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)
library(ggplot2)
library(broom)
```

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:

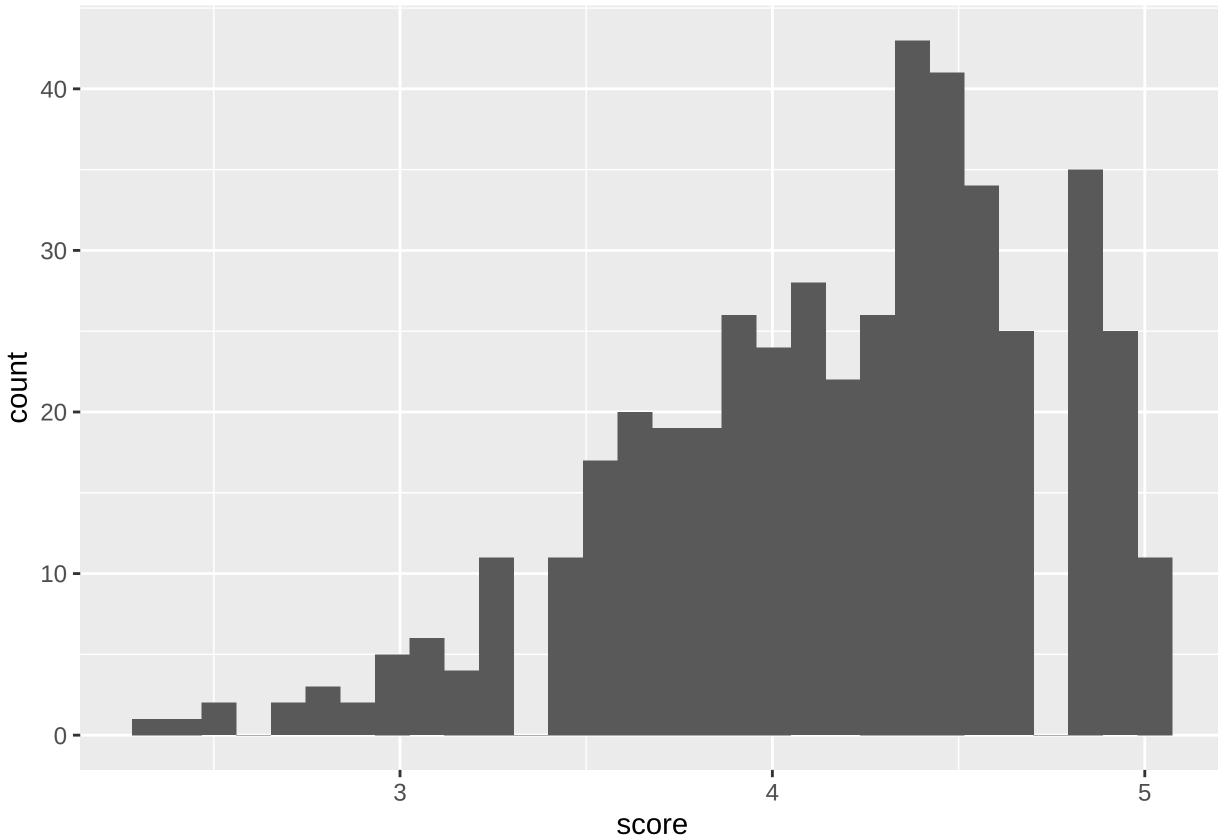
```
?evals
```

Exploring the data

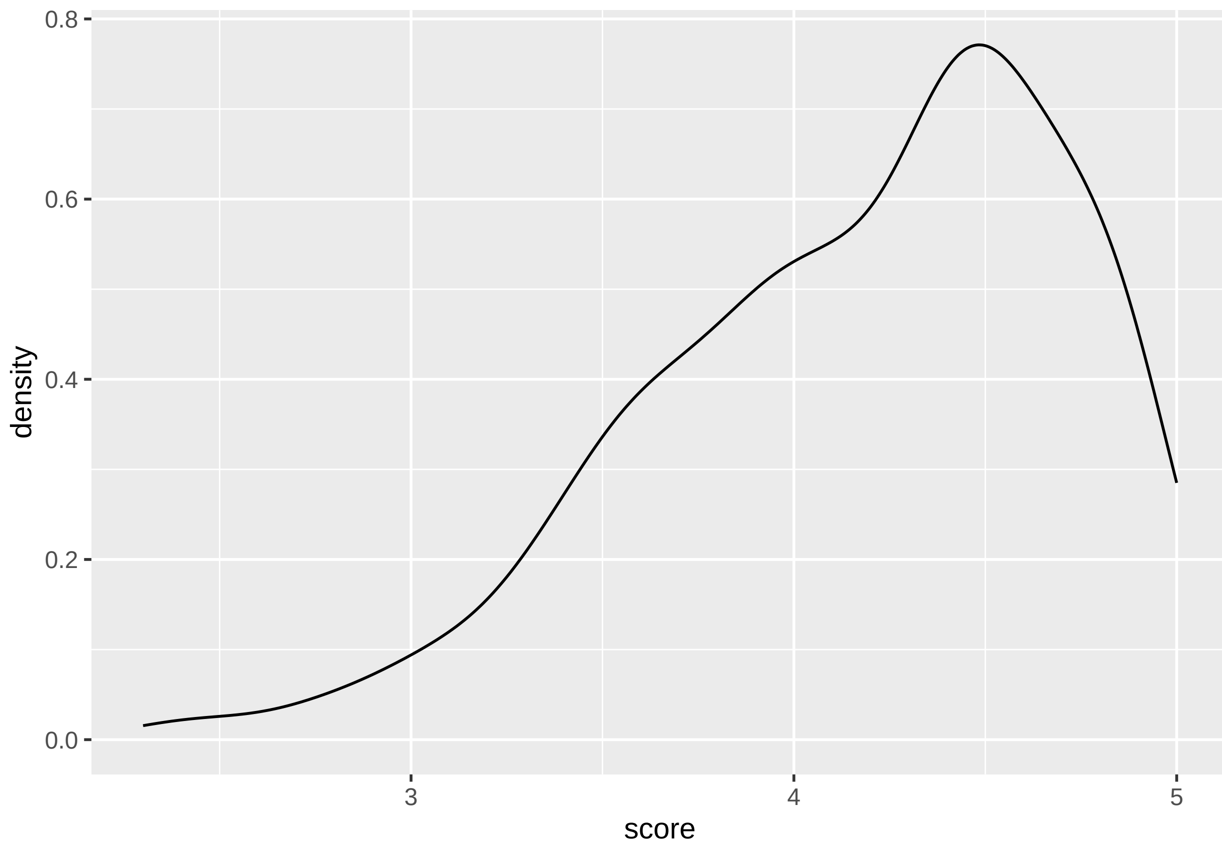
1. Is this an observational study or an experiment? The original research question posed in the paper is whether beauty leads directly to the differences in course evaluations. Given the study design, is it possible to answer this question as it is phrased? If not, rephrase the question. **Exercise 1 Response This is an observational study. Another way to phrase this question would be if the data is observational or experimental.**

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? **Exercise 2 Response**

```
ggplot(data = evals, aes(x = score)) +
  geom_histogram()
```




```
ggplot(data = evals, aes(x = score)) +
  geom_density()
```



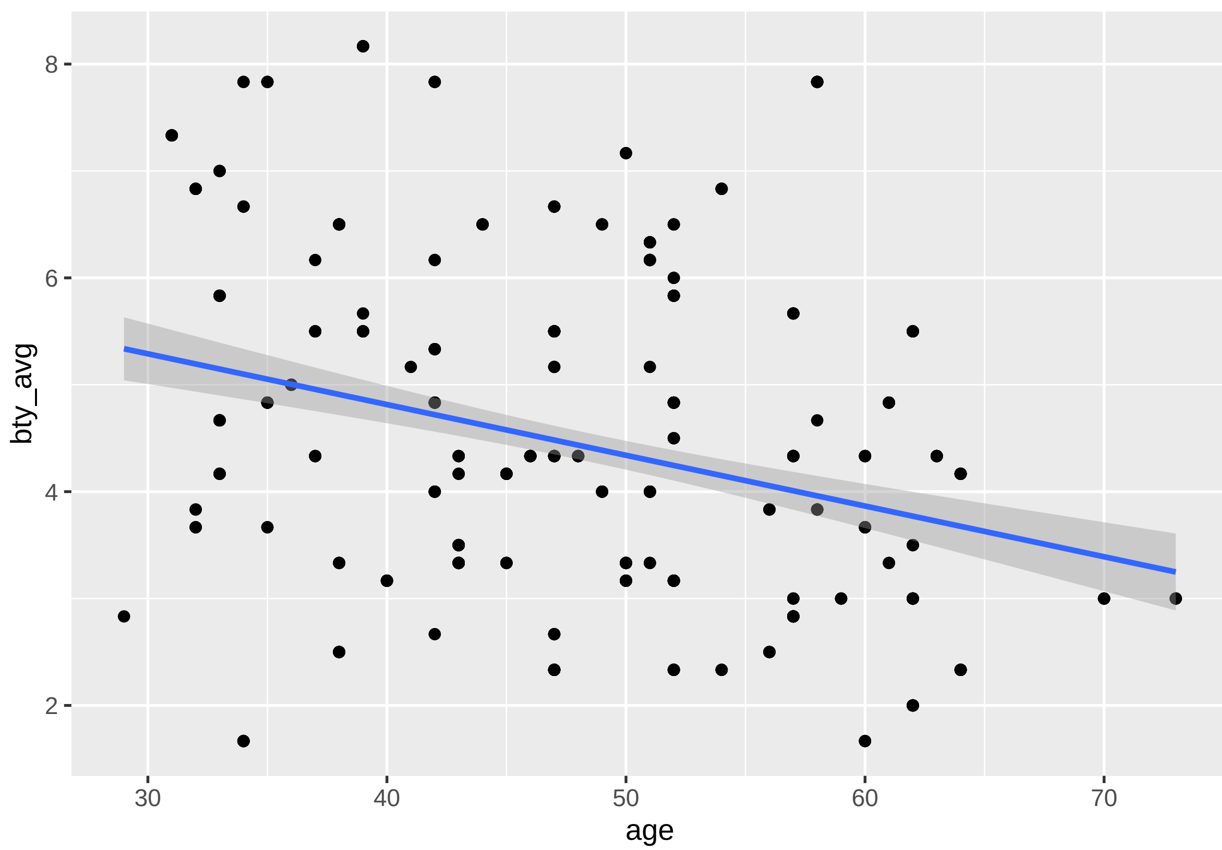

