Multiple linear regression

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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" by Hamermesh and Parker found that instructors who are viewed to be better looking receive higher instructional ratings.

Here, you will analyze the data from this study in order to learn what goes into a positive professor evaluation.

Getting Started

Load packages

In this lab, you will explore and visualize the data using the **tidyverse** suite of packages. The data can be found in the companion package for OpenIntro resources, **openintro**.

Let's load the packages.

```
library(tidyverse)
library(openintro)
library(GGally)
```

This is the first time we're using the `GGally` package. You will be using the `ggpairs` function from this package later in the lab.

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. The result is a data frame where each row contains a different course and columns represent variables about the courses and professors. It's called `evals`.

```
glimpse(evals)
```

```
## Rows: 463
## Columns: 23
## $ course_id     <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 1~
## $ prof_id       <int> 1, 1, 1, 1, 2, 2, 2, 3, 3, 4, 4, 4, 4, 4, 4, 4, 4, 5, 5,~
## $ score         <dbl> 4.7, 4.1, 3.9, 4.8, 4.6, 4.3, 2.8, 4.1, 3.4, 4.5, 3.8, 4~
## $ rank          <fct> tenure track, tenure track, tenure track, tenure track, ~
```

```
## $ ethnicity     <fct> minority, minority, minority, minority, not minority, no~
## $ gender        <fct> female, female, female, female, male, male, male, male, ~
## $ language      <fct> english, english, english, english, english, english, en~
## $ age           <int> 36, 36, 36, 36, 59, 59, 59, 51, 51, 40, 40, 40, 40, 40, ~
## $ cls_perc_eval <dbl> 55.81395, 68.80000, 60.80000, 62.60163, 85.00000, 87.500~
## $ cls_did_eval  <int> 24, 86, 76, 77, 17, 35, 39, 55, 111, 40, 24, 24, 17, 14,~
## $ cls_students  <int> 43, 125, 125, 123, 20, 40, 44, 55, 195, 46, 27, 25, 20, ~
## $ cls_level     <fct> upper, upper, upper, upper, upper, upper, upper, upper, ~
## $ cls_profs     <fct> single, single, single, single, multiple, multiple, mult~
## $ cls_credits   <fct> multi credit, multi credit, multi credit, multi credit, ~
## $ bty_f1lower   <int> 5, 5, 5, 5, 4, 4, 4, 5, 5, 2, 2, 2, 2, 2, 2, 2, 2, 7, 7,~
## $ bty_f1upper   <int> 7, 7, 7, 7, 4, 4, 4, 2, 2, 5, 5, 5, 5, 5, 5, 5, 5, 9, 9,~
## $ bty_f2upper   <int> 6, 6, 6, 6, 2, 2, 2, 5, 5, 4, 4, 4, 4, 4, 4, 4, 4, 9, 9,~
## $ bty_m1lower   <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 3, 7, 7,~
## $ bty_m1upper   <int> 4, 4, 4, 4, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 6, 6,~
## $ bty_m2upper   <int> 6, 6, 6, 6, 3, 3, 3, 3, 3, 2, 2, 2, 2, 2, 2, 2, 2, 6, 6,~
## $ bty_avg       <dbl> 5.000, 5.000, 5.000, 5.000, 3.000, 3.000, 3.000, 3.333, ~
## $ pic_outfit    <fct> not formal, not formal, not formal, not formal, not form~
## $ pic_color     <fct> color, color, color, color, color, color, color, color, ~
```

We have observations on 21 different variables, some categorical and some numerical. The meaning of each variable can be found by bringing up the help file:

```
?evals
```

Exploring the data

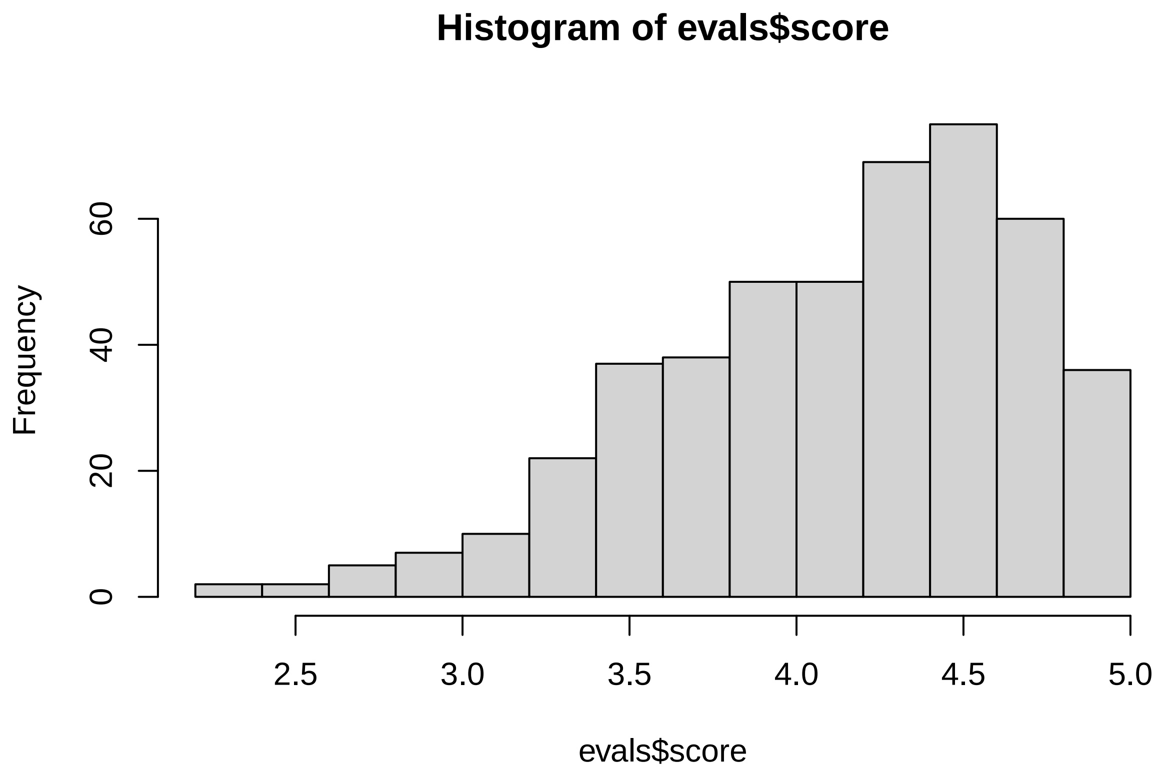
1. Is this an observational study or an experiment? The original research question posed in the paper is whether beauty leads directly to the differences in course evaluations. Given the study design, is it possible to answer this question as it is phrased? If not, rephrase the question.

Q1: This is an observational study. We cannot answer the question, cannot establish causation. A more appropriate question would be: Is there a relationship between beauty and course evaluations?

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?

Q2: The evaluation scores are left skewed, this is as expected. Most the students gives the positive feedback.

