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
```

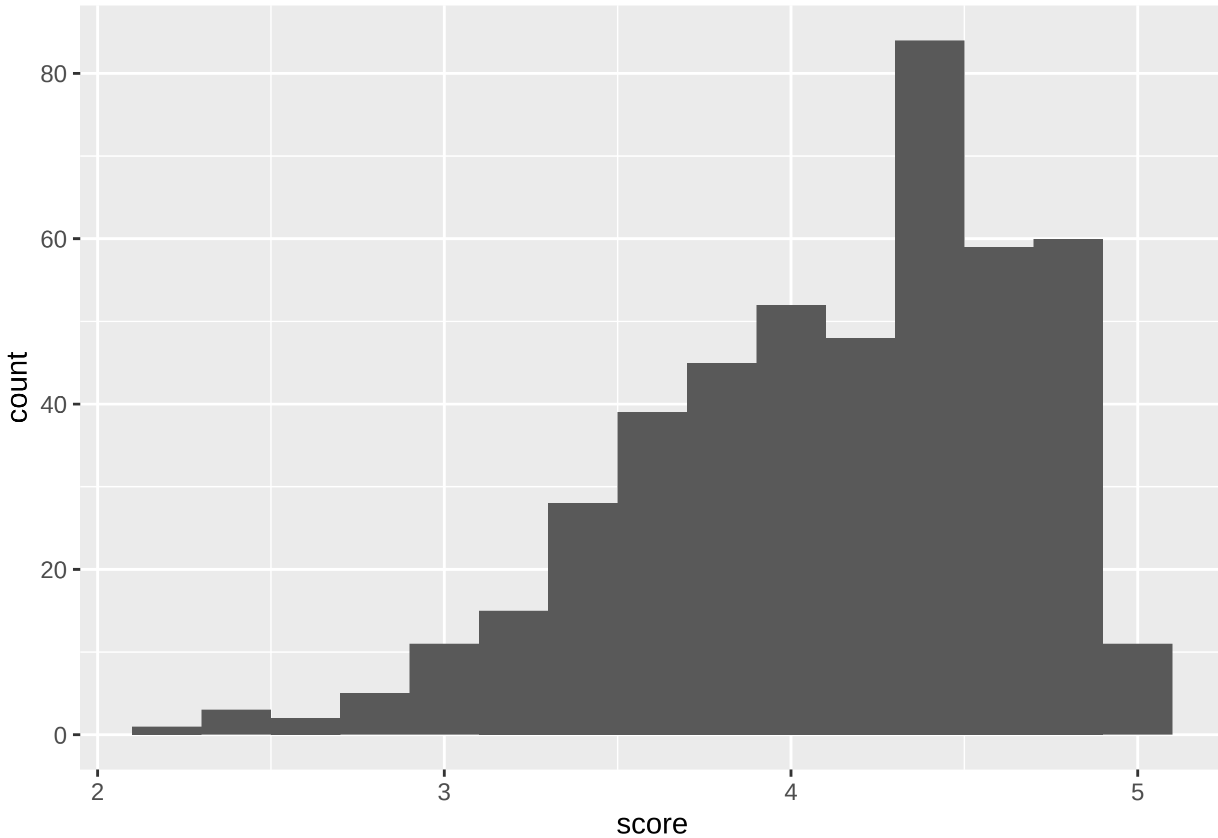
Exploring the data

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.

This is an observational study because the data is collected in a way that does not interfere "with how the data arise". The original research question posed - "whether beauty leads directly to the differences in course evaluations" cannot be answered because an observational study on it's own cannot show a causal connection. If you did want to ask the original research question, an experiment would need to be set up to test it. Instead I would ask the question "is beauty correlated with 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?

```
evals |> ggplot(aes(x = score)) +
  geom_histogram(binwidth = .2)
```

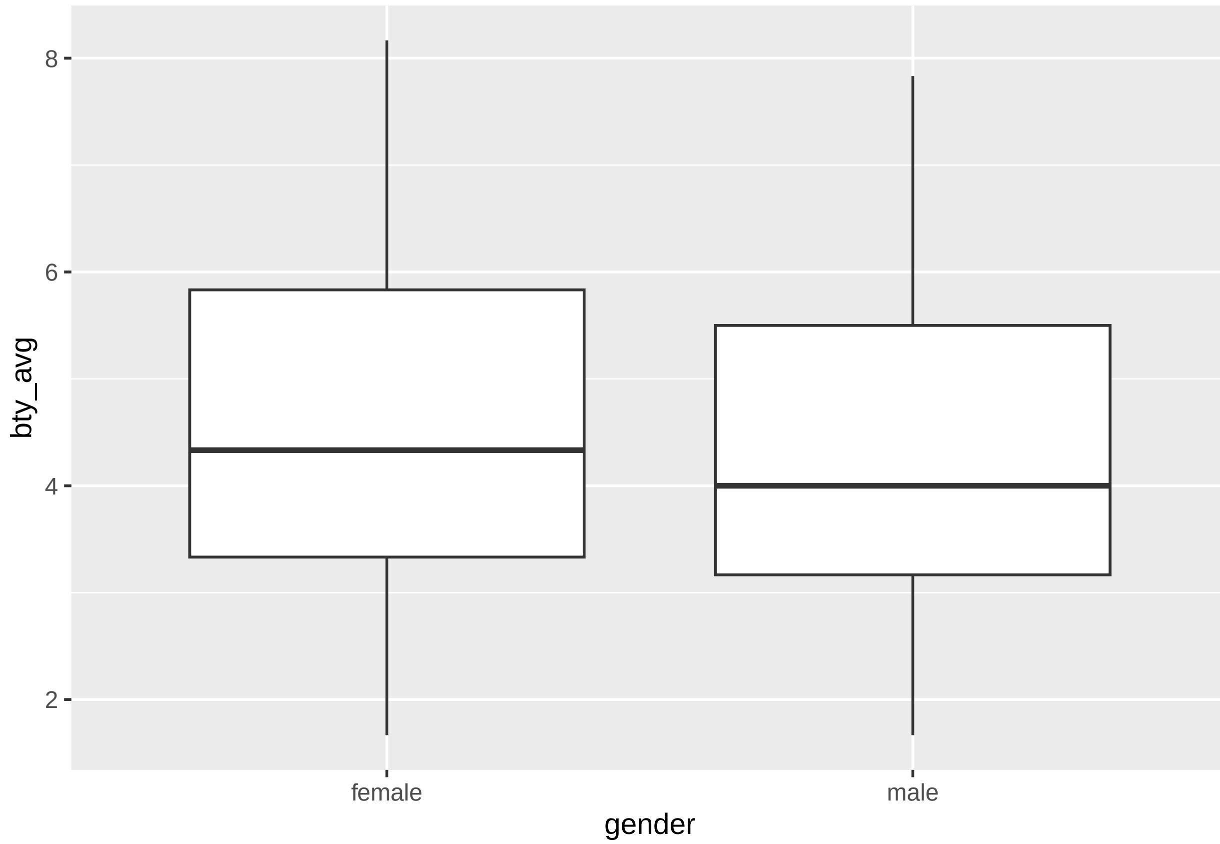


The distribution of score is normal and skewed to the left. That tells us that in general the students rate courses high. This is not exactly what I expected because my assumption was that students who did not like the course and students who really like the course would be the ones to rate it, so I was expecting a distribution that had 2 peaks, one for low and one for high ratings.

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

One relationship I would be interested to see is the beauty average with gender.