```
evals %>%
  summarise(median = median(score),
            mean = mean(score),
            max = max(score),
            nmax = sum(score == max(.$score)),
            min = min(score),
            nmin = sum(score == min(.$score)),
            iqr = IQR(score),
            sd = sd(score)
  )
```

```
## # A tibble: 1 x 8
##   median  mean   max  nmax   min  nmin   iqr    sd
##    <dbl> <dbl> <dbl> <int> <dbl> <int> <dbl> <dbl>
## 1    4.3  4.17     5    11   2.3     1   0.8 0.544
```

The distribution is positively skewed. This means that students rated their instructors highly. The median rating was 4.3, and the mean rating was 4.17. The maximum rating was 5, and the minimum rating was 2.3.

3. Excluding `score`, select two other variables and describe their relationship with each other using an appropriate visualization. **Exericse 3 The two selected variables are `age` and `bty_avg`. The explanatory variable is the age of the professor, a numerical variable. The response variable is the average beauty rating of the professor, a numerical variable.**

```r
ggplot(data = evals, aes(x = age, y=bty_avg)) +
  geom_point()+
  geom_smooth(method=lm)
```

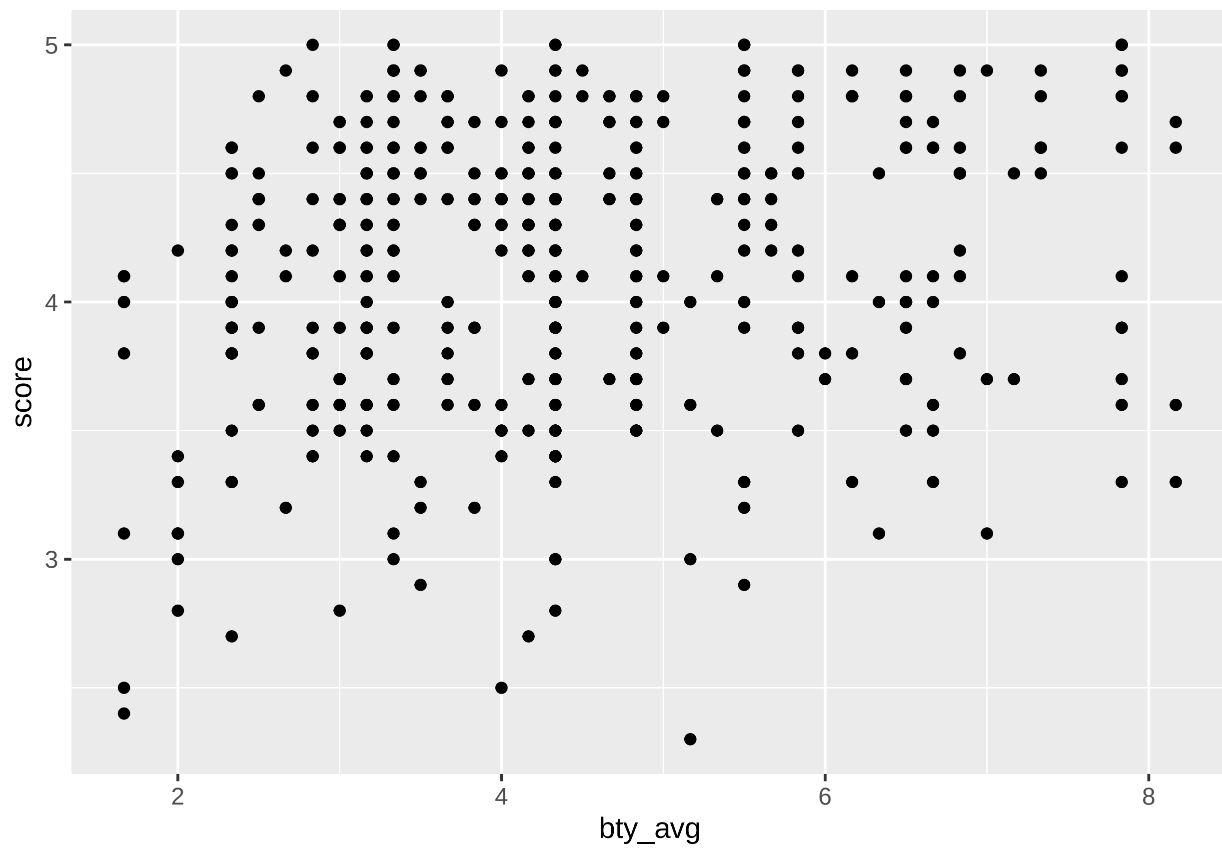


There is a slightly negative relationship between the two variables. The relationship is not very strong.

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:

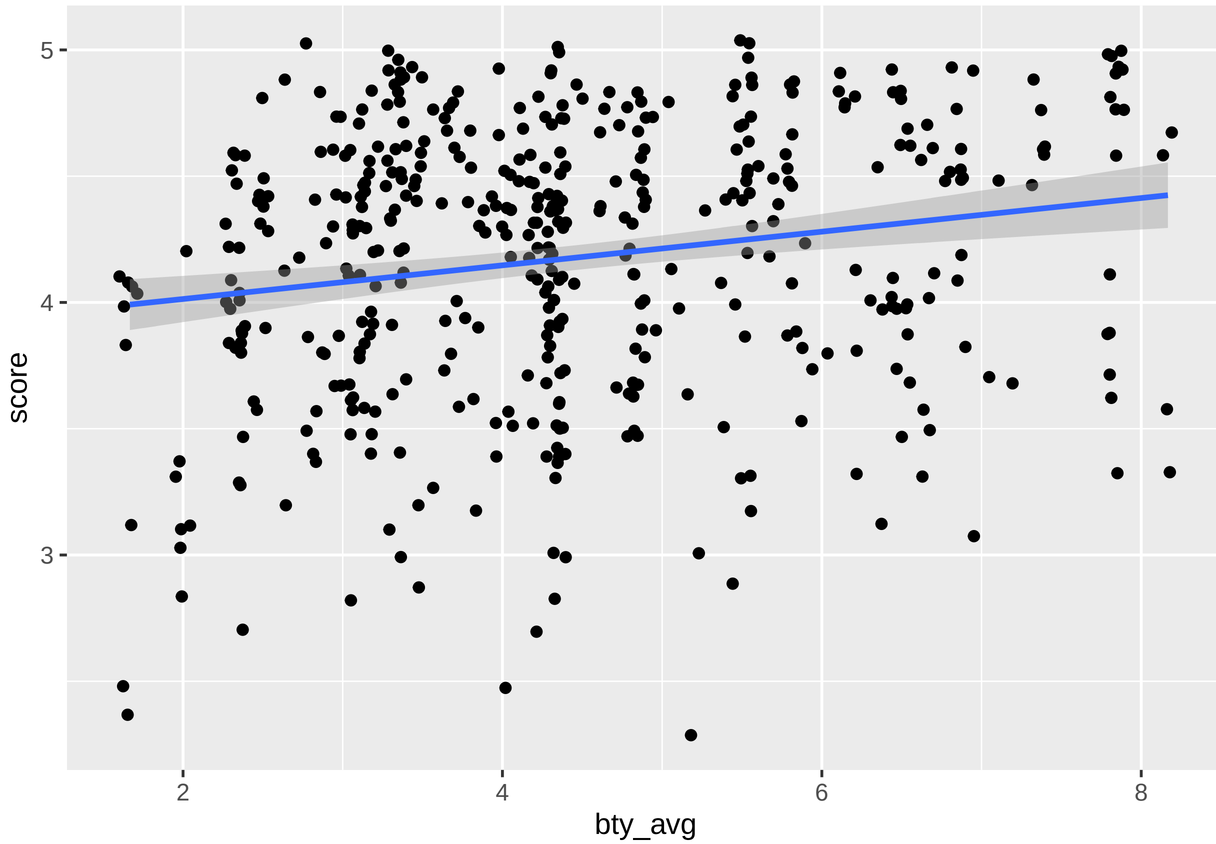
```r
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_point()
```



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? **Exericse 4 Response**

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



The ggplot2 documentation (ggplot2.tidyverse.org/reference/geom_point.html#overplotting) cites that a potential problem with scatterplots are overplotting. This means that if there are too many points, they may be plotted on top of another, affecting the appearance of the plot. By using the geom_jitter() function, it adds a small amount of variation to the location of each point, so that overplotting does not affect the appearance of the plot.

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? **Exercise 5 Response**

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

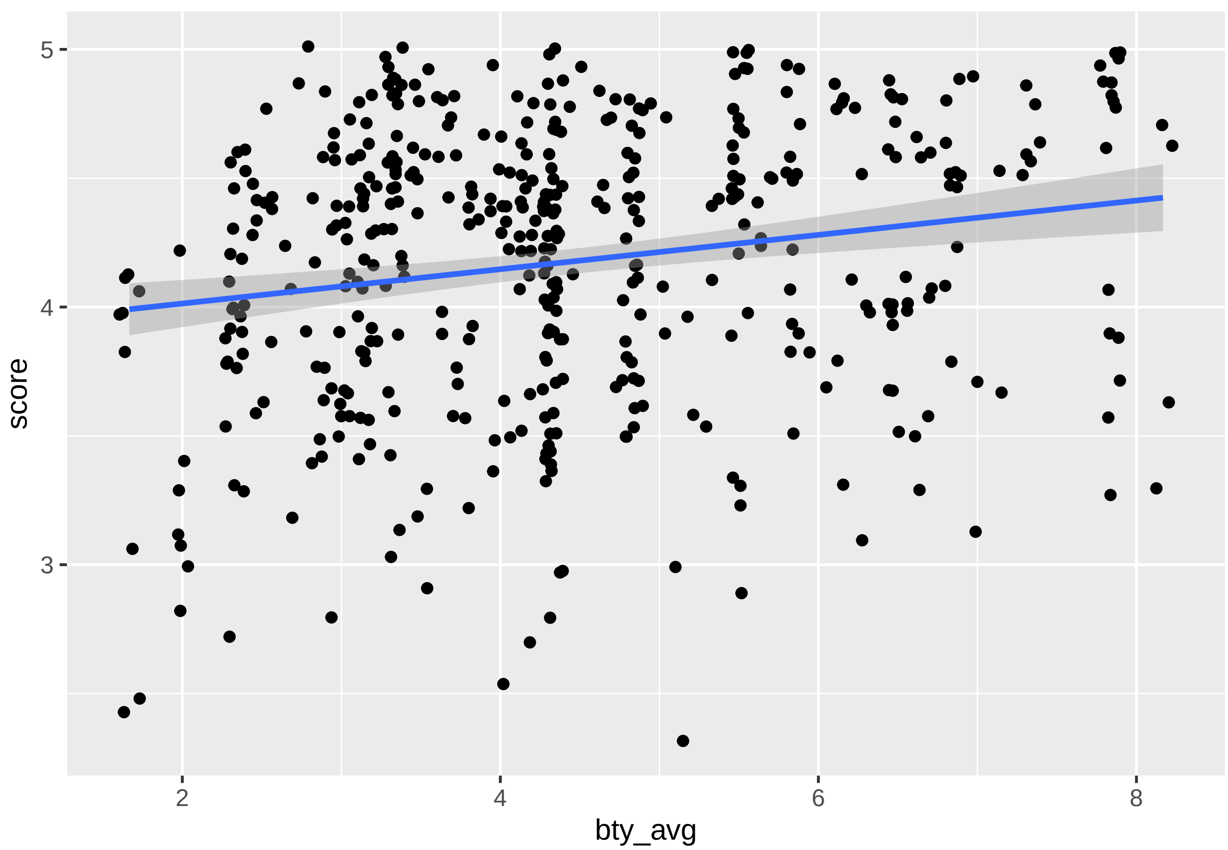
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5348 on 461 degrees of freedom
## Multiple R-squared:  0.03502,	Adjusted R-squared:  0.03293
## F-statistic: 16.73 on 1 and 461 DF,  p-value: 5.083e-05
```

