STAT 100B Lab 7

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Summer 2020 Session B

Setup for Lab

```r
download.file("http://www.openintro.org/stat/data/evals.RData", destfile = "evals.RData")
load("evals.RData")
attach(evals)
```

Lab Exercises

Exercise 1

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

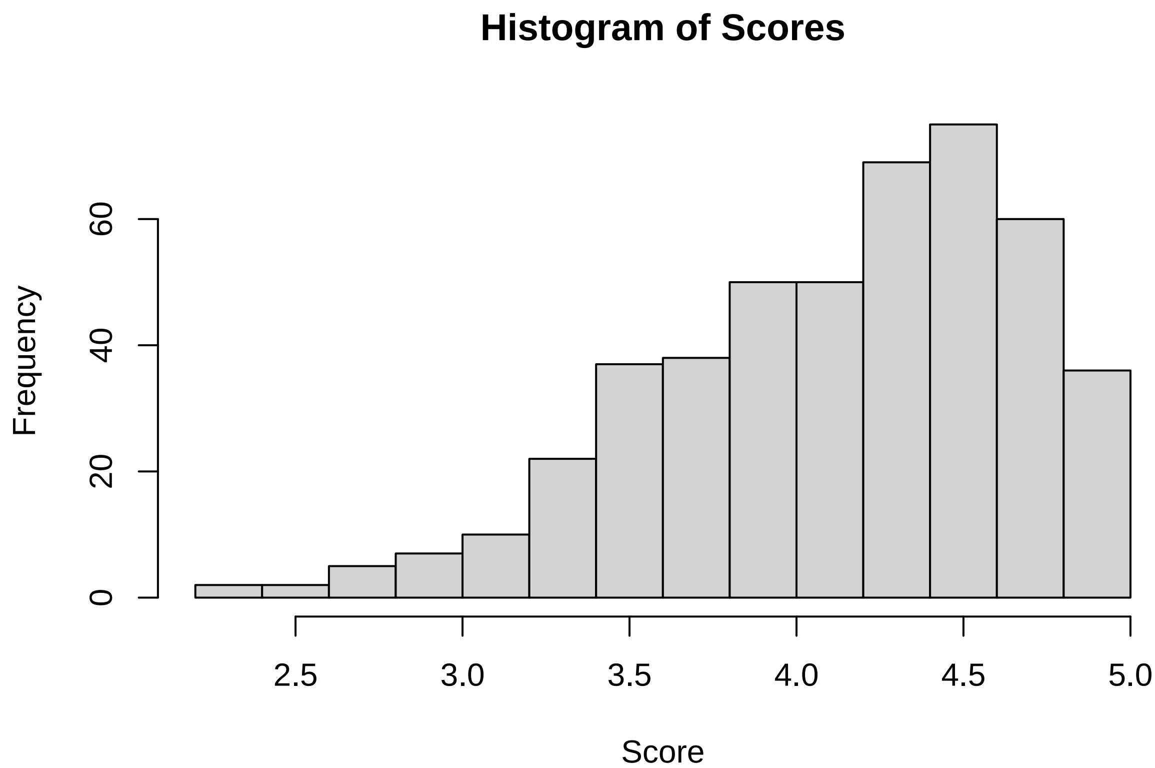
Answer

In this case, this is an observational study. There was nothing in the description to indicate that the groups studied were deliberately chosen and tested against question. Instead, the data was gathered *post hoc*. It is not possible to answer this question as it is phrased, as an observational study shows correlation, which does not indicate causation. Instead, the researchers using this observational study could ask whether an relationship or trend exists between the two factors, but not anything about causation.

Exercise 2

Check 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?*

```r
hist(evals$score, main = "Histogram of Scores", xlab = "Score")
```



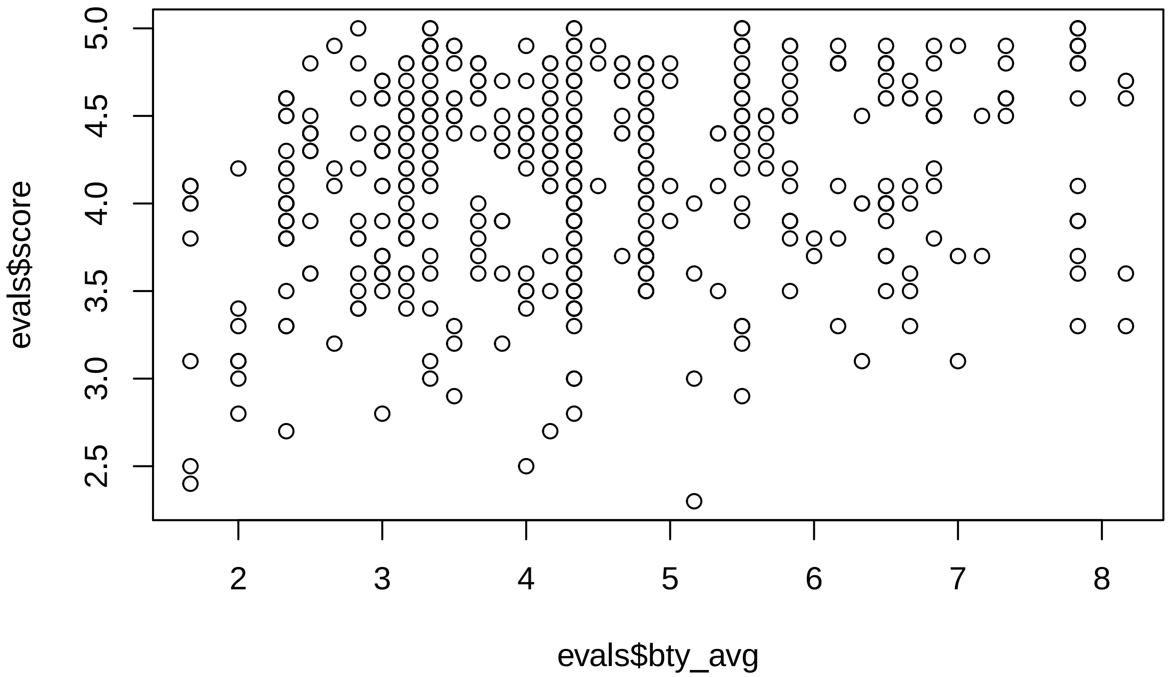
Answer

As shown by the histogram, the distribution of the data appears skewed to the left. This tells us that students have a tendency to rate their courses more favorably. I expected the ratings to be skewed higher because from my personal observations, students tend to not take course evaluations seriously, and will likely tend to default to giving higher scores, unless they had a serious issue with the professor.