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

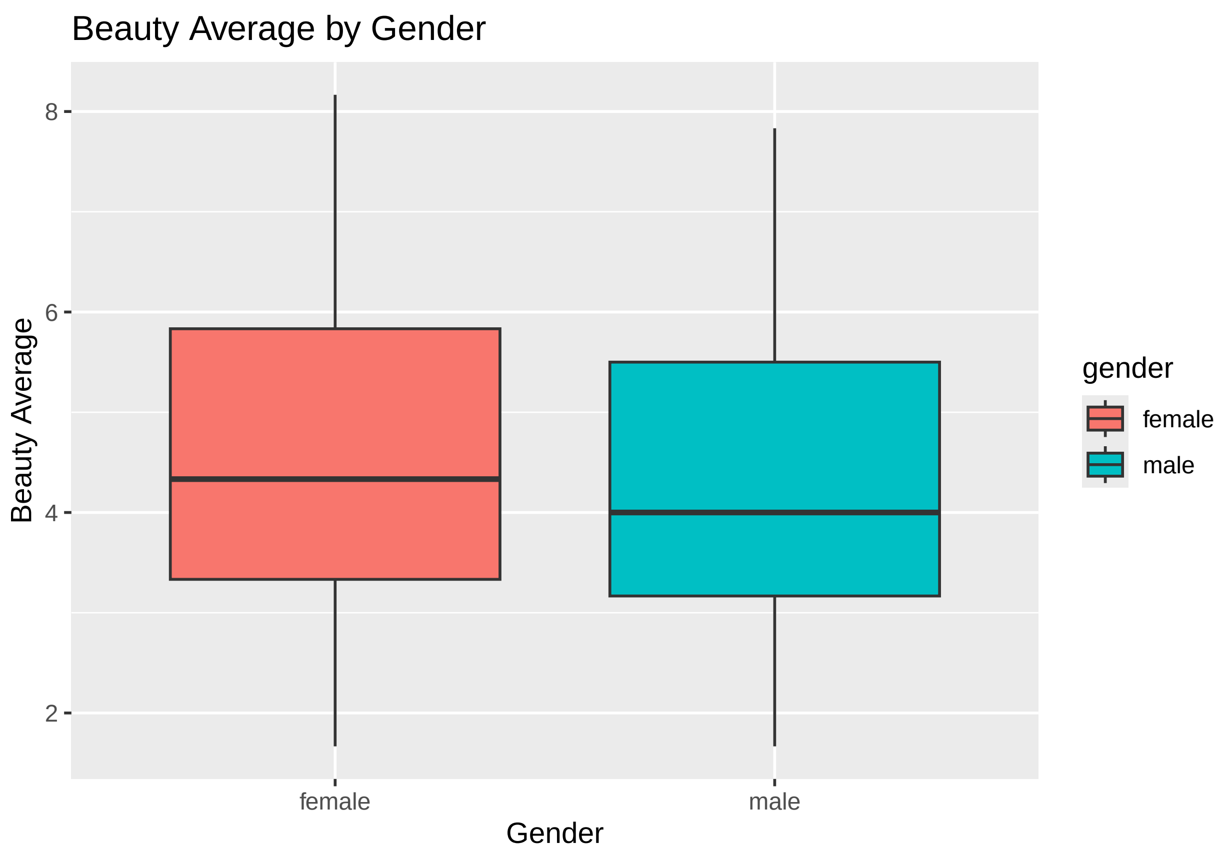


3. Excluding `score`, select two other variables and describe their relationship with each other using an appropriate visualization.

Comparing the two variables: Gender and Beauty Average, we can see the mean of the Gender and Beauty Average for female are higher than male.

```
library(ggplot2)
```

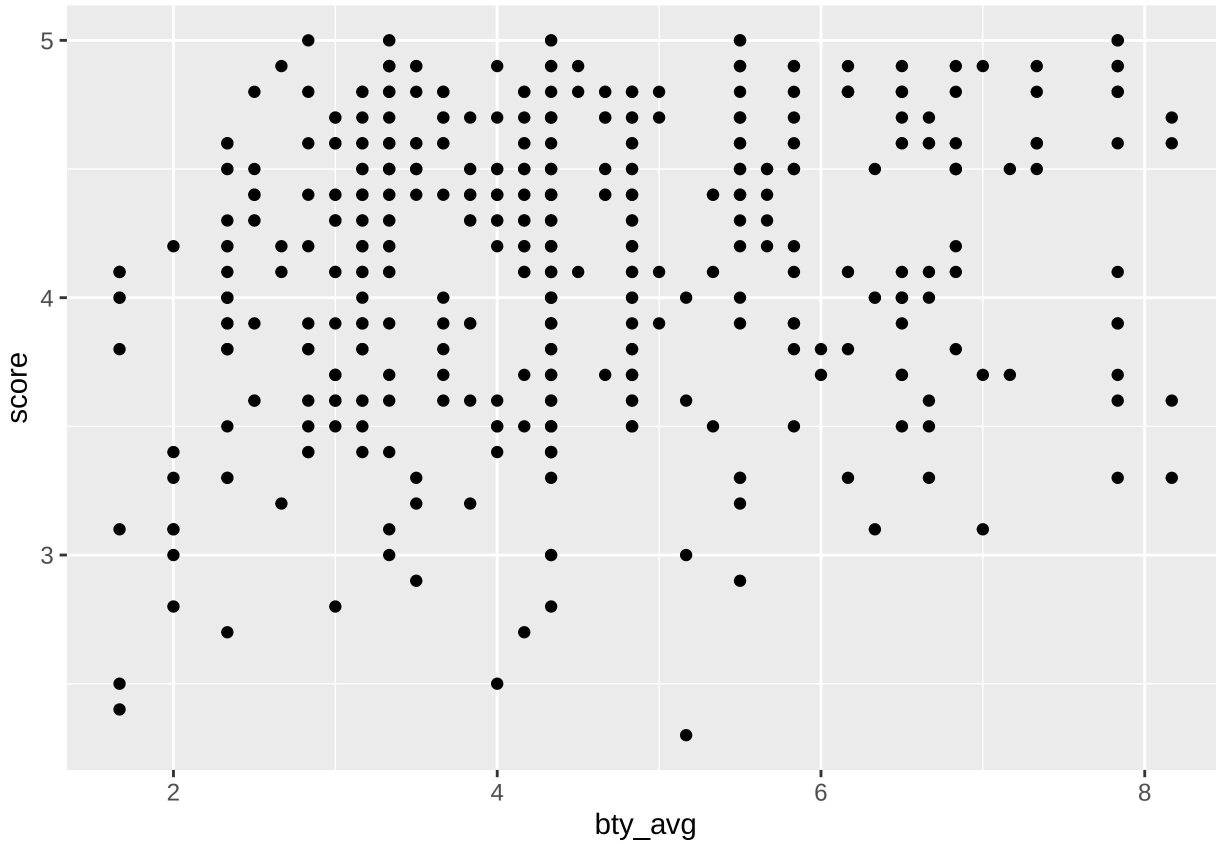
```
ggplot(evals, aes(x = gender, y = bty_avg, fill = gender)) +
  geom_boxplot() +
  labs(title = "Beauty Average by Gender",
       x = "Gender", y = "Beauty Average")
```



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:

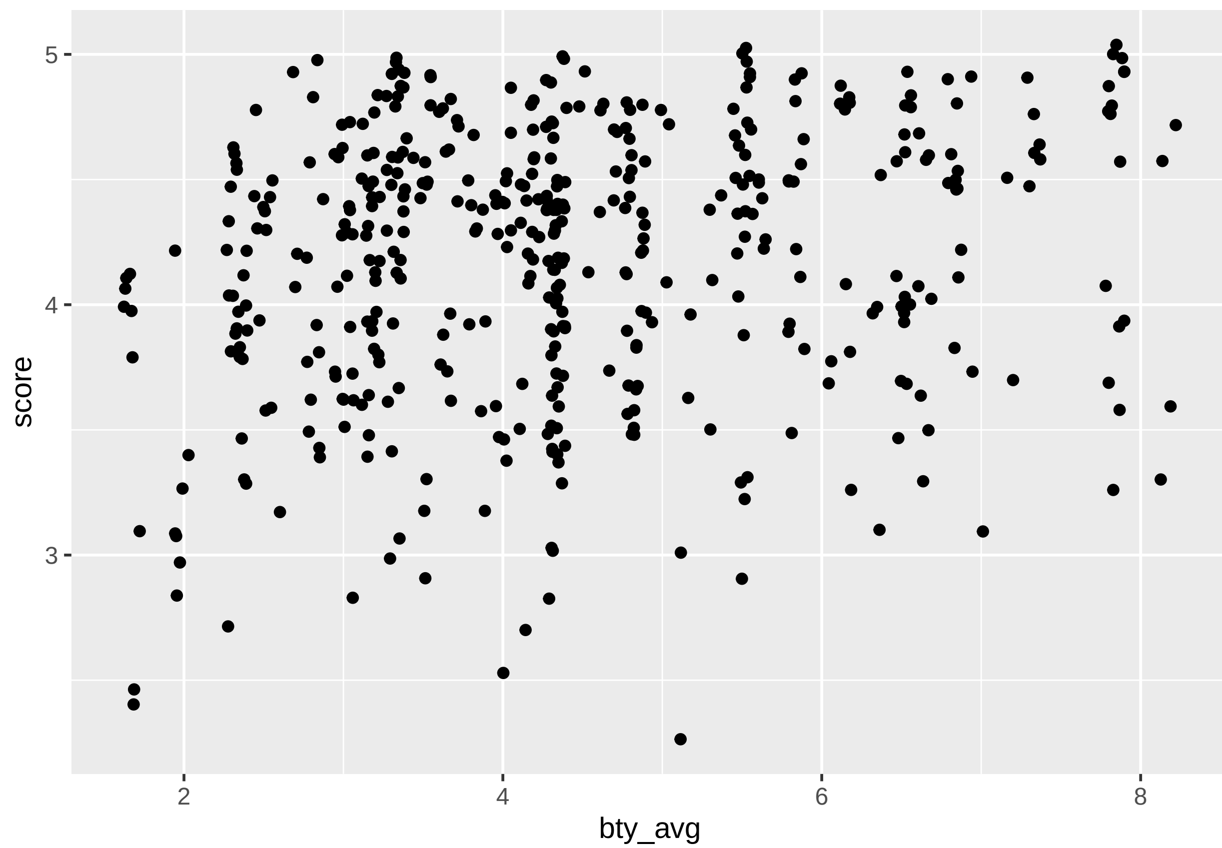
```
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_point()
```



Before you 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 `geom_jitter` as your layer. What was misleading about the initial scatterplot?

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



Q4: The second plot shows more overlapping scores and more natural variation.

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. 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?

Q5: score = 3.88034 + 0.06664 x bty_avg. The slope of the line is 0.0664, which means there is an upward positive correlation. Being that the r-squared is 3.3%, this is a small variation for the average beauty rating to be a statistically significant predictor.

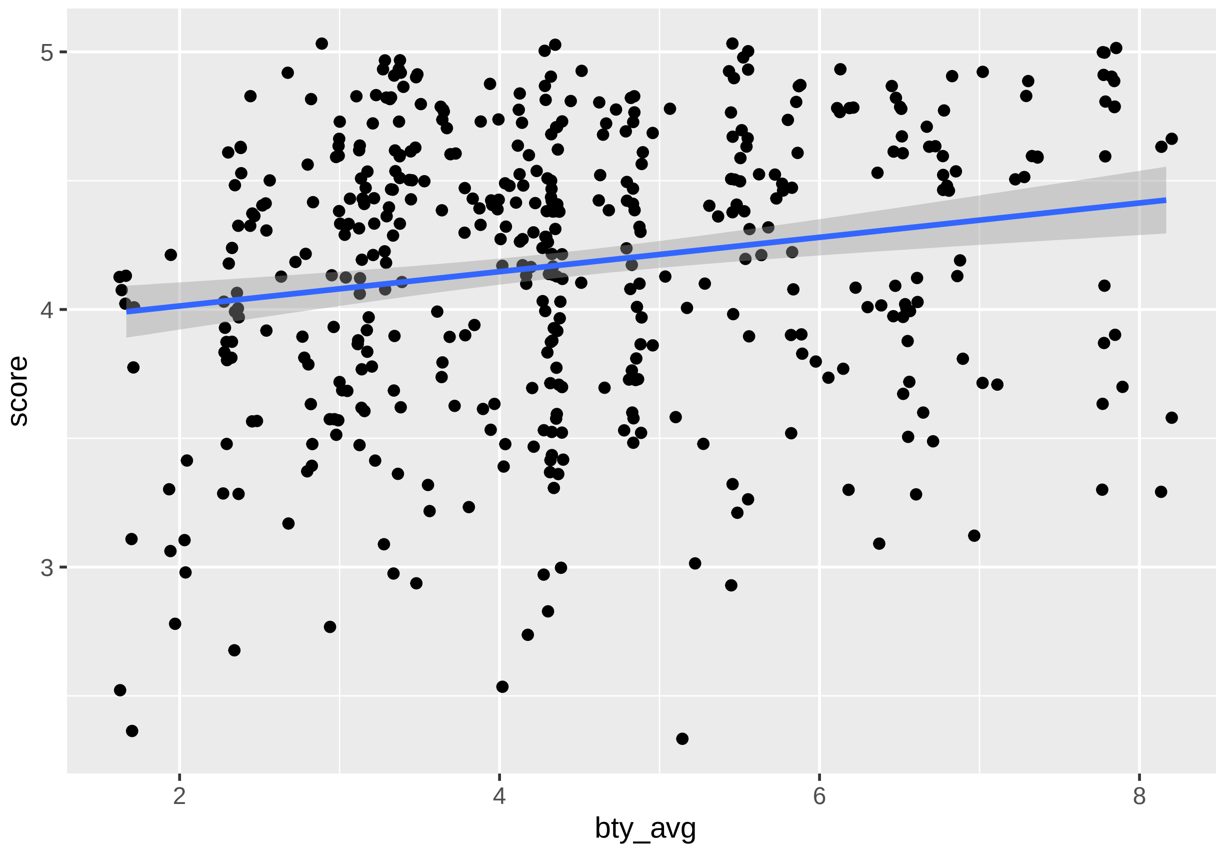
```
m_bty <- lm(evals$score ~ evals$bty_avg)
summary(m_bty)
```

```
##
## Call:
## lm(formula = evals$score ~ evals$bty_avg)
##
## 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 ***
```

```
## evals$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
```