The R^2 value for this model is .5348 on 461 degrees of freedom. This means that a 53.48% of the variation in the professors' total evaluation score can be explained by the the beauty average. This is a significant predictor.

Note: check what the Pr (>|t|) value means

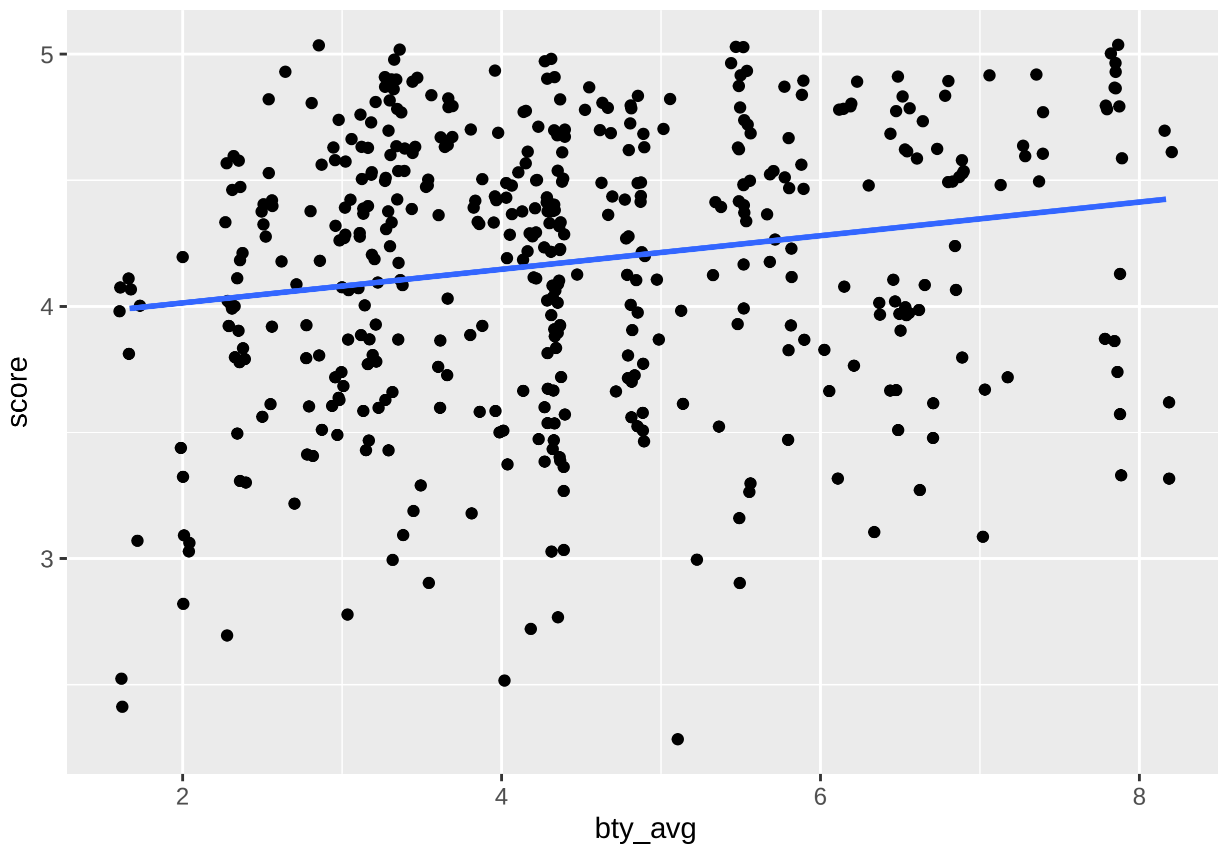
Add the line of the bet fit model to your plot using the following:

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



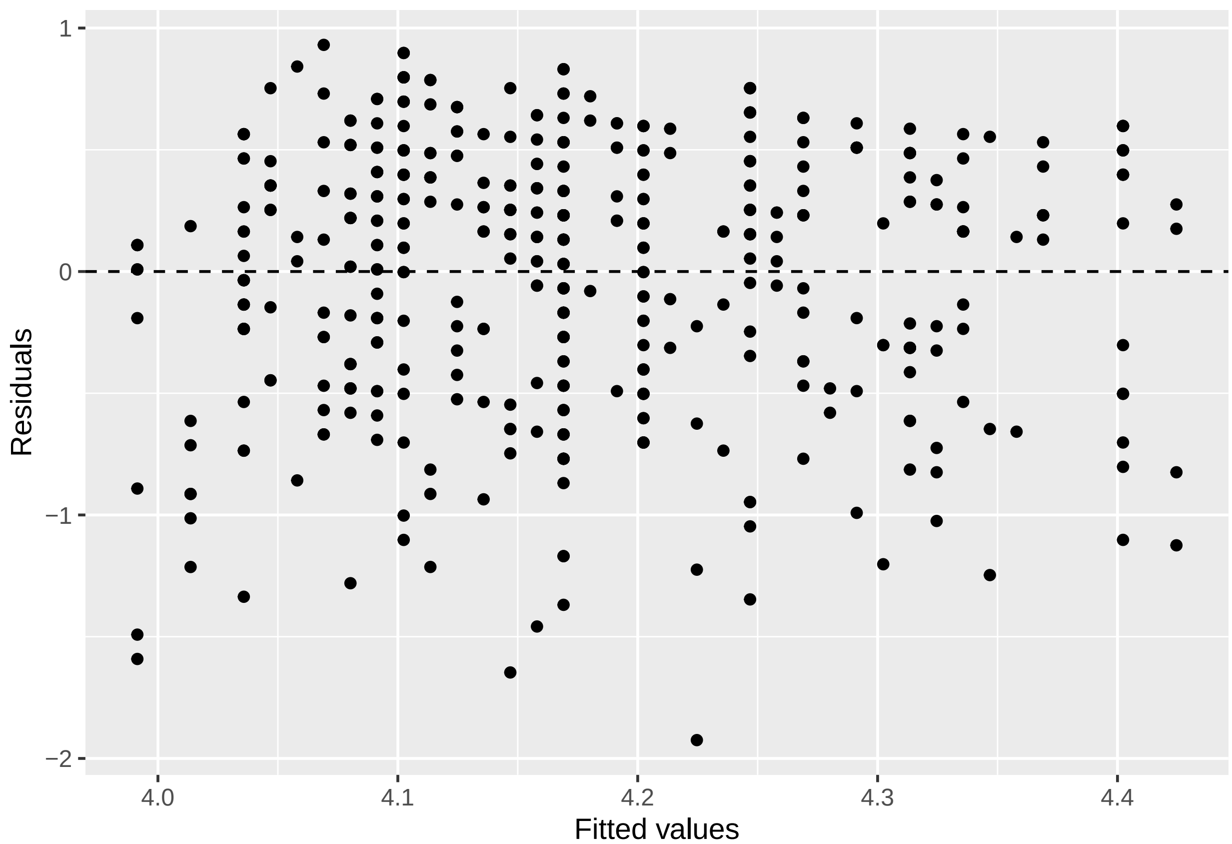
The blue line is the model. The shaded gray area around the line tells you about the variability you might expect in your predictions. To turn that off, use `se = FALSE`.

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

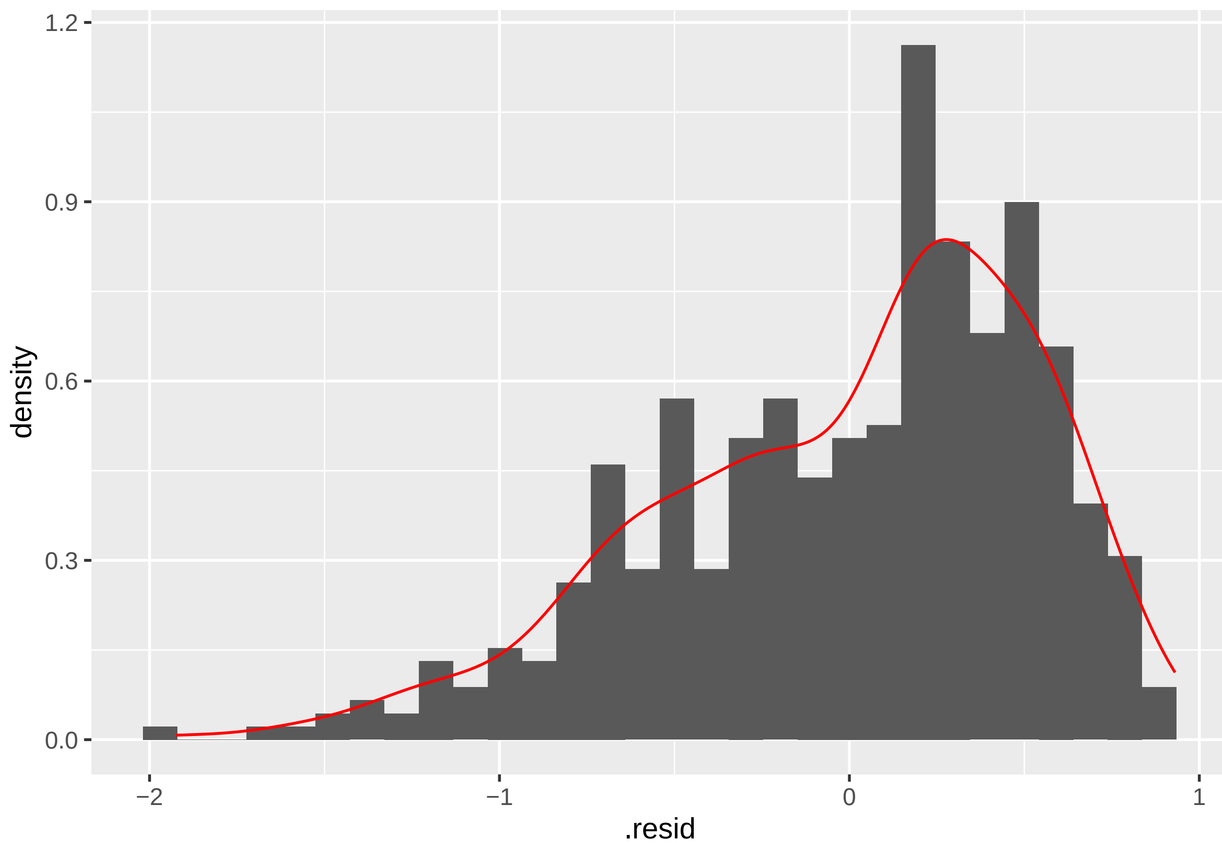


6. Use residual plots to evaluate whether the conditions of least squares regression are reasonable. Provide plots and comments for each one (see the Simple Regression Lab for a reminder of how to make these).
Exercise 6 Response

```
ggplot(data = m_bty, aes(x = .fitted, y = .resid)) +
  geom_point() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals")
```



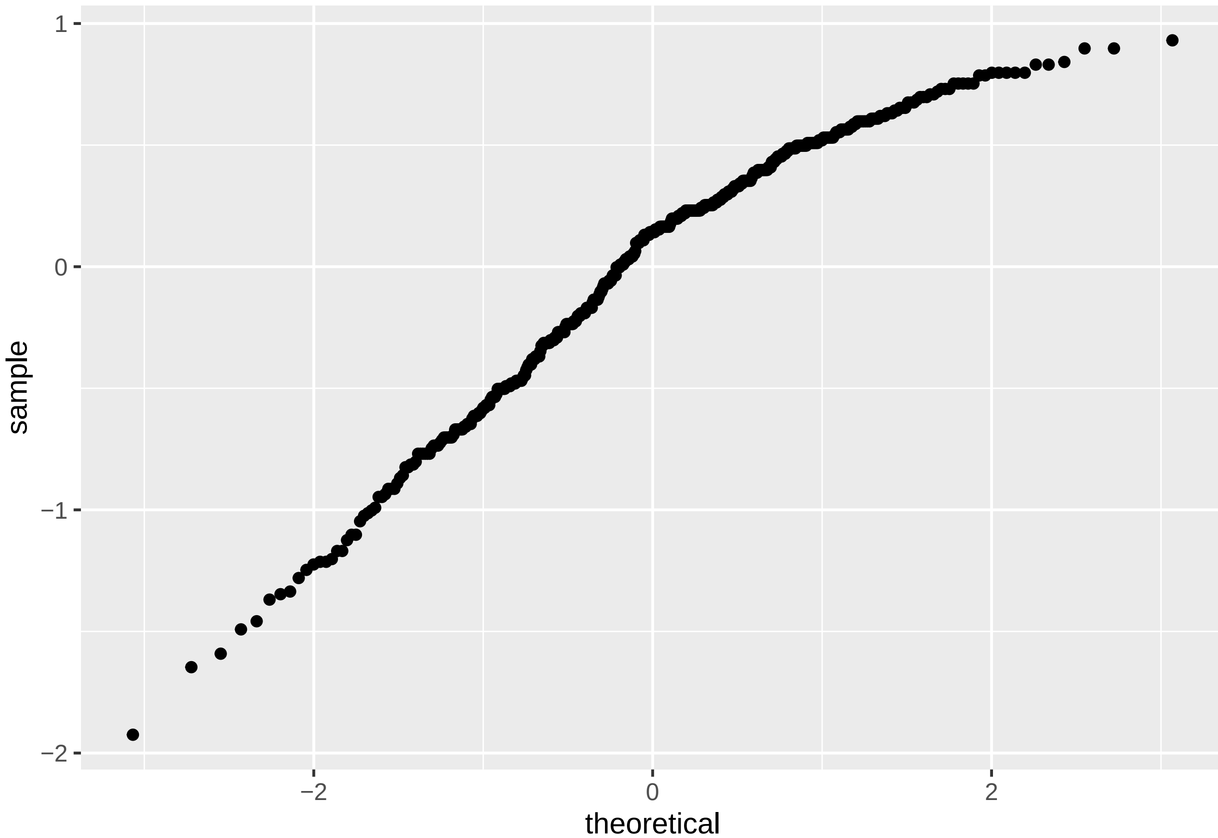

```
ggplot(data = m_bty, aes(x = .resid)) +
  geom_blank() +
  geom_histogram(aes(y=..density..))+
  geom_density(col= "red")
```




```
  xlab("Residuals")
```

```
## $x
## [1] "Residuals"
##
## attr(,"class")
## [1] "labels"
```

```
ggplot(data = m_bty, aes(sample = .resid)) +
  stat_qq()
```