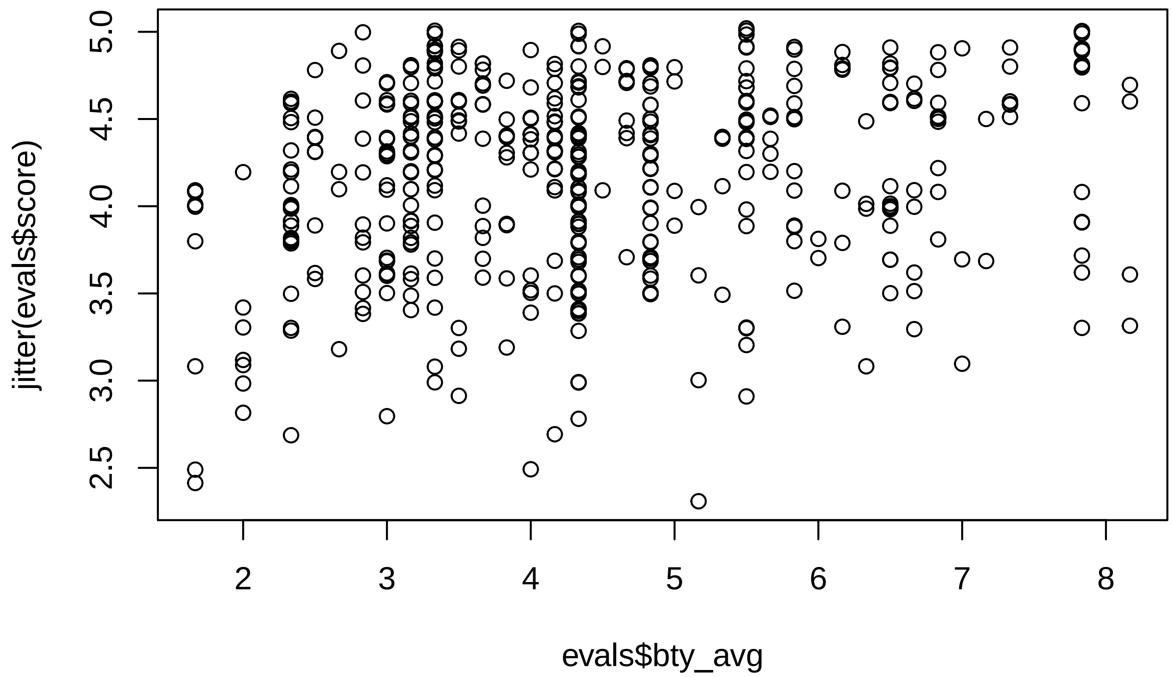
Exercise 3

Replot the scatterplot, but this time use the function `jitter()` *on the y- or x-coordinate. What was misleading about the initial scatterplot?*

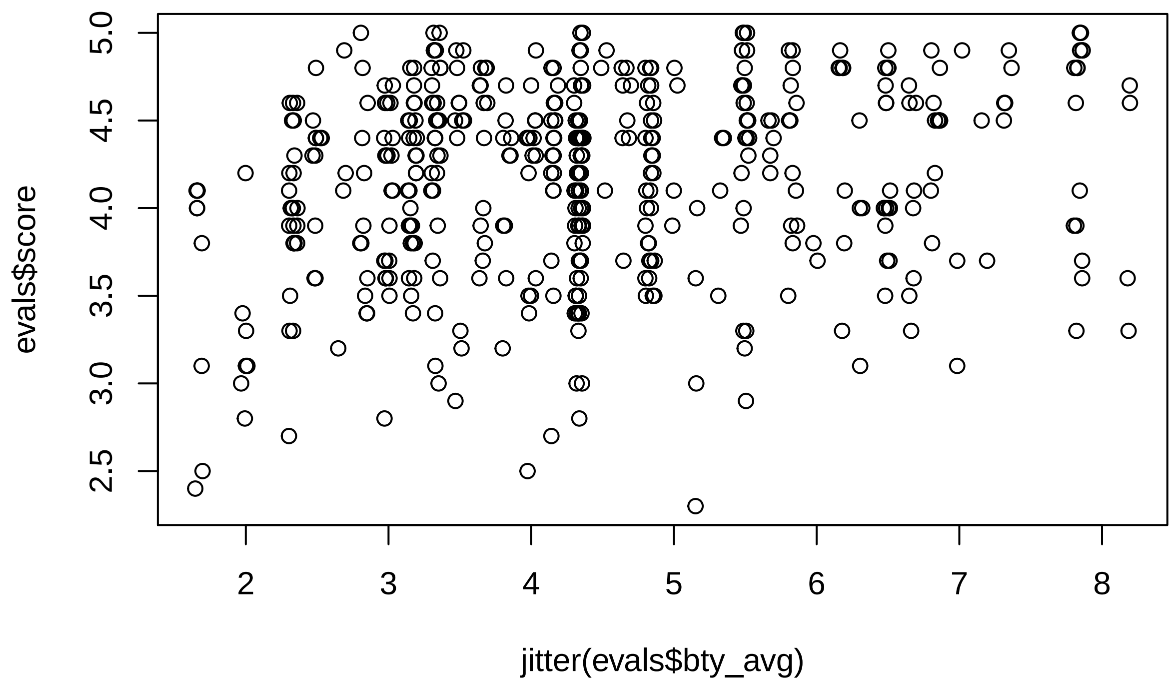
```r
plot(evals$score ~ evals$bty_avg)
```



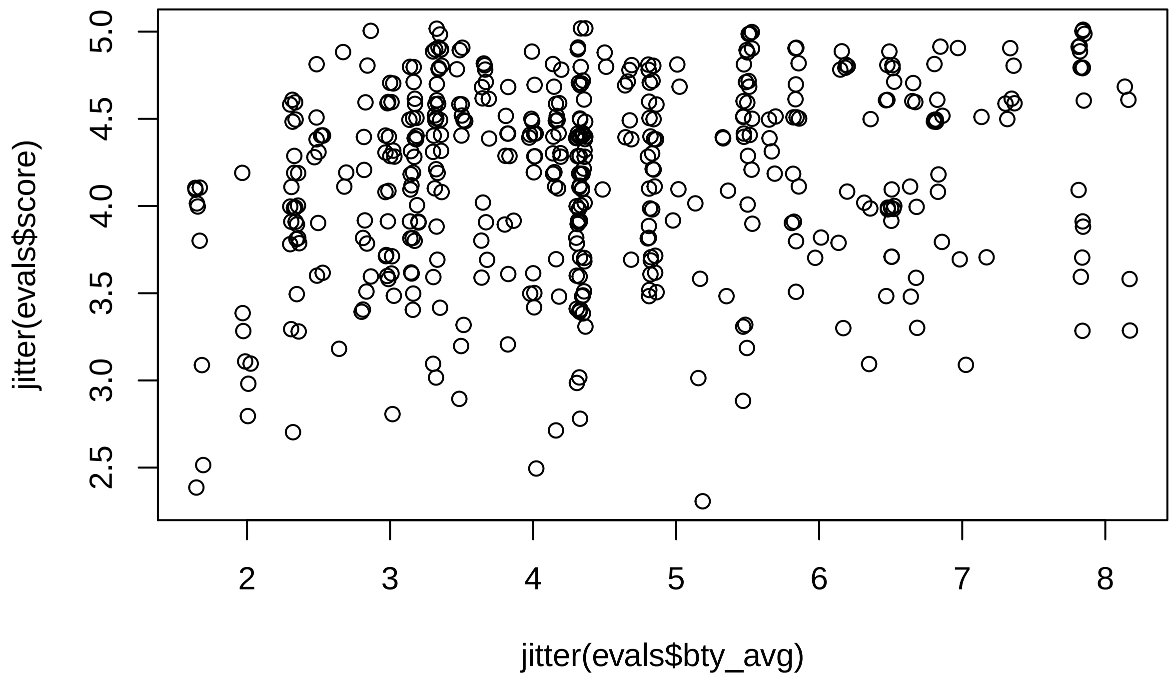

```
plot(jitter(evals$score) ~ evals$bty_avg)
```




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




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



Answer

The `jitter()` function allowed us to see that there were more points where originally, multiple points appeared as a single point. This tells us that there is a more data than shown in the original plot, and that the resulting analysis will give different conclusions than originally expected.

