Lab 4

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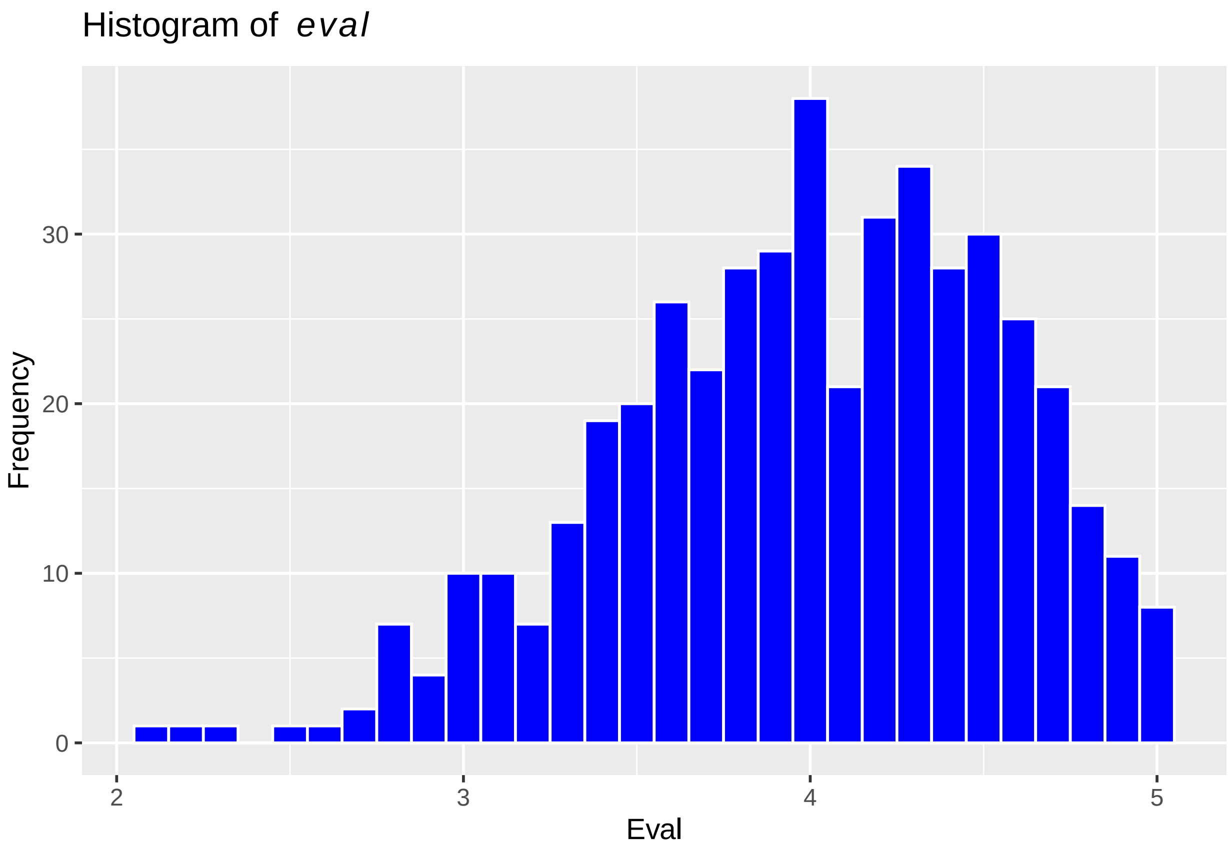
Data load:

```
# Read in the data
Beauty <- read.table("Beauty.txt", header = T, sep = " ")
```

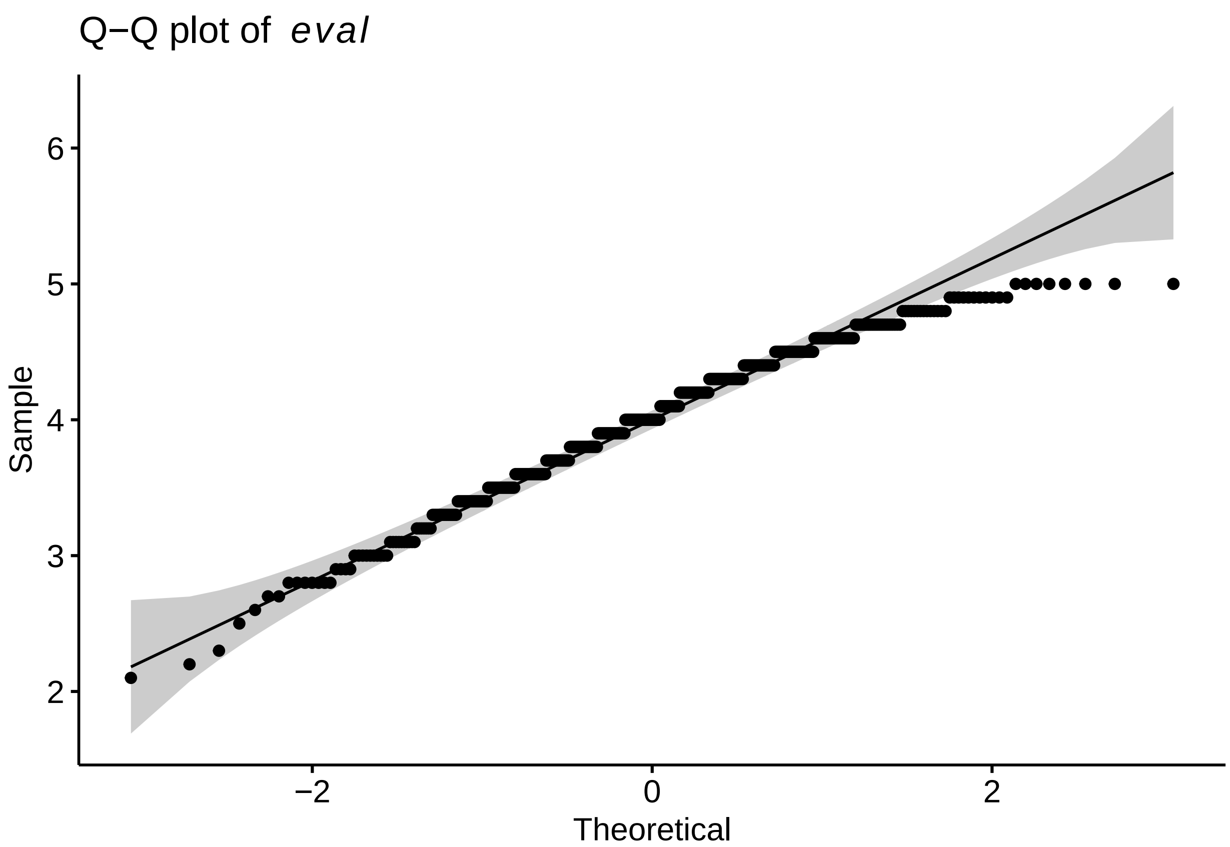
Exercise 1

```
# Histogram of eval, as it is
hist_eval <- ggplot(Beauty, aes(x = eval)) + geom_histogram(color = "white",
    fill = "blue") + labs(title = "Histogram of " ~ italic(eval),
    x = "Eval", y = "Frequency")

