

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” 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, 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, 2, 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, ~
```

```
evals <- evals
```

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

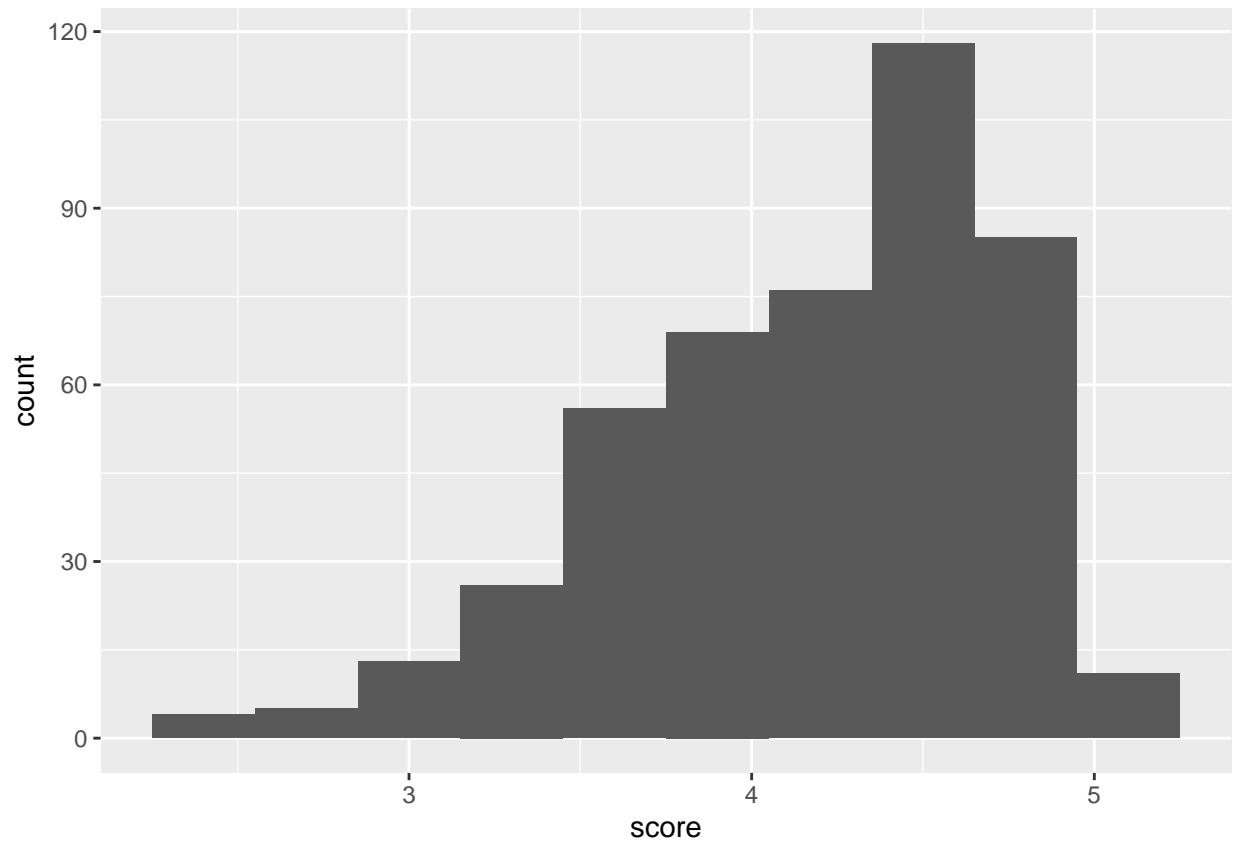
1. Is this an observational study or an experiment? The original research question posed in the paper is whether beauty leads directly to the differences in course evaluations. Given the study design, is it possible to answer this question as it is phrased? If not, rephrase the question.

Observational, they're just observing the students, they're not changing anything as you'd do in an experimental. "Does professor's perceived beauty effect their students 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?

Scores are skewed right, with many students giving high scores, although not that many seem to give a perfect 5. This makes sense to me, seems students are fairly evaluating, and enjoyed their courses. I did expect a bigger spike on 1 that doesn't appear, often you see in google or amazon reviews i find people who do not like something give it more extreme ratings to really express their displeasure

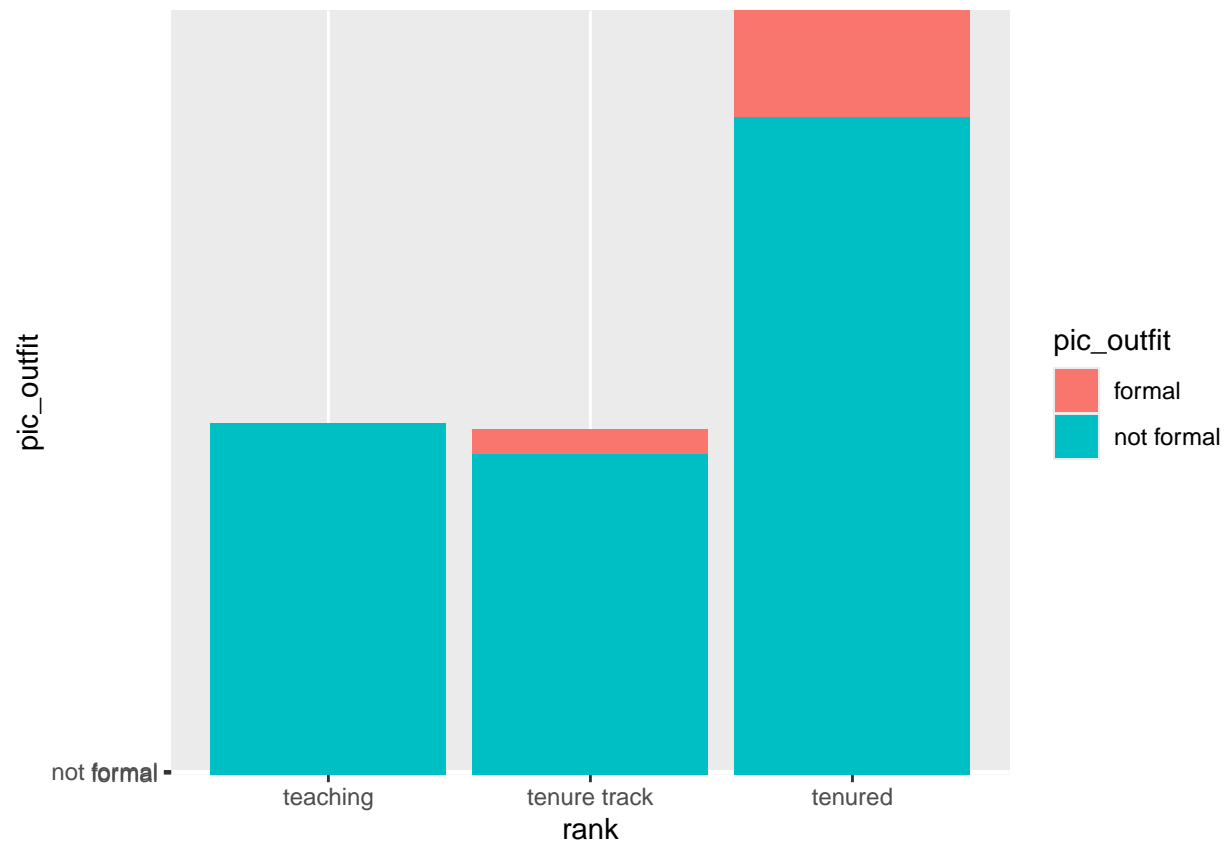
```
ggplot(evals, aes(x=score)) +
  geom_histogram(bins=10)
```



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

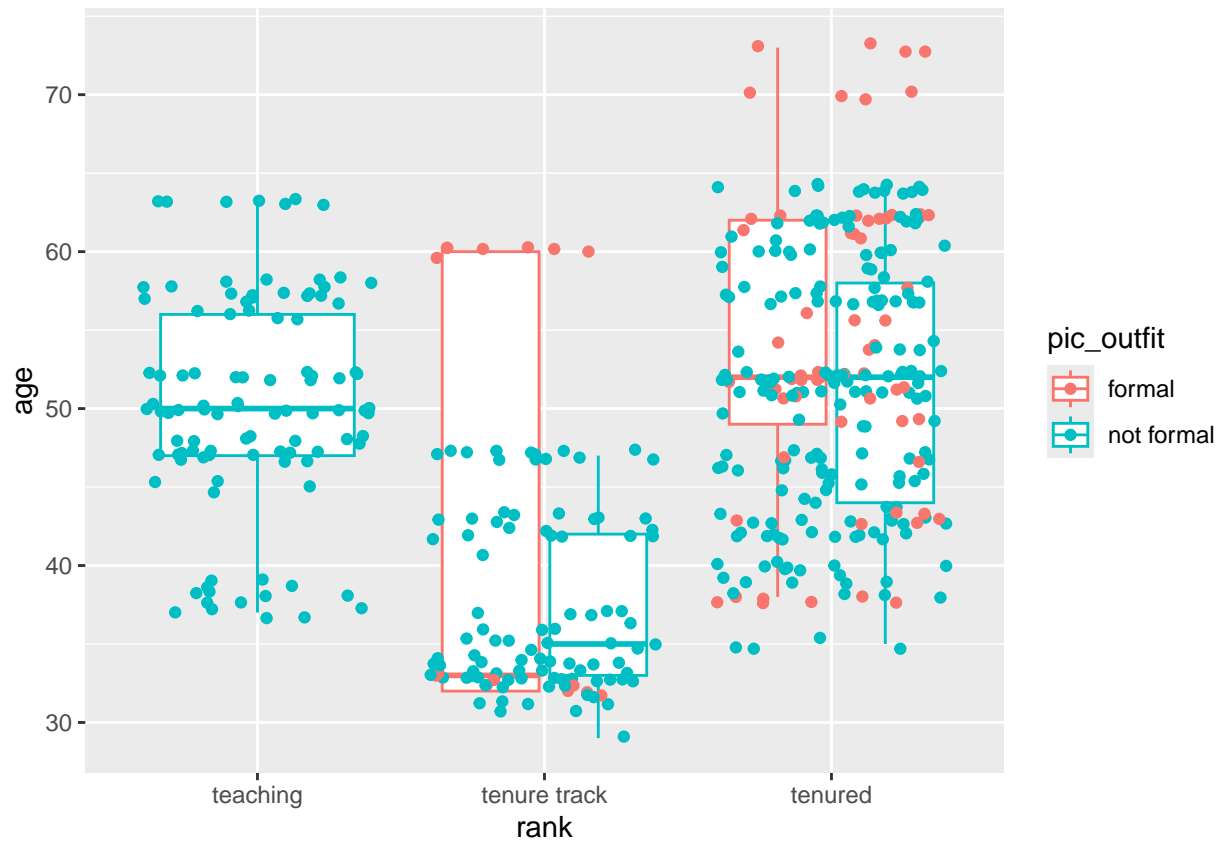
Expectation: Looking at rank of professor and outfit in picture, i expect tenured professors to not care as much about being formal, once you're tenured you can do whatever you want, while the professors who are still working towards it maybe will be more formal.