Exercise 4

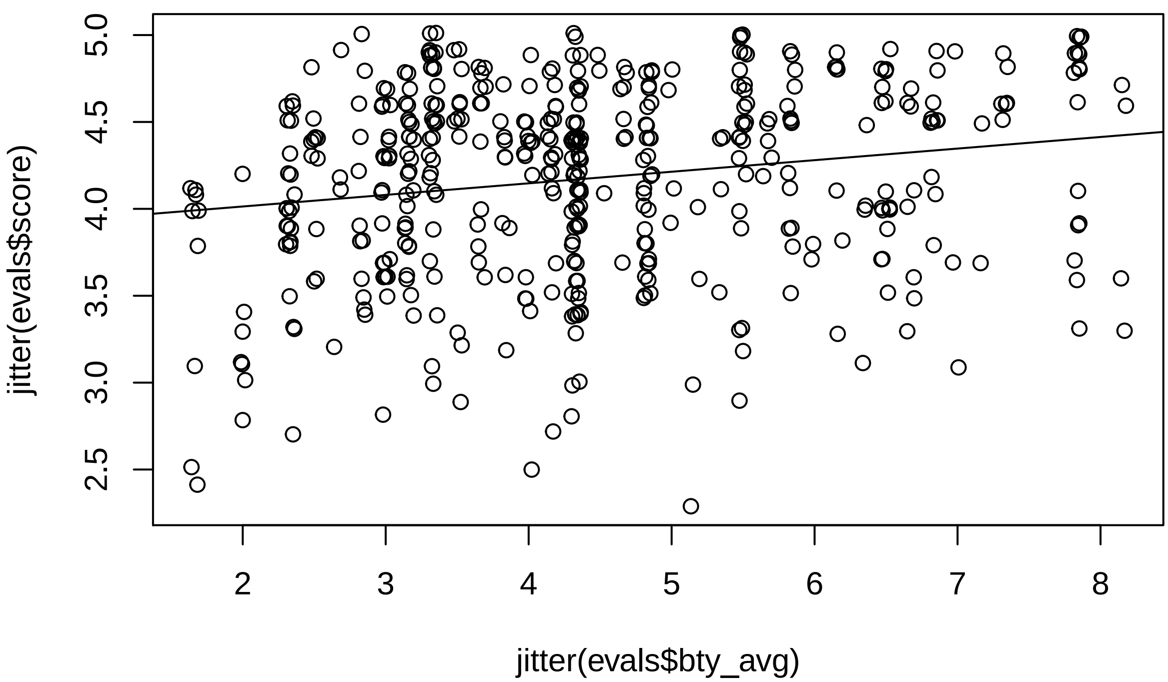
Let's see if the apparent trend in the plot is something more than natural variation. Fit a linear model called `m_bty` *to predict average professor score by average beauty rating and add the line to your plot using* `abline(m_bty)`. *Write out the equation for the linear model and interpret the slope. Is average beauty score a statistically significant predictor? Does it appear to be a practically significant predictor?*

```
m_bty = lm(evals$score ~ evals$bty_avg)
summary(m_bty)
```

```
##
## Call:
## lm(formula = evals$score ~ evals$bty_avg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.9246 -0.3690  0.1420  0.3977  0.9309
##
## Coefficients:
```

```
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     3.88034    0.07614   50.96  < 2e-16 ***
## evals$bty_avg   0.06664    0.01629    4.09 5.08e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5348 on 461 degrees of freedom
## Multiple R-squared:  0.03502,    Adjusted R-squared:  0.03293
## F-statistic: 16.73 on 1 and 461 DF,  p-value: 5.083e-05
```

```r
plot(jitter(evals$score) ~ jitter(evals$bty_avg))
abline(m_bty)
```



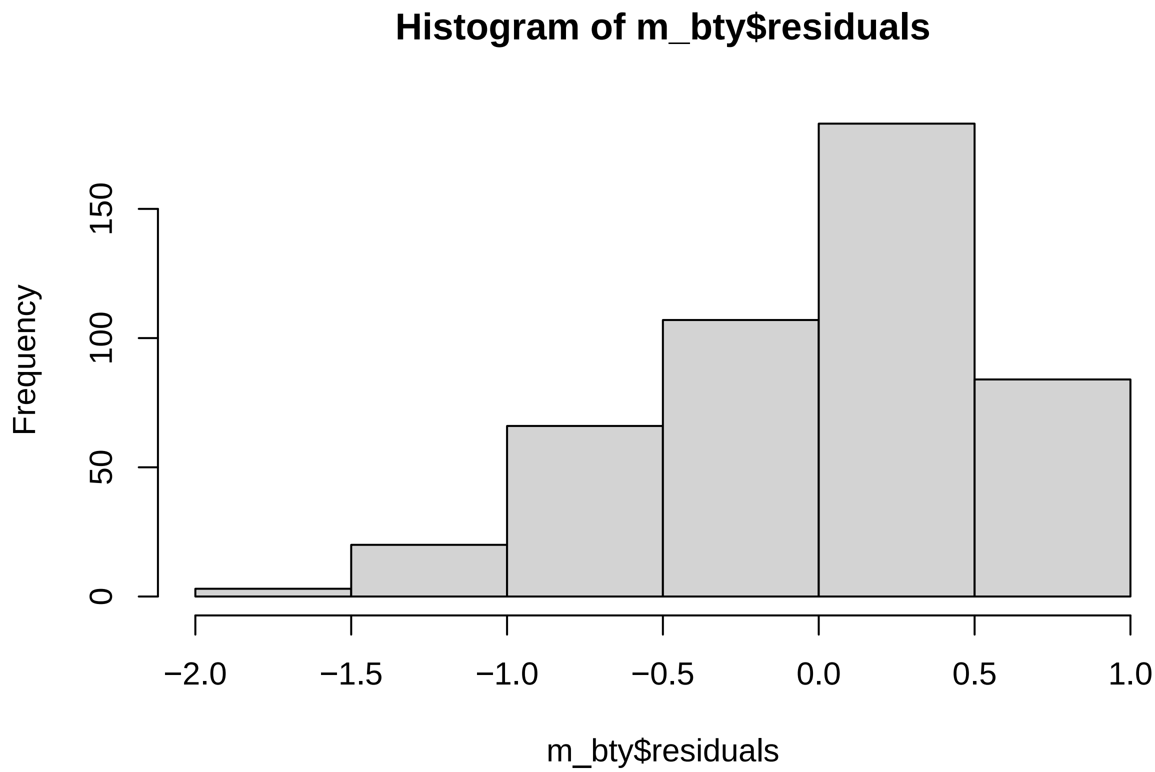
Answer

The equation for this linear model is $\hat{score} = 3.88034 + 0.06664 \times bty\_avg$. The slope coefficient 0.06664 indicates that for every point increase in the the average beauty rating of the professor, score will increase by 0.06664 points. The regression table indicates that `bty_avg` is a very statistically significant predictor of `score`. This may not be practically significant, as the R^2 value for the model is low, 0.03502.

