and rating**

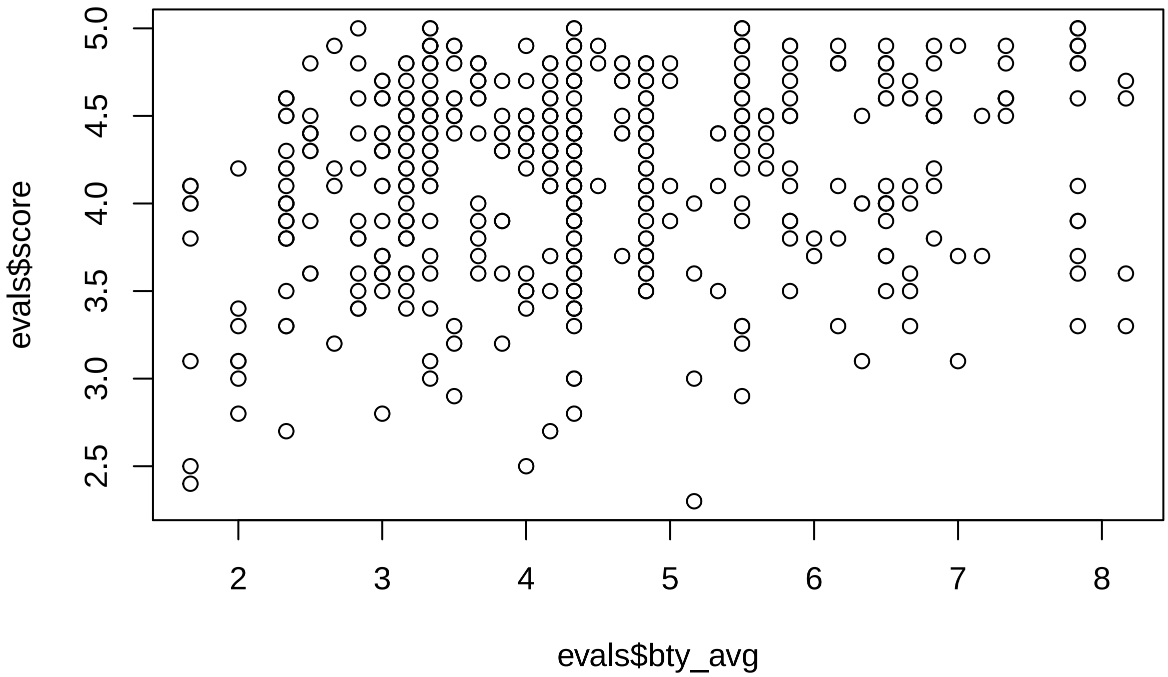
```
plot(evals$age, evals$score)
```



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:

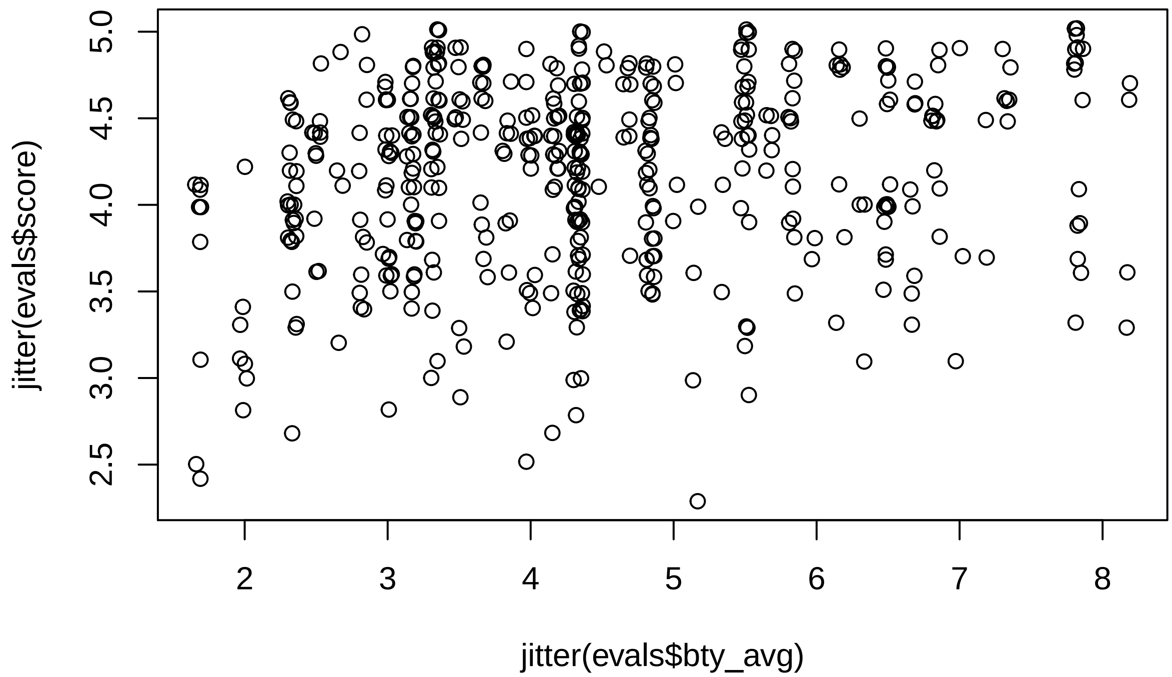
```
plot(evals$score ~ evals$bty_avg)
```



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?

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?