```
ggplot(evals, aes(fill=pic_outfit,x=rank, y=pic_outfit)) +  
  geom_bar(position="stack",stat = "identity")
```



Reality: Whoops, I want to apologize to the tenured profs, the tenured professors are actually more likely to be wearing formal outfits for their pics. I wonder if its actually mostly just an age thing.

```
ggplot(evals, aes(color=pic_outfit, x=rank, y=age)) +  
  geom_boxplot() +  
  geom_jitter()
```

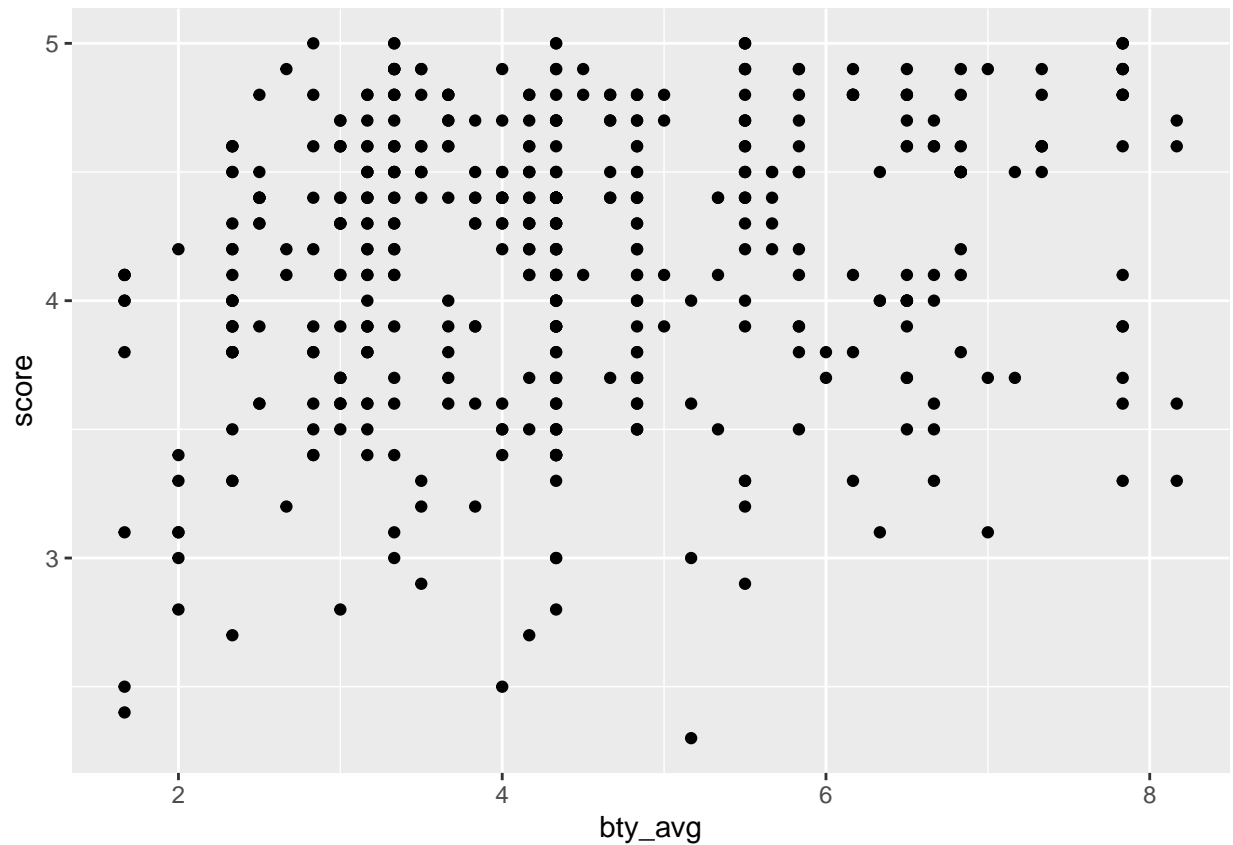


The oldest and the youngest in tenure track seem to be more formal. Age seems to effect outfit formality for the already tenured only alittle bit

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:

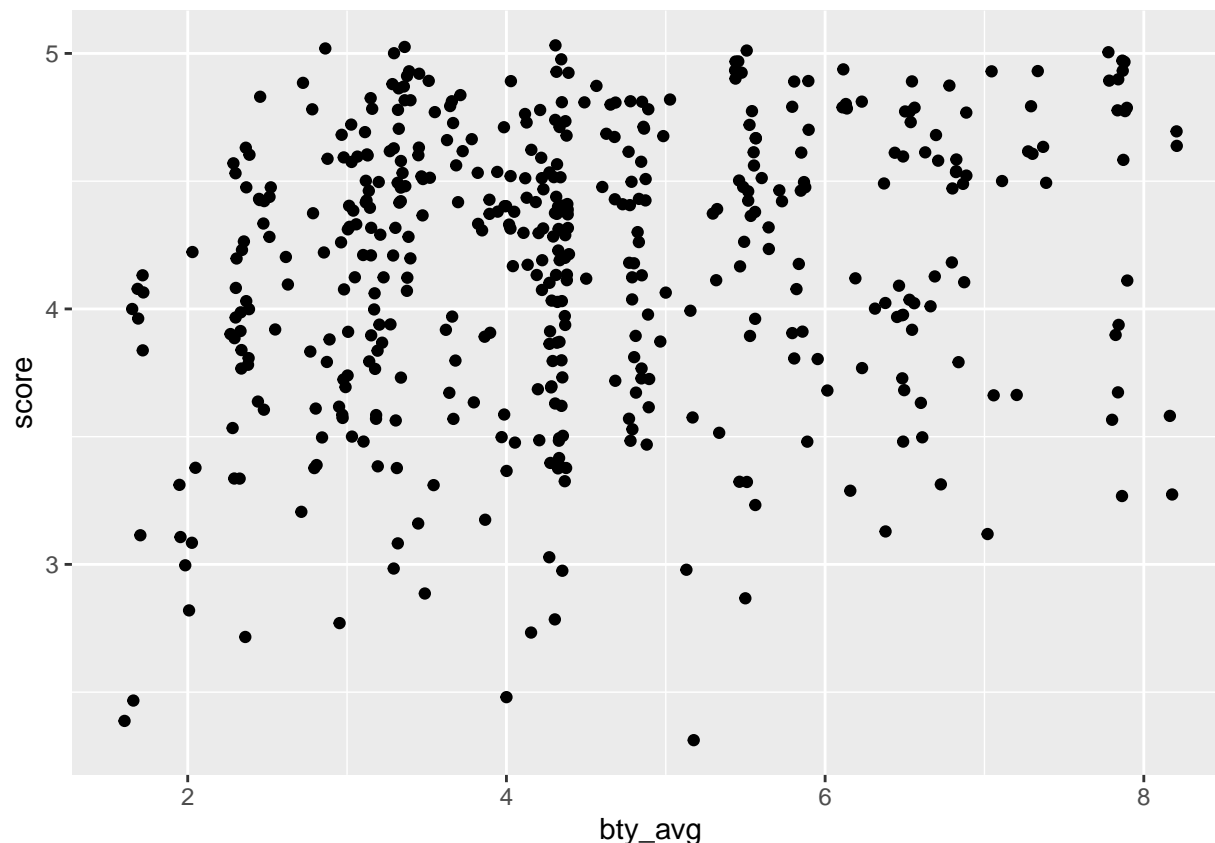
```
ggplot(data = evals, aes(x = bty_avg, y = score)) +  
  geom_point()
```



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()
```



Age is a discrete variable, lots of points stacked on the same age

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?

$$\text{Score} = 3.88 + 0.066(\text{Beauty_Average})$$

Average beauty score is a statistically significant predictor. If the professor was rated a 10 (which surprisingly no one was), you'd expect their score to be ~0.60 higher than a prof rated a 1 which seems like it could be practically significant predictor. The r-squared is pretty low though, suggesting that beauty is not explaining that much of the variation in professors scores.