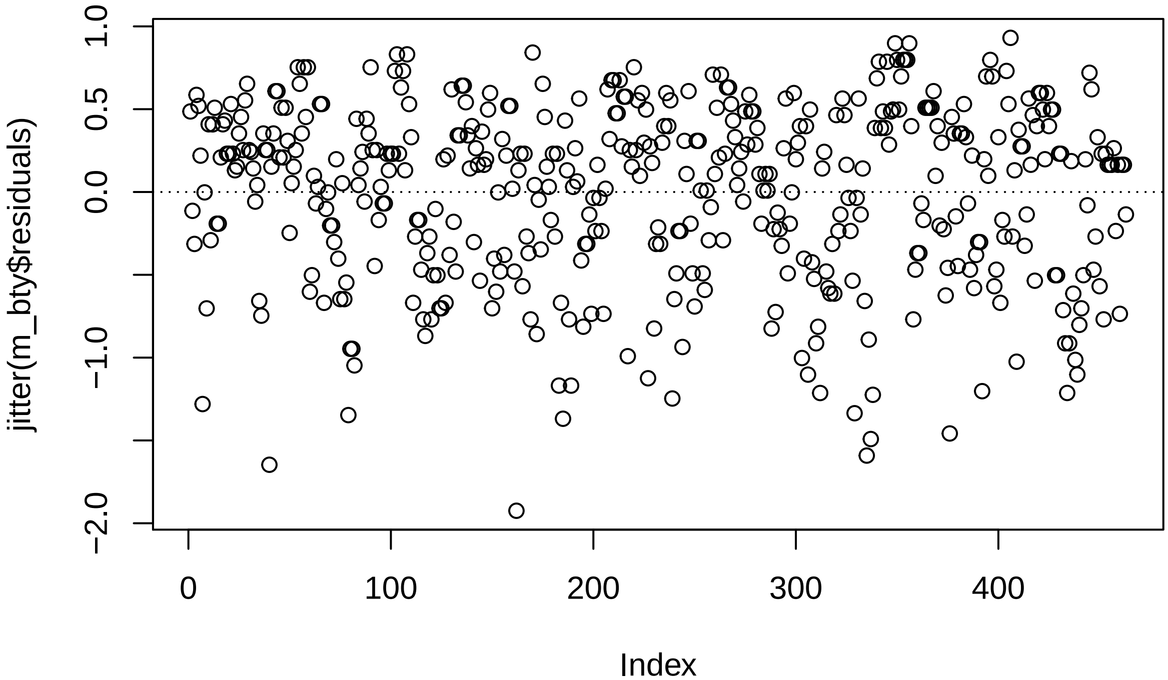
Exercise 5

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

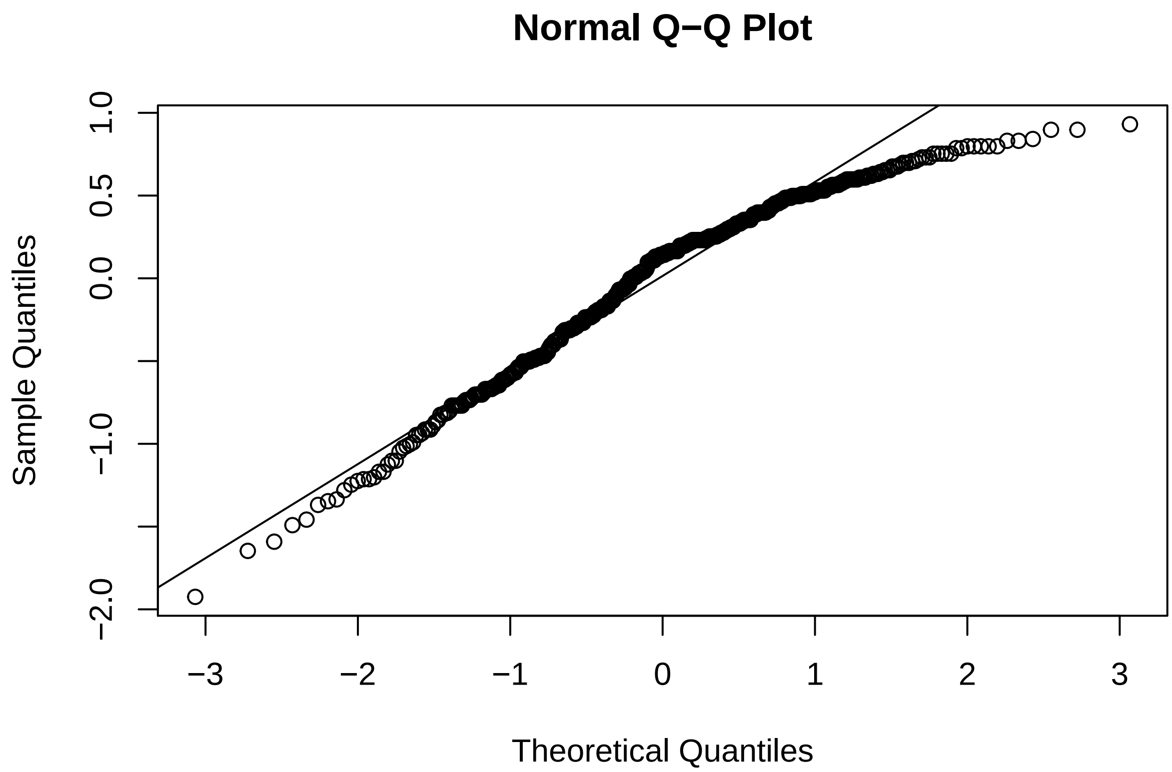
```r
hist(m_bty$residuals)
```




```r
plot(jitter(m_bty$residuals))
abline(h=0, lty=3)
```




```
qqnorm(m_bty$residuals)
qqline(m_bty$residuals)
```



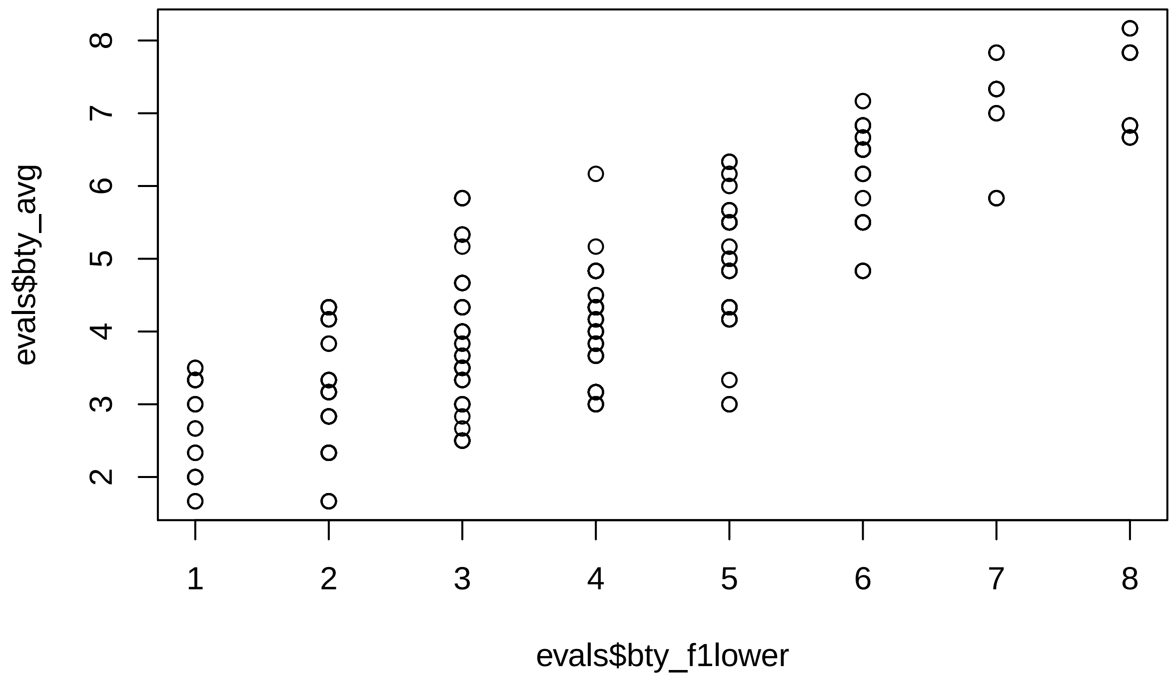
Answer

The histogram of the residuals indicates that this data may not be normal, and is instead skewed left. This does not appear to satisfy the condition of *nearly normal residuals*. The residual scatter plot shows that there may be a pattern in the data, as the many of the data points seem to cluster around certain points. This may show that the condition of *linearity* may not be satisfied.

Exercise 6

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.