```
evals |> ggplot(aes(x = gender, y = bty_avg)) +
  geom_boxplot()
```

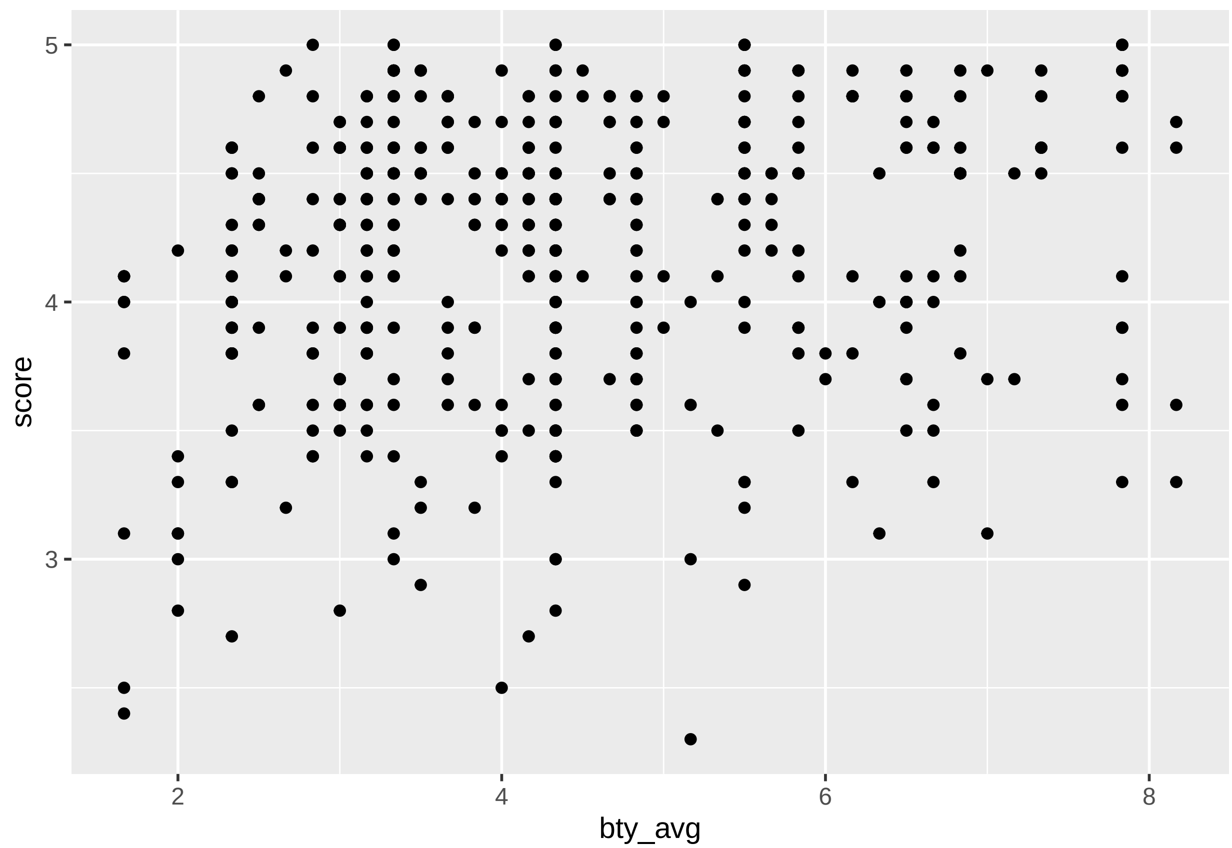


According to the boxplot, women are more likely to be rated as more beautiful than men.

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:

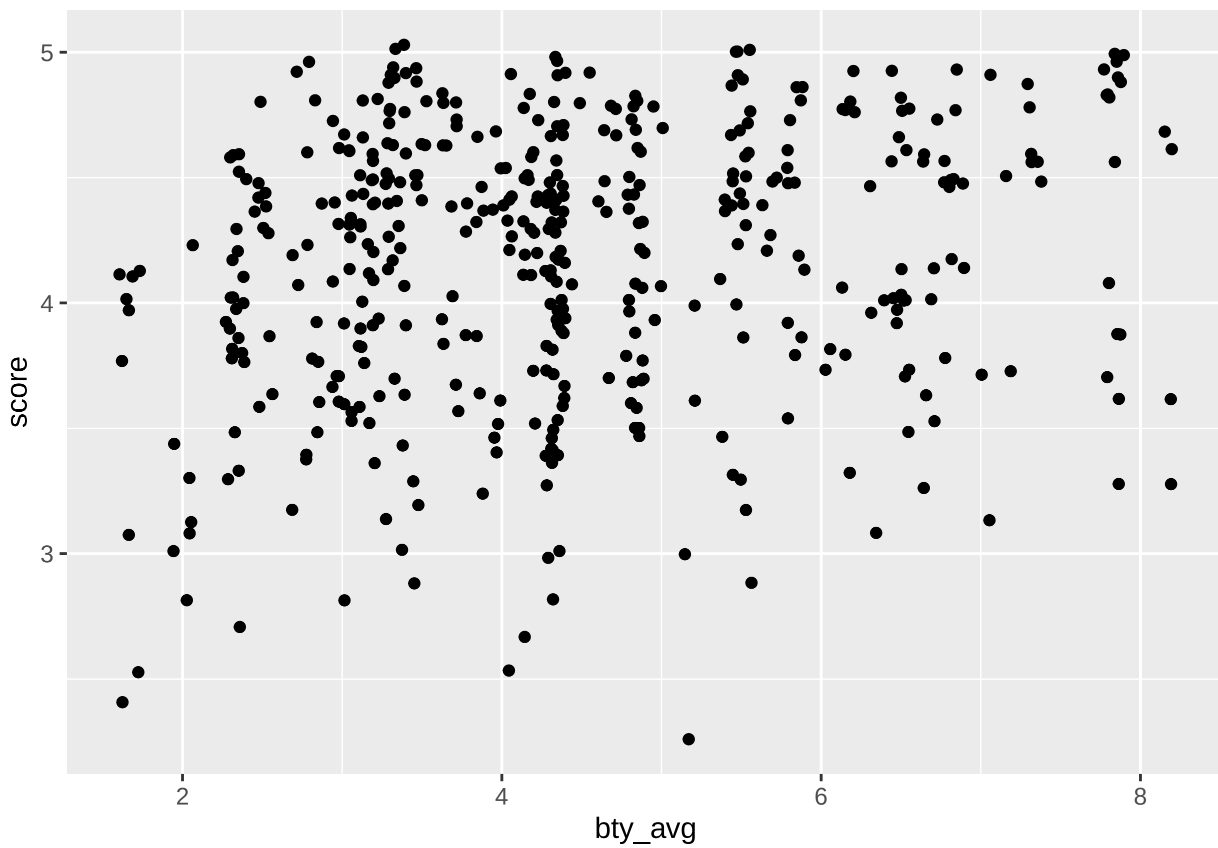
```
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_point()
```



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()
```



`geom_jitter` adds a little bit of noise to the graphed data so that rather than having points overlap they are separated a bit - with the "jitter". With the "jitter" you can see there are more points than what originally appeared, specifically for the higher scores. The misleading part of the initial scatterplot was where the higher density of ratings was.

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?

```r
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
```

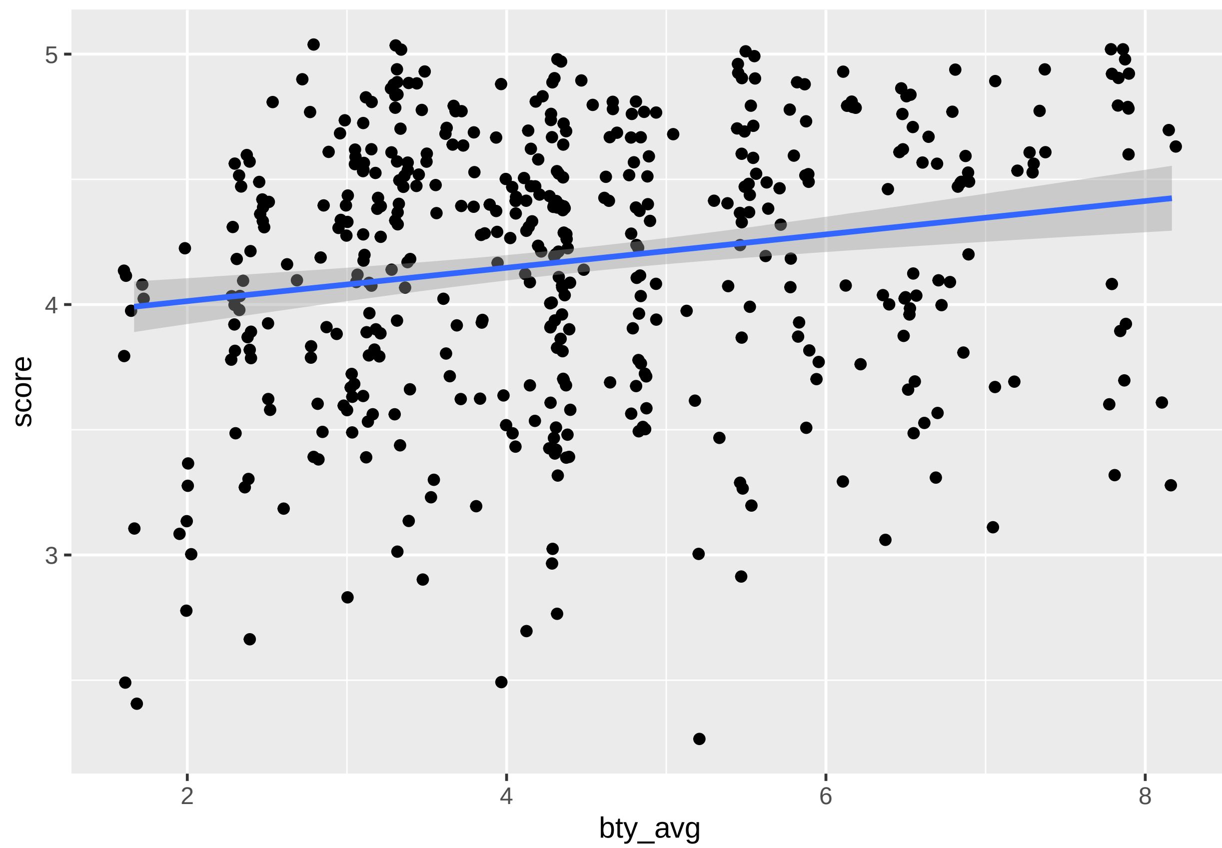
The equation for the linear model is:

score = 3.88034 + 0.06664*bty_avg

The average beauty score appears to be a significant predictor because the p value is less than 0.05. However even though it is statistically significant it does not appear to be a practically significant predictor because the Rsquared value is really low meaning that for the linear model only 0.03293 of the variation is explained by the least squares line.