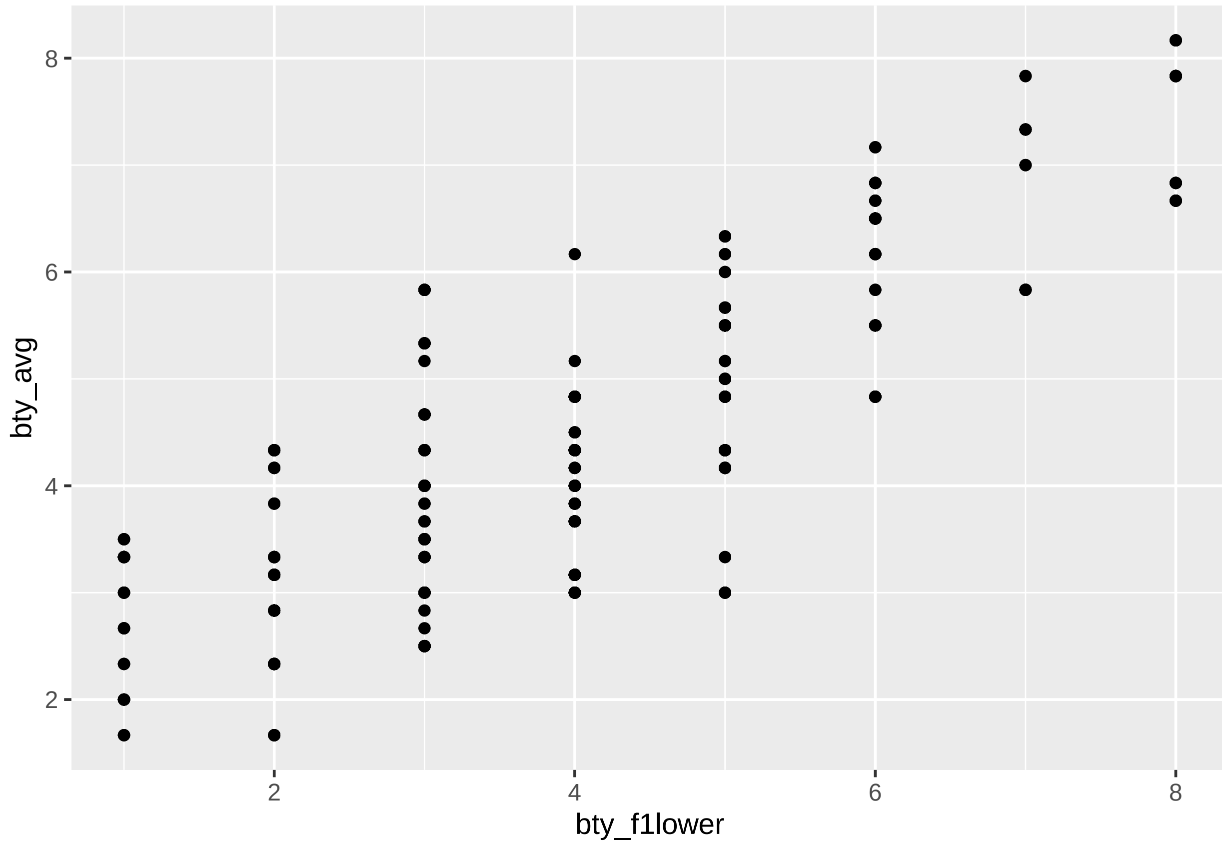


Question: The distribution is not exactly normal, as there is a slight peak near the zero values. It seems that the distribution is bimodal. In this instance, would it be ideal to complete a log transformation? **The conditions for the least squares line is reasonable as it meets the following conditions: 1. The data shows a linear trend; 2. The residuals are normally distributed, or at least nearly normal. 3. There is constant variability, meaning that the points around the least squares line remains roughly constant, and there are not any patterns. 4. The observations are independent.**

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()
```

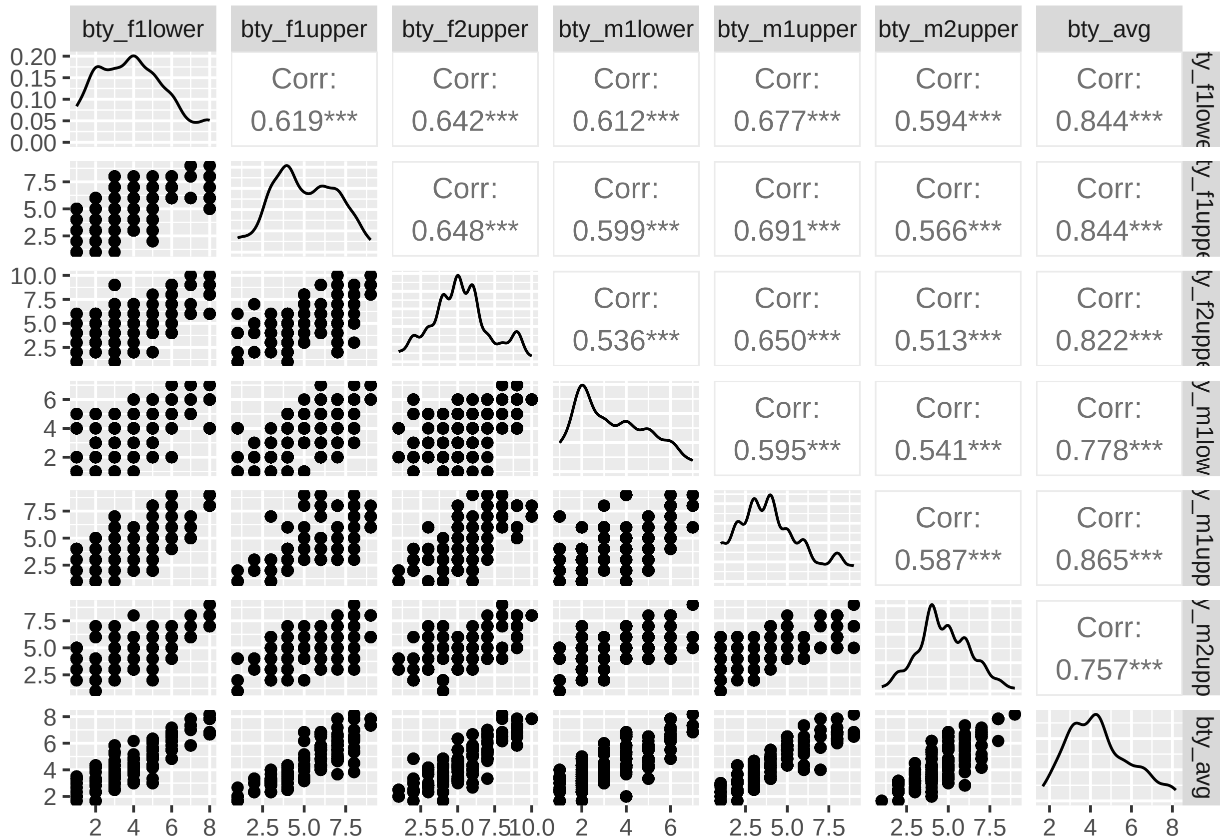



```
evals %>%
  summarise(cor(bty_avg, bty_f1lower))
```

```
## # 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.

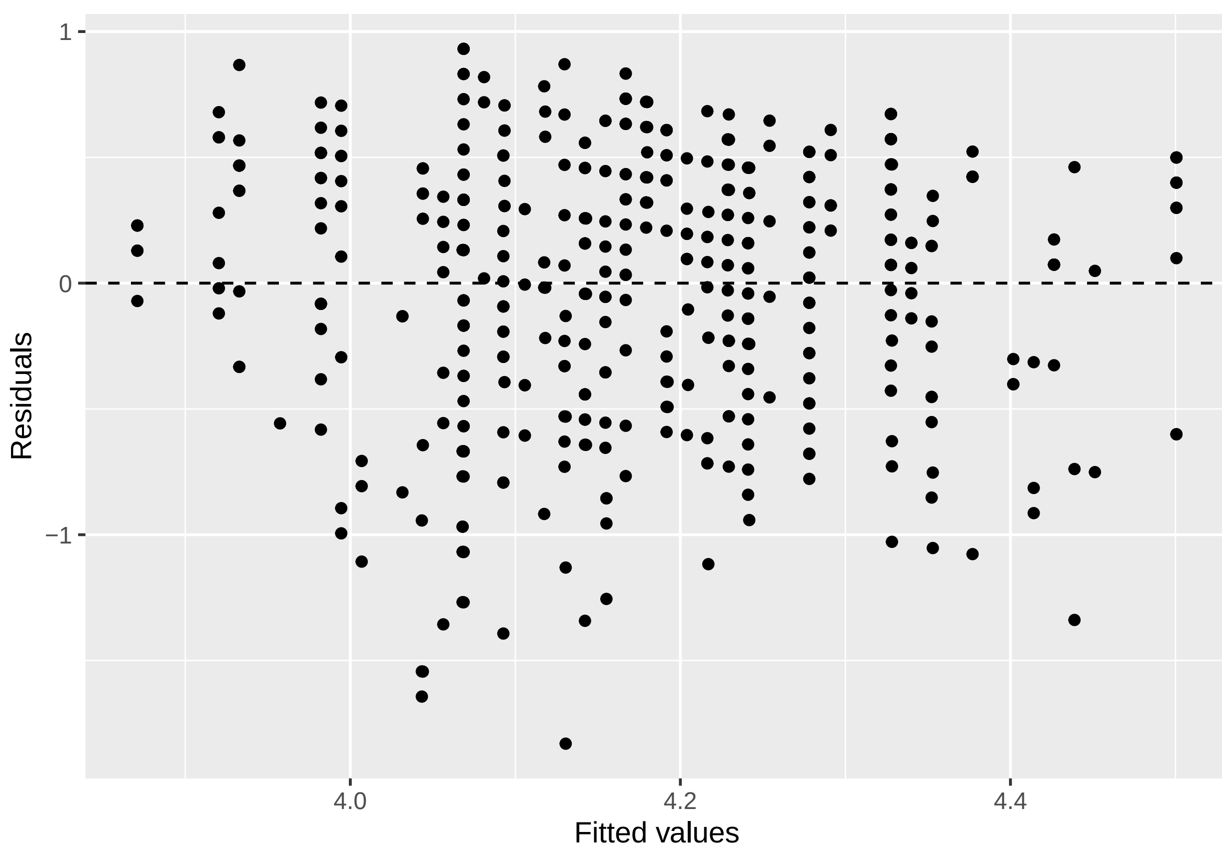
```
m_bty_gen <- lm(score ~ bty_avg + gender, data = evals)
summary(m_bty_gen)
```