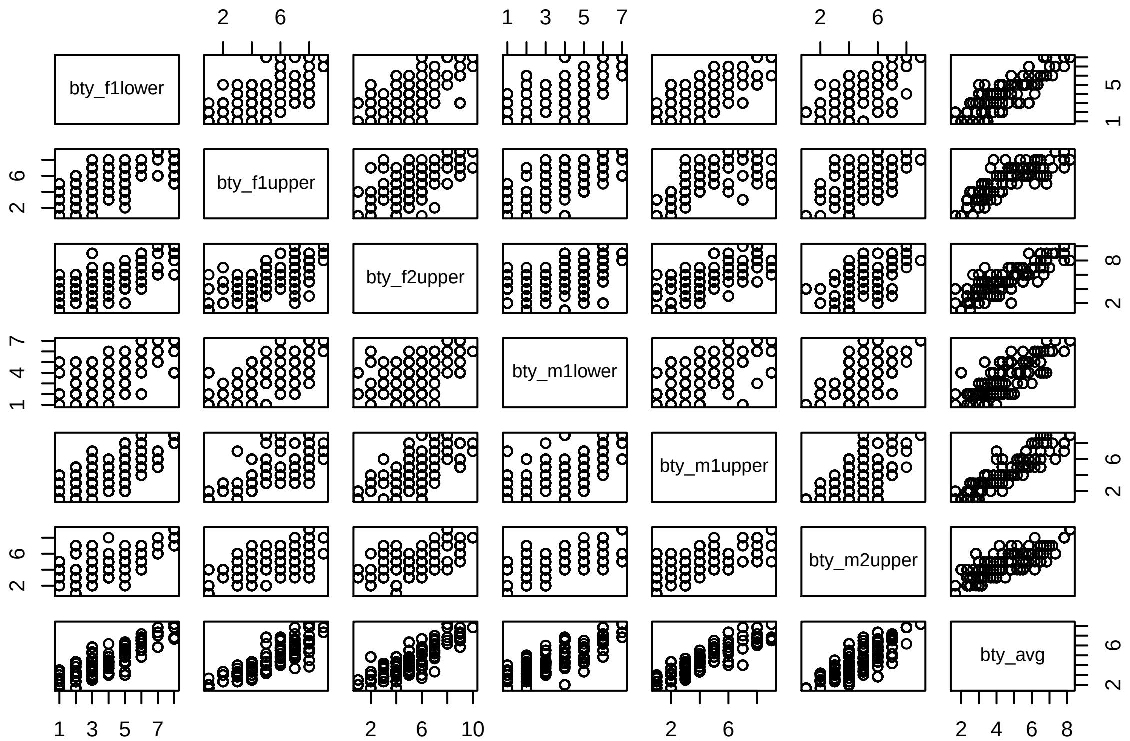
```
plot(evals$bty_avg ~ evals$bty_f1lower)
```




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

```
## [1] 0.8439112
```

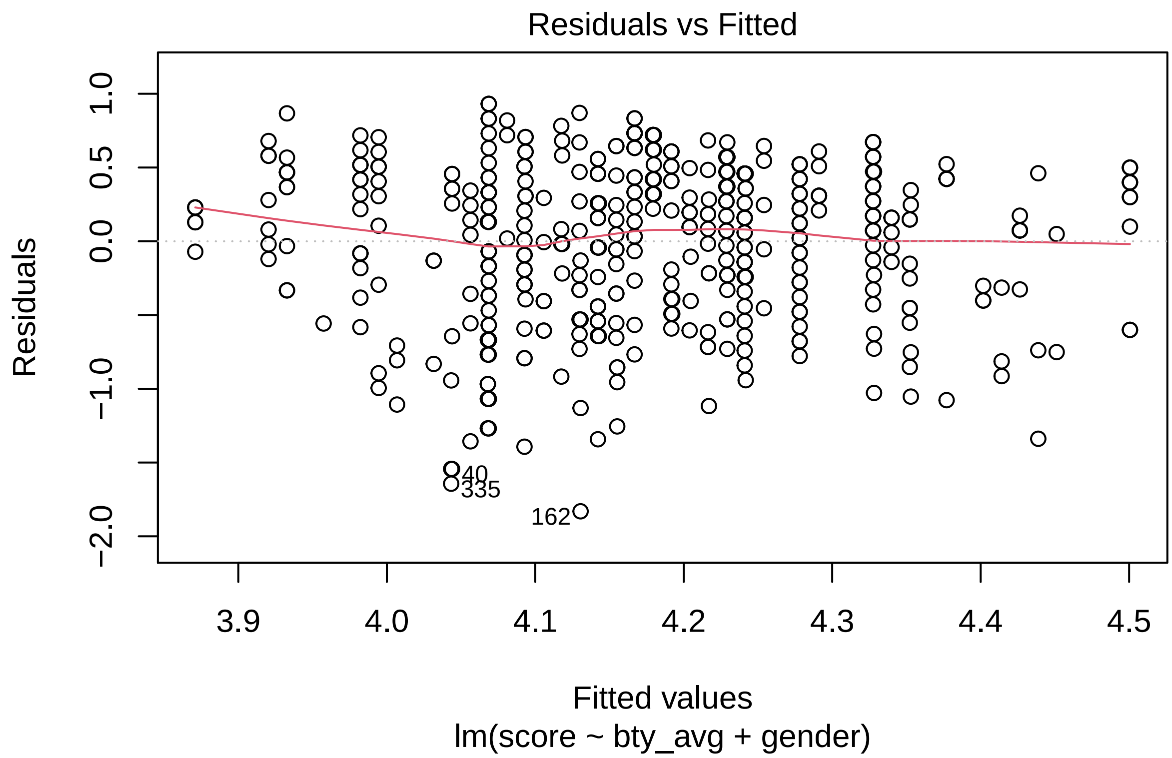
```r
plot(evals[,13:19])
```



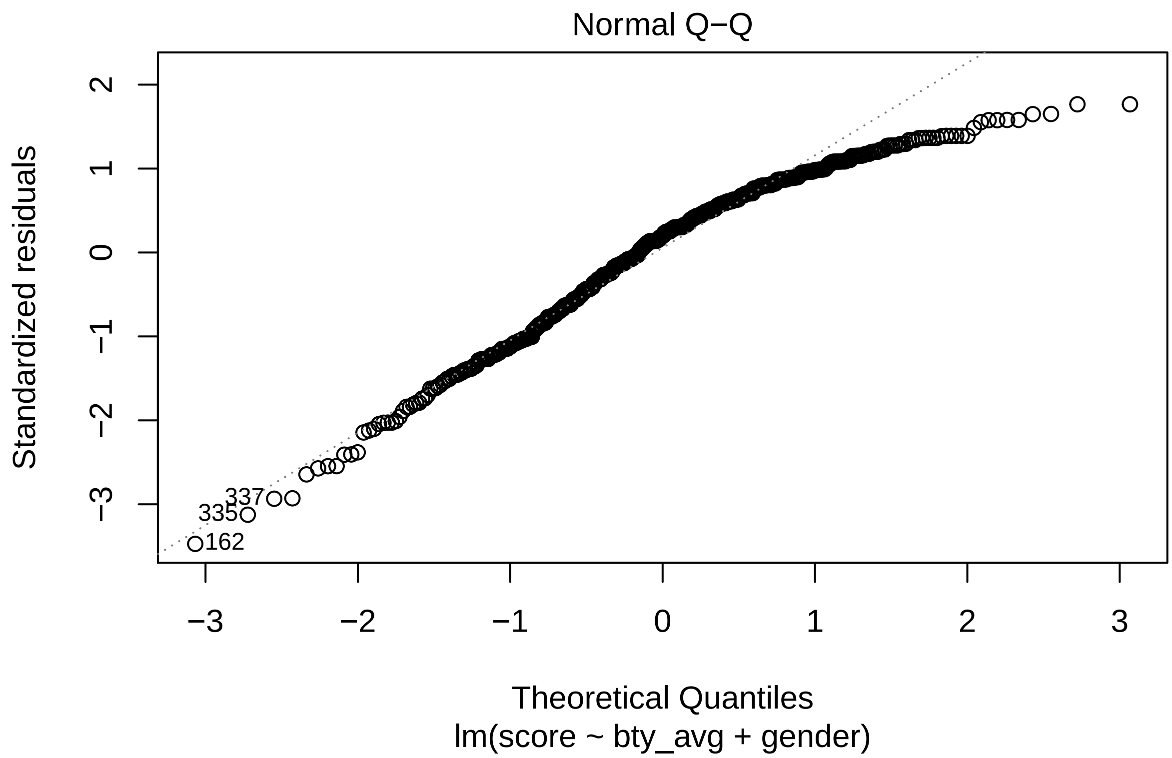

```
m_bty_gen <- lm(score ~ bty_avg + gender, data = evals)
summary(m_bty_gen)
```