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

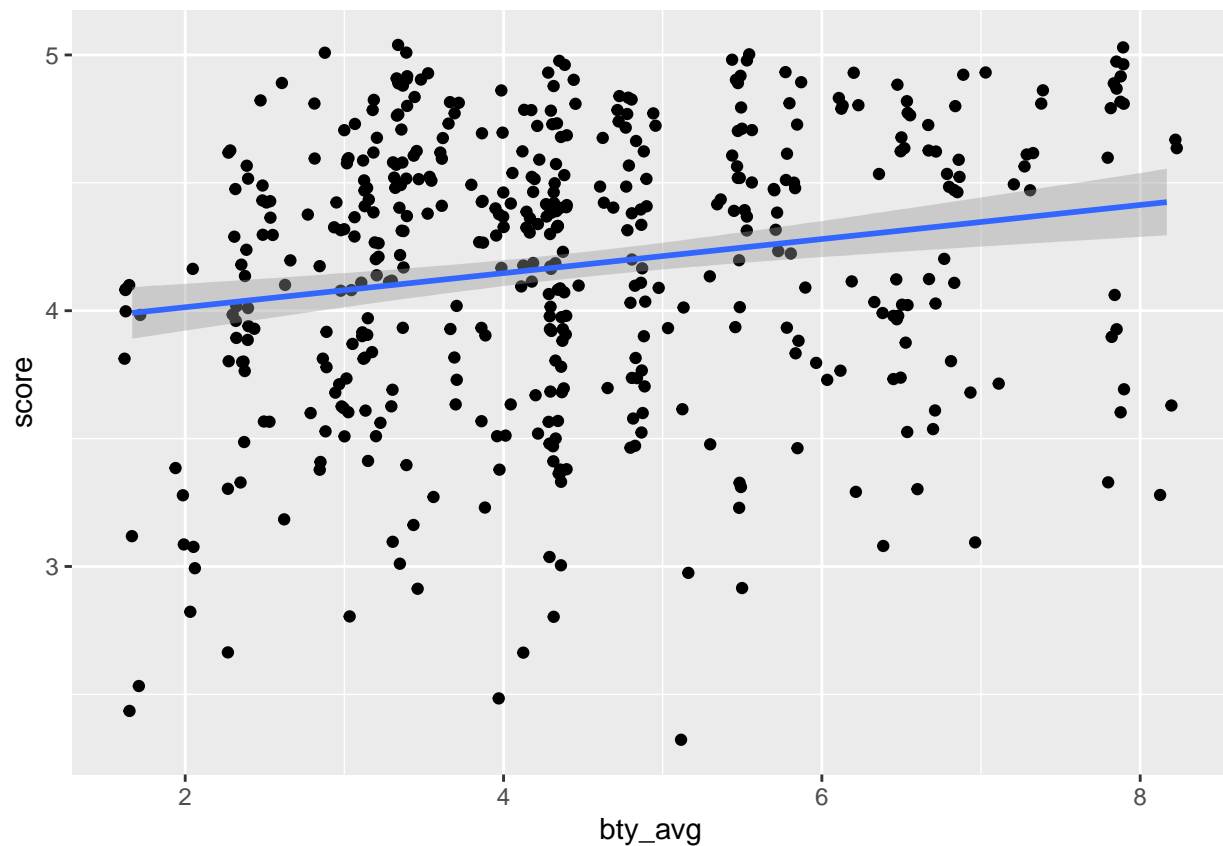
```
summary(m_bty)
```

```
##
## 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
```