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



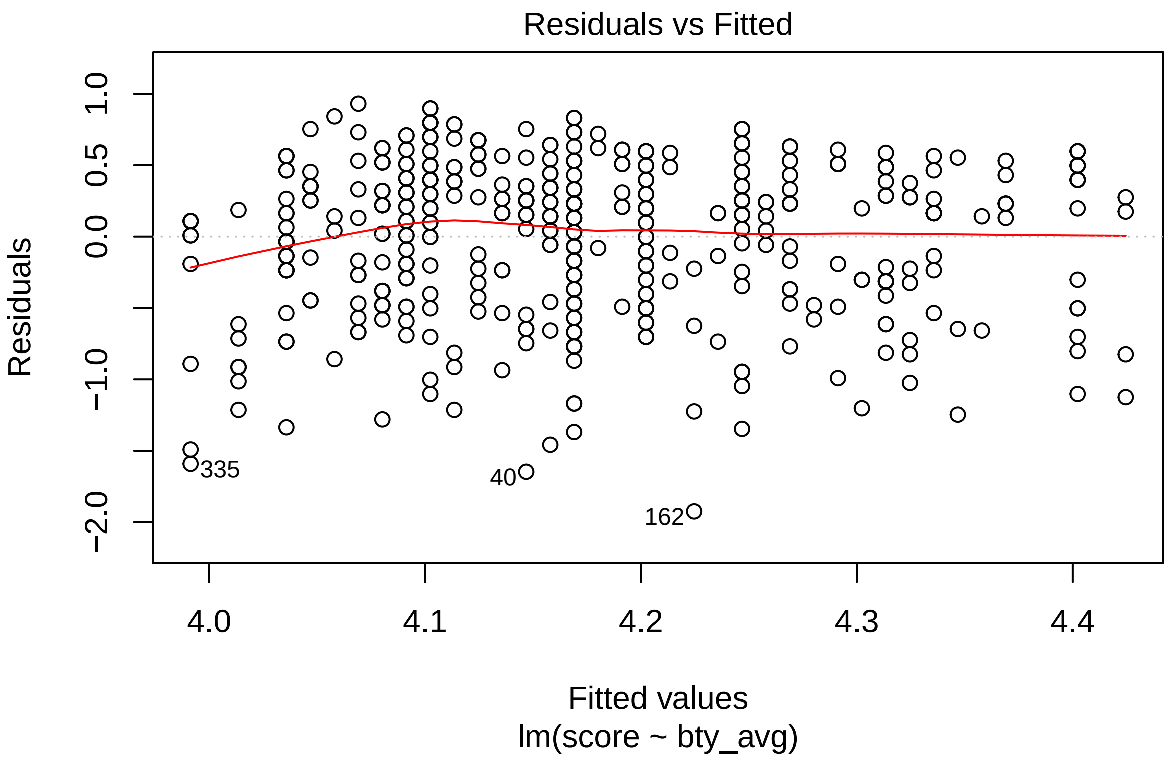
Misleading: that the number of eval scores for a given beauty score wasn't shown graphically

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 significant predictor? Does it appear to be a practically significant predictor?

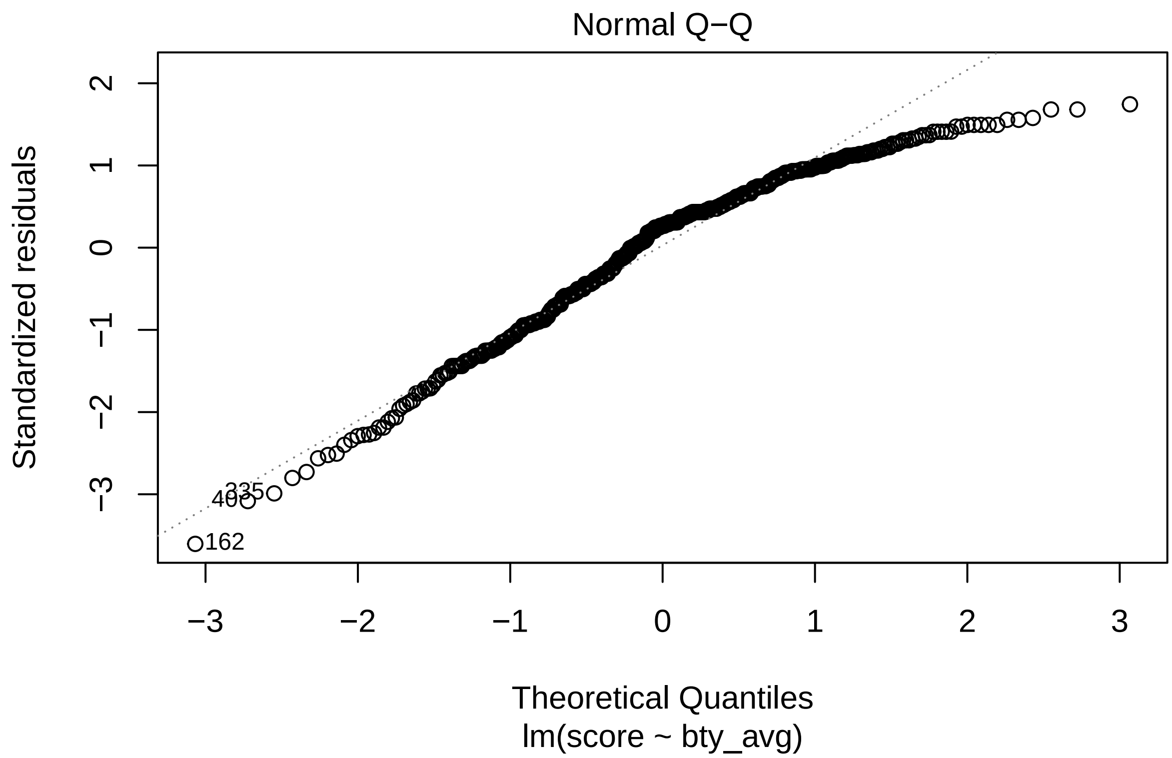
```
m_bty <- lm(score ~ bty_avg, data=evals)
m_bty
```

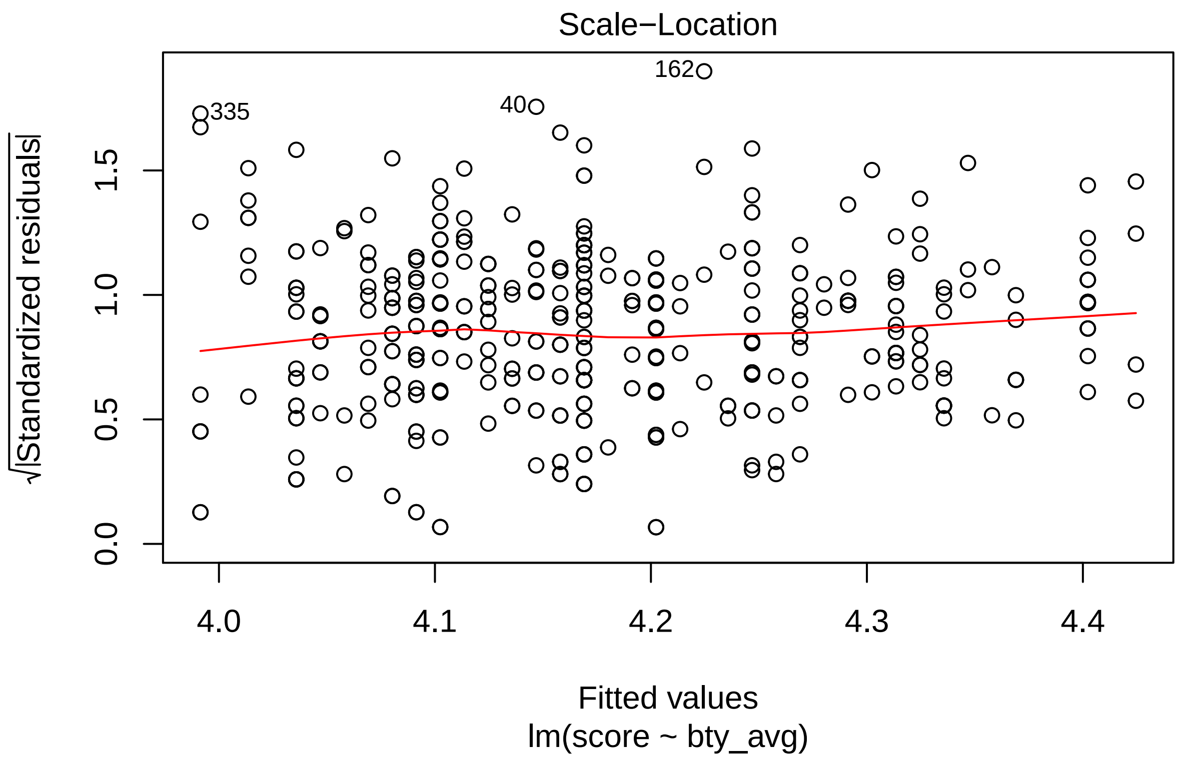
```
##
## Call:
## lm(formula = score ~ bty_avg, data = evals)
##
## Coefficients:
## (Intercept)      bty_avg
##     3.88034      0.06664
```

```
plot(m_bty)
```