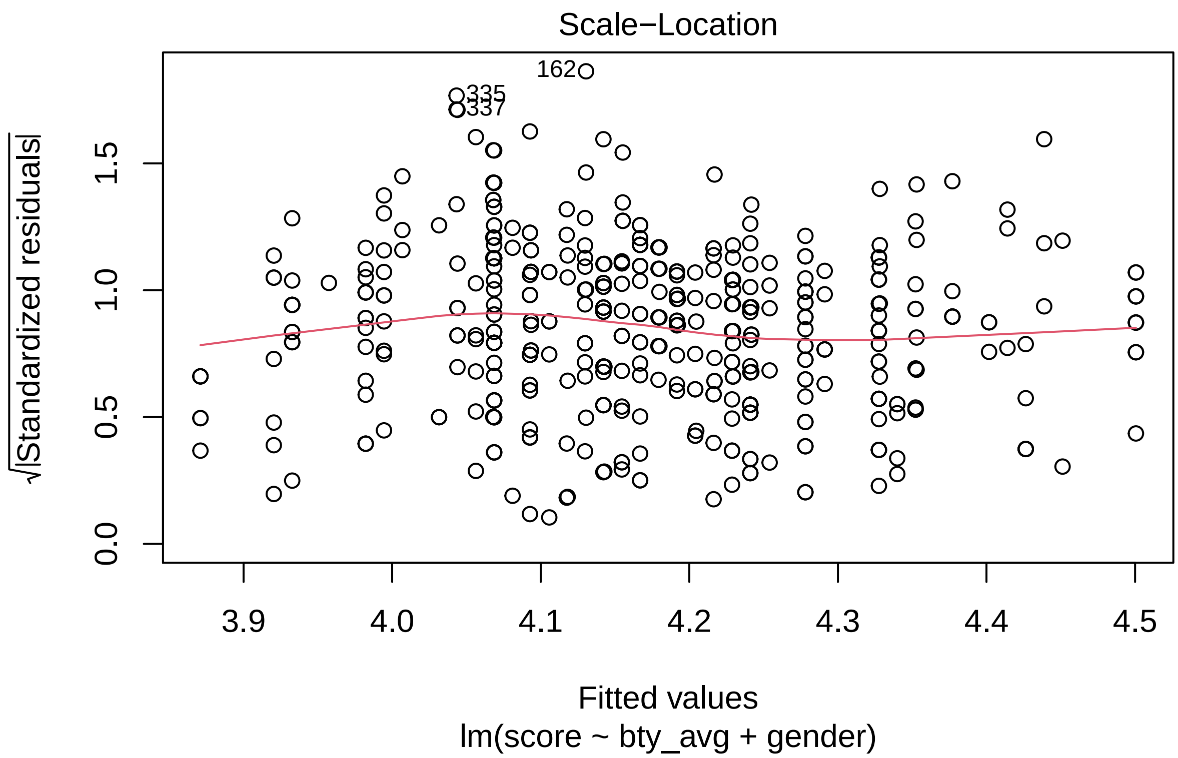
```
##
## Call:
## lm(formula = score ~ bty_avg + gender, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.8305 -0.3625  0.1055  0.4213  0.9314
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.74734    0.08466  44.266  < 2e-16 ***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

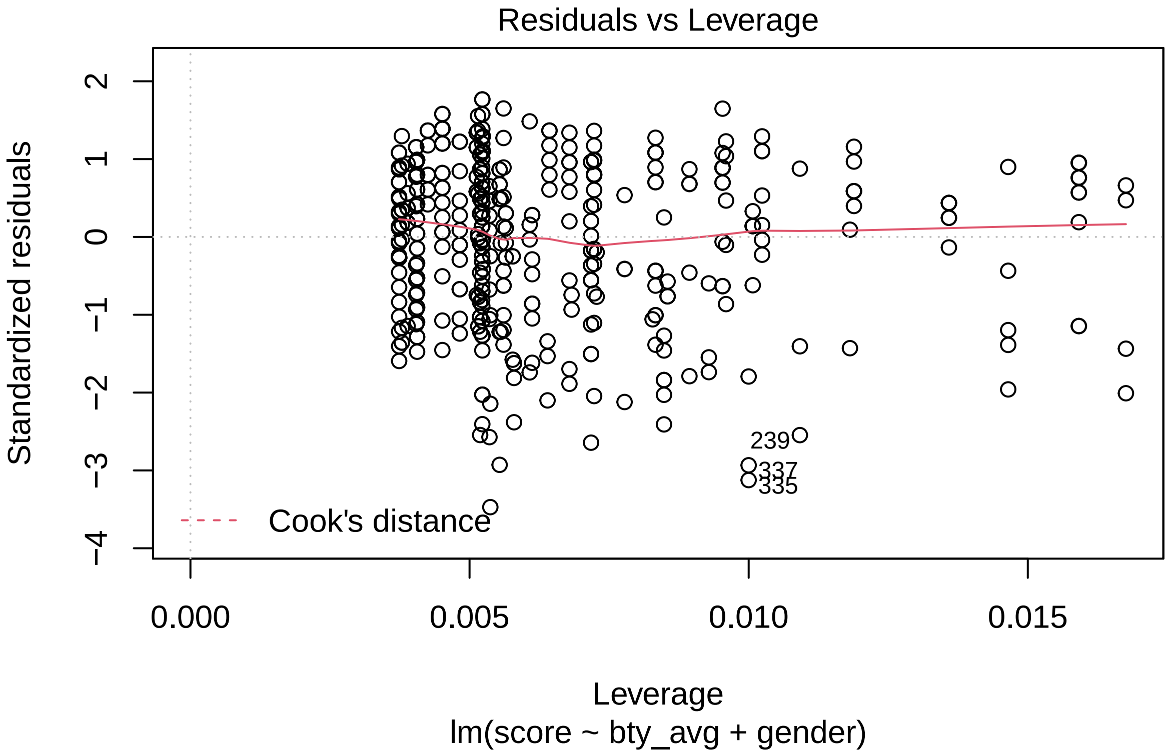
```
plot(m_bty_gen)
```



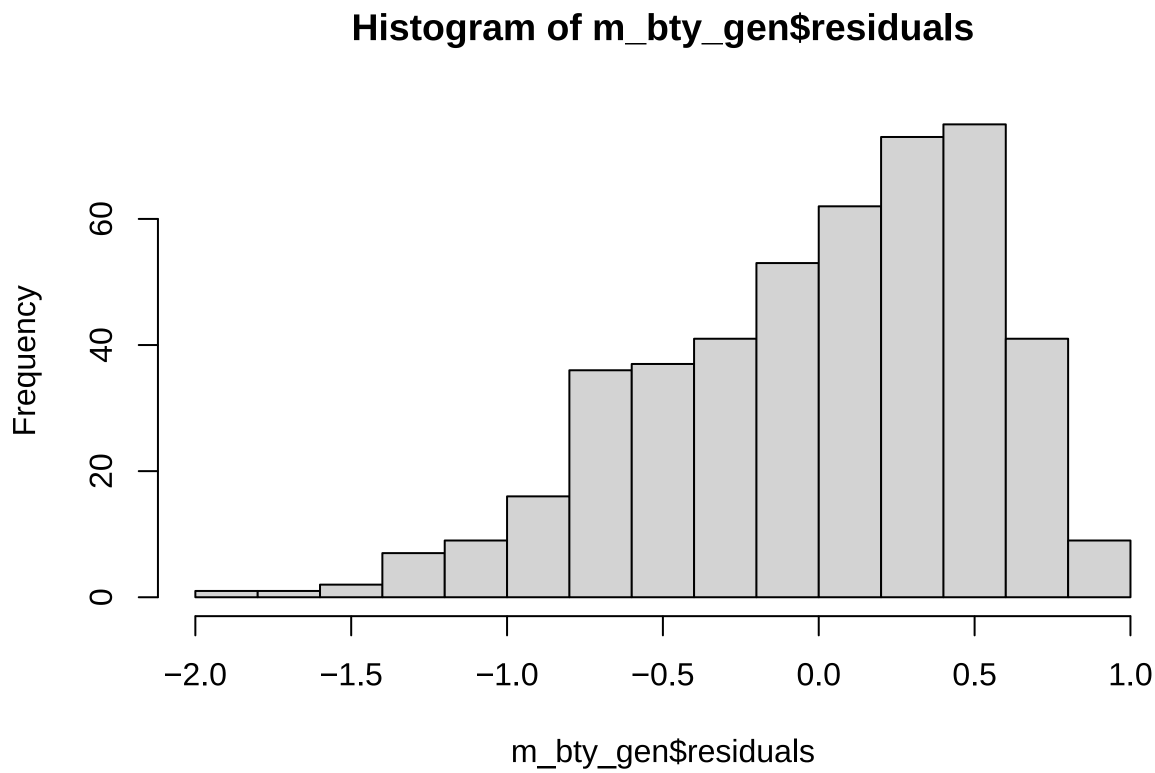
Residuals vs Fitted
Residuals
1.0
0.5
0.0
−1.0
−2.0
3.9
4.0
4.1
4.2
4.3
4.4
4.5
40
335
162
Fitted values
lm(score ~ bty_avg + gender)


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(score ~ bty_avg + gender)
337
335
162
−3
−2
−1
0
1
2
3

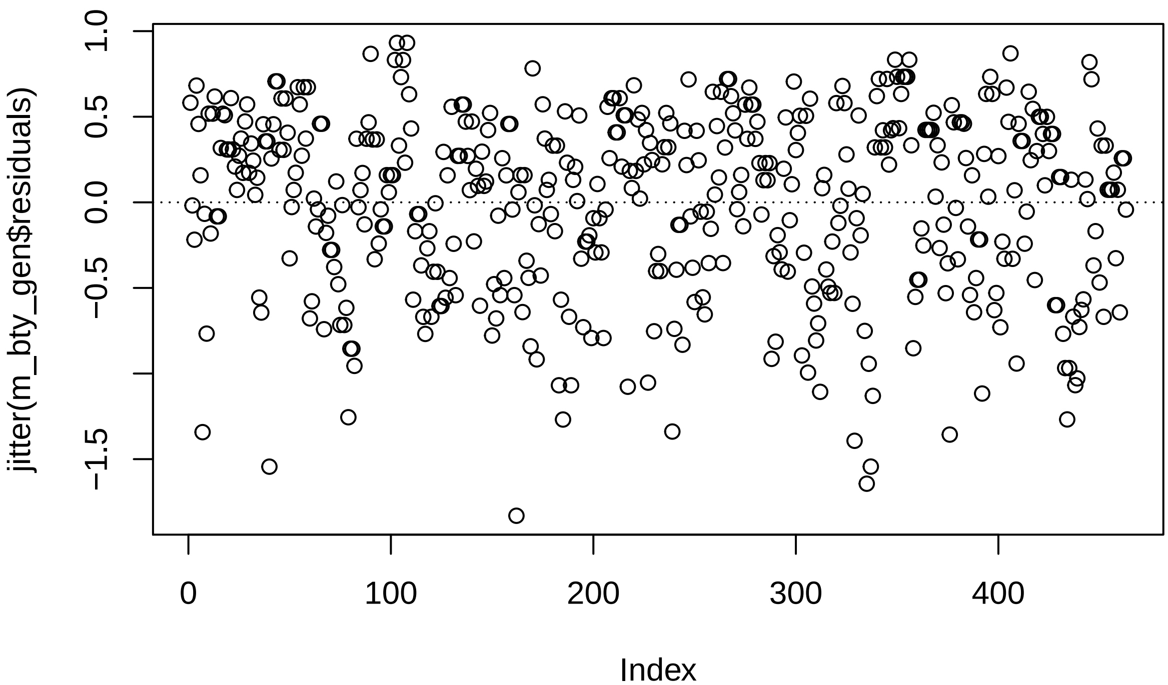

Scale−Location
162
335
337
√|Standardized residuals|
0.0
0.5
1.0
1.5
3.9
4.0
4.1
4.2
4.3
4.4
4.5
Fitted values
lm(score ~ bty_avg + gender)