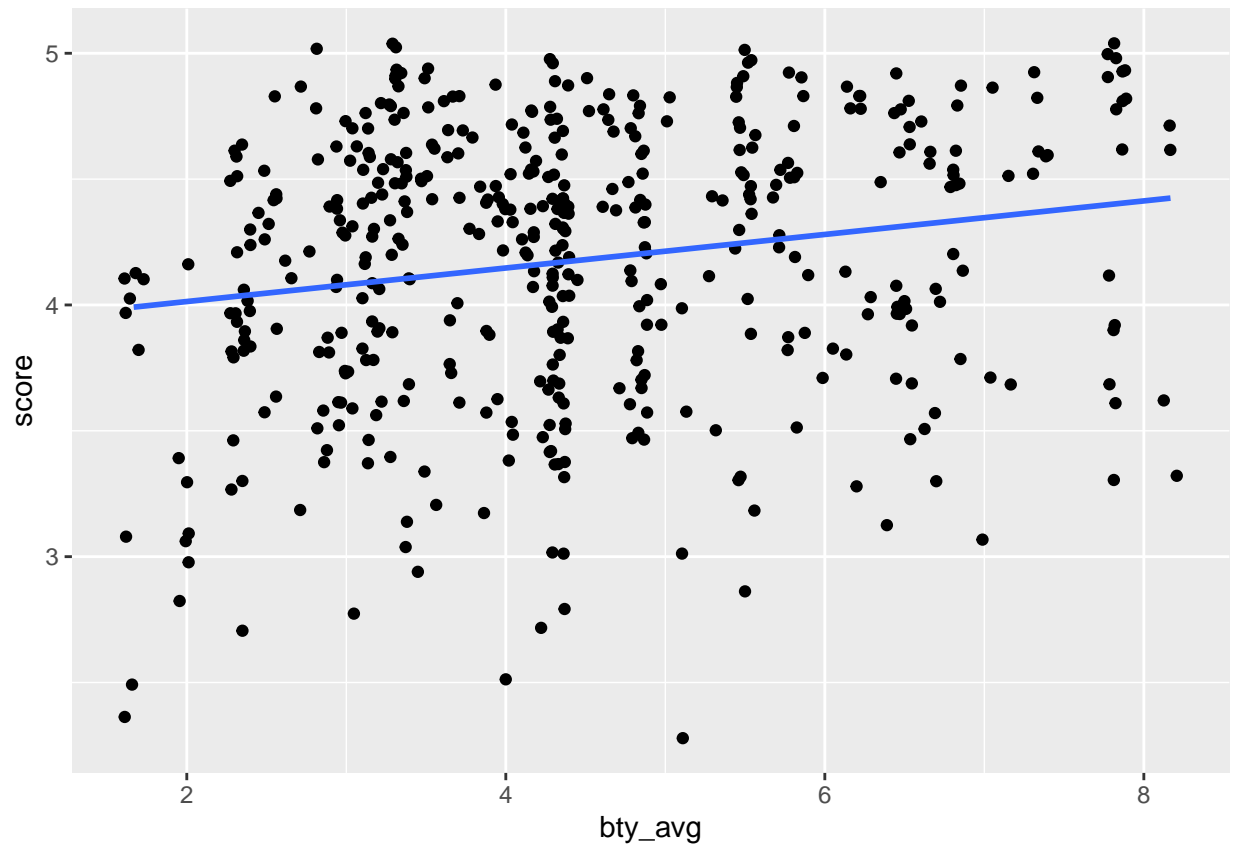
Add the line of the bet fit model to your plot using the following:

```
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`.

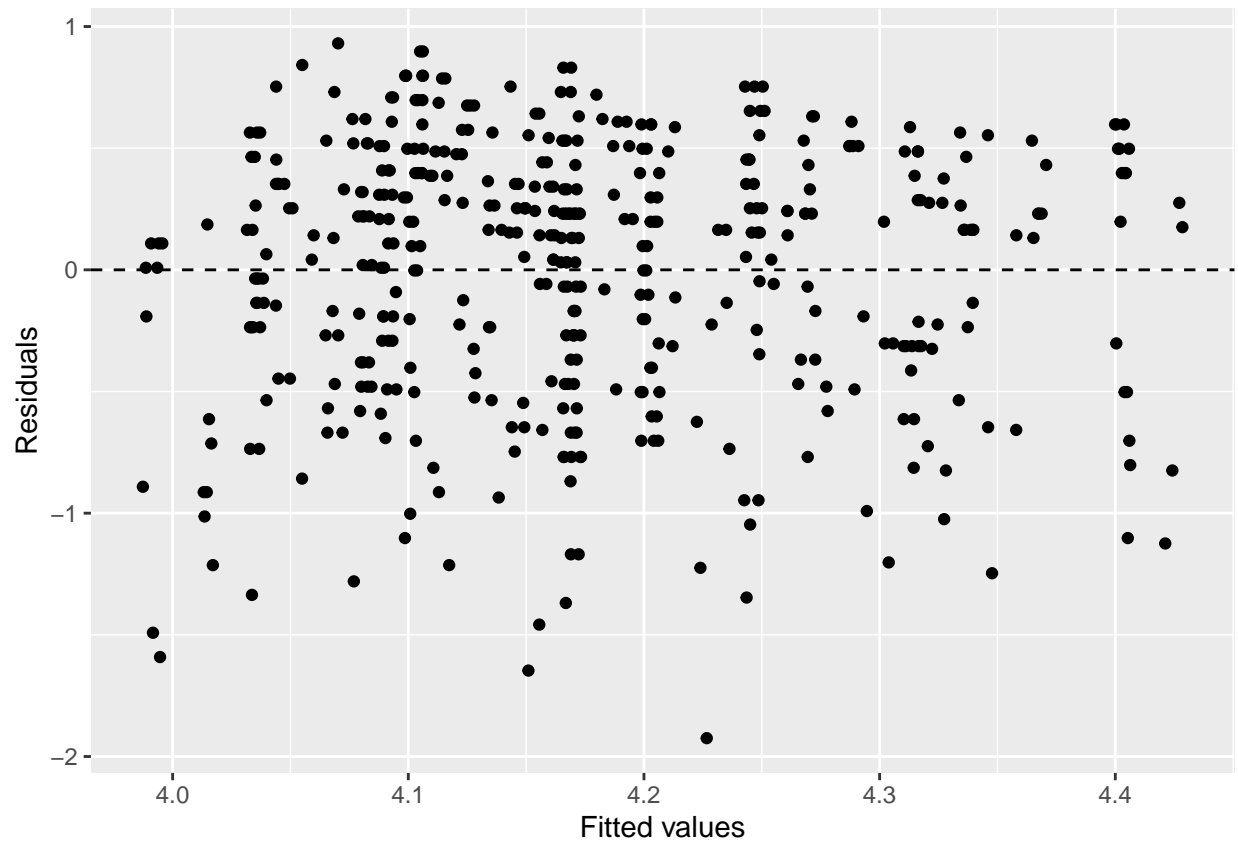
```
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_jitter() +
  geom_smooth(method = "lm", se = FALSE)
```

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).

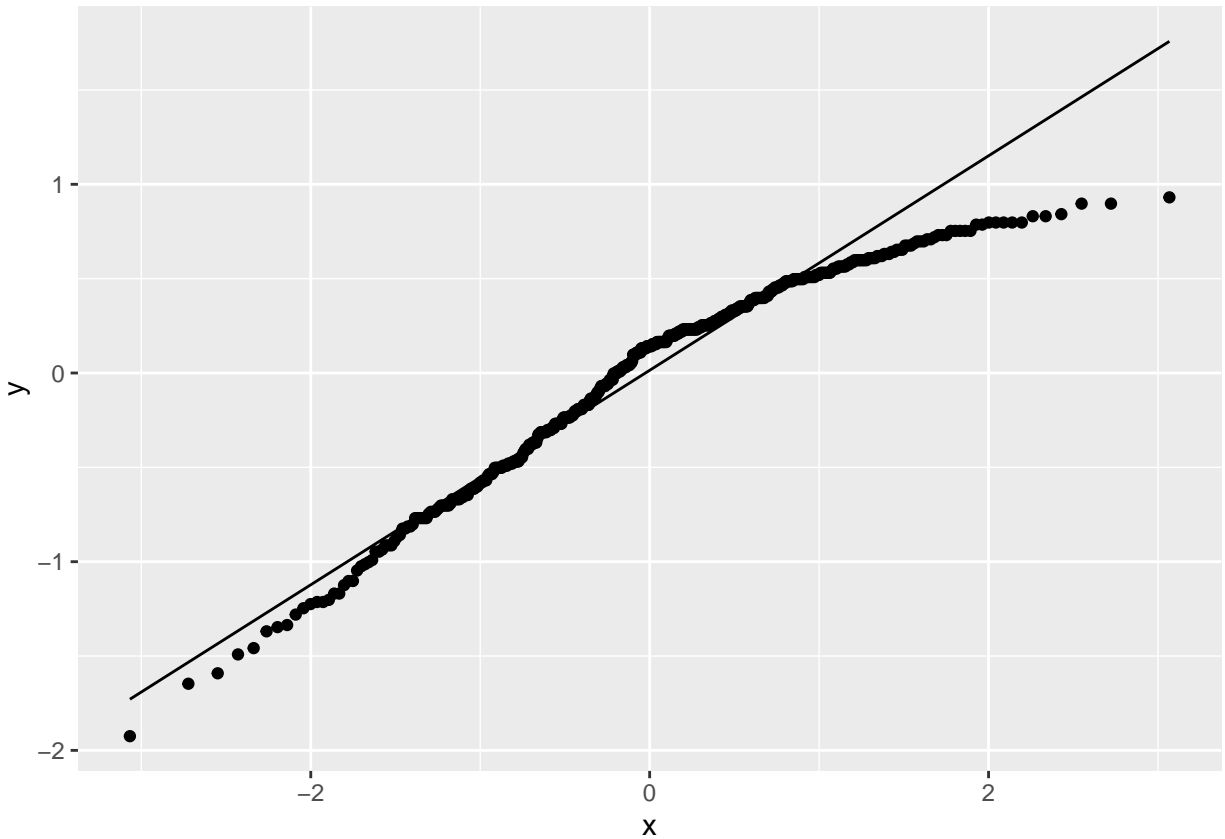
(1) **linearity:** The residuals seem evenly distributed, there doesn't seem to be much of a curve implying that a linear model could be a good fit for our data

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



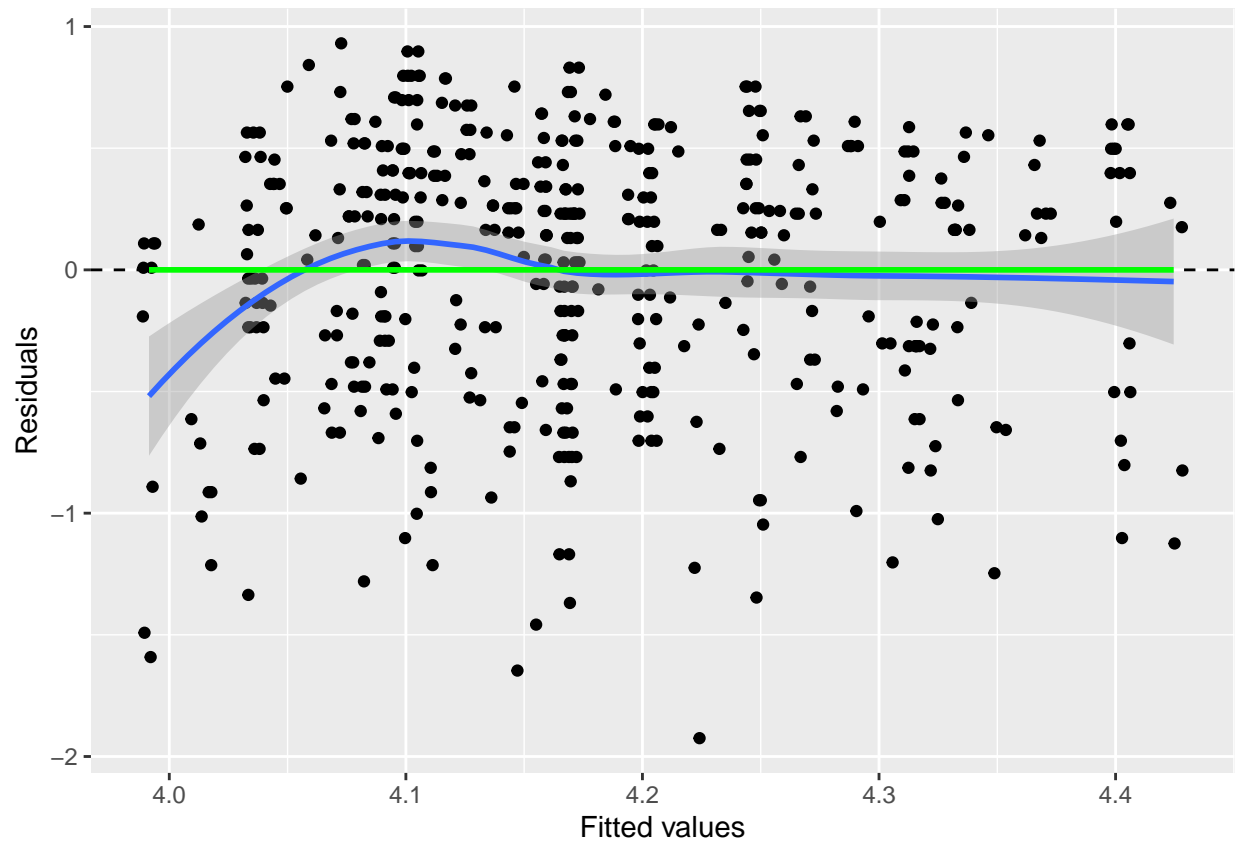
(2) nearly normal residuals: i think it looks nearly normal, although it could be a bit left skewed

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



(3) constant variability: the residual errors have close to a mean value of zero, although there is a tail