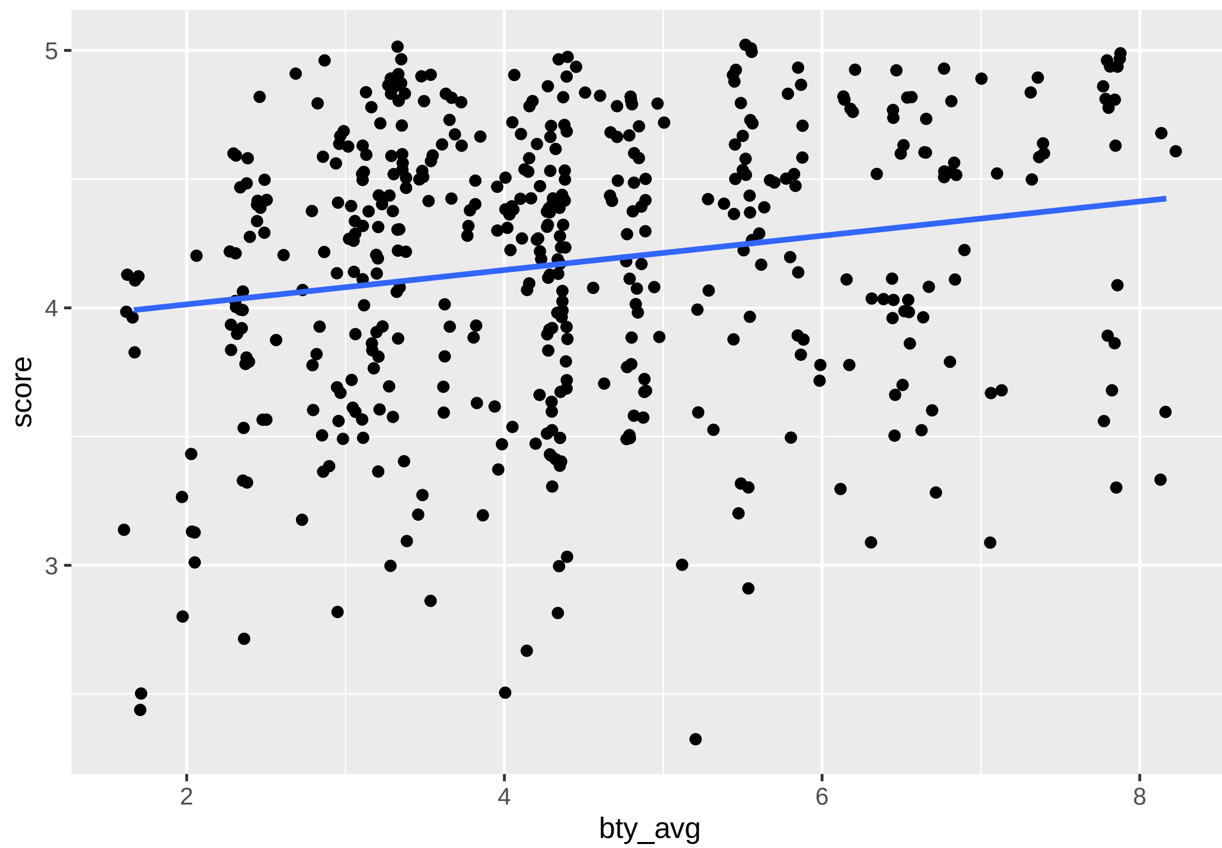
Add the line of the bet fit model to your plot using the following:

```
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`.

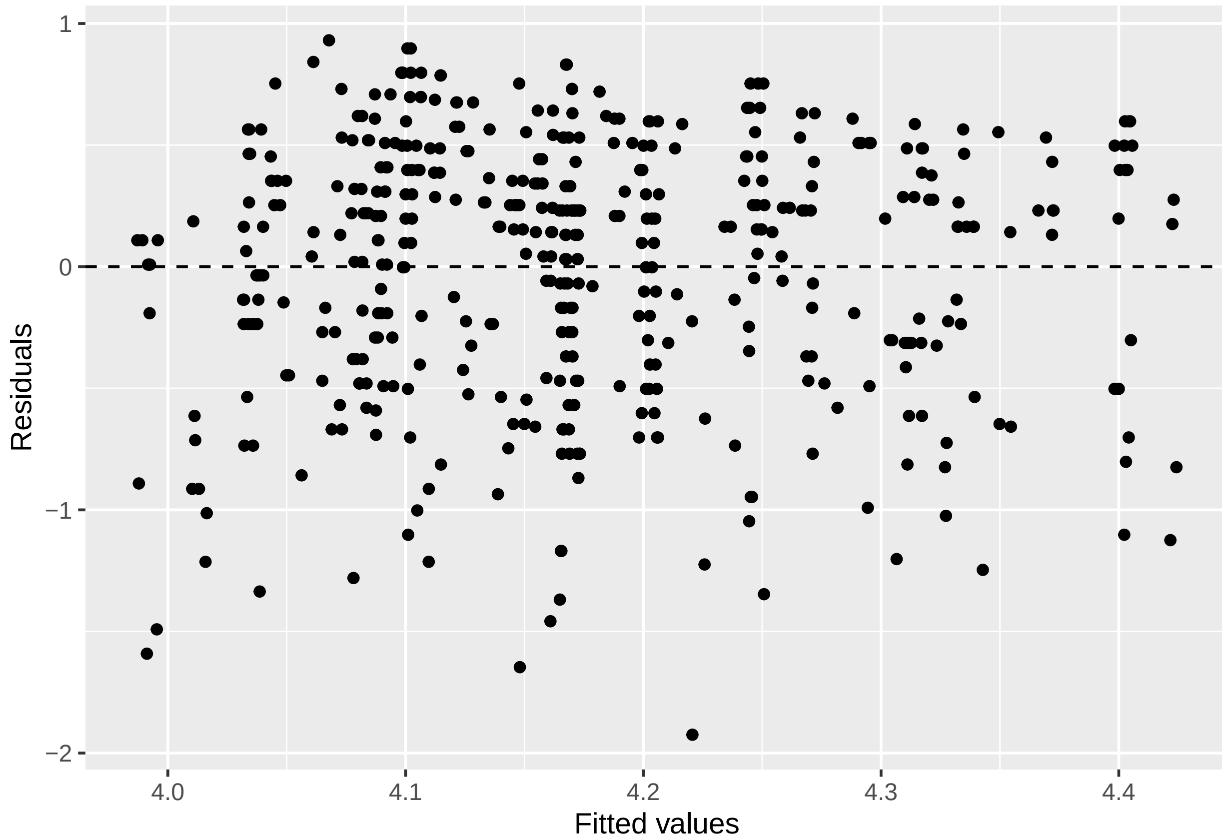
```
ggplot(data = evals, aes(x = bty_avg, y = score)) +
  geom_jitter() +
  geom_smooth(method = "lm", se = FALSE)
```



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).

First, as in lab 8 - check for linearity. I used geom_jitter because of the known overlapping points.

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

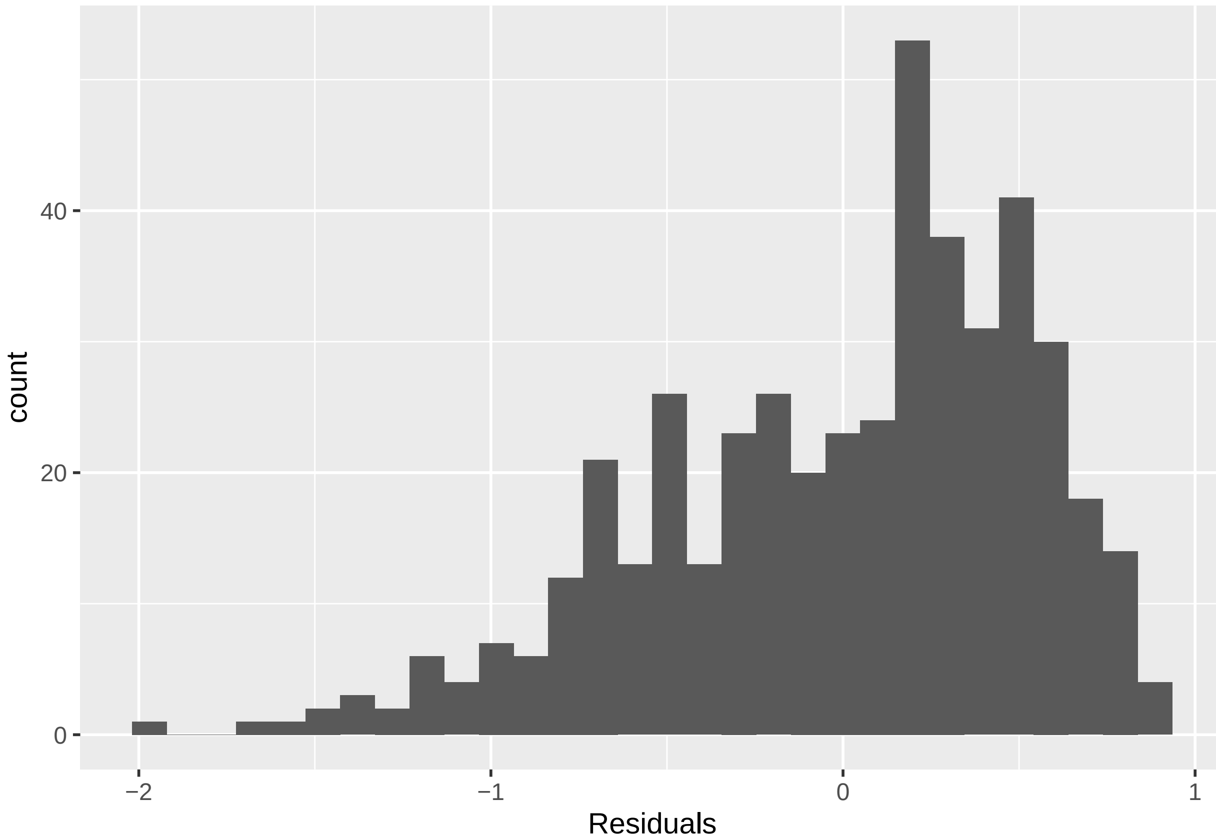


This is a plot of residuals vs fitted predicted values. It appears that the residuals are distributed around 0 (for the most part) and there is no specific trend to them except for that there does appear to be more points condensed above 0 and more spread out below 0.

Next as in lab 8, check for normality.

The first way can be done with a histogram.

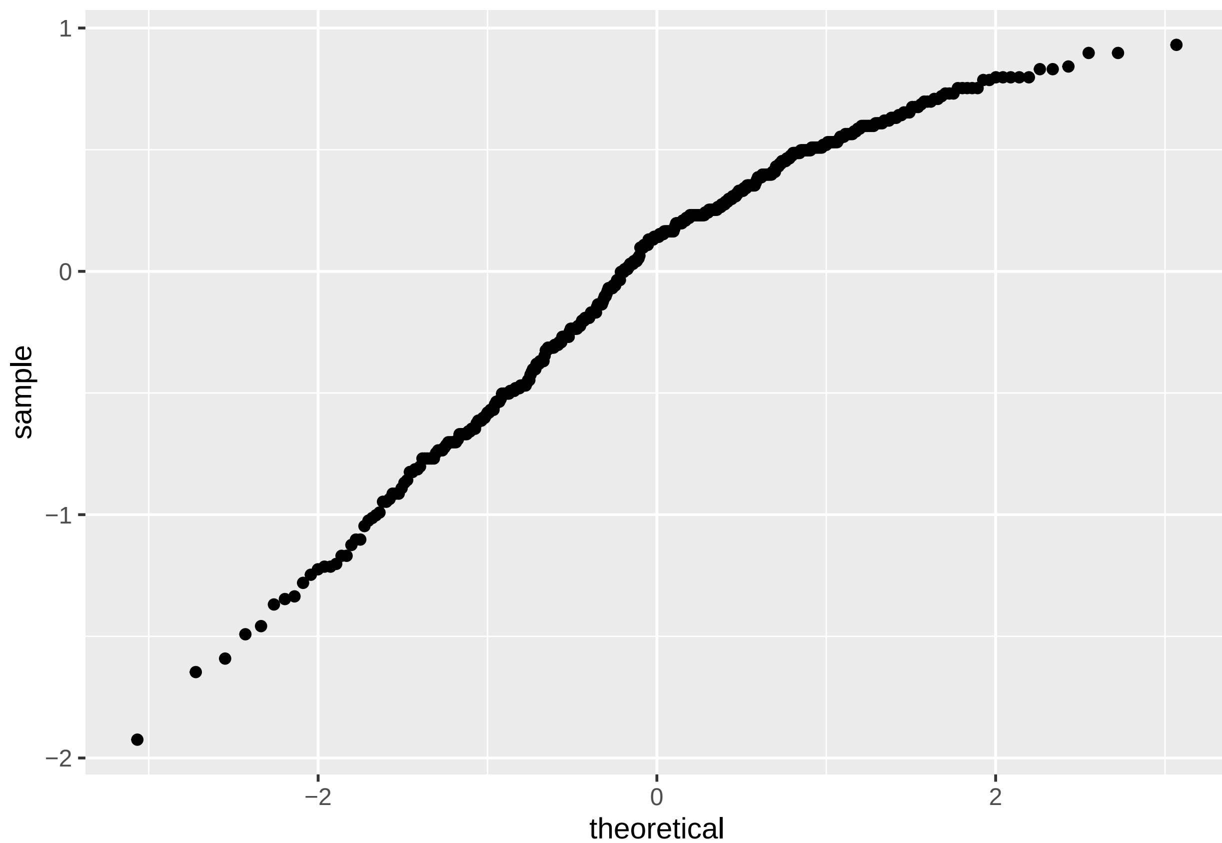
```
ggplot(data = m_bty, aes(x = .resid)) +
  geom_histogram() +
  xlab("Residuals")
```



It appears the residuals are nearly normal but are skewed to the left.

This can also be observed with a normal probability plot of the residuals.

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



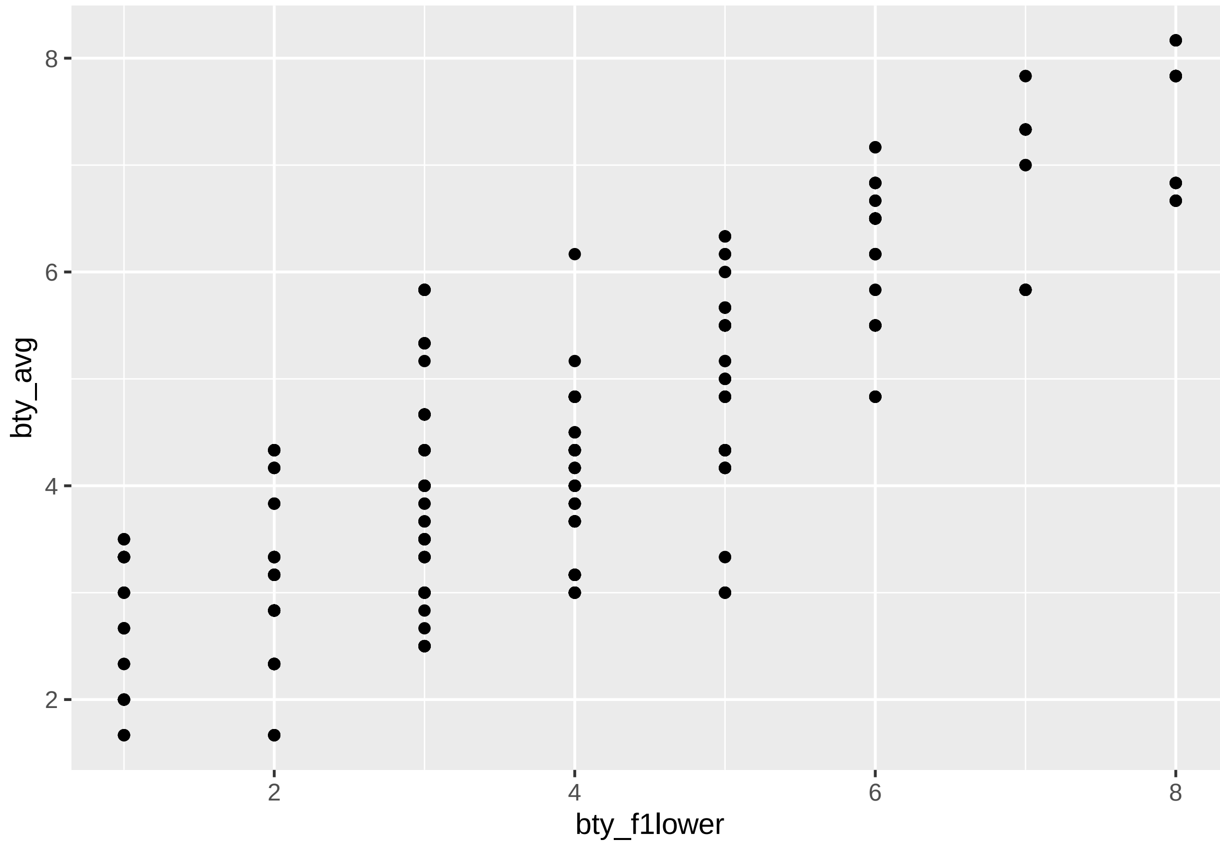
In both cases, the slight left skew of the data can be seen.

I would say that the conditions of least squares regression are reasonably met. There are some minor discrepancies but the least squares regression should still give us valuable insights.

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()
```