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

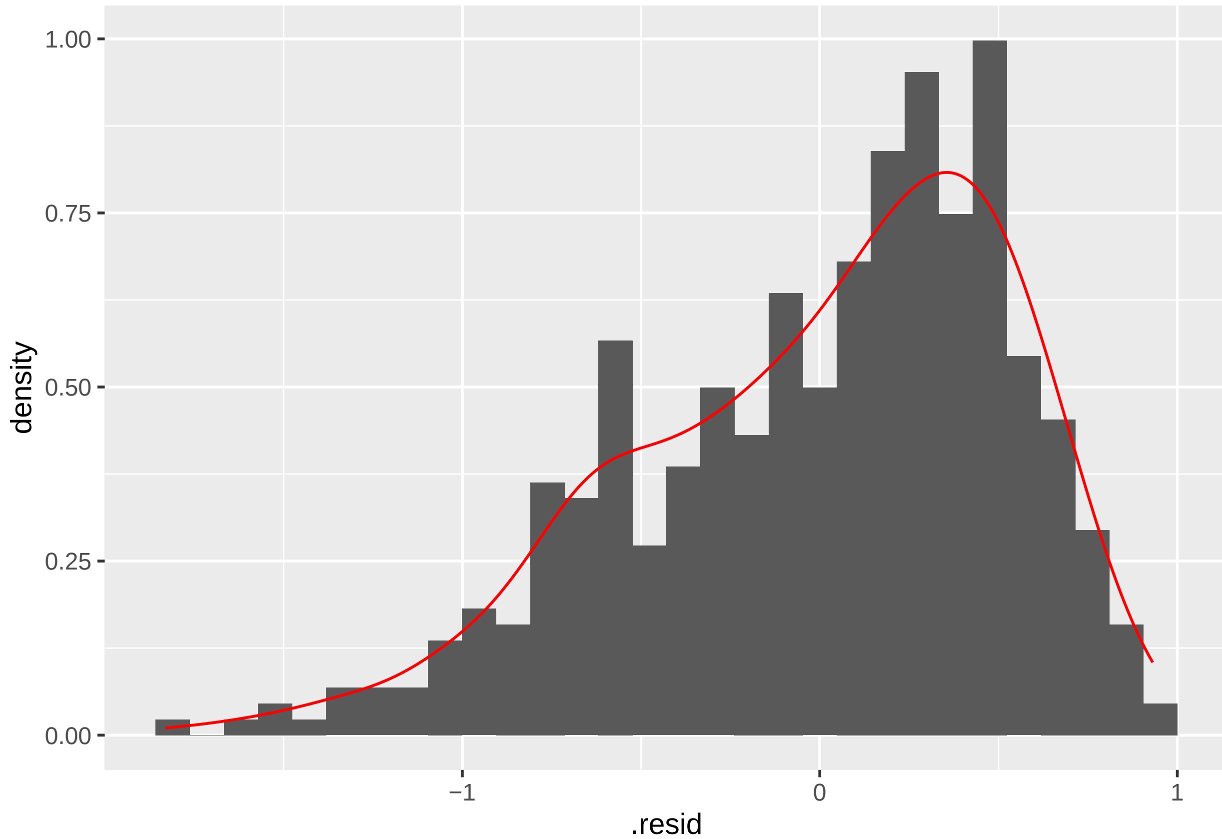
```
## Residual standard error: 0.5287 on 460 degrees of freedom
## Multiple R-squared:  0.05912,    Adjusted R-squared:  0.05503
## F-statistic: 14.45 on 2 and 460 DF,  p-value: 8.177e-07
```

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. **Exercise 7 Response**

```
ggplot(data = m_bty_gen, aes(x = .fitted, y = .resid)) +
  geom_point() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals")
```



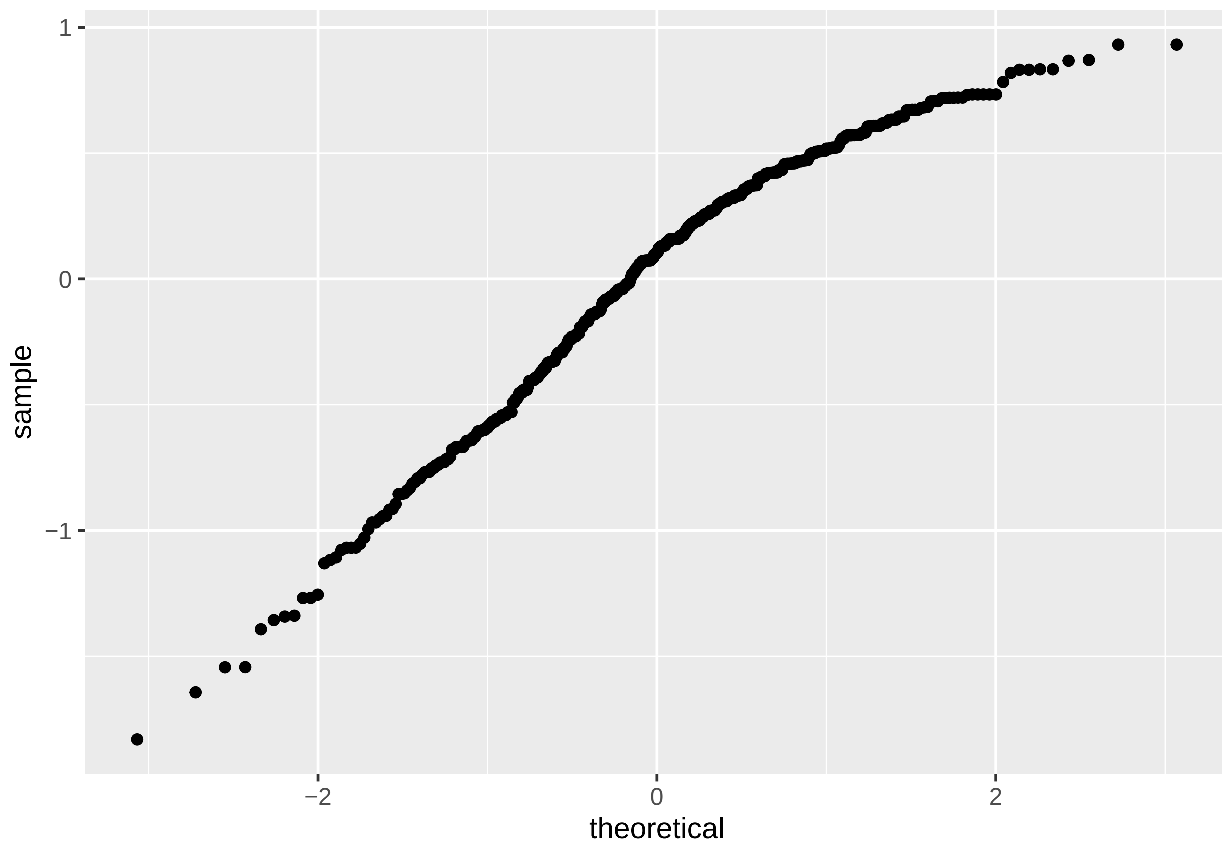

```
ggplot(data = m_bty_gen, aes(x = .resid)) +
  geom_blank() +
  geom_histogram(aes(y=..density..))+
  geom_density(col= "red")
```




```
  xlab("Residuals")
```

```
## $x
## [1] "Residuals"
##
## attr(,"class")
## [1] "labels"
```

```
ggplot(data = m_bty_gen, aes(sample = .resid)) +
  stat_qq()
```



The distribution is not exactly normal, as there is a slight peak near the zero values. Should I do a log transformation? **The conditions are met as there are: * no extreme outliers that would be a concern, * no patterns detected in the residuals plot, * and a nearly linear trend in the qq plot.**

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`?