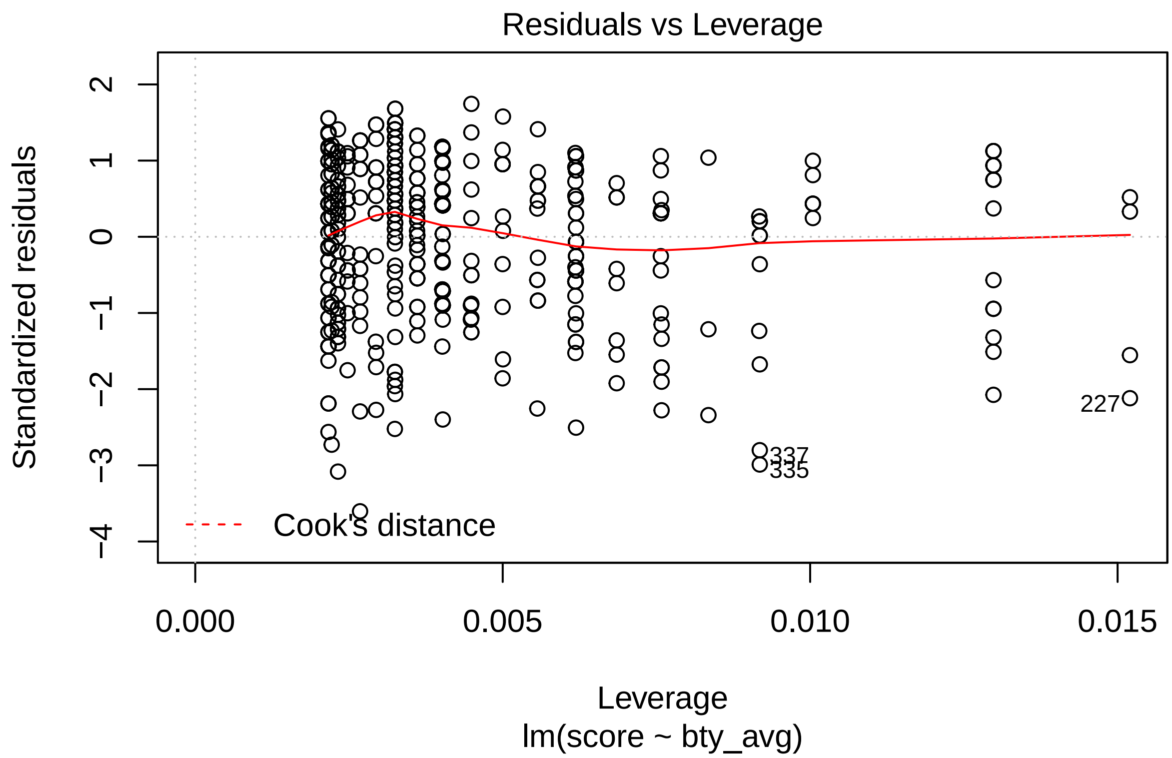
Residuals vs Fitted
Residuals
1.0
0.5
0.0
−1.0
−2.0
335
40
162
4.0
4.1
4.2
4.3
4.4
Fitted values
lm(score ~ bty_avg)


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(score ~ bty_avg)
162
40
335
−3
−2
−1
0
1
2
3



Scale−Location
162
335
40
√|Standardized residuals|
0.0
0.5
1.0
1.5
4.0
4.1
4.2
4.3
4.4
Fitted values
lm(score ~ bty_avg)

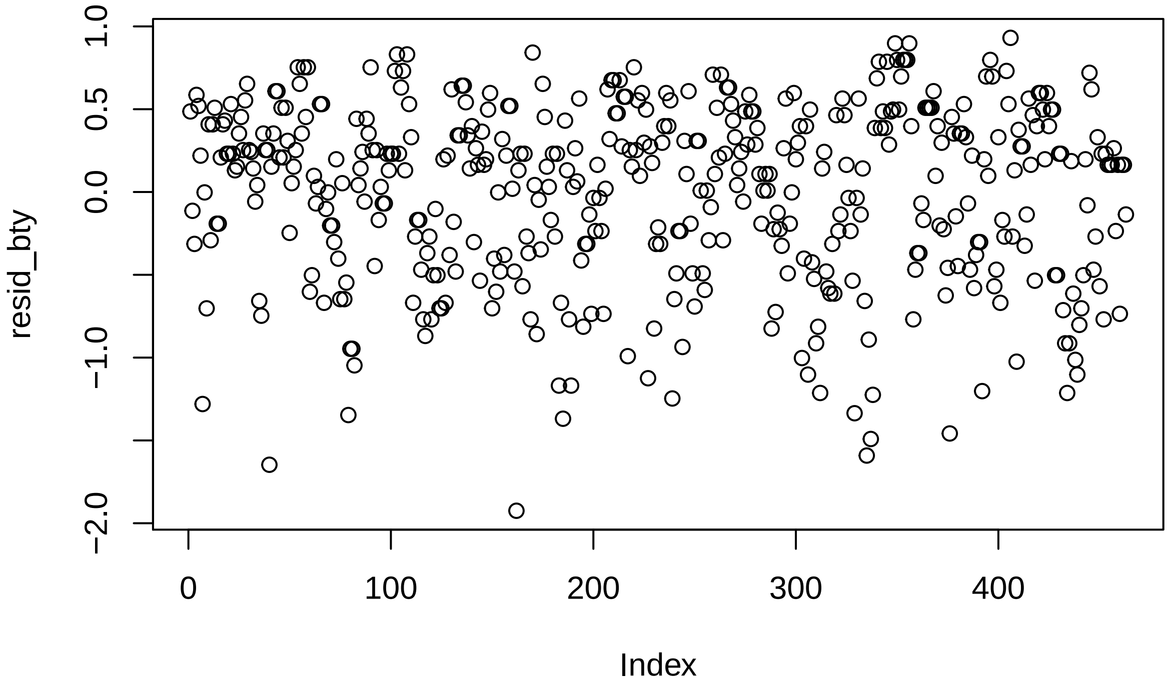

```
abline(m_bty)
```



_____score = 3.88034 + 0.06664 * bty_avg

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).

```
resid_bty = resid(m_bty)
plot(resid_bty)
```