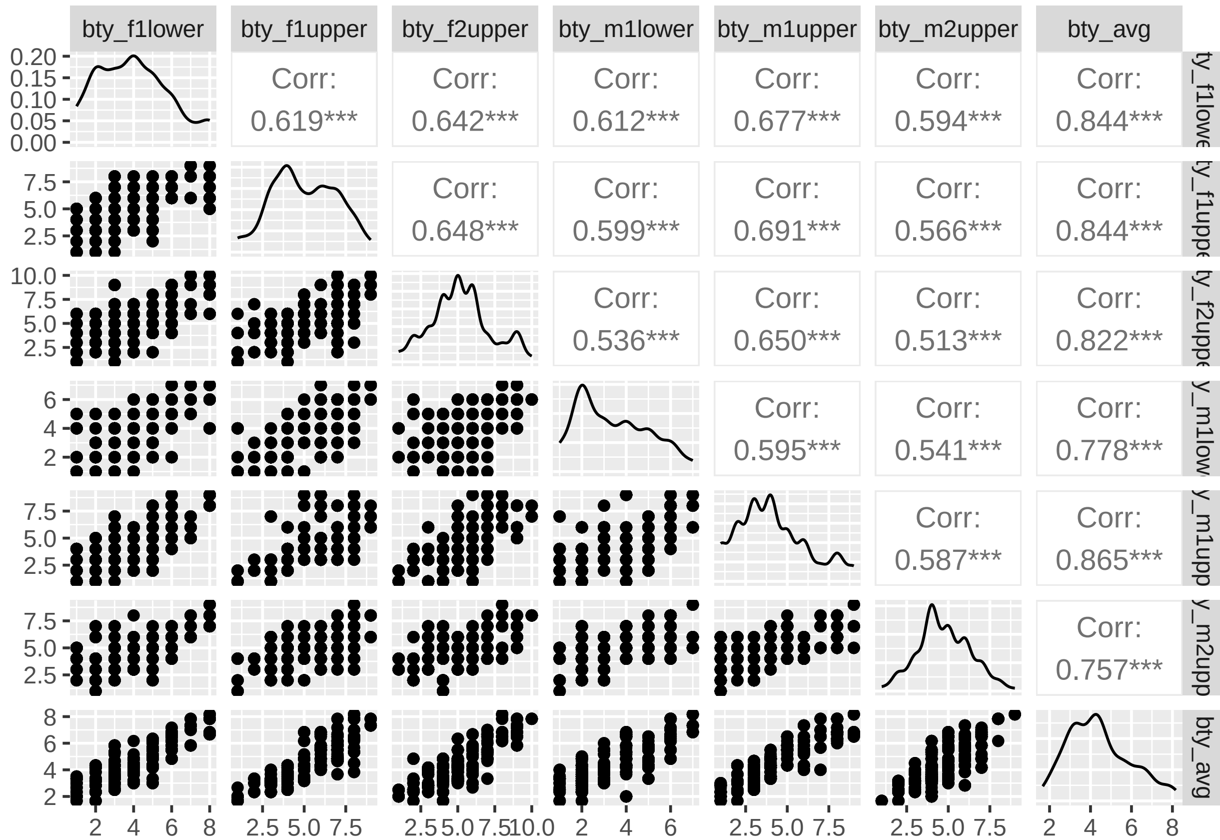



```
evals %>%
  summarise(cor(bty_avg, bty_f1lower))
```

```
## # 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
##
```