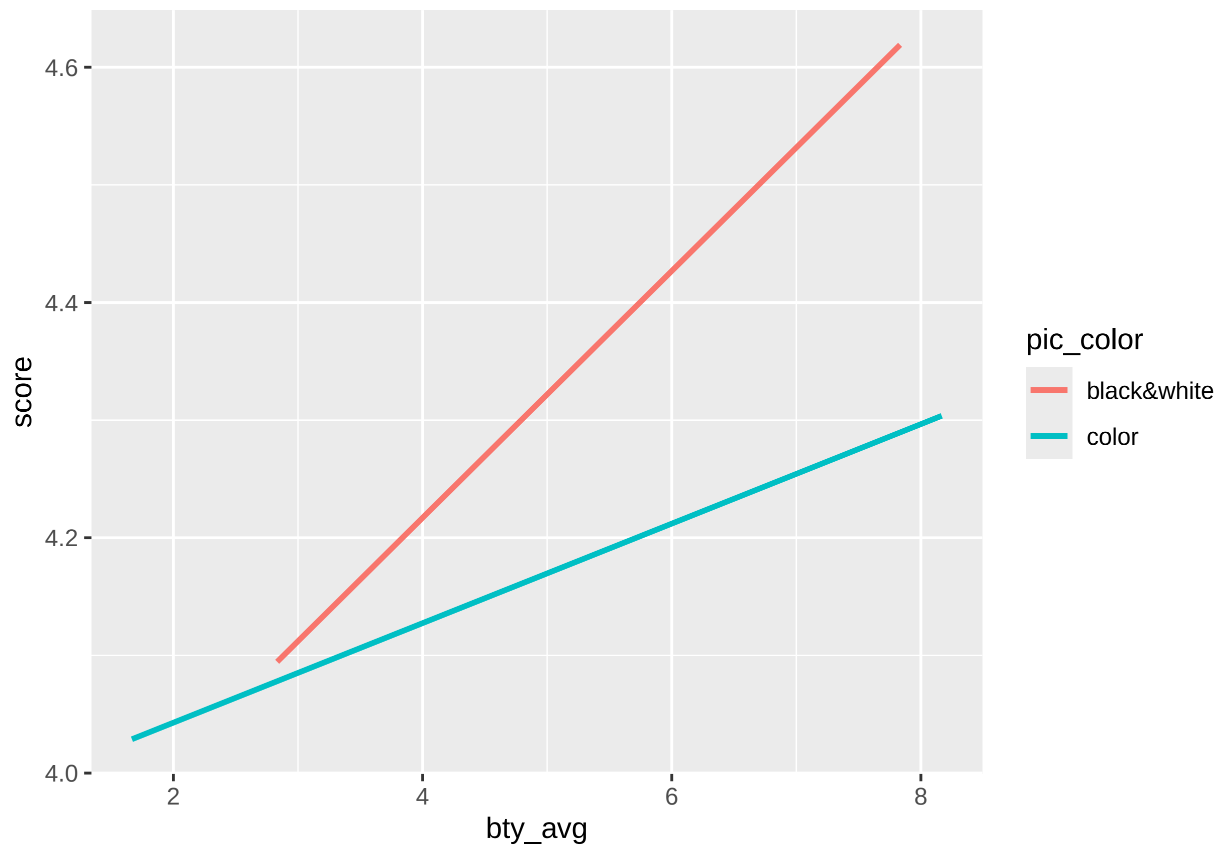
Beauty average is still a significant predictor of score. The addition of gender to the model did not change the parameter estimate for beauty average.

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.

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

```r
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? **Exercise 9 Response The formula for this line is as follows:**

$\widehat{score} = \beta_1(btyavg) + \beta_2(piccolor) + \beta_0 + \epsilon_i$

where: * $\widehat{score}$ = the predicted score * β_1 = the coefficient associated with beauty average * β_2 = the coefficient associated with the color pictures * β_0 = the coefficient * ϵ_i = the residual associated with the ι-th observation. **According to the plot, the black and white pictures tend to have higher course evaluation scores.**

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`. **Exercise 10 Response**

```
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
```

When R is given categorical data, it makes the first categorical value in the sequence a reference, and the other categorical values are the difference from the reference. The tenure track and tenured values are somewhat treated like new indicator variables, as seen in 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, 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. **Exercise 11 Response I would expect the language of the university where the student received their degree to have the highest p-value.**

Let's run the model…

```r
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. **Exercise 12 Response**

```r
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
```

My suspicions were slightly off. Based on the summary output, it seems that the number of professors teaching sections in the course in sample did not affect the professor's evaluation score.

13. Interpret the coefficient associated with the ethnicity variable. **Exercise 13 Response The coefficient associated with the ethnicity variable is .123. This indicates there is a slight relationship between the ethnicity of the professor and the received evaluation score.**

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? **Exercise 14 Response**

```
m_full_v2 <- 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_full_v2)
```

```
##
## 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
```

Removing the cls_profs indicator changed some of the p-values, but not significantly. Since the p-values did not significantly change, this may indicate that there is not collinearity among the cls_profs variable and the other variables.

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. **Exercise 15 Response**

```r
tidy(m_full_v2) |>
  filter(p.value < 0.05) |>
  pull(term)
```

```
## [1] "(Intercept)"           "gendermale"            "languagenon-english"
## [4] "age"                   "cls_perc_eval"         "cls_creditsone credit"
## [7] "bty_avg"               "pic_colorcolor"
```

```r
m_full_v3 <- lm(score ~ gender + language + age + cls_perc_eval +
                  cls_credits + bty_avg + pic_color, data = evals)
summary(m_full_v3)
```

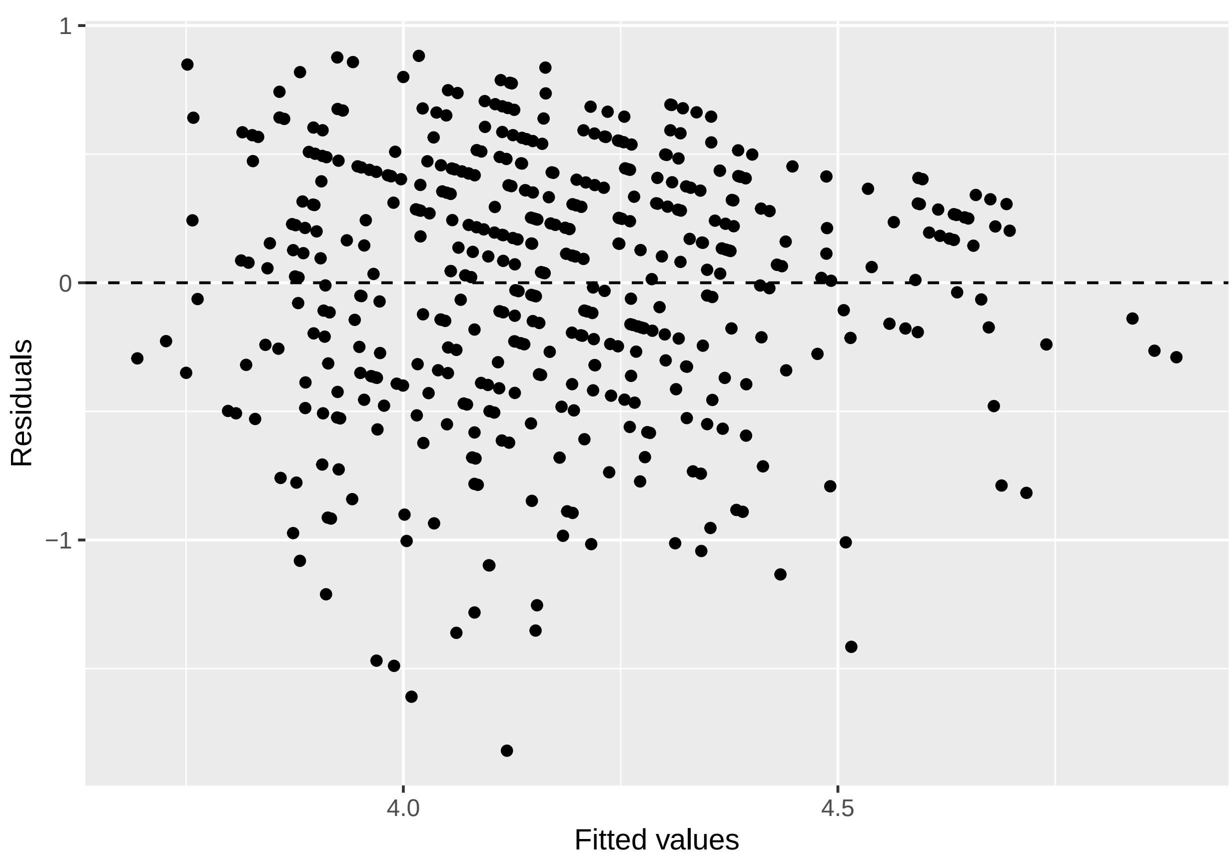
```
##
## Call:
## lm(formula = score ~ gender + language + age + cls_perc_eval +
##     cls_credits + bty_avg + pic_color, data = evals)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.81919 -0.32035  0.09272  0.38526  0.88213
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)             3.967255   0.215824  18.382  < 2e-16 ***
## gendermale              0.221457   0.049937   4.435 1.16e-05 ***
## languagenon-english    -0.281933   0.098341  -2.867  0.00434 **
## age                    -0.005877   0.002622  -2.241  0.02551 *
## cls_perc_eval           0.004295   0.001432   2.999  0.00286 **
## cls_creditsone credit   0.444392   0.100910   4.404 1.33e-05 ***
```

```
## bty_avg                0.048679   0.016974   2.868  0.00432 **
## pic_colorcolor        -0.216556   0.066625  -3.250  0.00124 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5014 on 455 degrees of freedom
## Multiple R-squared:  0.1631, Adjusted R-squared:  0.1502
## F-statistic: 12.67 on 7 and 455 DF,  p-value: 6.996e-15
```