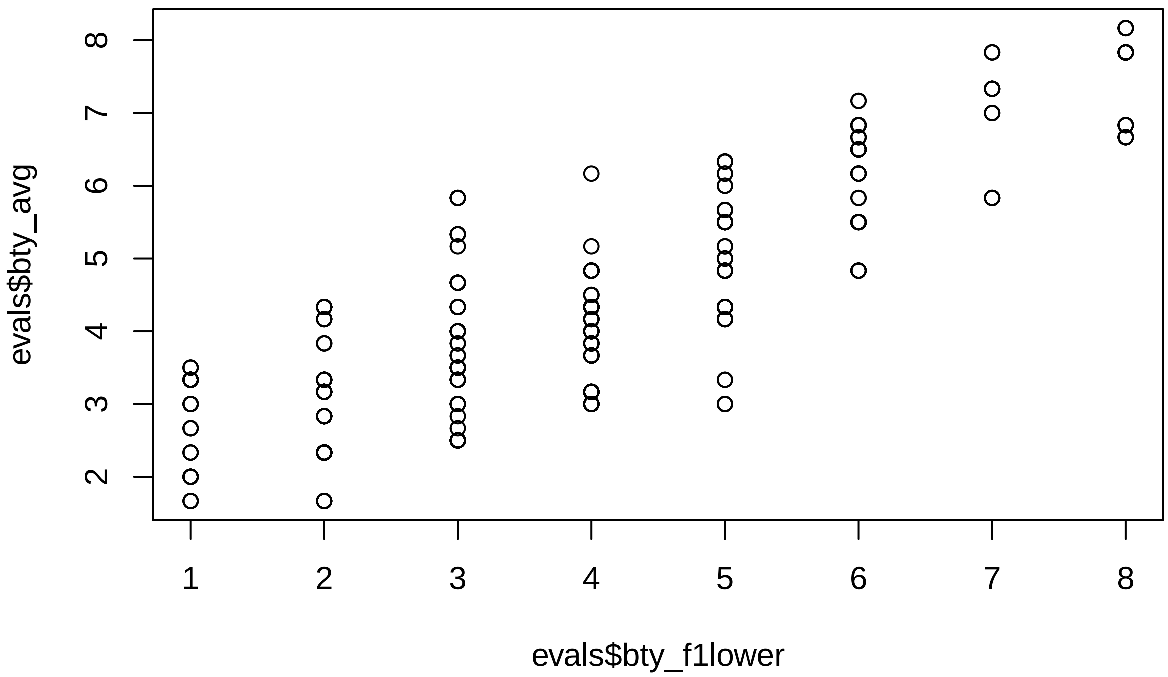


There are no patterns in the residuals that would make us doubt the model.

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.

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

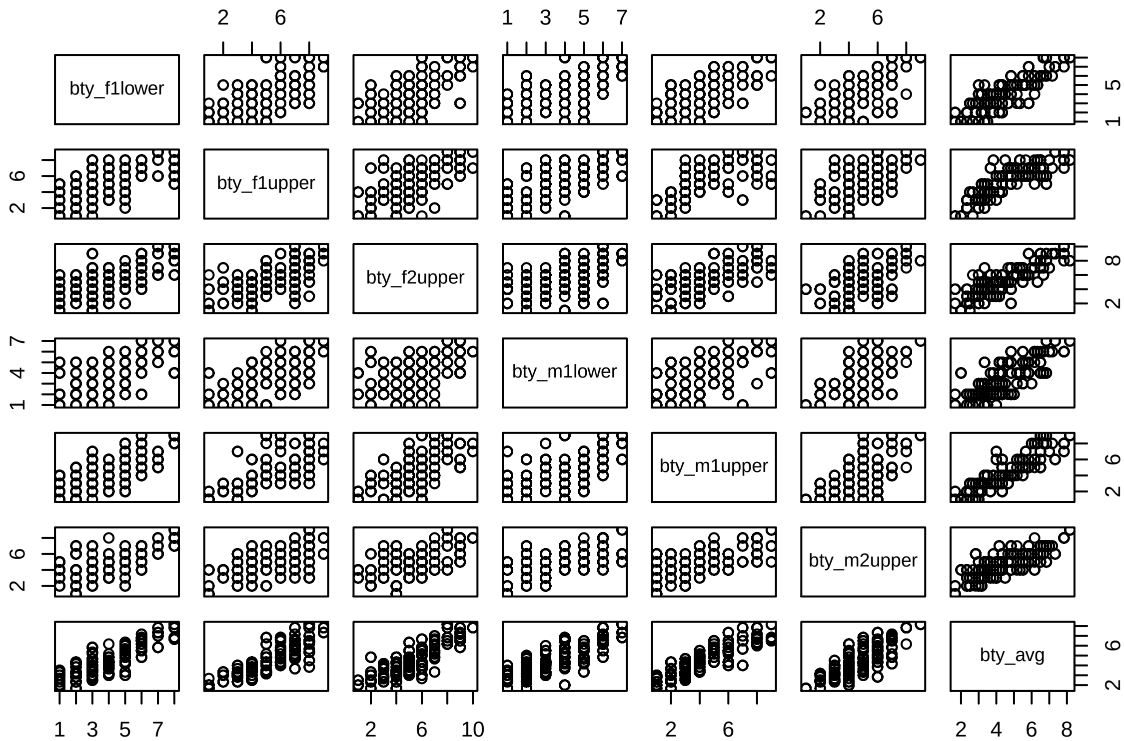



```r
cor(evals$bty_avg, evals$bty_f1lower)
```

```
## [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.

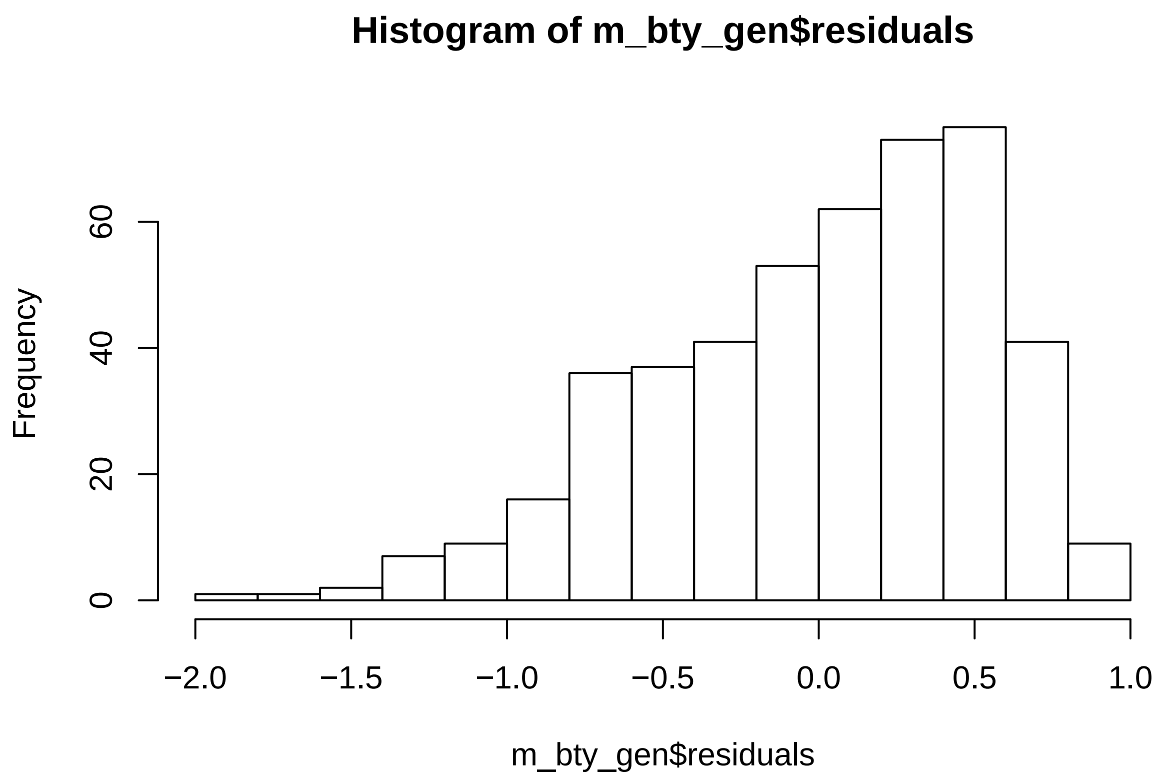
```
m_bty_gen <- lm(score ~ bty_avg + gender, data = evals)
summary(m_bty_gen)
```