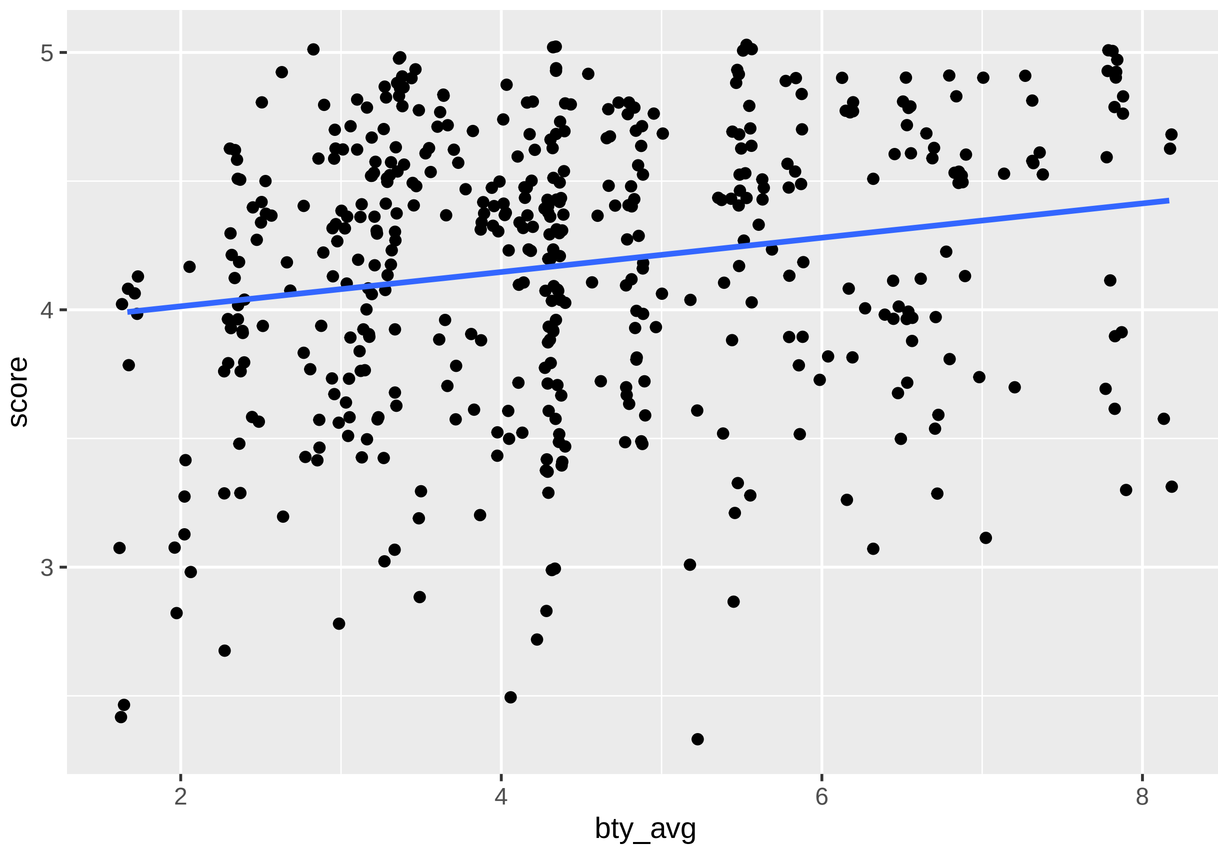
Add the line of the bet fit model to your plot using the following:

```
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_jitter() +
  geom_smooth(method = "lm")
```



The blue line is the model. The shaded gray area around the line tells you about the variability you might expect in your predictions. To turn that off, use `se = FALSE`.

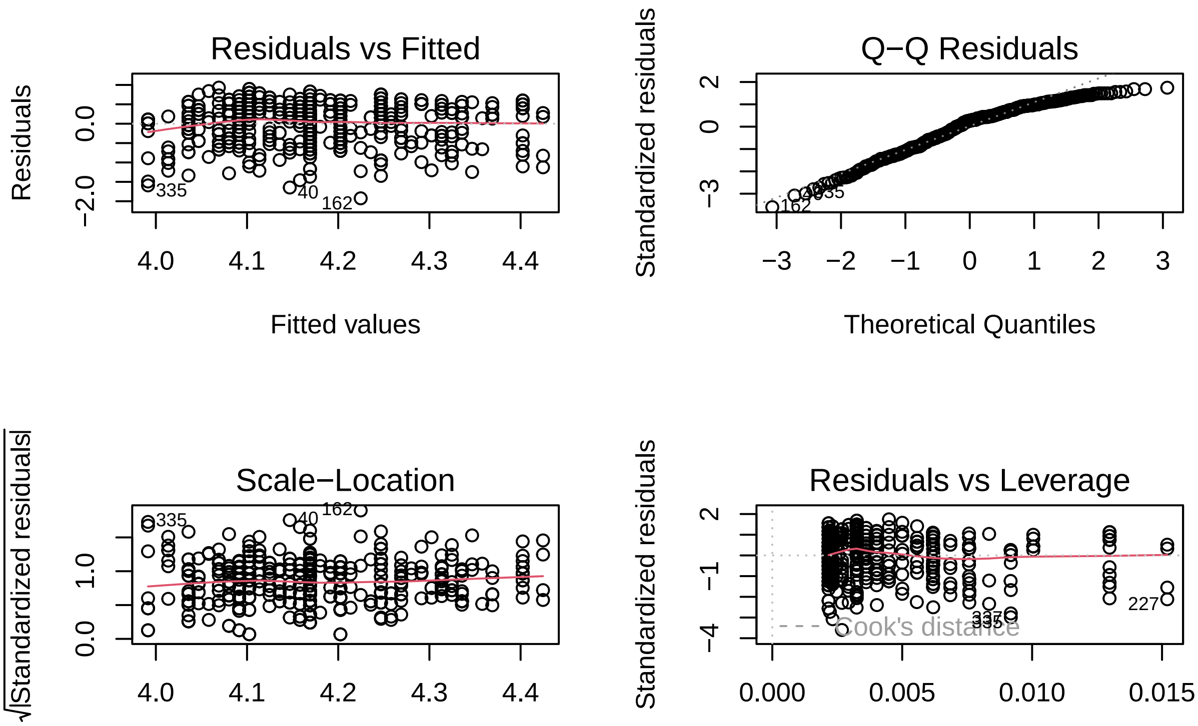
```
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_jitter() +
  geom_smooth(method = "lm", se = FALSE)
```



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).

Q6: The three conditions for least squares regression are 1.linearity 2.constant variability 3.nearly normal distribution. The Residuals vs Fitted plot does not show a linear pattern. The QQ- plot shows most the point are approximately follow a straight line and nearly normal distribution.