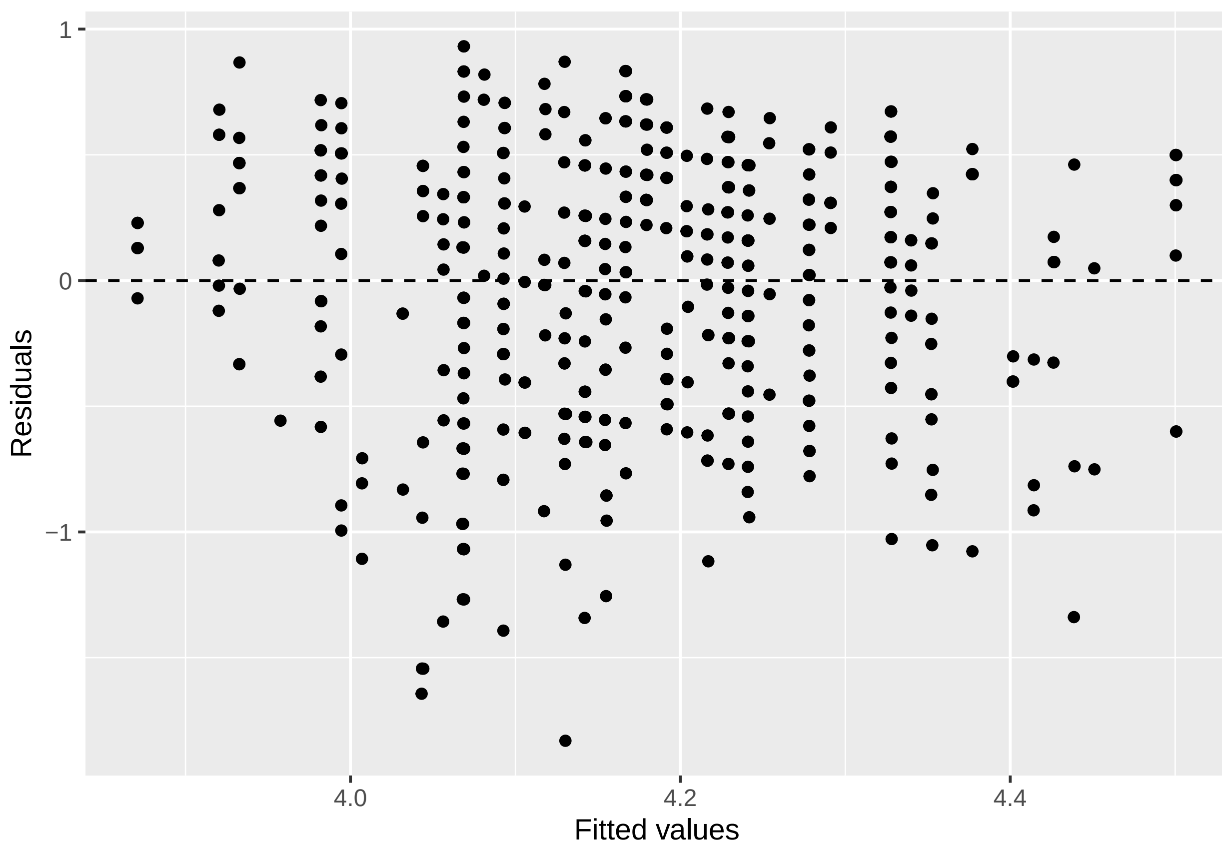
```
## Residual standard error: 0.5287 on 460 degrees of freedom
## Multiple R-squared:  0.05912,    Adjusted R-squared:  0.05503
## F-statistic: 14.45 on 2 and 460 DF,  p-value: 8.177e-07
```

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.

As mentioned previously, the residuals need to be linear and normally distributed. This can be checked in the same way it was previously.

First, as in lab 8 - check for linearity

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

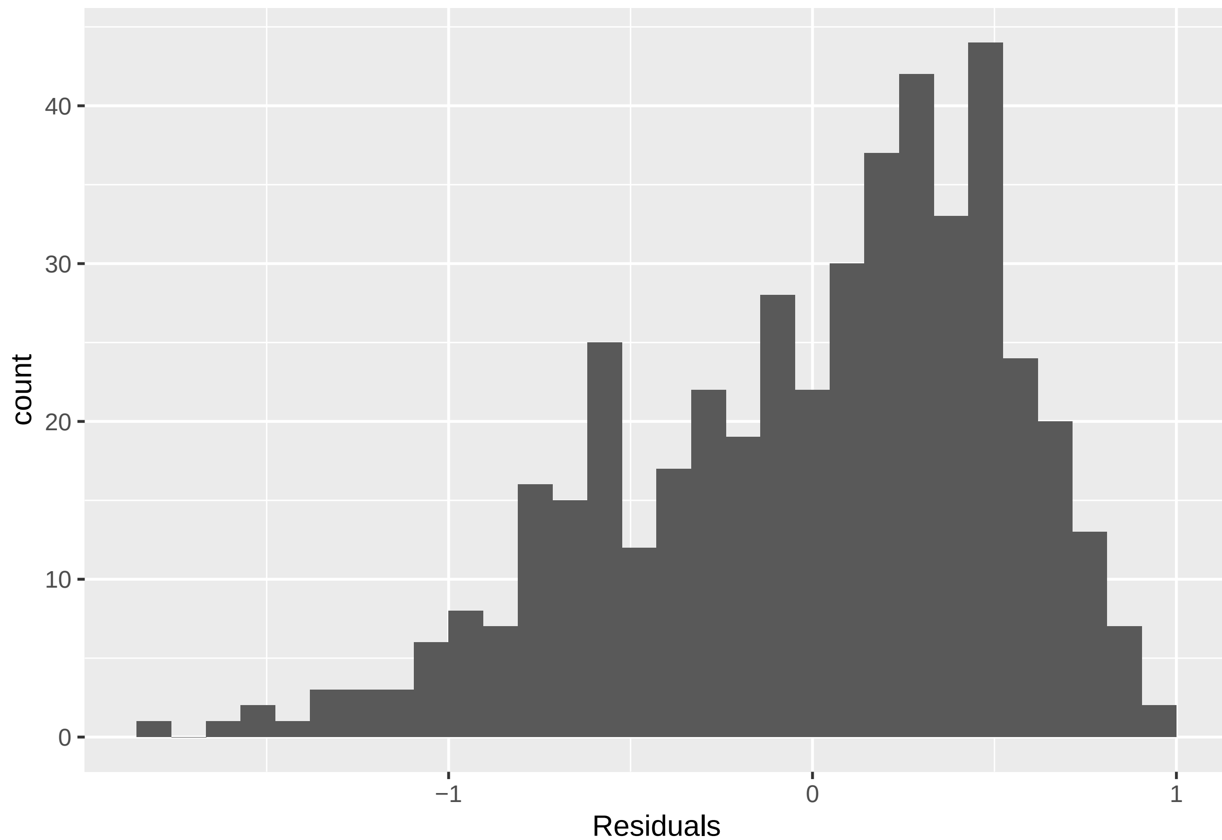


This is a plot of residuals vs fitted predicted values. It appears that the residuals are distributed around 0 and there is no specific trend to them.

Next as in lab 8, check for normality.

The first way can be done with a histogram.

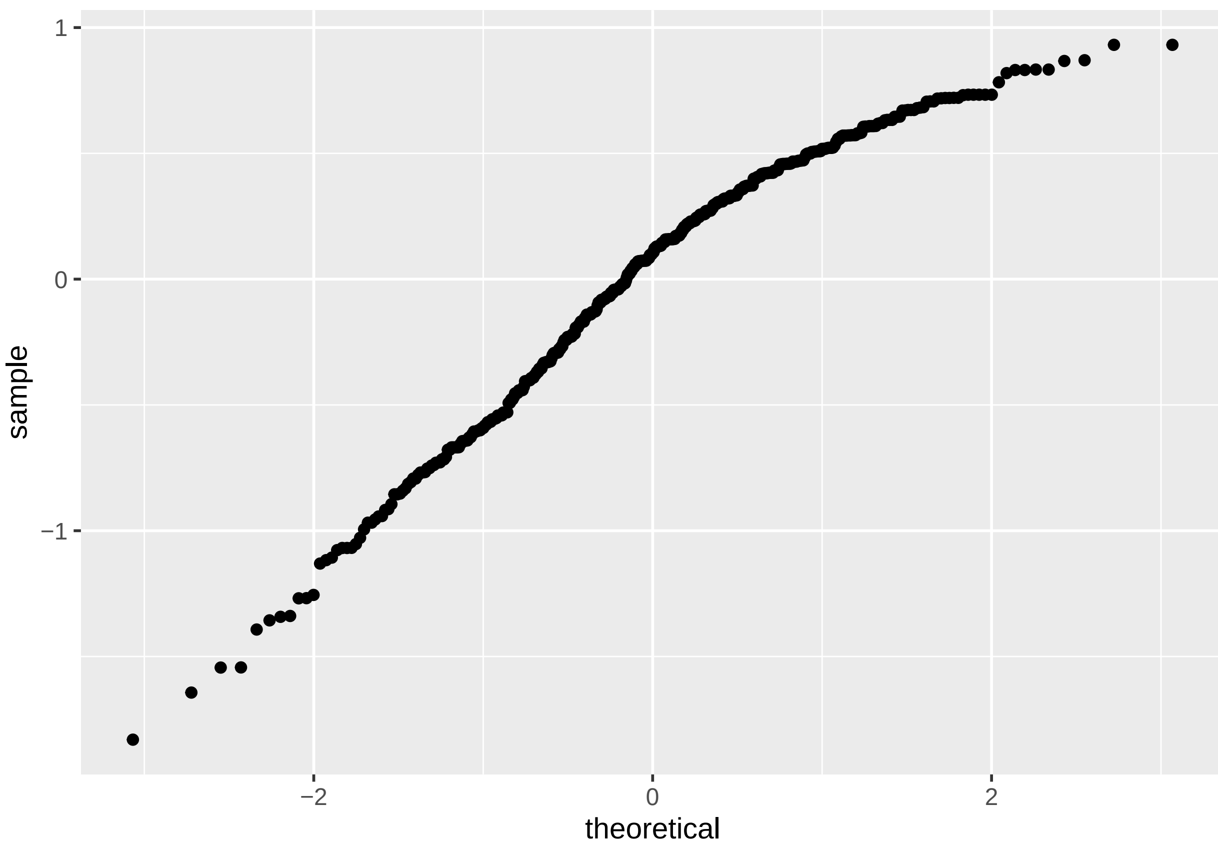
```r
ggplot(data = m_bty_gen, aes(x = .resid)) +
  geom_histogram() +
  xlab("Residuals")
```



It appears the residuals are nearly normal but are skewed to the left slightly.