```
##
## 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
##
```

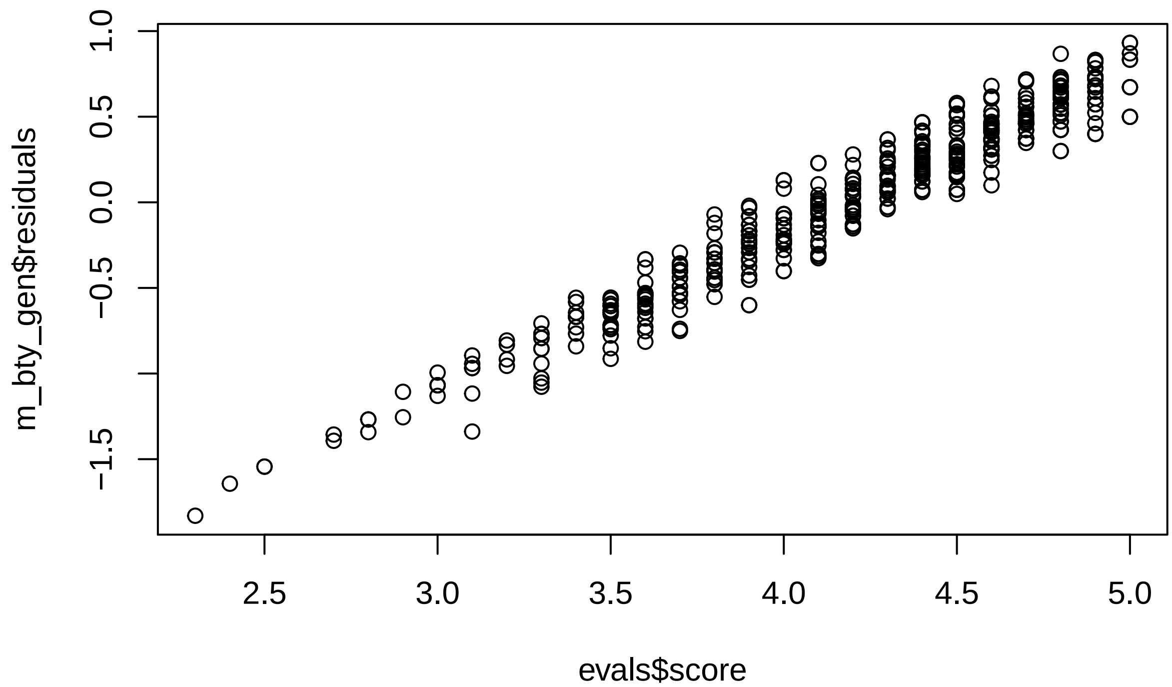
```
## Residual standard error: 0.5287 on 460 degrees of freedom
## Multiple R-squared:  0.05912,    Adjusted R-squared:  0.05503
## F-statistic: 14.45 on 2 and 460 DF,  p-value: 8.177e-07
```

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(m_bty_gen$residuals ~ evals$score)
```



The residuals seem skewed and not reasonable based on these plots

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 still a significant predictor of `score`. Its just that being male moves the ranking up, but the slope (impact) of bty_avg is still the same for both genders