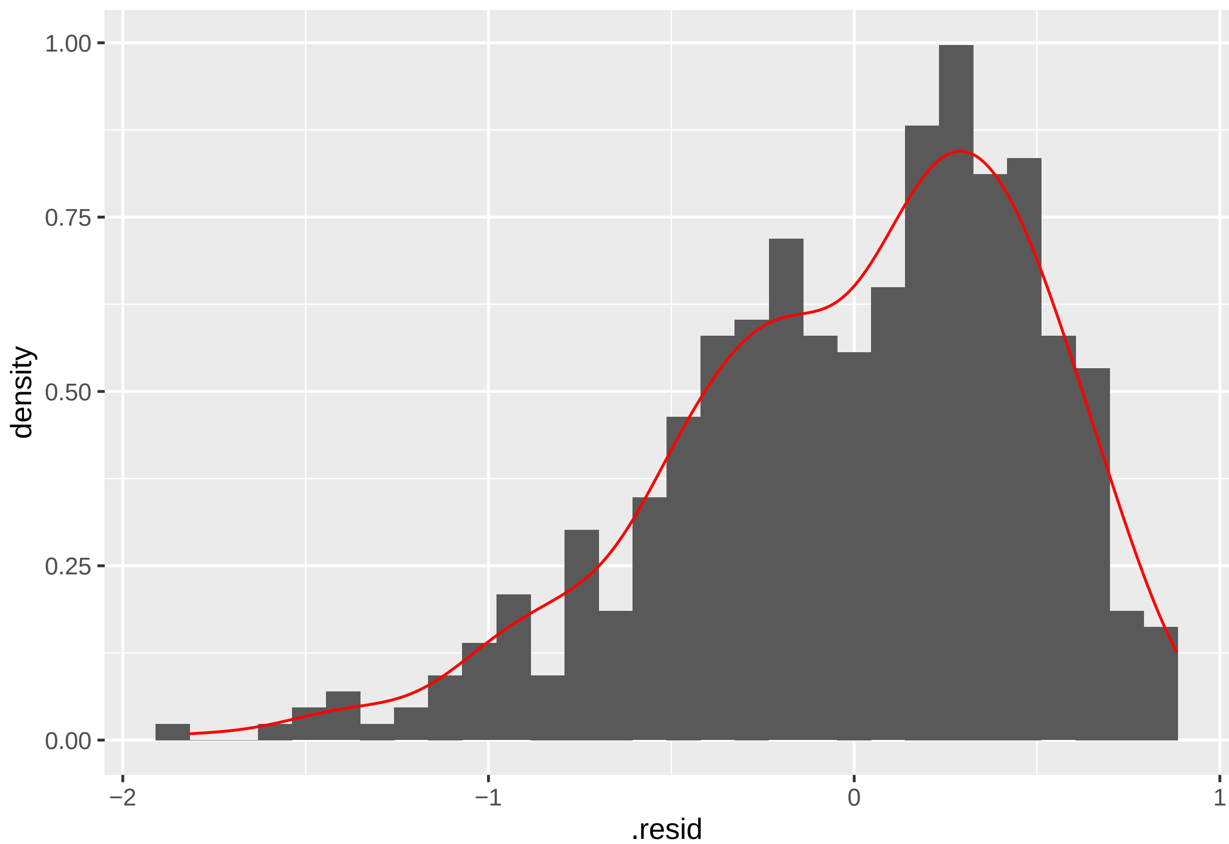
$\widehat{score} = \hat{\beta}_1 * gender + \hat{\beta}_2 * language + \hat{\beta}_3 * age + \hat{\beta}_4 * clsperceval + \hat{\beta}_5 * clscredits + \hat{\beta}_5 * btyavg + \hat{\beta}_6 * piccolor$

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

```r
ggplot(data = m_full_v3, aes(x = .fitted, y = .resid)) +
  geom_jitter() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals")
```



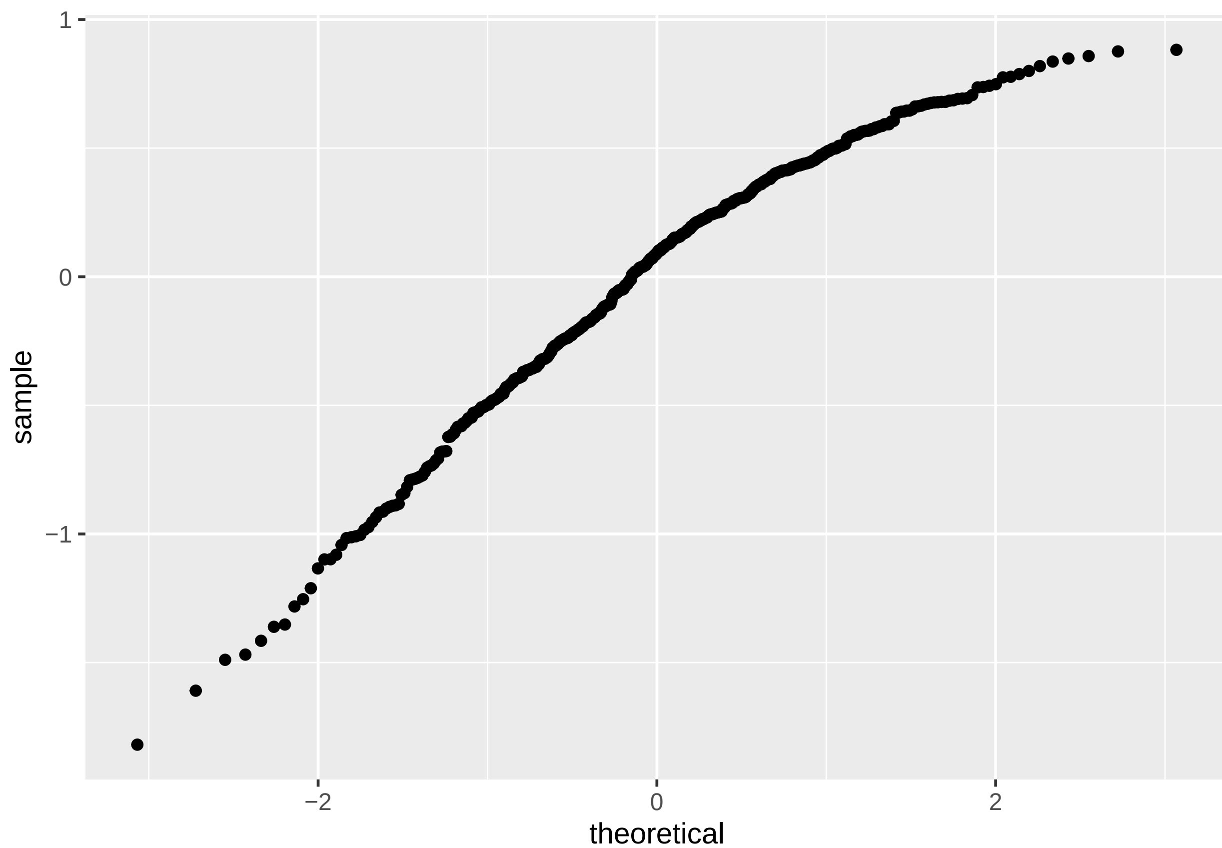

```r
ggplot(data = m_full_v3, aes(x = .resid)) +
  geom_blank() +
  geom_histogram(aes(y=..density..))+
  geom_density(col= "red")
```




```
  xlab("Residuals")
```

```
## $x
## [1] "Residuals"
##
## attr(,"class")
## [1] "labels"
```

```
ggplot(data = m_full_v3, aes(sample = .resid)) +
  stat_qq()
```



From the diagnostic plots, it does not seem that the model fits the criteria for a linear regression. There is a slight patter in the qqplot, as the variability gets smaller as the fitted values are larger, the distribution of the residuals is bimodal, although the plot may be affected by bin width, and the qqplot is slightly curved.

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?

As the data was collected over time, and may be in sequence of when it was collected. Therefore, this may impact the evaluations. For example, professors' age would increase over time, and their performance may improve as they proceed in their roles. If the `evals` dataset included a date, it may be preferrable to plot the residuals in order of their data collection.

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. **Exercise 18 Response Based on the final model produced, a professor with a high rating may be a young english-speaking male with a high beauty score and a black and white photo where a higher proportion of the class completed an evaluation for a one credit course.**

19. Would you be comfortable generalizing your conclusions to apply to professors generally (at any university)? Why or why not? **Exercise 19 Response I would not be comfortable generalizing the conclusions to apply to professors generally as the data was collected over time and may include duplicate values for professors, and the conditions to apply a linear regression were not fully met. To be more comfortable generalizing the conclusions, I would further**

investigate how many years of data are in this set, if the demographics of students and professors are similar to other universities, and potentially complete a log transformation so the residuals are more evenly distributed.