This can also be observed with a normal probability plot of the residuals.

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



I would say that the conditions of linearity and normality are met and therefor the p values and parameter estimates can be trusted.

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`?

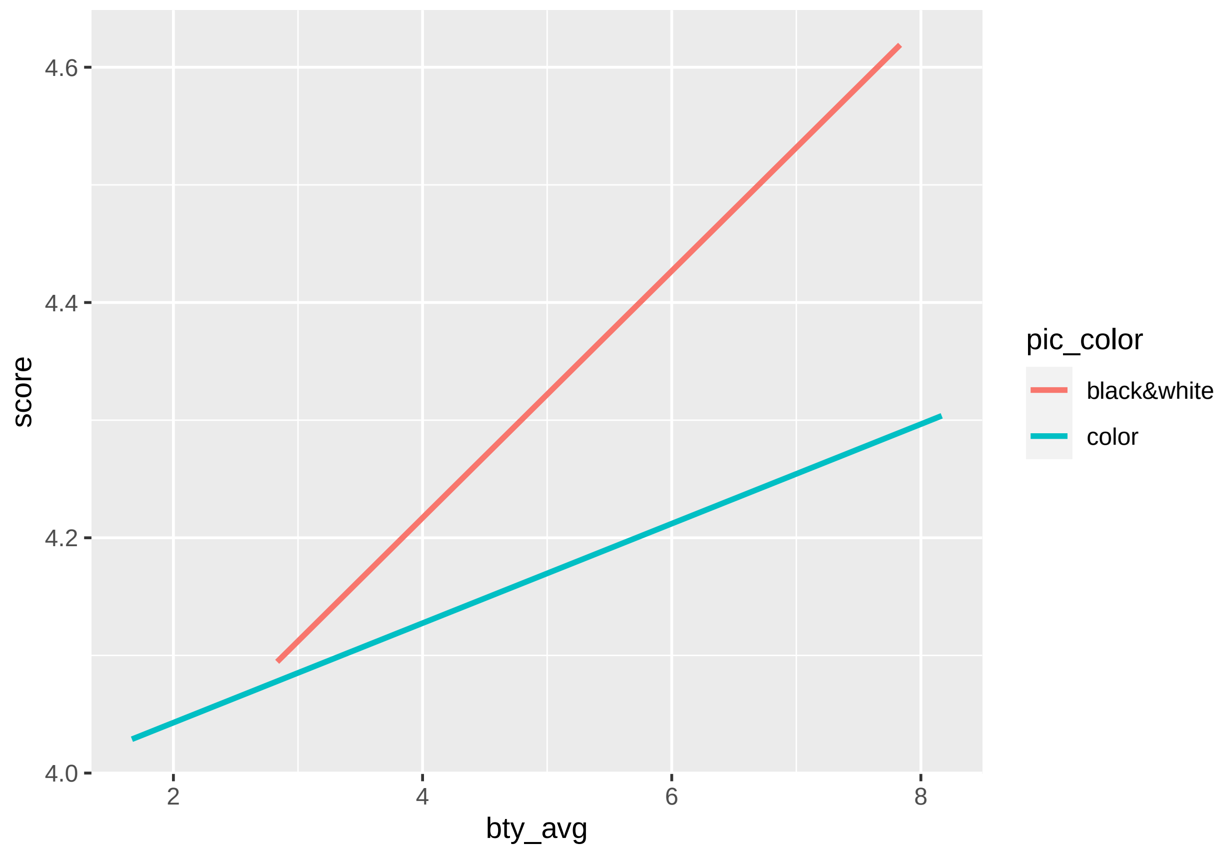
According to the model bty_avg is still a significant predictor of score (p value less than 0.05). The addition of gender to the model has changed the parameter estimate for bty_avg (from 0.06664 to 0.07416). Based on the adjusted Rsquared - it went from 0.03293 to 0.05503 which is an improvement - so the model got better.

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?

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

```
##
## Call:
## lm(formula = score ~ bty_avg + gender + pic_color, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.7807 -0.3587  0.1142  0.4113  0.8839
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.95031    0.11173  35.354  < 2e-16 ***
## bty_avg          0.06171    0.01676   3.683 0.000258 ***
## gendermale       0.18750    0.05016   3.738 0.000209 ***
## pic_colorcolor -0.18851    0.06837  -2.757 0.006064 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5249 on 459 degrees of freedom
```

```
## Multiple R-squared:  0.07445,    Adjusted R-squared:  0.0684
## F-statistic: 12.31 on 3 and 459 DF,  p-value: 9.321e-08
```

The equation of the line if you now include picture color is:

score = 3.95031 + 0.06171 x bty_avg + 0.18750 x gendermale + -0.18851 x pic_colorcolor

or simplified, with the picture color being colored - thereform pic_colorcolor = 1:

score = 3.95031 + 0.06171 x bty_avg + 0.18750 x gendermale + -0.18851 x 1

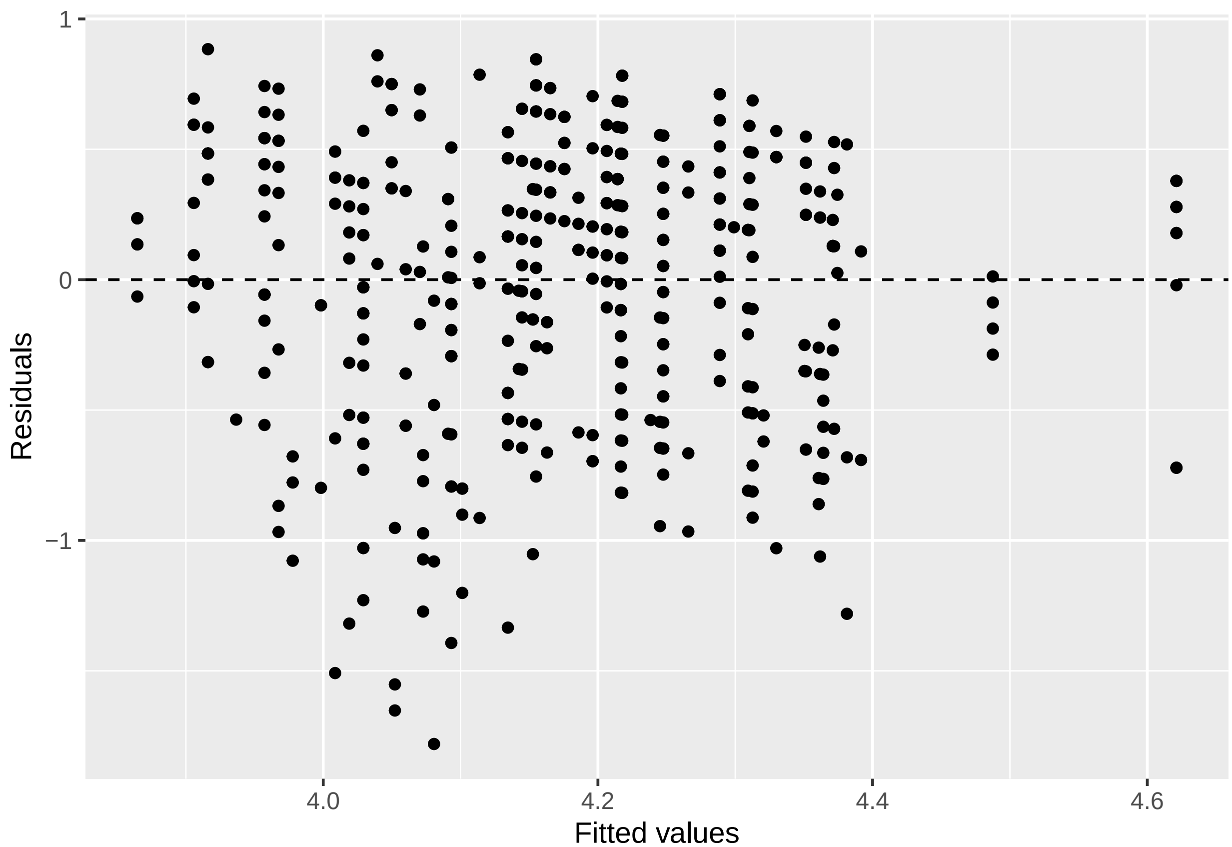
score = 3.7618 + 0.06171 x bty_avg + 0.18750 x gendermale

Based on this, for two professors who received the same beauty rating, and I will also assume have the same gender - the black and white pictures would get multiplied by 0 and the color pictures multiplied by 1. Based on this that means that a black and white picture would score higher than a color picture.

As mentioned previously, the residuals need to be linear and normally distributed. This can be checked in the same way it was previously.