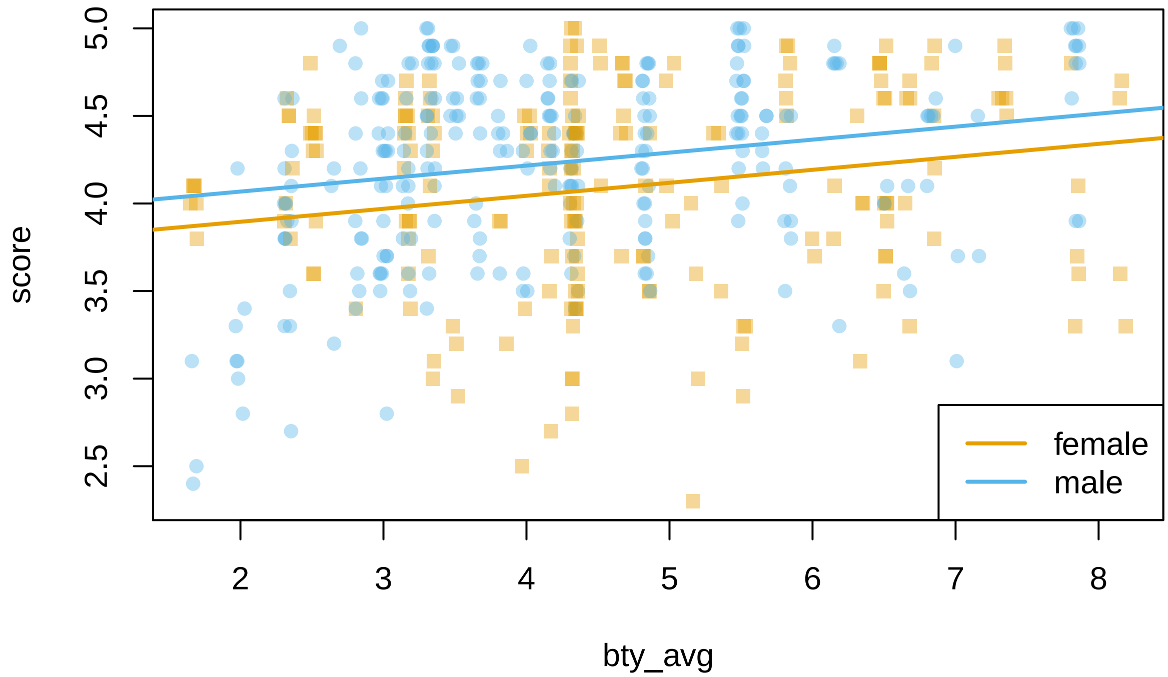
Note that the estimate for `gender` is now called `gendermale`. You'll see this name change whenever you introduce a categorical variable. The reason is that R recodes `gender` from having the values of `female` and `male` to being an indicator variable called `gendermale` that takes a value of 0 for 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)
```



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?

```
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
```

Equation: score = 3.74734 + 0.07416 * bty_avg + 0.17239 * 1

given equal bty_avg, males tend to get a higher score

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`.

R seems to list 2 options when there are 3 categorical values, so (n-1) listings for categorical features with n values

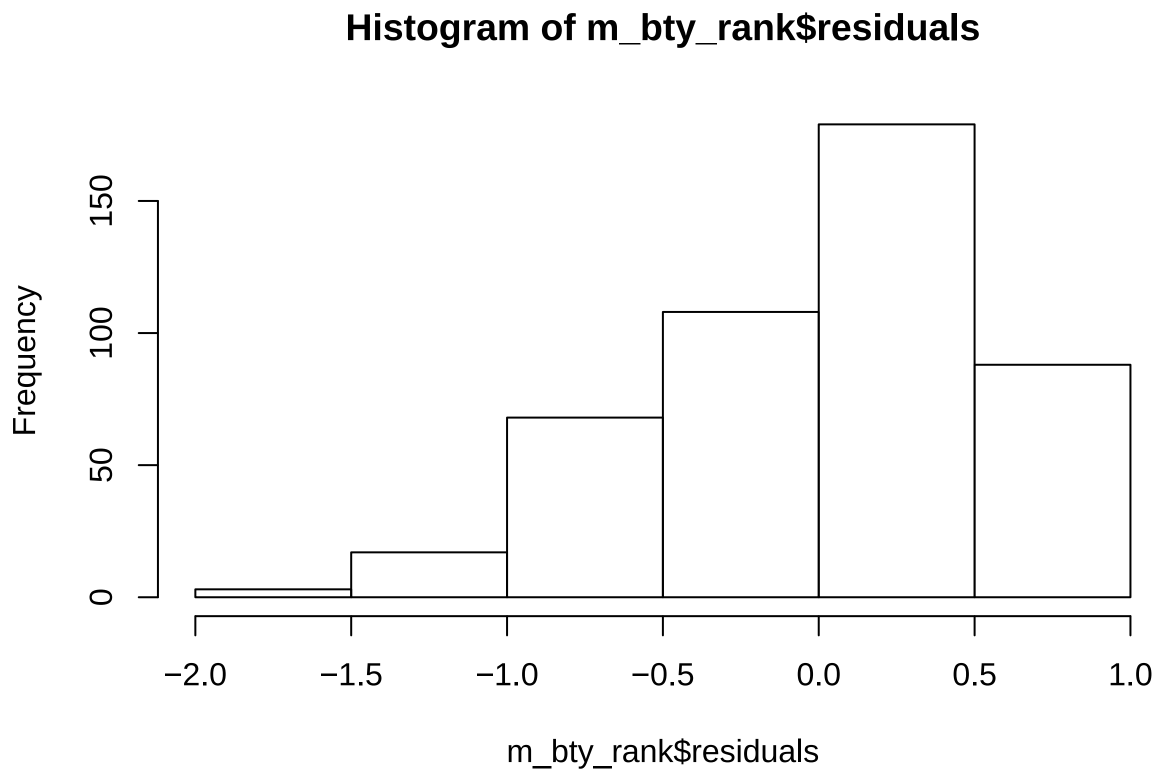
```
unique(evals$rank)
```

```
## [1] tenure track tenured      teaching
## Levels: teaching tenure track tenured
```

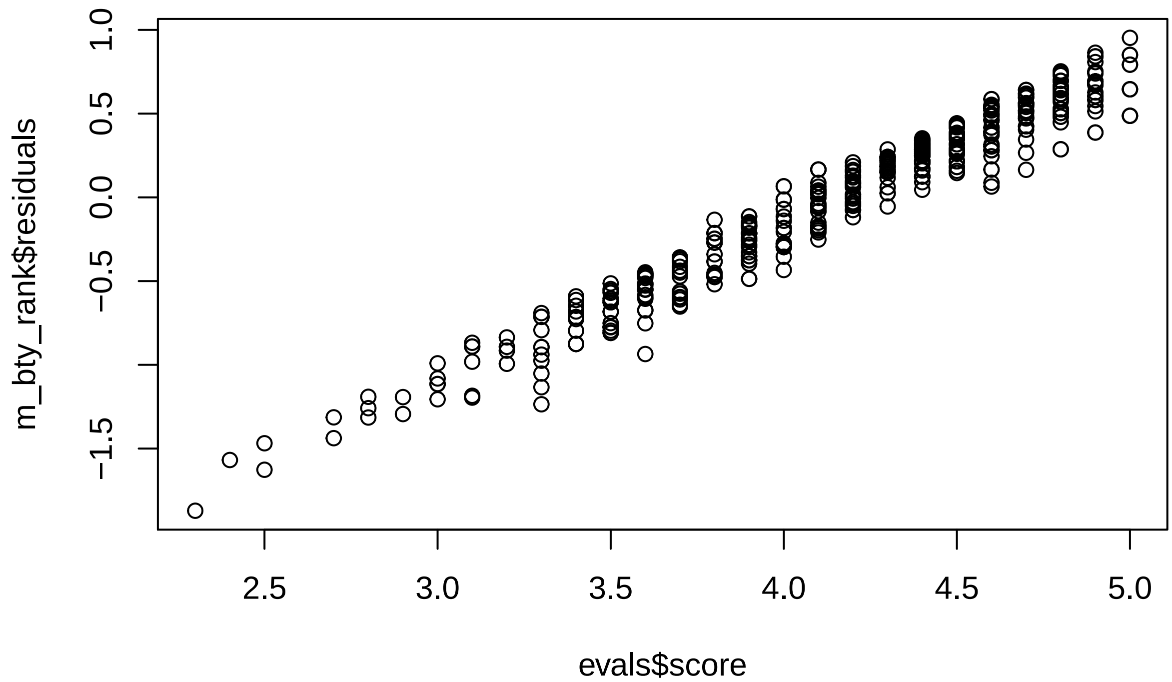
```
m_bty_rank <- lm(score ~ bty_avg + rank, data = evals)
summary(m_bty_rank)
```