```
ggplot(data = m_bty, aes(x = .fitted, y = .resid)) +
  geom_jitter() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals") +
  geom_smooth() +
  geom_smooth(method="lm", se = FALSE, color="green")
```

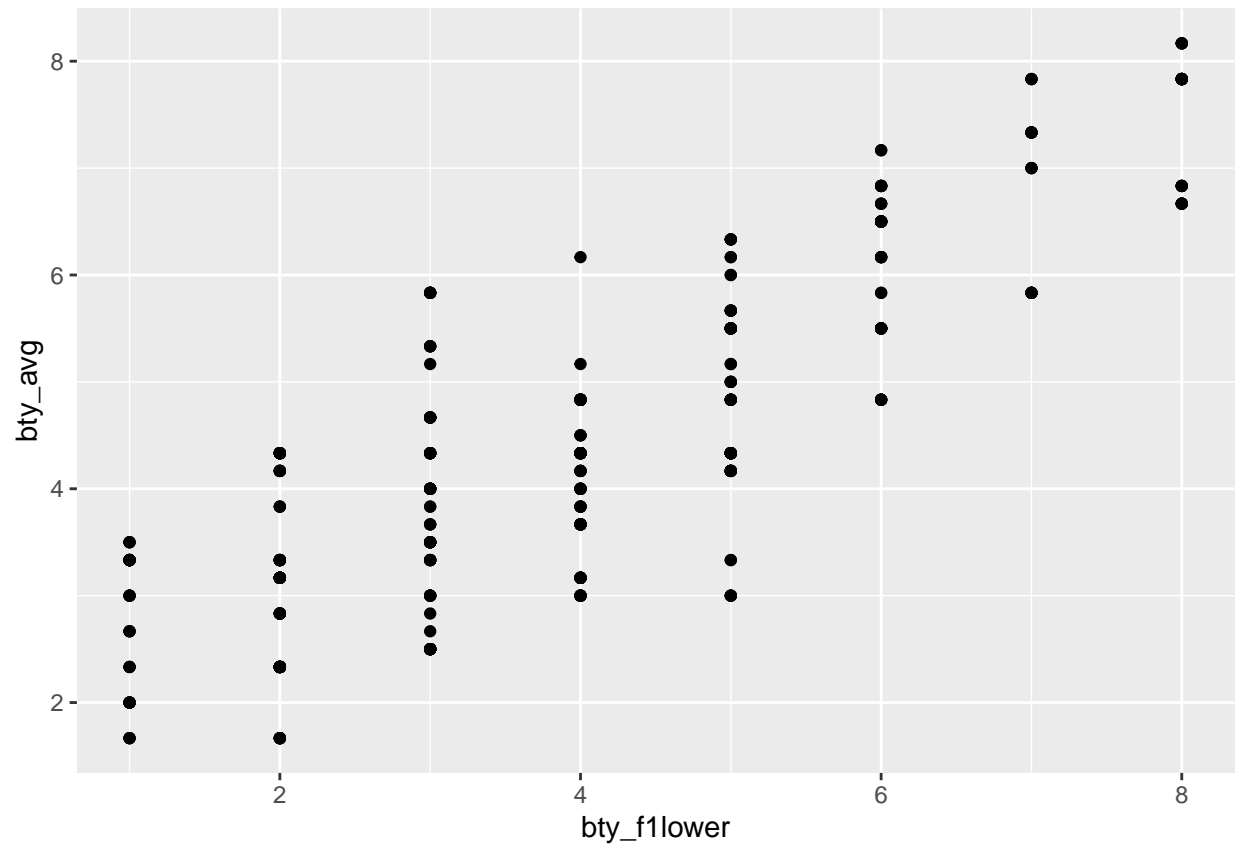


I think a linear model could be a good candidate after looking at the 3 conditions

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_follower, y = bty_avg)) +  
  geom_point()
```

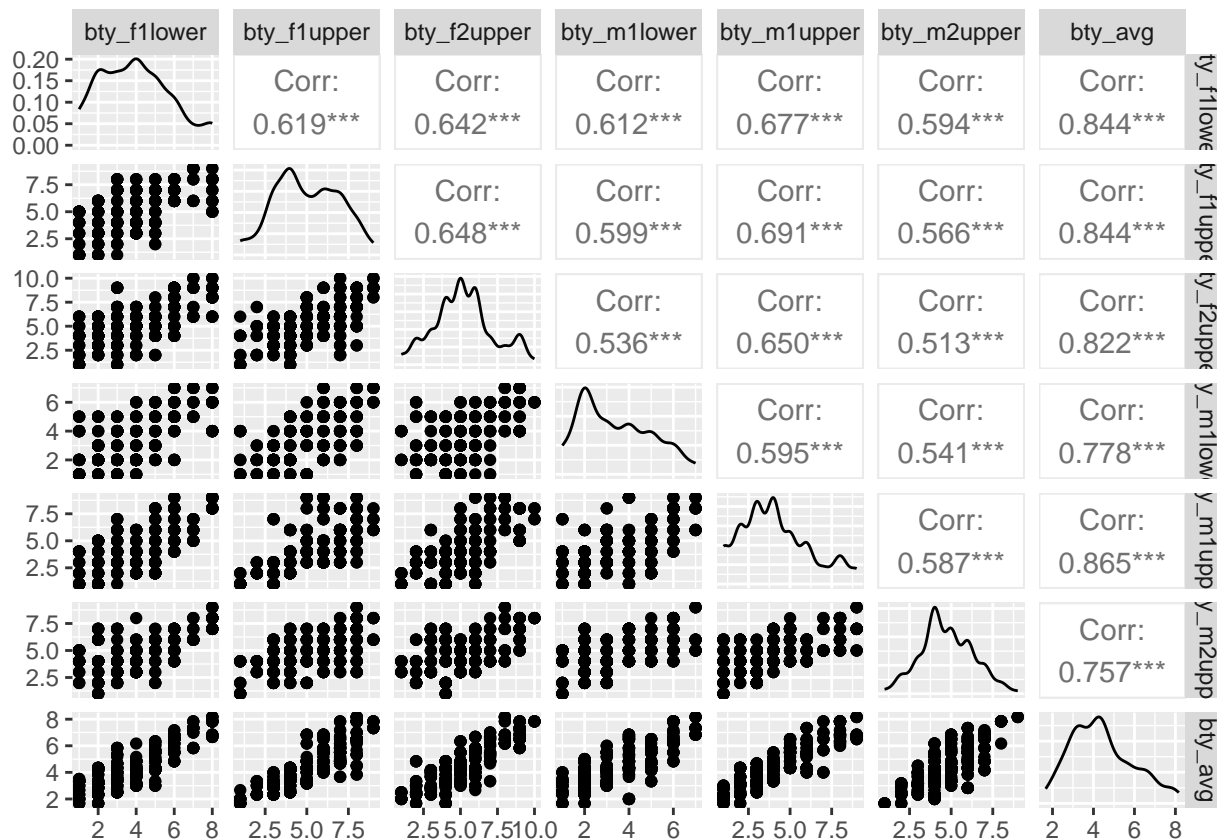


```
evals %>%
  summarise(cor(bty_avg, bty_f1lower))
```

```
## # 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
##
```