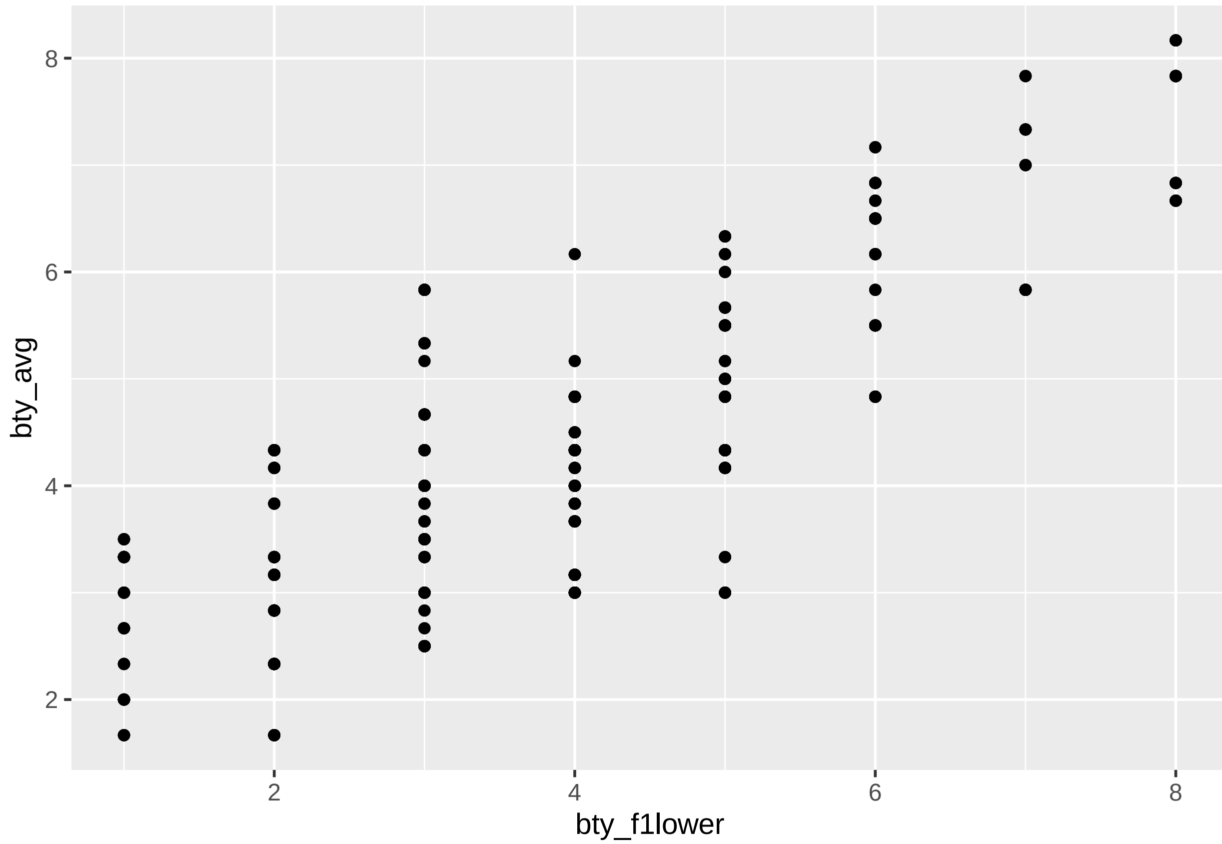
```
par(mfrow = c(2,2))
plot(m_bty)
```



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.

```
ggplot(data = evals, aes(x = bty_f1lower, y = bty_avg)) +
  geom_point()
```

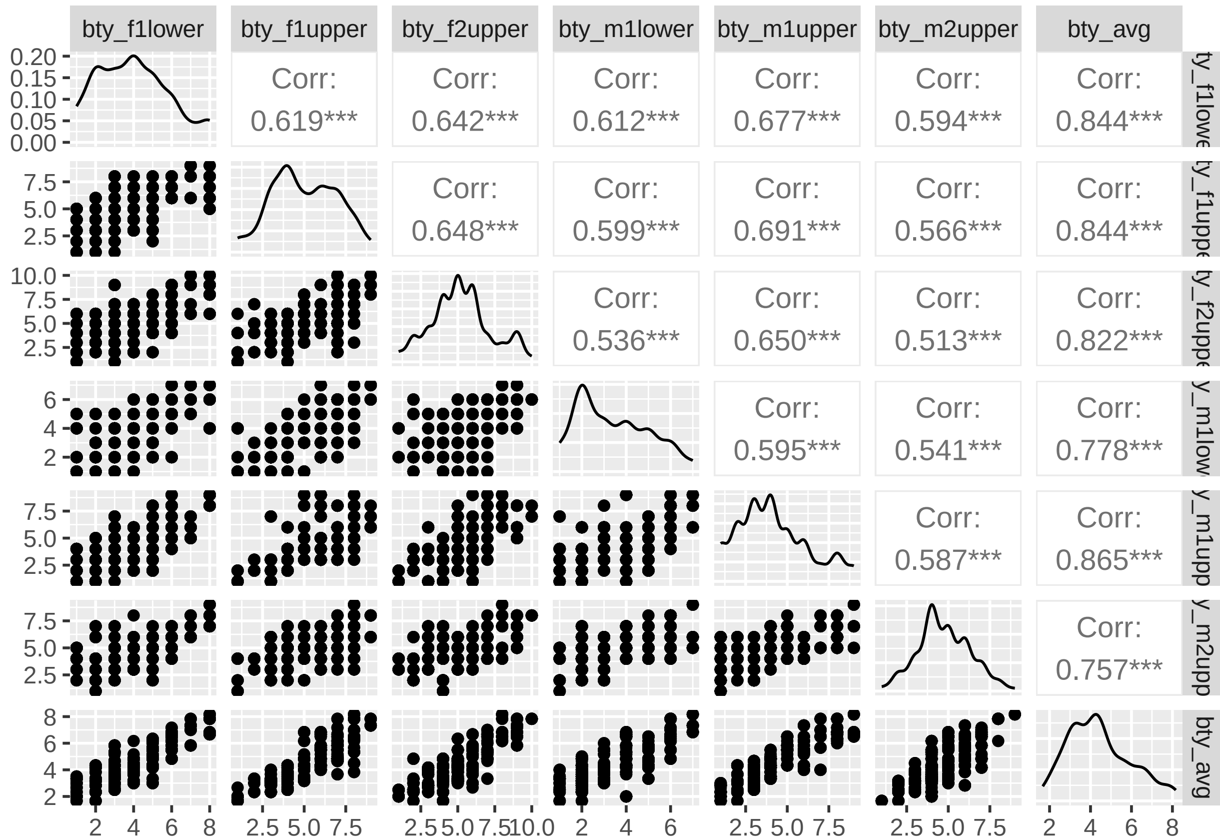



```
evals %>%
  summarise(cor(bty_avg, bty_f1lower))
```

```
## # A tibble: 1 x 1
##   `cor(bty_avg, bty_f1lower)`
##                         <dbl>
## 1                       0.844
```

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

```
evals %>%
  select(contains("bty")) %>%
  ggpairs()
```



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 you've accounted for the professor's gender, you can add the gender term into the model.