```
##
## 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
```

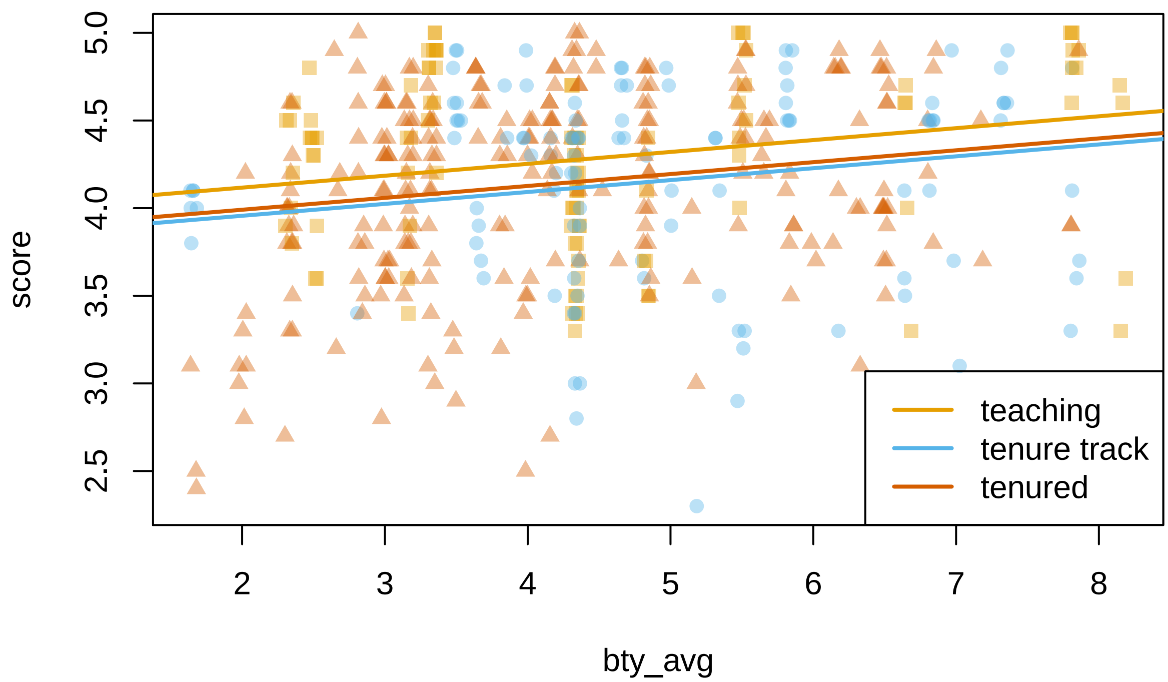
```
hist(m_bty_rank$residuals)
```




```
plot(m_bty_rank$residuals ~ evals$score)
```




```
multiLines(m_bty_rank)
```



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.

Honestly, I could see any one of these features having an impact... But as for the highest... maybe the features that are really ABOUT the teacher, ie - rank, ethnicity, gender, language, age, bty_xxx, and not so much the ones dealing with class features

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
```

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

My guess was wrong, there were quite a few features that were not direct features of the professor that did seem to have an impact, such as cls_perc_eval, cls_creditsone, . . .

13. Interpret the coefficient associated with the ethnicity variable.

_____The ethnicity variable does seem to have an effect (probability it has no effect is .11), but it doesnt seem to have quit the effect that some of the other d, such as the ***s._____

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

```
##
## Call:
## lm(formula = score ~ rank + ethnicity + 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
## -1.86459 -0.31747  0.09691  0.36665  1.01067
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           3.9795672  0.2941055  13.531  < 2e-16 ***
## ranktenure track     -0.1408493  0.0834608  -1.688 0.092181 .
## ranktenured          -0.0477920  0.0663241  -0.721 0.471541
## ethnicitynot minority  0.1755015  0.0789159   2.224 0.026652 *
## languagenon-english  -0.1845349  0.1127236  -1.637 0.102319
## age                  -0.0067053  0.0031375  -2.137 0.033126 *
## cls_perc_eval         0.0053596  0.0015658   3.423 0.000676 ***
## cls_students          0.0005379  0.0003833   1.403 0.161192
## cls_levelupper        0.0333579  0.0581566   0.574 0.566534
## cls_profssingle      -0.0027165  0.0527979  -0.051 0.958990
## cls_creditsone credit  0.5561149  0.1171551   4.747 2.78e-06 ***
## bty_avg               0.0416147  0.0178030   2.338 0.019851 *
## pic_outfitnot formal  -0.1094498  0.0751457  -1.457 0.145953
## pic_colorcolor       -0.1640205  0.0715040  -2.294 0.022259 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5065 on 449 degrees of freedom
## Multiple R-squared:  0.157,  Adjusted R-squared:  0.1326
## F-statistic: 6.435 on 13 and 449 DF,  p-value: 3.07e-11
```

Answer:

So looking at (just picking one) age…

In the first model:

age -0.0090072 0.0031359 -2.872 0.00427 **

In the second model:

age -0.0067053 0.0031375 -2.137 0.033126 *

So age's significance went down when a pretty significant feature was taken out of the model.

Meaning being that this model does not have independent features like the question stated.

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.