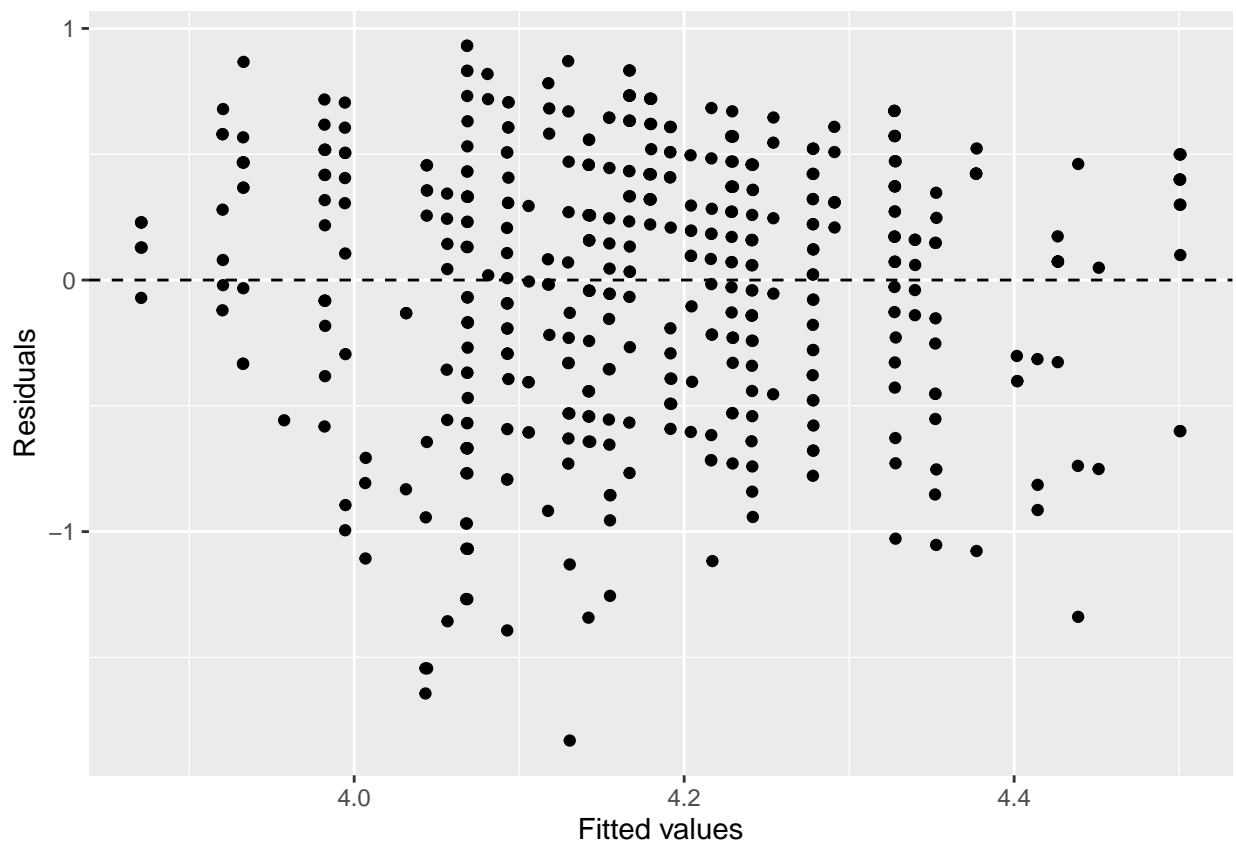
```
## Residual standard error: 0.5287 on 460 degrees of freedom
## Multiple R-squared:  0.05912,    Adjusted R-squared:  0.05503
## F-statistic: 14.45 on 2 and 460 DF,  p-value: 8.177e-07
```

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.

the conditions for this model are reasonable

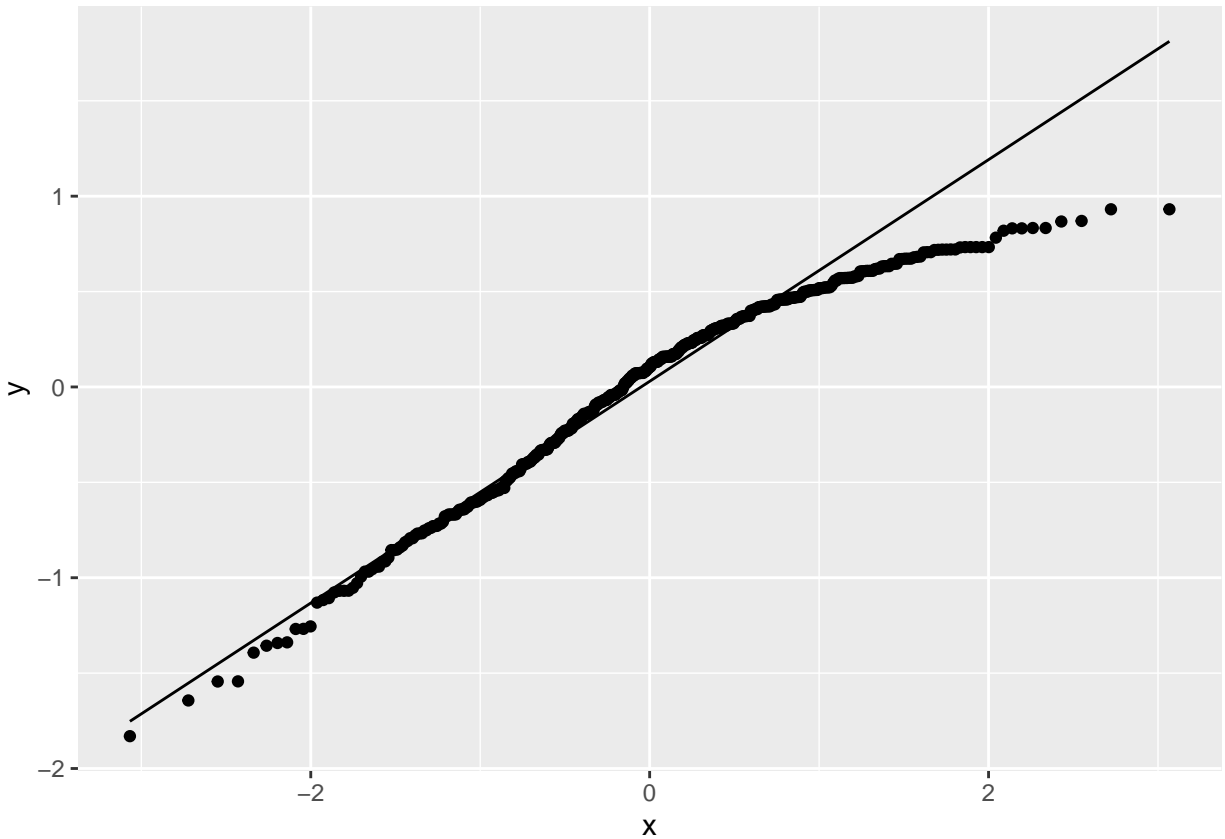
- (1) linearity: The residuals seem evenly distributed, there doesn't seem to be much of a curve implying that a linear model could be a good fit for our data

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



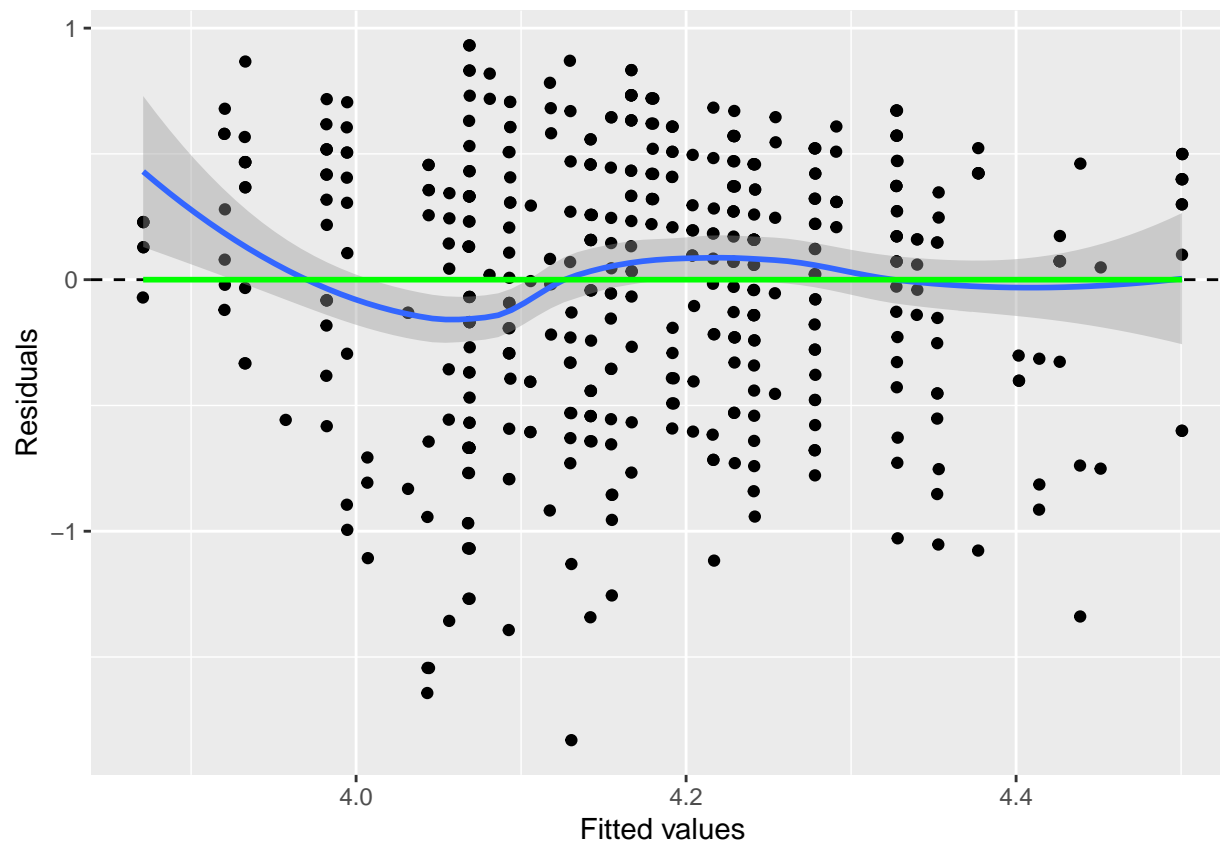
- (2) nearly normal residuals: i think it looks nearly normal, although it could be left skewed