```r
hist(m_bty_gen$residuals)
```




```r
plot(jitter(m_bty_gen$residuals))
abline(h=0, lty=3)
```



Answer

These plots indicate that the conditions of *independence*, *nearly normal residuals*, *linearity*, and *constant variability* are met by this model.

Exercise 7

Is `bty_avg` *still a significant predictor of* `score`*? Has the addition of* `gender` *to the model changed the parameter estimate for* `bty_avg`*?*

```
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
```

Answer

It appears that `bty_avg` is still very statistically significant and therefore a significant predictor of score. The addtion of gender into the model has not drastically changed the parameter estimate of `bty_avg`.

Exercise 8

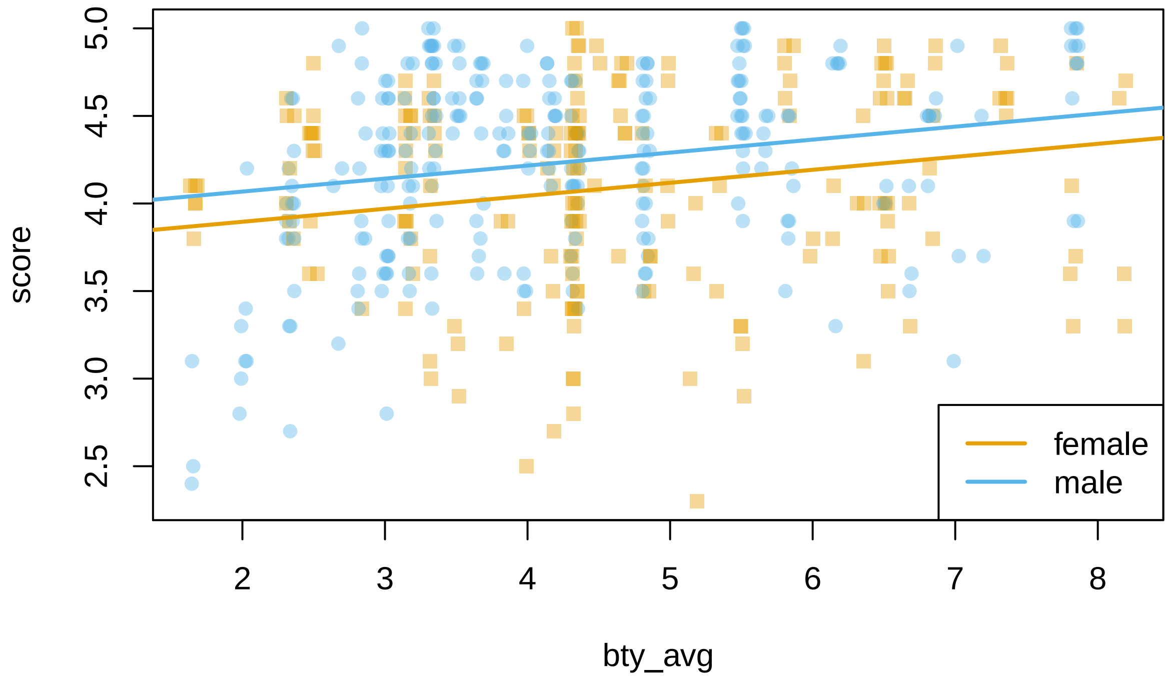
What is the equation of the line corresponding to males? (Hint: for males, the parameter estimate is mulitplied by 1). For two professors who received the same beauty rating, which gender tends to have the higher course evaluation score?

Answer

```
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
```

```
multiLines(m_bty_gen)
```



The equation of the line is $\hat{score} = 3.74734 + 0.07416 \times bty\_avg + 0.17239$. The gender that tends to have the higher course evaluation score is males.

Exercise 9

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 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
```

Answer

R will treat variables that appear to have more than one factor level by organizing each factor using dummy variables. R does not list all of the variables, omitting one of them. The omitted variable model is represented by the base model without any dummy variable coefficients.

Exercise 10

Which variable would you expect to have the highest p-value in this model? Why? Hint: Think about which variable you would expect to not have any association with the professor score.

Answer

I would expect `pic_color` to have the highest p-value in this model, as I would not reasonably assume that the picture color would affect the average score of a professor as much as the other variables.