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

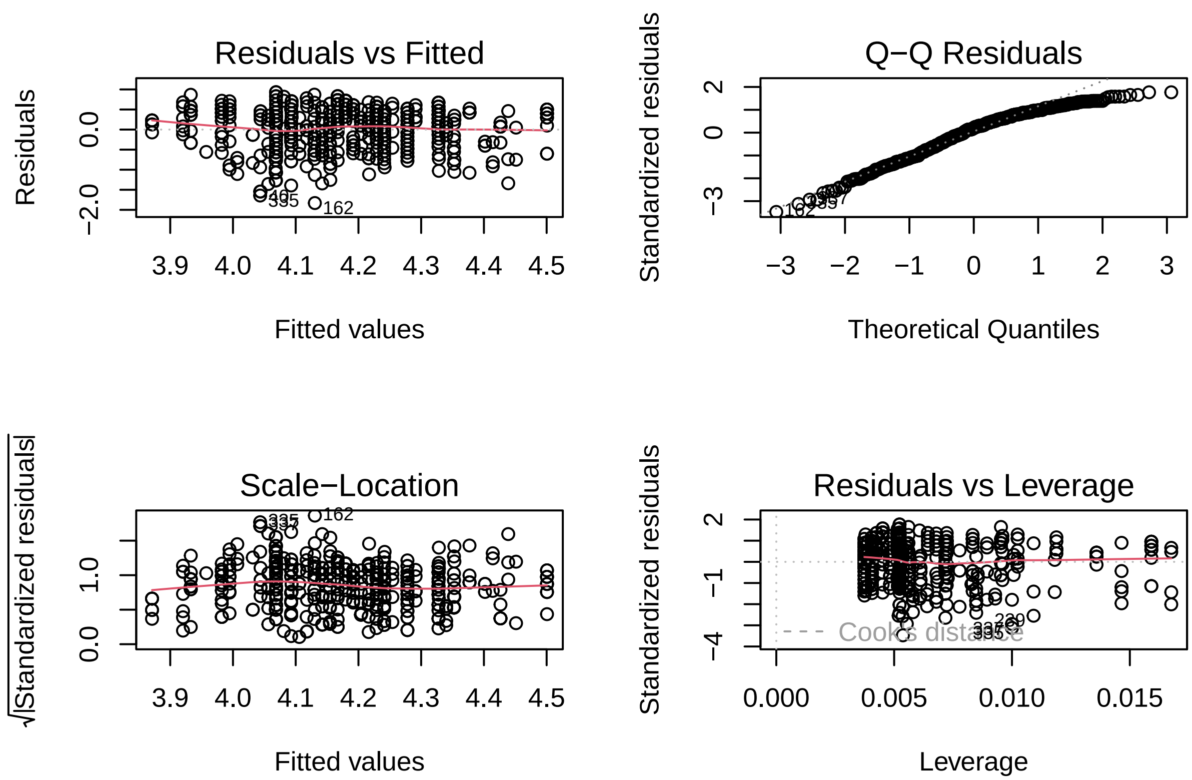
```
##
## Call:
## lm(formula = score ~ bty_avg + gender, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8305 -0.3625  0.1055  0.4213  0.9314
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.74734    0.08466  44.266  < 2e-16 ***
## 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
```

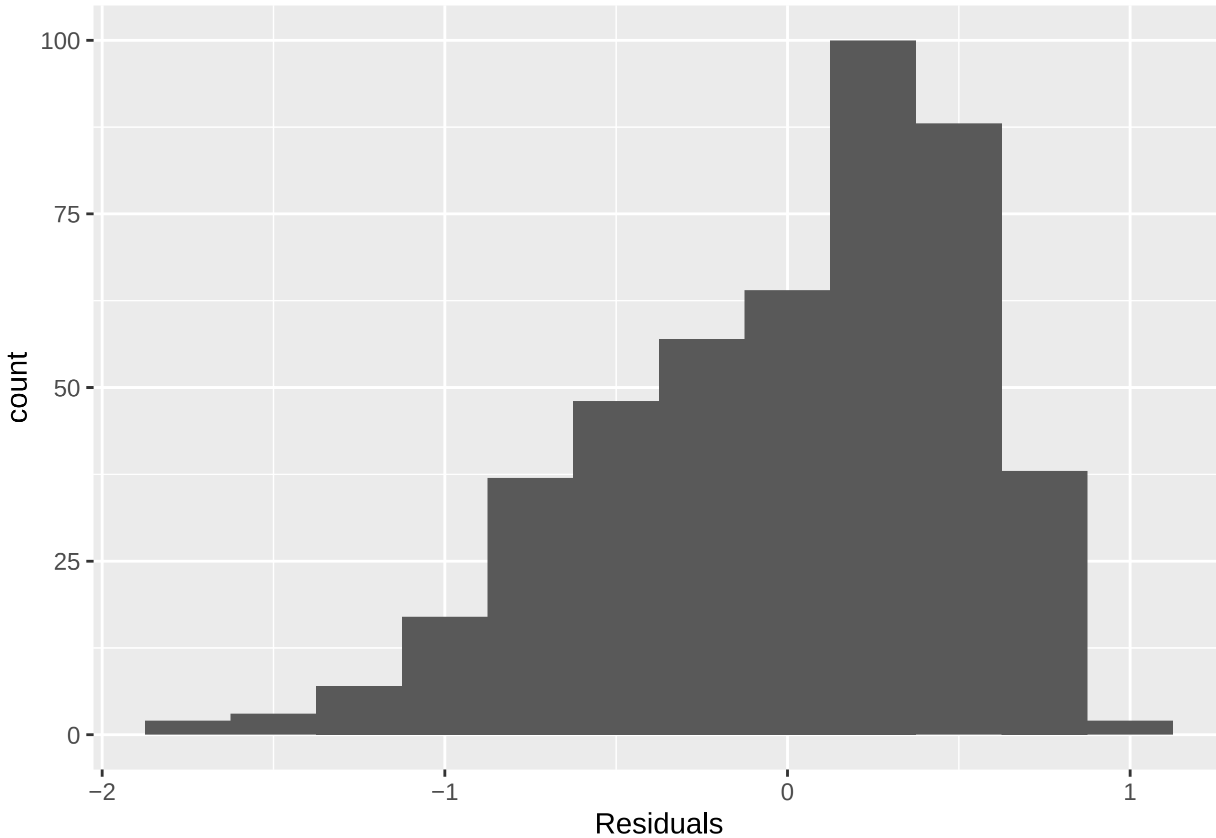
7. P-values and parameter estimates should only be trusted if the conditions for the regression are reasonable. Verify that the conditions for this model are reasonable using diagnostic plots.

Q7: The regression conditions for this model are not reasonable, the residuals are not uniformly. The residuals are looks like a normally distributed with a left skew.

```r
m_bty_gen <- lm(score ~ bty_avg + gender, data = evals)
par(mfrow = c(2,2))
plot(m_bty_gen)
```




```r
ggplot(data = m_bty_gen, aes(x = .resid)) +
  geom_histogram(binwidth = 0.25) +
  xlab("Residuals")
```



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`?