First, as in lab 8 - check for linearity

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

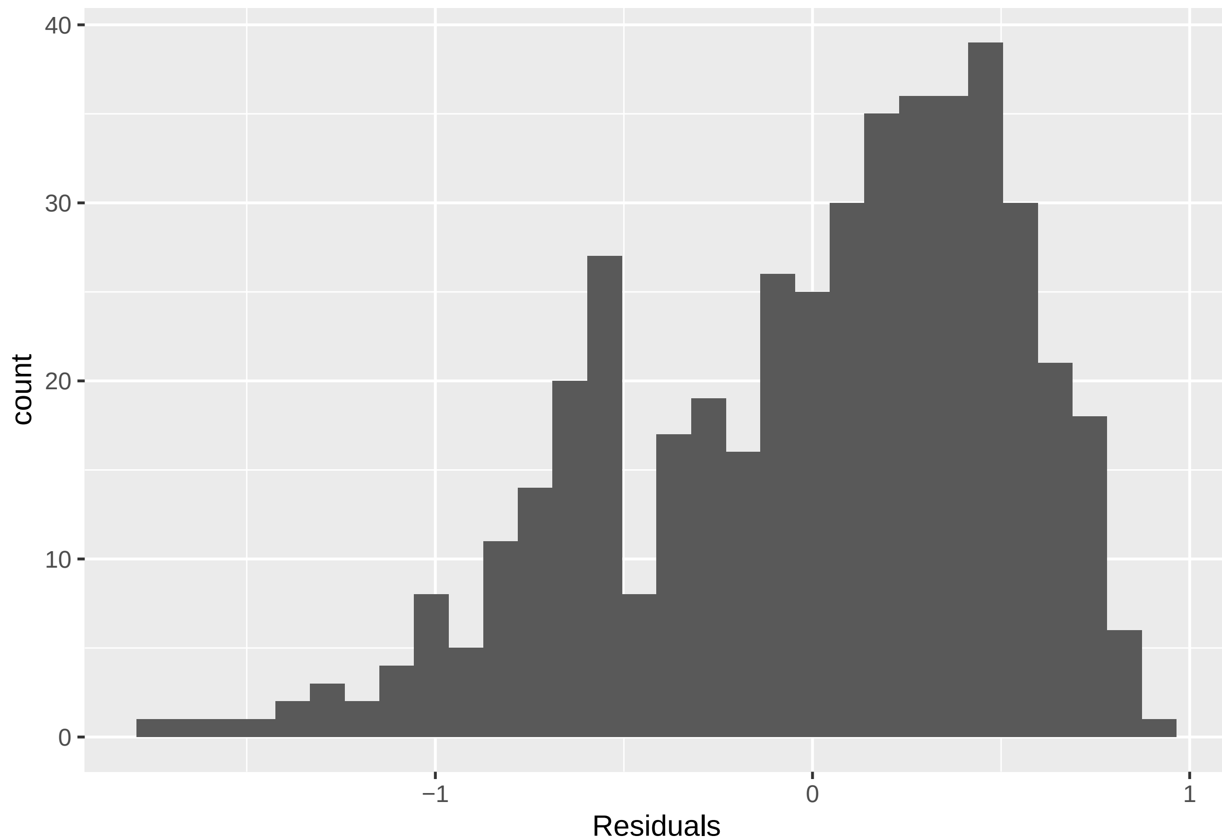


This is a plot of residuals vs fitted predicted values. It appears that the residuals are distributed around 0 and there is no specific trend to them except that most fall to the left.

Next as in lab 8, check for normality.

The first way can be done with a histogram.

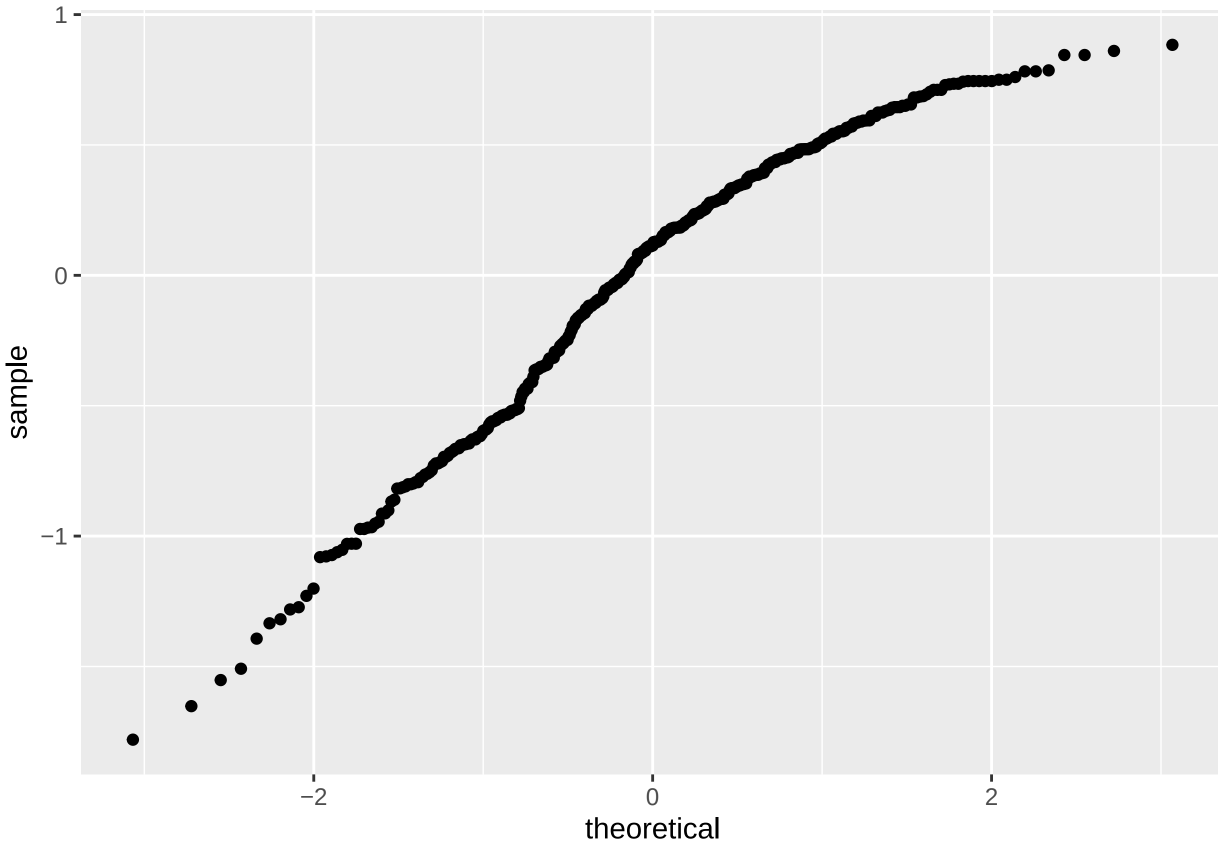
```
ggplot(data = m_bty_gen_color, aes(x = .resid)) +
  geom_histogram() +
  xlab("Residuals")
```



It appears the residuals are nearly normal but are skewed to the left slightly.

This can also be observed with a normal probability plot of the residuals.

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



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

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

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

```
##
## Call:
## lm(formula = score ~ bty_avg + rank, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8713 -0.3642  0.1489  0.4103  0.9525
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        3.98155    0.09078  43.860  < 2e-16 ***
## bty_avg            0.06783    0.01655   4.098 4.92e-05 ***
## ranktenure track -0.16070    0.07395  -2.173   0.0303 *
```

```
## ranktenured      -0.12623    0.06266  -2.014   0.0445 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5328 on 459 degrees of freedom
## Multiple R-squared:  0.04652,    Adjusted R-squared:  0.04029
## F-statistic: 7.465 on 3 and 459 DF,  p-value: 6.88e-05
```

When there is a categorical variable which has more than two levels it appears that there are the number of levels minus 1 dummy variables created to include those levels. Whatever category comes alphabetically first is left out, so in this case "teaching" would be represented if `ranktenure track` and `ranktenured` were set to 0. The rank of tenure track would be represented if `ranktenure track` is set to 1 and `ranktenured` set to 0. Finally, tenured would be represented if `ranktenured` is set to 1 and `ranktenure track` set to 0.

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.

Out of the variables, my expectation is that the language of the university where they got their degree would not have much association with the professor score (and therfore would have a high 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.

The language of the university where they got their degree from has a p value of 0.03965 - which is smaller, but is close to 0.05. So my suspicion was not technically correct. It looks like the highest p- value is 0.77806 which is for cls_profssingle which is if there is one or multiple professors.

13. Interpret the coefficient associated with the ethnicity variable.

The coefficient associated with the ethnicity variable is 0.1234929 - that would be coded as ethnic minority would be 0 and ethnic not minority would be 1 - indicating that a minority would score LOWER than a not minority (with all else held constant). In other words if everything else is held constant not being an ethnic minority results in a 0.1234929 higher score. It should be noted the p value for this indicates its not a significant predictor, the p value is 0.11698.

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?

```
m_minus_one <- 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_minus_one)
```

```
##
## 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
```

I dropped class profs which had the highest p value. With the refit model coefficients and significance of other explanatory variables did change. Now the variable with the highest p value is cls_level To note is dropping the original largest p value in the model improved the adjusted R squared from 0.1617 to 0.1634, thus improving the model. If cls_profs was collinear with another variable then the coefficients wouldn't really change and the Rsquared wouldn't really change.

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.

Backward elimination starts off with including ALL of the potential predictor variables, then variables are eliminated one at a time from the model until the adjusted R squared is no longer improved. Each elimination step eliminates the variable which leads to the largest improvement in the R squared.

First I went through each and found that eliminating cls_profs was the only variable that when removed lead to an improvement in R squared. Then I did another iteration - removing every variable and seeing if it improved R squared - and none did. The closest one was removing the cls_level, but even this did not improve R squared.

```
m_elimination <- 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_elimination)
```