Exercise 11

Check your suspicions from the previous exercise. Which variable has the largest p-value from model output? Does it make sense?

```
m_full <- lm(score ~ rank + ethnicity + gender + language + age + cls_perc_eval + cls_students + cls_lev
summary(m_full)
```

```
##
## Call:
## lm(formula = score ~ rank + ethnicity + gender + language + age +
##     cls_perc_eval + cls_students + cls_level + cls_profs + cls_credits +
##     bty_avg + pic_outfit + pic_color, data = evals)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.77397 -0.32432  0.09067  0.35183  0.95036
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            4.0952141  0.2905277  14.096  < 2e-16 ***
## ranktenure track      -0.1475932  0.0820671  -1.798  0.07278 .
## ranktenured           -0.0973378  0.0663296  -1.467  0.14295
## ethnicitynot minority  0.1234929  0.0786273   1.571  0.11698
## gendermale             0.2109481  0.0518230   4.071 5.54e-05 ***
## languagenon-english   -0.2298112  0.1113754  -2.063  0.03965 *
## age                   -0.0090072  0.0031359  -2.872  0.00427 **
## cls_perc_eval          0.0053272  0.0015393   3.461  0.00059 ***
## cls_students           0.0004546  0.0003774   1.205  0.22896
```

```
## cls_levelupper         0.0605140  0.0575617   1.051  0.29369
## cls_profssingle       -0.0146619  0.0519885  -0.282  0.77806
## cls_creditsone credit  0.5020432  0.1159388   4.330 1.84e-05 ***
## bty_avg                0.0400333  0.0175064   2.287  0.02267 *
## pic_outfitnot formal  -0.1126817  0.0738800  -1.525  0.12792
## pic_colorcolor        -0.2172630  0.0715021  -3.039  0.00252 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.498 on 448 degrees of freedom
## Multiple R-squared:  0.1871, Adjusted R-squared:  0.1617
## F-statistic: 7.366 on 14 and 448 DF,  p-value: 6.552e-14
```

Answer

The variable with the largest p-value is `cls_profssingle` with `0.77806`. This does not make sense to me, and I believe that this should influence students' perceptions as much as the other variables might. I assumed that pic_color would have a high p-value, but was wrong, as the regression table shows that it statistically significant.

Exercise 12

Using backward selection and p-value (0.05) as the selection criterion, determine the best model. You do not need to show all steps in your answer, just write out the best linear model for predicting score based on the final model you settle on.

```r
m_drop1 <- lm(score ~ rank + ethnicity + gender + language + age + cls_perc_eval + cls_students + cls_le
summary(m_drop1)
```

```
##
## Call:
## lm(formula = score ~ rank + ethnicity + gender + 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
## ethnicitynot minority  0.1274458  0.0772887   1.649 0.099856 .
## gendermale             0.2101231  0.0516873   4.065 5.66e-05 ***
## 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
```

```
m_drop2 <- lm(score ~ rank + ethnicity + gender + language + age + cls_perc_eval + cls_students + cls_c
summary(m_drop2)
```

```
##
## Call:
## lm(formula = score ~ rank + ethnicity + gender + language + age +
##     cls_perc_eval + cls_students + cls_credits + bty_avg + pic_outfit +
##     pic_color, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.7761 -0.3187  0.0875  0.3547  0.9367
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            4.0856255  0.2888881  14.143  < 2e-16 ***
## ranktenure track      -0.1420696  0.0818201  -1.736 0.083184 .
## ranktenured           -0.0895940  0.0658566  -1.360 0.174372
## ethnicitynot minority  0.1424342  0.0759800   1.875 0.061491 .
## gendermale             0.2037722  0.0513416   3.969 8.40e-05 ***
## languagenon-english   -0.2093185  0.1096785  -1.908 0.056966 .
## age                   -0.0087287  0.0031224  -2.795 0.005404 **
## cls_perc_eval          0.0053545  0.0015306   3.498 0.000515 ***
## cls_students           0.0003573  0.0003585   0.997 0.319451
## cls_creditsone credit  0.4733728  0.1106549   4.278 2.31e-05 ***
## bty_avg                0.0410340  0.0174449   2.352 0.019092 *
## pic_outfitnot formal  -0.1172152  0.0716857  -1.635 0.102722
## pic_colorcolor        -0.1973196  0.0681052  -2.897 0.003948 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4975 on 450 degrees of freedom
## Multiple R-squared:  0.185,  Adjusted R-squared:  0.1632
## F-statistic:  8.51 on 12 and 450 DF,  p-value: 1.275e-14
```

```
m_drop3 <- lm(score ~ rank + ethnicity + gender + language + age + cls_perc_eval + cls_credits + bty_av
summary(m_drop3)
```

```
##
## Call:
## lm(formula = score ~ rank + ethnicity + gender + language + age +
##     cls_perc_eval + cls_credits + bty_avg + pic_outfit + pic_color,
##     data = evals)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.78424 -0.31397  0.09261  0.35904  0.92154
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            4.152893   0.280892  14.785  < 2e-16 ***
## ranktenure track      -0.142239   0.081819  -1.738 0.082814 .
## ranktenured           -0.083092   0.065532  -1.268 0.205469
## ethnicitynot minority  0.143509   0.075972   1.889 0.059535 .
## gendermale             0.208080   0.051159   4.067 5.61e-05 ***
## languagenon-english   -0.222515   0.108876  -2.044 0.041558 *
## age                   -0.009074   0.003103  -2.924 0.003629 **
## cls_perc_eval          0.004841   0.001441   3.359 0.000849 ***
## cls_creditsone credit  0.472669   0.110652   4.272 2.37e-05 ***
## bty_avg                0.043578   0.017257   2.525 0.011903 *
## pic_outfitnot formal  -0.136594   0.068998  -1.980 0.048347 *
## pic_colorcolor        -0.189905   0.067697  -2.805 0.005246 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4975 on 451 degrees of freedom
## Multiple R-squared:  0.1832, Adjusted R-squared:  0.1632
## F-statistic: 9.193 on 11 and 451 DF,  p-value: 6.364e-15
```

```r
m_drop4 <- lm(score ~ ethnicity + gender + language + age + cls_perc_eval + cls_credits + bty_avg + pic_
summary(m_drop4)
```

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

```
## F-statistic: 10.85 on 9 and 453 DF,  p-value: 2.441e-15
```

```r
m_drop5 <- lm(score ~ ethnicity + gender + language + age + cls_perc_eval + cls_credits + bty_avg + pic_
summary(m_drop5)
```

```
##
## Call:
## lm(formula = score ~ ethnicity + gender + 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 ***
## ethnicitynot minority  0.167872   0.075275   2.230  0.02623 *
## gendermale             0.207112   0.050135   4.131 4.30e-05 ***
## 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
```

Answer

The final model determined by backwards selection is:

$\hat{score} = 3.771922 + 0.1668722 \times ethnicity\_notminority + 0.207112 \times gender\_male - 0.206178 \times language\_nonenglish - 0.006046 \times age + 0.004656 \times cls\_perc\_eval + 0.505306 \times cls\_credit\_onecredit + 0.051069 \times bty\_avg - 0.190579 \times pic\_colorcolor$

Exercise 13

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?

Answer

I believe that this is likely to affect the conditions of linear regression by introducing multicollinearity problems through overlapping data. I also believe that this would break the condition of independence.

Exercise 14

Based on your final model, describe the characteristics of a professor and course at the University of Texas at Austin that would be associated with a high evaluation score.

Answer

A course with a high evaluation score would have a professor that is not a minority, is a male, received education at an English school, who is younger, had a higher percentage of students who completed evaluations, who taught a one-credit class, had a higher average beauty rating, and did not have a color picture.

Exercise 15

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

Answer

No. First of all, these conclusions are likely to be specific to the school where the study was conducted, based on demographic, location, and many of other factors. Second of all, generalizing this conclusion would be considered extrapolation, making conclusions about data not originally described in the study.