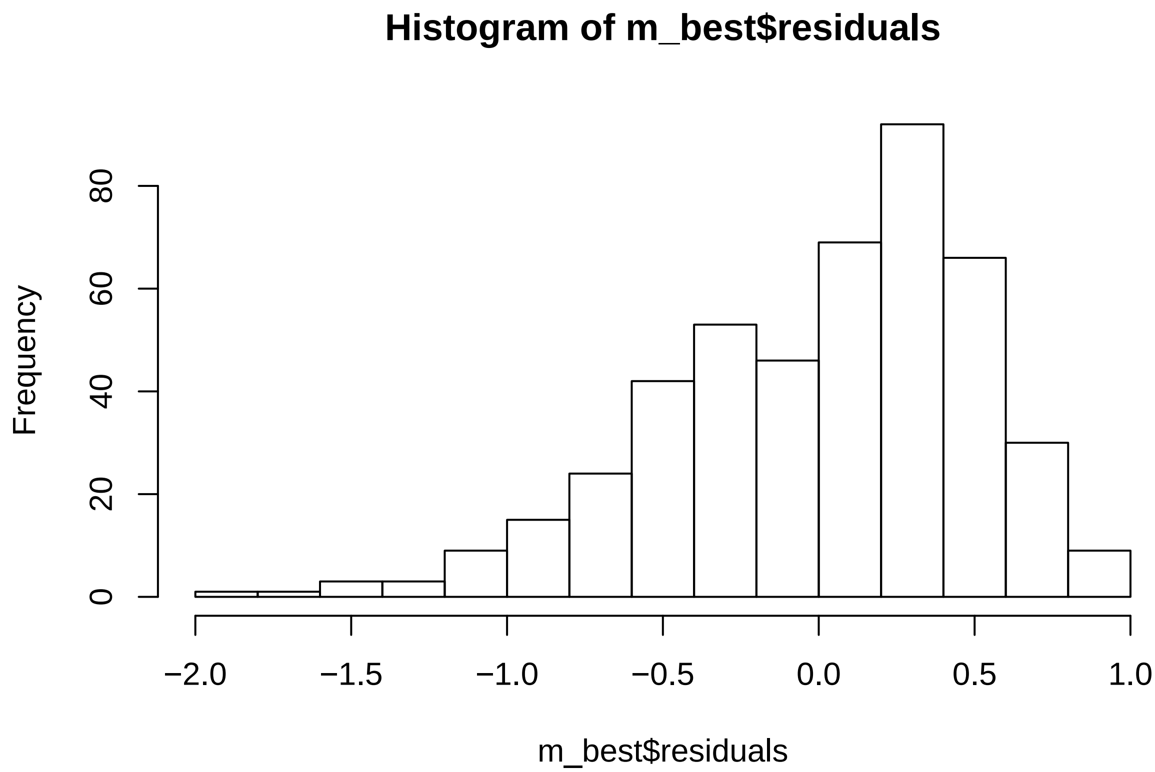
```r
m_best <- lm(score ~ ethnicity + gender + age + cls_perc_eval + cls_credits + bty_avg + pic_color, data

summary(m_best)
```

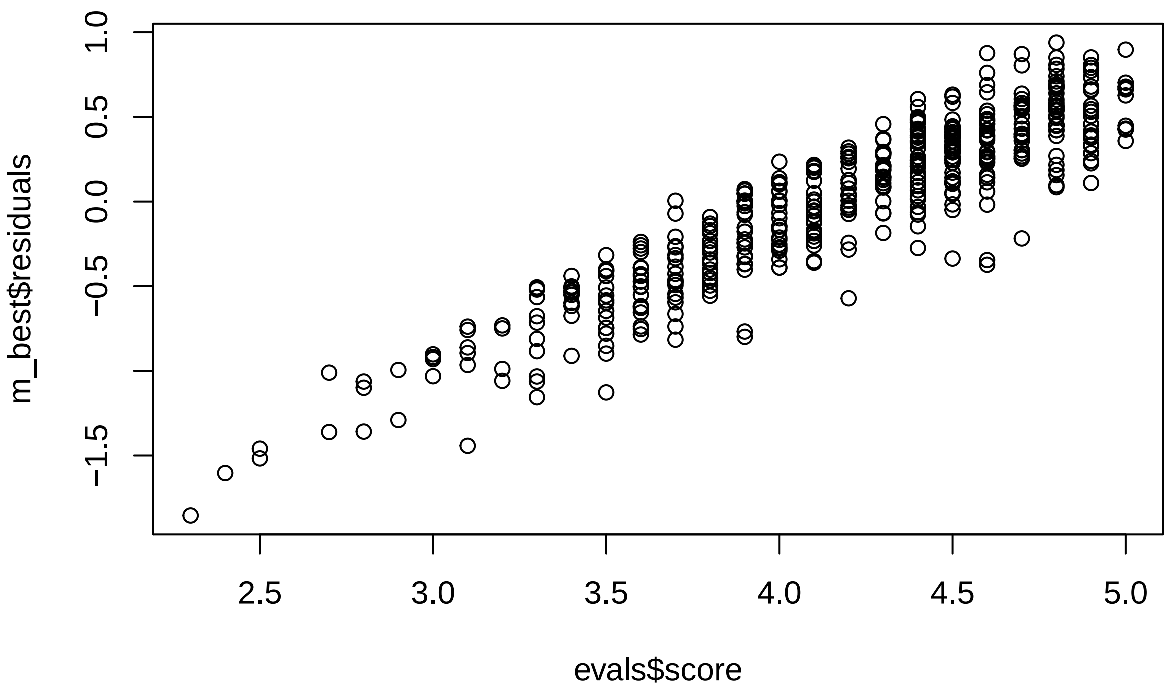
```
##
## Call:
## lm(formula = score ~ ethnicity + gender + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_color, data = evals)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.85434 -0.33568  0.09247  0.38288  0.93903
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            3.690771   0.229181  16.104  < 2e-16 ***
## ethnicitynot minority  0.216955   0.071348   3.041  0.00250 **
## gendermale             0.201574   0.050220   4.014 6.99e-05 ***
## age                   -0.006034   0.002621  -2.302  0.02176 *
## cls_perc_eval          0.004719   0.001439   3.278  0.00113 **
## cls_creditsone credit  0.527806   0.103839   5.083 5.44e-07 ***
## bty_avg                0.052431   0.016975   3.089  0.00213 **
## pic_colorcolor        -0.170149   0.066780  -2.548  0.01116 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5008 on 455 degrees of freedom
## Multiple R-squared:  0.1649, Adjusted R-squared:  0.1521
## F-statistic: 12.84 on 7 and 455 DF,  p-value: 4.344e-15
```

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

```r
hist(m_best$residuals)
```




```
plot(m_best$residuals ~ evals$score)
```



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?

Knowing that there are rows shared by a certain teacher, this would allow for better analysis. You could now analyze features grouped by particular teachers and teachers with known differences, not just based on classes.

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.

A high evaluation score would coincide with not-minority, male, young, class with lots of students answering survey, one credit courses, good looking teachers, and those with black and white pictures

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

I would not be comfortable applying these results to another school, there could be something special about UT that hasn't been identified.