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



(3) constant variability: the residual errors have close to a mean value of zero, although there is a tail

```
ggplot(data = m_bty_gen, aes(x = .fitted, y = .resid)) +
  geom_jitter() +
  geom_hline(yintercept = 0, linetype = "dashed") +
  xlab("Fitted values") +
  ylab("Residuals") +
  geom_smooth() +
  geom_smooth(method="lm", se = FALSE, color="green")
```

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

`btv_avg` is still a significant predictor of `score`. the addition of `gender` to the model, increased the parameter estimate for `btv_avg`. 0.06664 -> 0.07416

```
summary(m_btv)
```

```
##
## Call:
## lm(formula = score ~ btv_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 ***
## btv_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
```

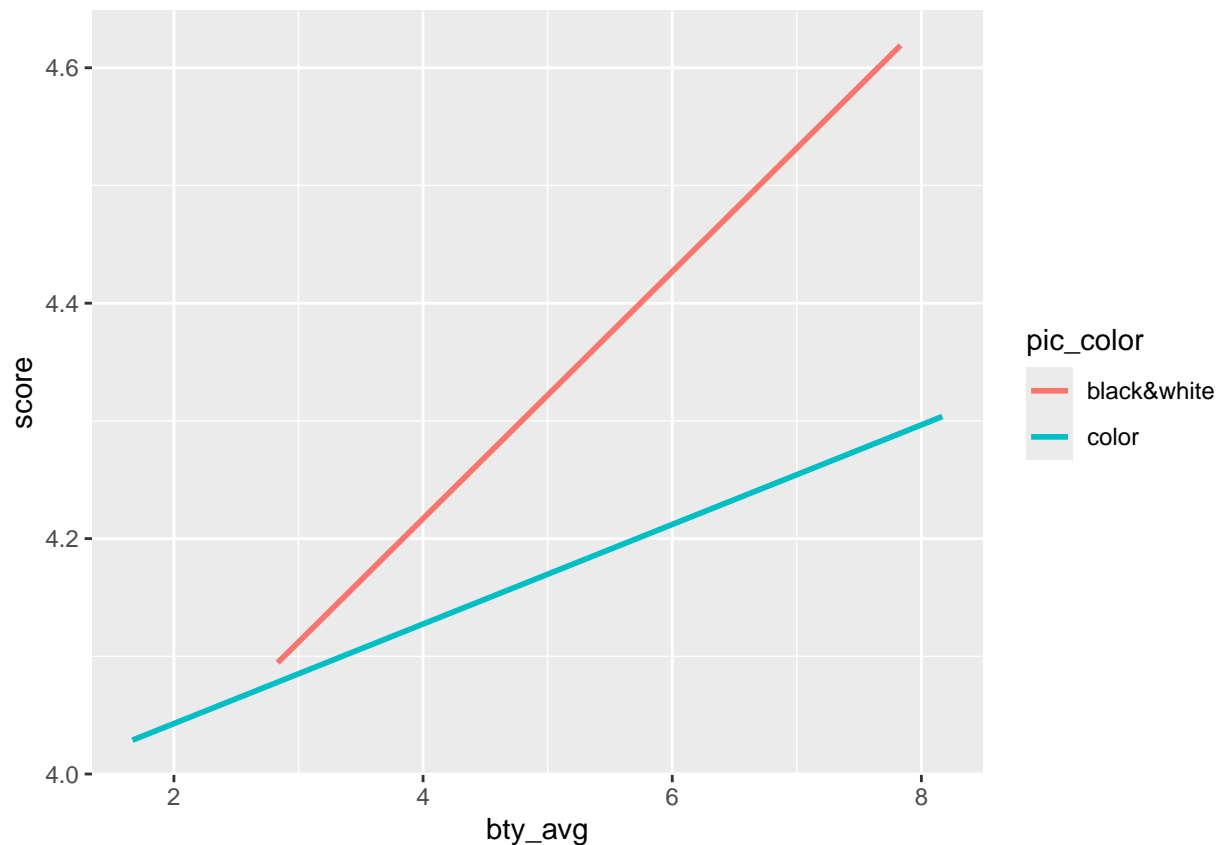
```
summary(m_bty_gen)
```

```
##
## 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
```

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.

```
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?

$\text{score} = b_0 + b_1 \text{bty_avg} + b_2 \text{pic_color}$ $\text{score} = 4.06318 + 0.05548 \text{bty_avg} + -0.16059 \text{pic_color}$

For two professors who received the same beauty rating, black and white pictures tends to have the higher course evaluation score

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

```
##
## Call:
## lm(formula = score ~ bty_avg + pic_color, data = evals)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.8892 -0.3690  0.1293  0.4023  0.9125
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.06318    0.10908  37.249 < 2e-16 ***
## bty_avg        0.05548    0.01691   3.282  0.00111 **
```

```
## pic_colorcolor -0.16059    0.06892  -2.330  0.02022 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5323 on 460 degrees of freedom
## Multiple R-squared:  0.04628,    Adjusted R-squared:  0.04213
## F-statistic: 11.16 on 2 and 460 DF,  p-value: 1.848e-05
```

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 `therelevel()` 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`.

It codes them as `ranktenure track` and `ranktenured`, with `teaching` as the reference level

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

##
## 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.

```
?evals
```

“number of professors” seems like it would have the least association with the score, the ratio for one professor shouldn’t really be effected by having multiple professors teaching the same class. Unless the students are somehow aware that another prof is doing a better job?

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.

I was correct, `cls_profssingle` had a $\text{Pr}(>|t|)$ of 0.77806, the highest of any of the variables

13. Interpret the coefficient associated with the ethnicity variable.

while holding all other variables constant, a professor who is not minority would be expected to have a score 0.1234929 higher than a similar professor who is 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?

Some coefficients changed slightly, but the significance did not change for the other explanatory variables. This suggests that `cls_profs` was likely collinear with other explanatory variables. If removing it didn't change the model much, one of the other variables is providing similar info

```
m_full1 <- 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_full1)
```

```
##
## 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.

Using a p value threshold of 0.05 the backwards-selection model is:

score ~ gender + ethnicity + language + age + cls_perc_eval + cls_credits + bty_avg + pic_color

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

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

ggplot

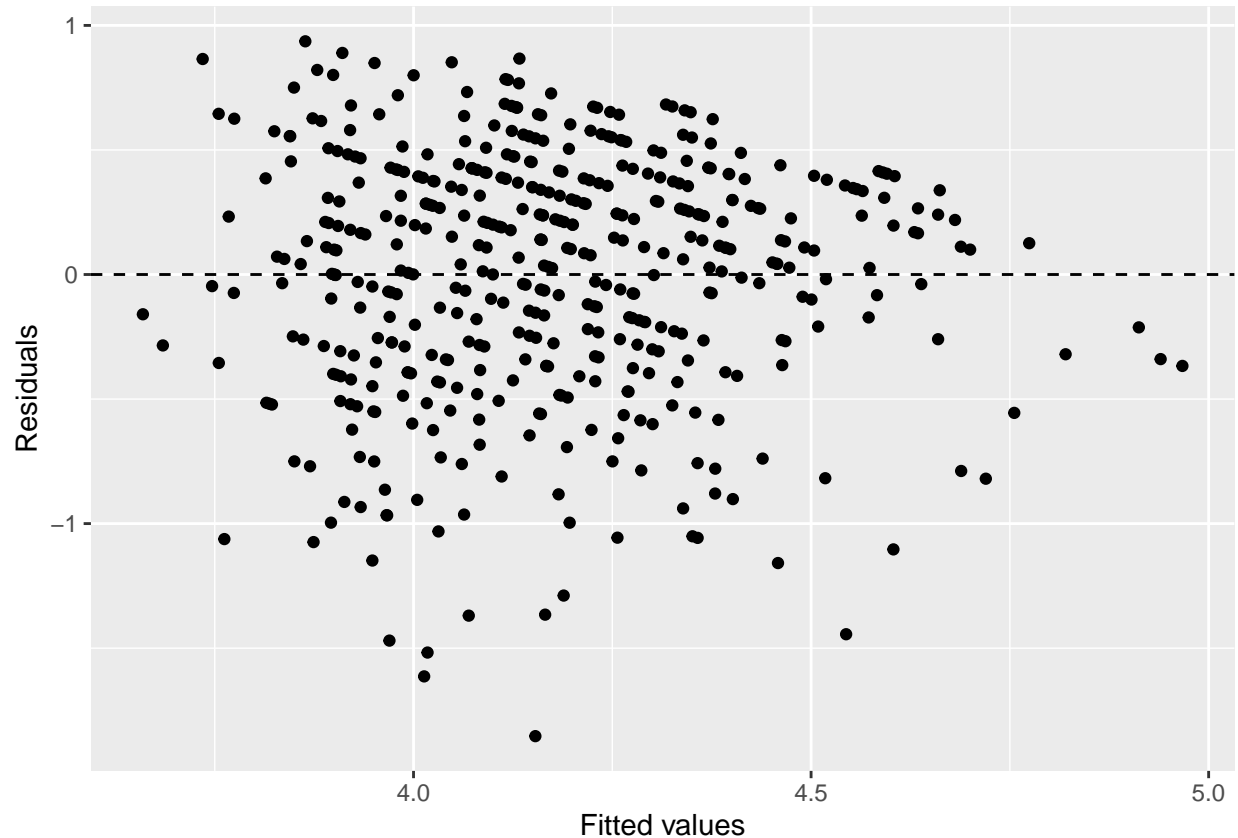
```
## function (data = NULL, mapping = aes(), ..., environment = parent.frame())
## {
##     UseMethod("ggplot")
## }
## <bytecode: 0x000001d9a8a95770>
## <environment: namespace:ggplot2>
```