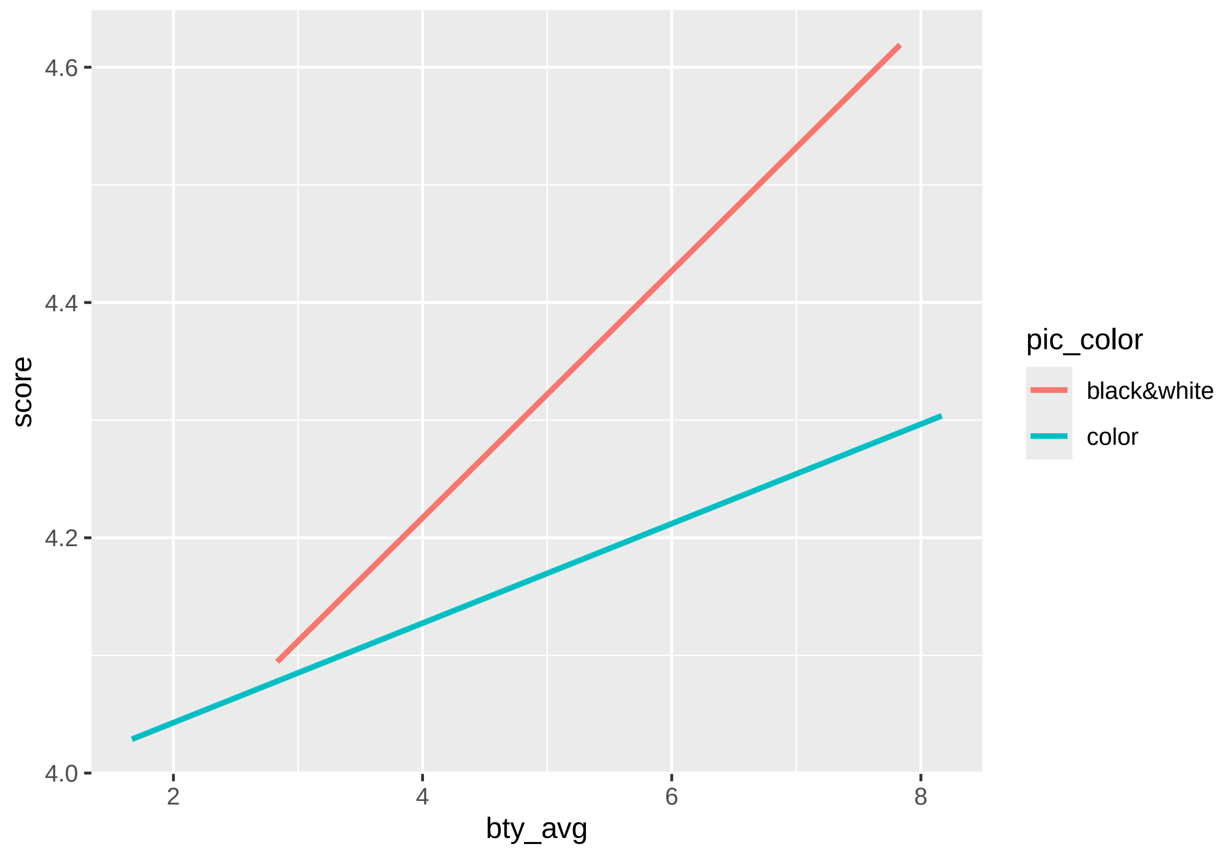
Q8: Yes, the 'bty_avg' still a significant predictor of 'score' Addition of 'gender' to the model had increases the significance of bty_avg, but decreases the adjusted R-square (had change the parameter estimated for bty_avg).

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 `male` and `female` to being an indicator variable called `gendermale` that takes a value of 0 for female professors and a value of 1 for male professors. (Such variables are often referred to as "dummy" variables.)

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

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

```
ggplot(data = evals, aes(x = bty_avg, y = score, color = pic_color)) +
 geom_smooth(method = "lm", formula = y ~ x, se = FALSE)
```



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

Q9: The male tend to have the 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`.

Q10: R has created two dummy variables: ranktenure track and ranktenured.

```
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
```

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, gender, ethnicity, 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.

I expect variable 'number of professors' to have the highest p-value in this model.

Let's run the model…

```
m_full <- lm(score ~ rank + gender + ethnicity + 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 + gender + 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
## -1.77397 -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
## gendermale             0.2109481  0.0518230   4.071 5.54e-05 ***
## ethnicitynot minority  0.1234929  0.0786273   1.571  0.11698
## 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.

Q12: clas_profssingle has the highest p-value(0.77806), that confirm my suspicions.

13. Interpret the coefficient associated with the ethnicity variable.

Q13: If all other variables are equal, the score increases by 0.1234929 when the professor is not from a minority.

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?

Q14: Yes, the coefficients and significance did change when we dropped the highest p-value.

```
m_full2 <- lm(score ~ rank + gender + ethnicity + language + age + cls_perc_eval
             + cls_students + cls_level + cls_credits + bty_avg
             + pic_outfit + pic_color, data = evals)
summary(m_full2)
```

```
##
## Call:
## lm(formula = score ~ rank + gender + ethnicity + language + age +
##     cls_perc_eval + cls_students + cls_level + cls_credits +
##     bty_avg + pic_outfit + pic_color, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.7836 -0.3257  0.0859  0.3513  0.9551
```

```
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           4.0872523  0.2888562  14.150  < 2e-16 ***
## ranktenure track     -0.1476746  0.0819824  -1.801 0.072327 .
## ranktenured          -0.0973829  0.0662614  -1.470 0.142349
## gendermale            0.2101231  0.0516873   4.065 5.66e-05 ***
## ethnicitynot minority 0.1274458  0.0772887   1.649 0.099856 .
## languagenon-english  -0.2282894  0.1111305  -2.054 0.040530 *
## age                  -0.0089992  0.0031326  -2.873 0.004262 **
## cls_perc_eval         0.0052888  0.0015317   3.453 0.000607 ***
## cls_students          0.0004687  0.0003737   1.254 0.210384
## cls_levelupper        0.0606374  0.0575010   1.055 0.292200
## cls_creditsone credit 0.5061196  0.1149163   4.404 1.33e-05 ***
## bty_avg               0.0398629  0.0174780   2.281 0.023032 *
## pic_outfitnot formal -0.1083227  0.0721711  -1.501 0.134080
## pic_colorcolor       -0.2190527  0.0711469  -3.079 0.002205 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4974 on 449 degrees of freedom
## Multiple R-squared:  0.187,  Adjusted R-squared:  0.1634
## F-statistic: 7.943 on 13 and 449 DF,  p-value: 2.336e-14
```

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.

score = 3.907030 + 0.163818 x ethnicity_not_minority + 0.202597 x gendermale - 0.246683 x language-english - 0.006925x age + 0.004942 x cls_perc_eval + 0.517205 x cls_creditsone_credit + 0.046732 x bty_avg - 0.180870 x pic_color

```
final_model <- step(m_full, direction = "backward", criterion = "p-value")
```

```
## Start:  AIC=-630.9
## score ~ rank + gender + ethnicity + 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
## - cls_profs      1    0.0197 111.11 -632.82
## - cls_level      1    0.2740 111.36 -631.76
## - cls_students   1    0.3599 111.44 -631.40
## - rank           2    0.8930 111.98 -631.19
## <none>                       111.08 -630.90
## - pic_outfit     1    0.5768 111.66 -630.50
## - ethnicity      1    0.6117 111.70 -630.36
## - language       1    1.0557 112.14 -628.52
## - bty_avg        1    1.2967 112.38 -627.53
## - age            1    2.0456 113.13 -624.45
## - pic_color      1    2.2893 113.37 -623.46
## - cls_perc_eval  1    2.9698 114.06 -620.69
## - gender         1    4.1085 115.19 -616.09
```