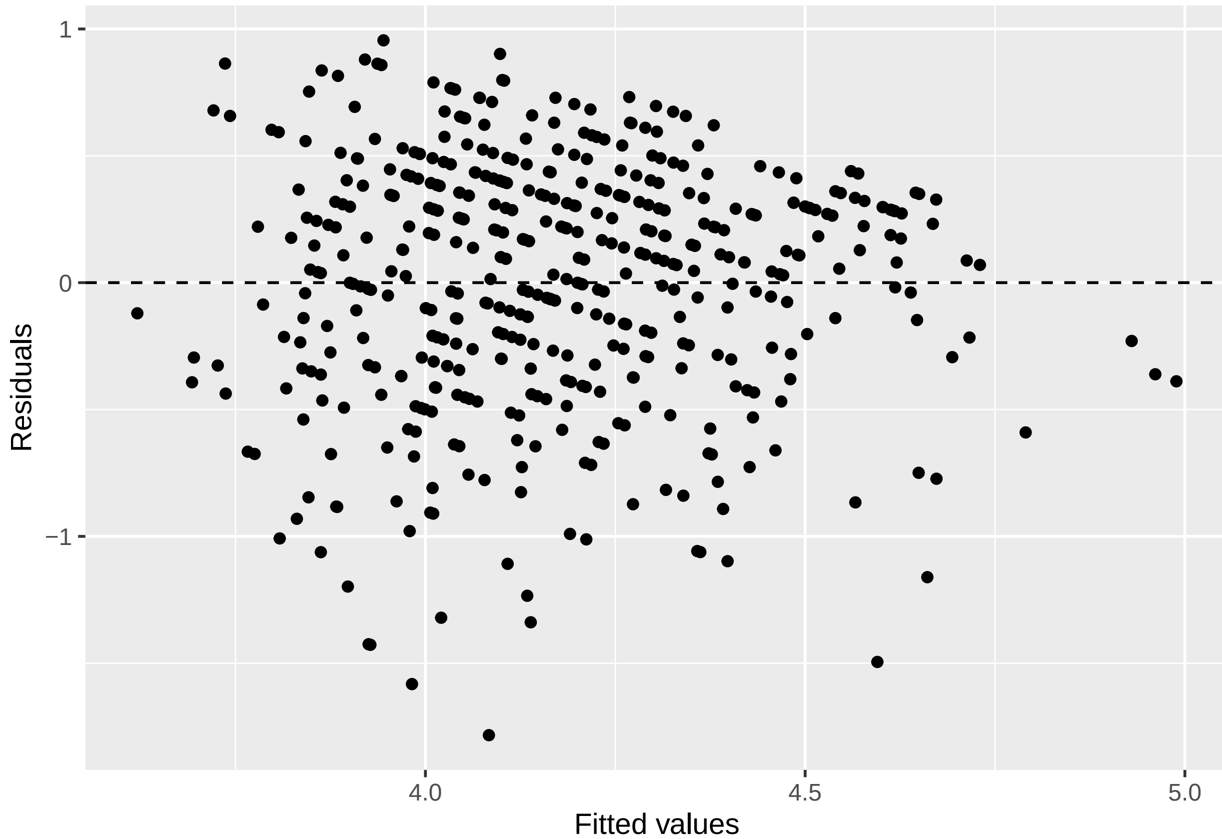
```
##
## Call:
## lm(formula = score ~ rank + gender + ethnicity + language + age +
##     cls_perc_eval + cls_students + cls_level + cls_credits +
```

```
##     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
```

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

First, as in lab 8 - check for linearity

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

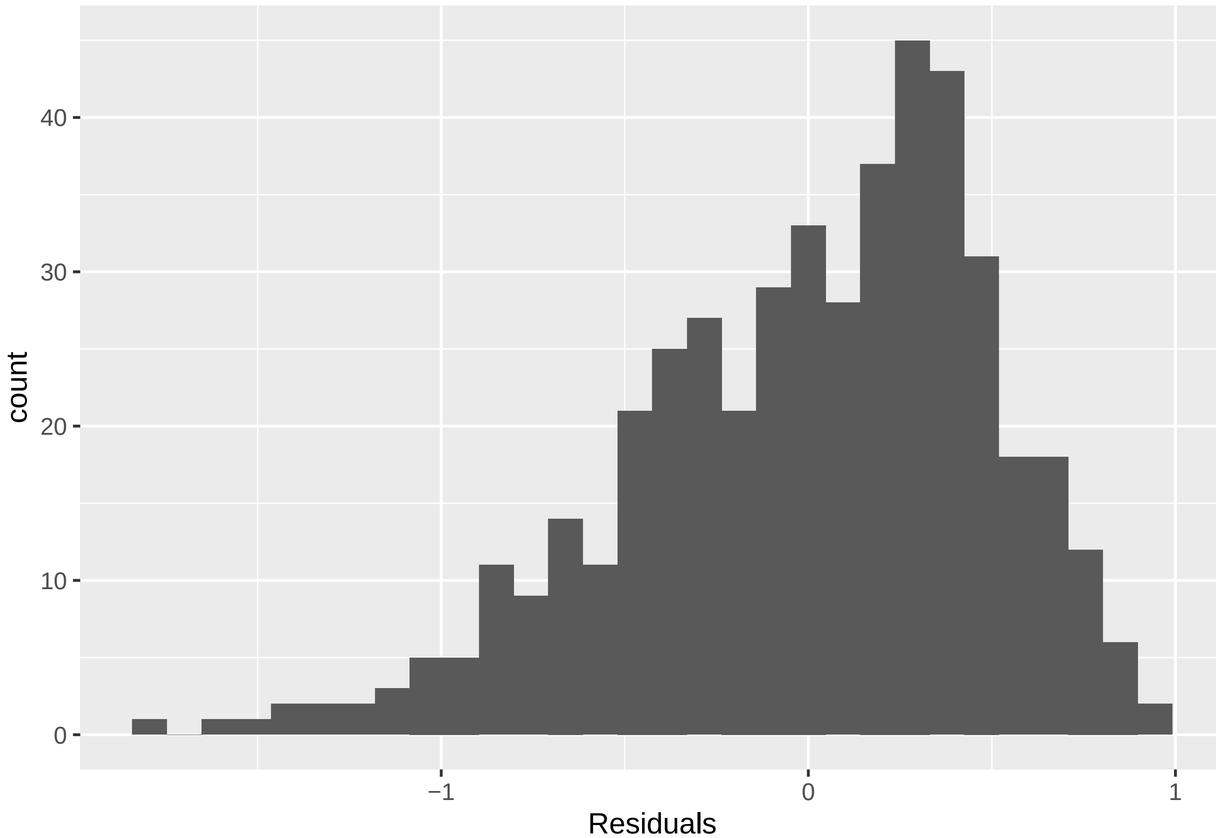


This is a plot of residuals vs fitted predicted values. It appears that the residuals are distributed around 0 and there is no specific trend to them except the points above 0 are more condensed then the points below 0.

Next as in lab 8, check for normality.

The first way can be done with a histogram.

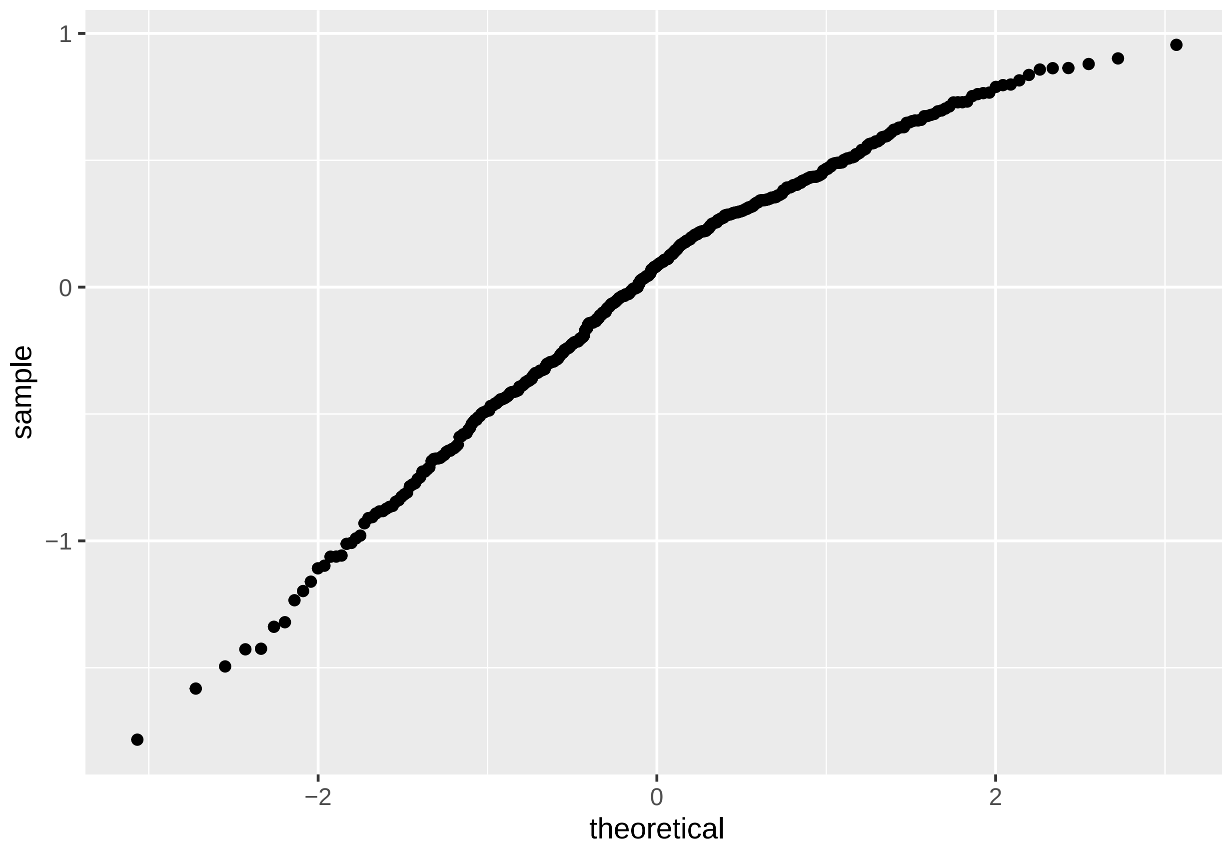
```
ggplot(data = m_elimination, aes(x = .resid)) +
  geom_histogram() +
  xlab("Residuals")
```



It appears the residuals are nearly normal but are skewed to the left slightly.

This can also be observed with a normal probability plot of the residuals.

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



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?

Considering the observations are taken from a sample of professors, and they may teach multiple courses, I think that this could inject co-linearity because if the same professor taught multiple courses students may rate them similarly (as in the different variables would be rated similarly from one observation to the next) so then variables that may not actually be co-linear would appear it because the same professor would likely get scored similarly.

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.

Based on my final model, but then removing the p values that are greater than 0.05, the characteristics of a professor and course at University of Texas Austin that would be associated with a high evaluation score are:

- Male
- English
- Younger
- More students evaluated
- one credit
- higher beauty average
- Black and white picture

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 at any university. This is because I think that the student demographics affect the scores and this could change based on university. I would be more comfortable generalizing if I knew how different student demographics impact the teacher scores.