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

Insert your answer here

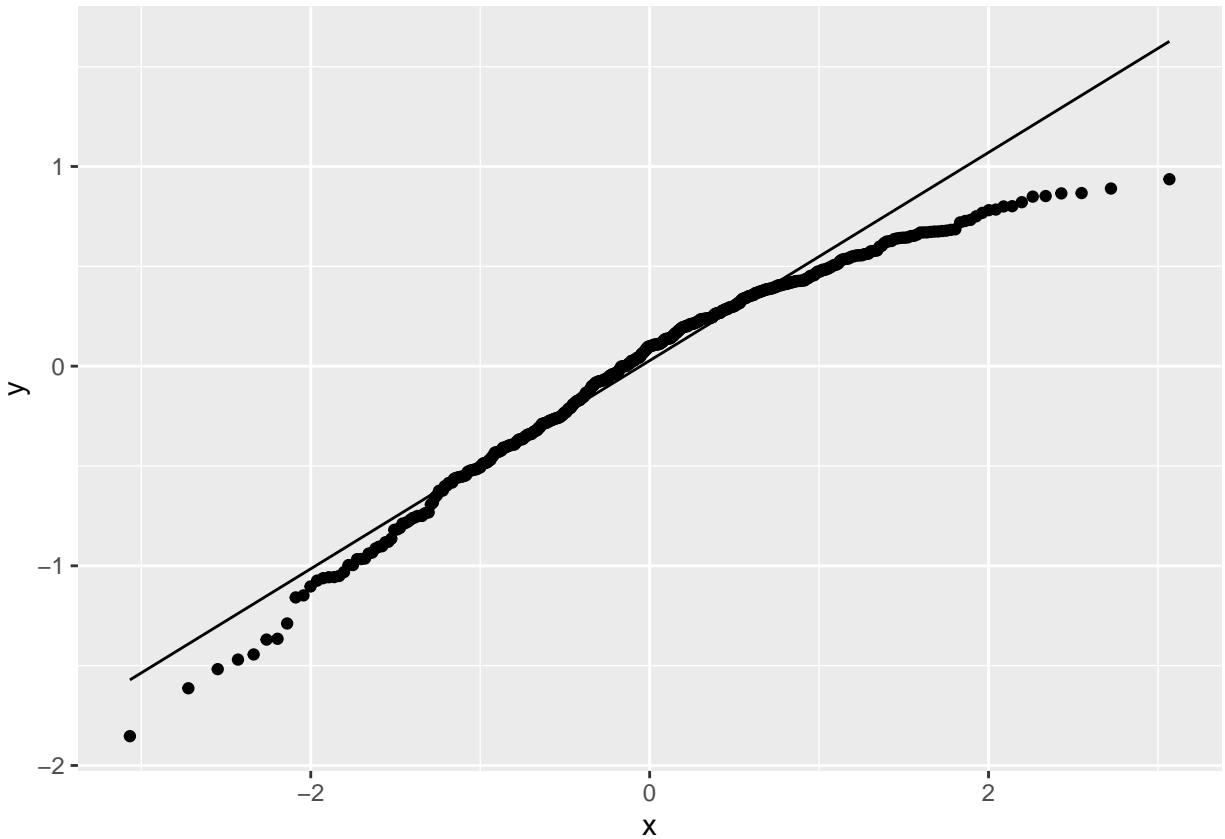
(1) linearity: The residuals seem vaguely linear, but I'm a bit confused at the tilt that seems to be happening

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



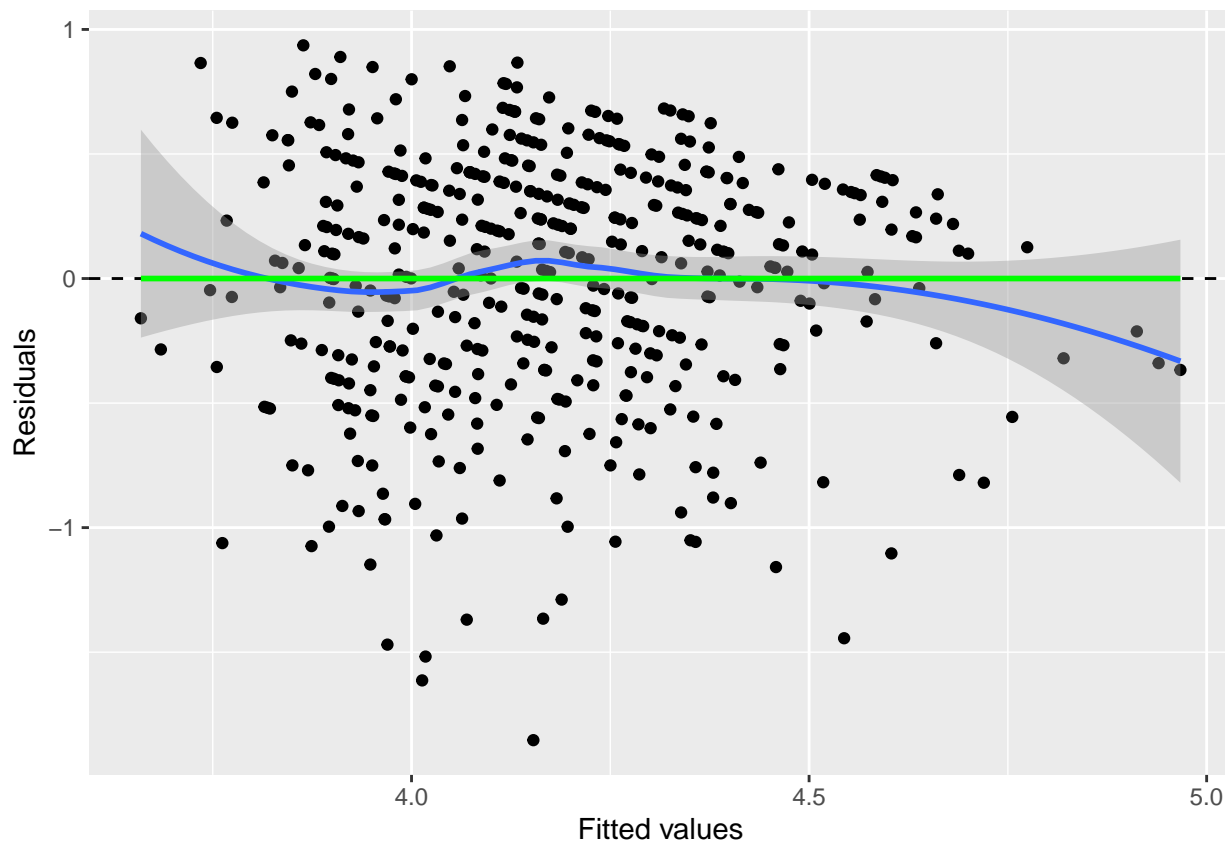
(2) nearly normal residuals: i think it looks nearly normal

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

(3) constant variability: the residual errors have close to a mean value of zero

```
ggplot(data = m_backwards_selection, aes(x = .fitted, y = .resid)) +  
  geom_point() +  
  geom_hline(yintercept = 0, linetype = "dashed") +  
  xlab("Fitted values") +  
  ylab("Residuals") +  
  geom_smooth() +  
  geom_smooth(method="lm", se = FALSE, color="green")
```



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?

One of the conditions of linear regression is that each observation is independent of the others. Considering the sample includes all courses each professor taught and each row represents a course, there may be repeated courses from the same professors, this would violate our assumption

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 young beautiful male non-minority professor teaching a 1 credit course, who studied at an english school, and has a black and white picture, and had a large proportion of their class give evaluations

?evals

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 generalizing my conclusions to apply to professors generally at any university, as it may not be accurately representative of the broader professor population. I would be much more comfortable generalizing if our data was from a broader random sample of professors, rather than just from one school.