```
## - cls_credits    1    4.6495 115.73 -613.92
##
## Step:  AIC=-632.82
## score ~ rank + gender + ethnicity + language + age + cls_perc_eval +
##     cls_students + cls_level + cls_credits + bty_avg + pic_outfit +
##     pic_color
##
##                Df Sum of Sq    RSS     AIC
## - cls_level     1    0.2752 111.38 -633.67
## - cls_students  1    0.3893 111.49 -633.20
## - rank          2    0.8939 112.00 -633.11
## <none>                      111.11 -632.82
## - pic_outfit    1    0.5574 111.66 -632.50
## - ethnicity     1    0.6728 111.78 -632.02
## - language      1    1.0442 112.15 -630.49
## - bty_avg       1    1.2872 112.39 -629.49
## - age           1    2.0422 113.15 -626.39
## - pic_color     1    2.3457 113.45 -625.15
## - cls_perc_eval 1    2.9502 114.06 -622.69
## - gender        1    4.0895 115.19 -618.08
## - cls_credits   1    4.7999 115.90 -615.24
##
## Step:  AIC=-633.67
## score ~ rank + gender + ethnicity + language + age + cls_perc_eval +
##     cls_students + cls_credits + bty_avg + pic_outfit + pic_color
##
##                Df Sum of Sq    RSS     AIC
## - cls_students  1    0.2459 111.63 -634.65
## - rank          2    0.8140 112.19 -634.30
## <none>                      111.38 -633.67
## - pic_outfit    1    0.6618 112.04 -632.93
## - ethnicity     1    0.8698 112.25 -632.07
## - language      1    0.9015 112.28 -631.94
## - bty_avg       1    1.3694 112.75 -630.02
## - age           1    1.9342 113.31 -627.70
## - pic_color     1    2.0777 113.46 -627.12
## - cls_perc_eval 1    3.0290 114.41 -623.25
## - gender        1    3.8989 115.28 -619.74
## - cls_credits   1    4.5296 115.91 -617.22
##
## Step:  AIC=-634.65
## score ~ rank + gender + ethnicity + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_outfit + pic_color
##
##                Df Sum of Sq    RSS     AIC
## - rank          2    0.7892 112.42 -635.39
## <none>                      111.63 -634.65
## - ethnicity     1    0.8832 112.51 -633.00
## - pic_outfit    1    0.9700 112.60 -632.65
## - language      1    1.0338 112.66 -632.38
## - bty_avg       1    1.5783 113.20 -630.15
## - pic_color     1    1.9477 113.57 -628.64
## - age           1    2.1163 113.74 -627.96
## - cls_perc_eval 1    2.7922 114.42 -625.21
```

```
## - gender         1    4.0945 115.72 -619.97
## - cls_credits    1    4.5163 116.14 -618.29
##
## Step:  AIC=-635.39
## score ~ gender + ethnicity + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_outfit + pic_color
##
##                Df Sum of Sq    RSS     AIC
## <none>                      112.42 -635.39
## - pic_outfit     1    0.7141 113.13 -634.46
## - ethnicity      1    1.1790 113.59 -632.56
## - language       1    1.3403 113.75 -631.90
## - age            1    1.6847 114.10 -630.50
## - pic_color      1    1.7841 114.20 -630.10
## - bty_avg        1    1.8553 114.27 -629.81
## - cls_perc_eval  1    2.9147 115.33 -625.54
## - gender         1    4.0577 116.47 -620.97
## - cls_credits    1    6.1208 118.54 -612.84
```

```r
summary(final_model)
```

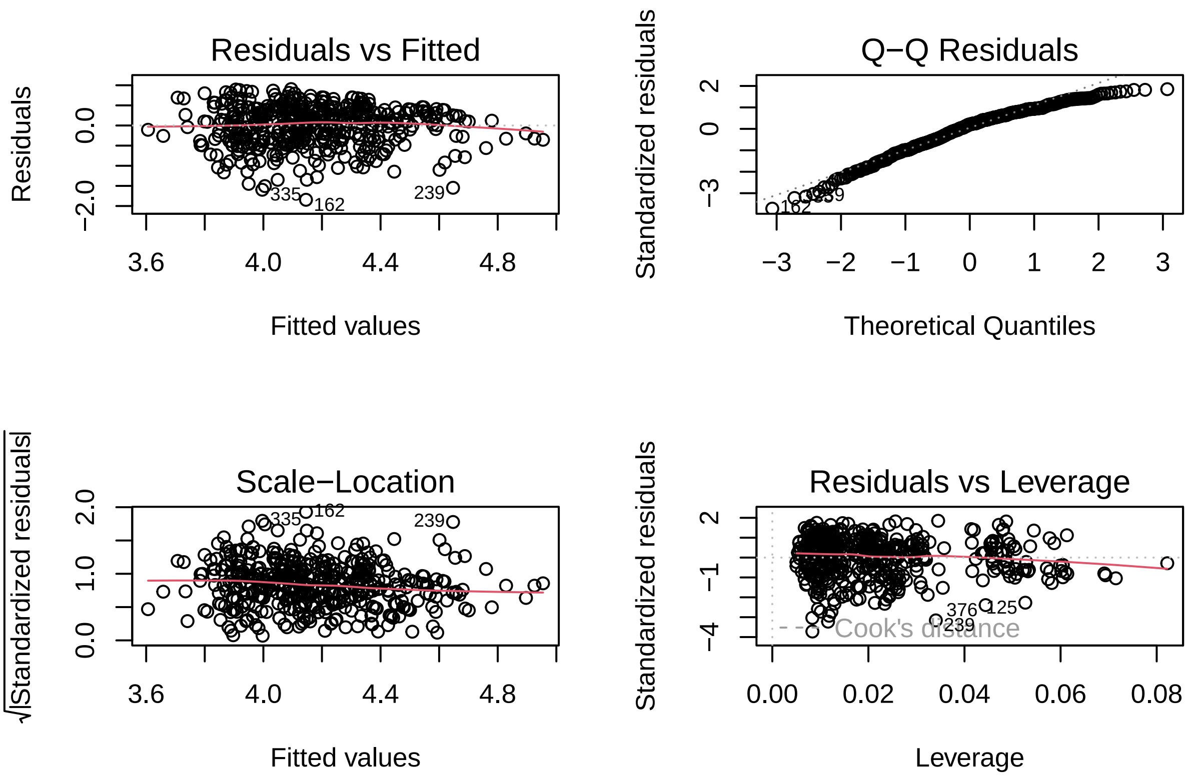
```
##
## Call:
## lm(formula = score ~ gender + ethnicity + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_outfit + pic_color, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8455 -0.3221  0.1013  0.3745  0.9051
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            3.907030   0.244889  15.954  < 2e-16 ***
## gendermale             0.202597   0.050102   4.044 6.18e-05 ***
## ethnicitynot minority  0.163818   0.075158   2.180 0.029798 *
## languagenon-english   -0.246683   0.106146  -2.324 0.020567 *
## age                   -0.006925   0.002658  -2.606 0.009475 **
## cls_perc_eval          0.004942   0.001442   3.427 0.000666 ***
## cls_creditsone credit  0.517205   0.104141   4.966 9.68e-07 ***
## bty_avg                0.046732   0.017091   2.734 0.006497 **
## pic_outfitnot formal  -0.113939   0.067168  -1.696 0.090510 .
## pic_colorcolor        -0.180870   0.067456  -2.681 0.007601 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4982 on 453 degrees of freedom
## Multiple R-squared:  0.1774, Adjusted R-squared:  0.161
## F-statistic: 10.85 on 9 and 453 DF,  p-value: 2.441e-15
```

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

Q16: These plots appear linearly related

```
par(mfrow = c(2,2))

plot(final_model)
```



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?

Yes, if the professors teach more than one course or student take more than one class with same professors.

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.

Q18: Base on the final model, the higher scores will be given to professors who are male, non-minority, old age, and teaching one credit class.

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

Q19: No, in order to make this study fair, we have to ensure the other schools with similar populations of professors and student.