hist_eval
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
# Q-Q plot on eval, as it is

ggqqplot(Beauty$eval) + labs(title = "Q-Q plot of " ~ italic(eval))
```



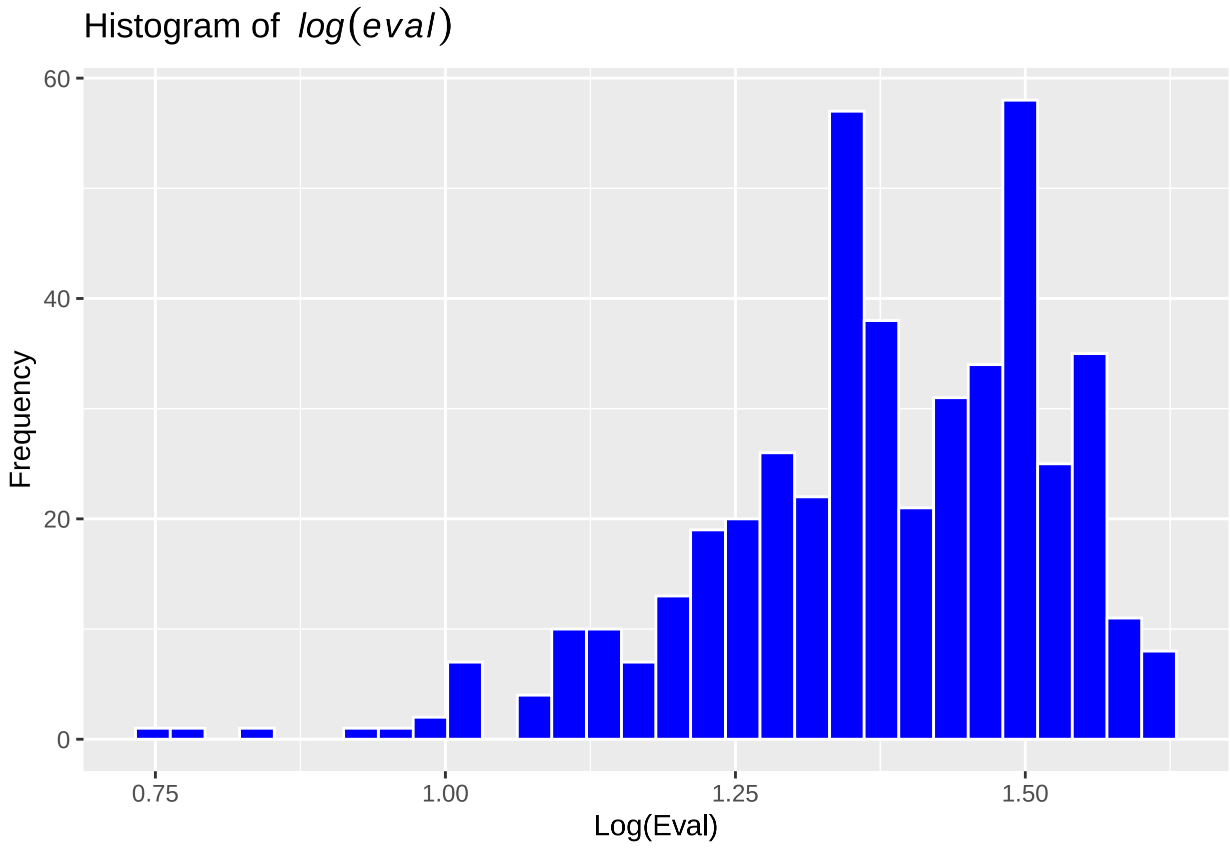

```
# Shapiro test for normality

shapiro.test(Beauty$eval)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  Beauty$eval
## W = 0.97751, p-value = 0.000001425
```

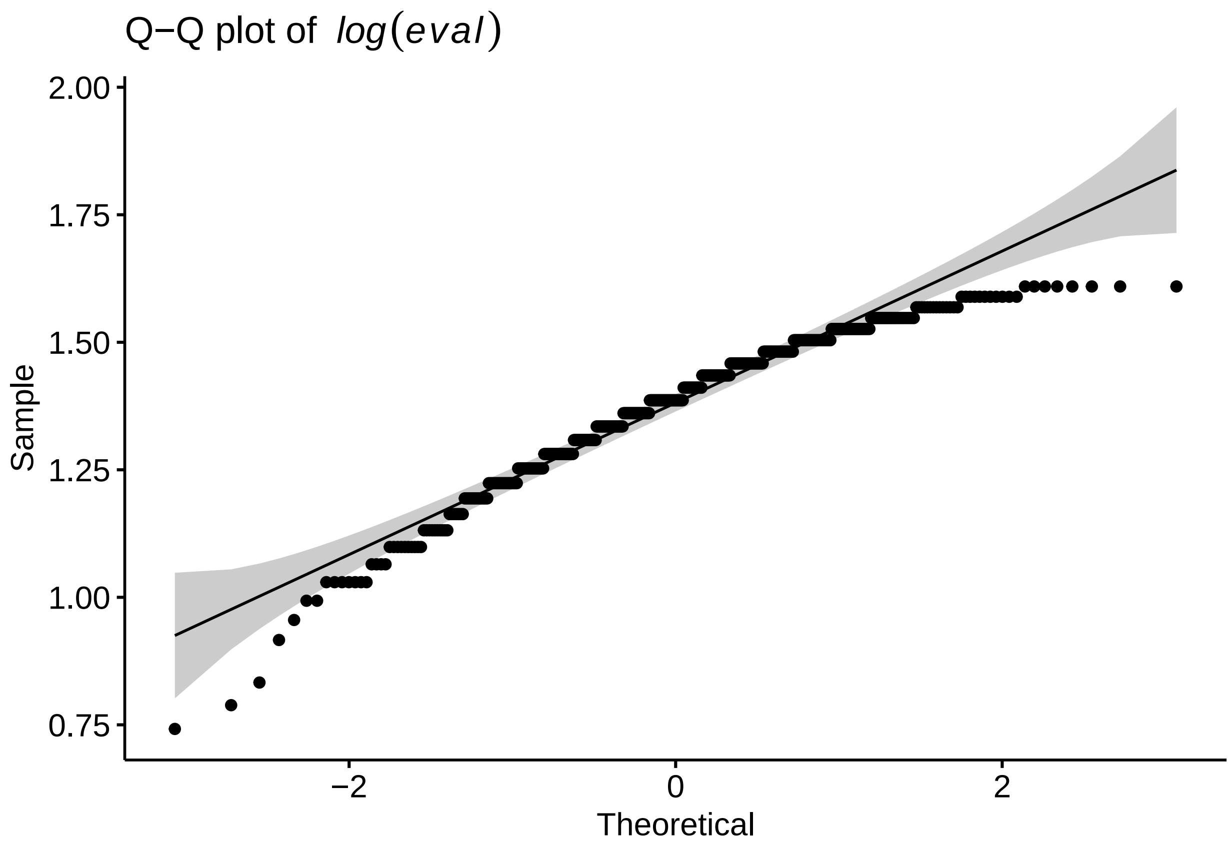
- Both the QQ plot and the *Shapiro test* point out that *eval* is not normally distributed.

```r
# Histogram of eval, as it is
hist_log.eval <- ggplot(Beauty, aes(x = log(eval))) + geom_histogram(color = "white",
    fill = "blue") + labs(title = "Histogram of " ~ italic(log(eval)),
    x = "Log(Eval)", y = "Frequency")

hist_log.eval
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
# Q-Q plot on eval, as it is

ggqqplot(log(Beauty$eval)) + labs(title = "Q-Q plot of " ~ italic(log(eval)))
```



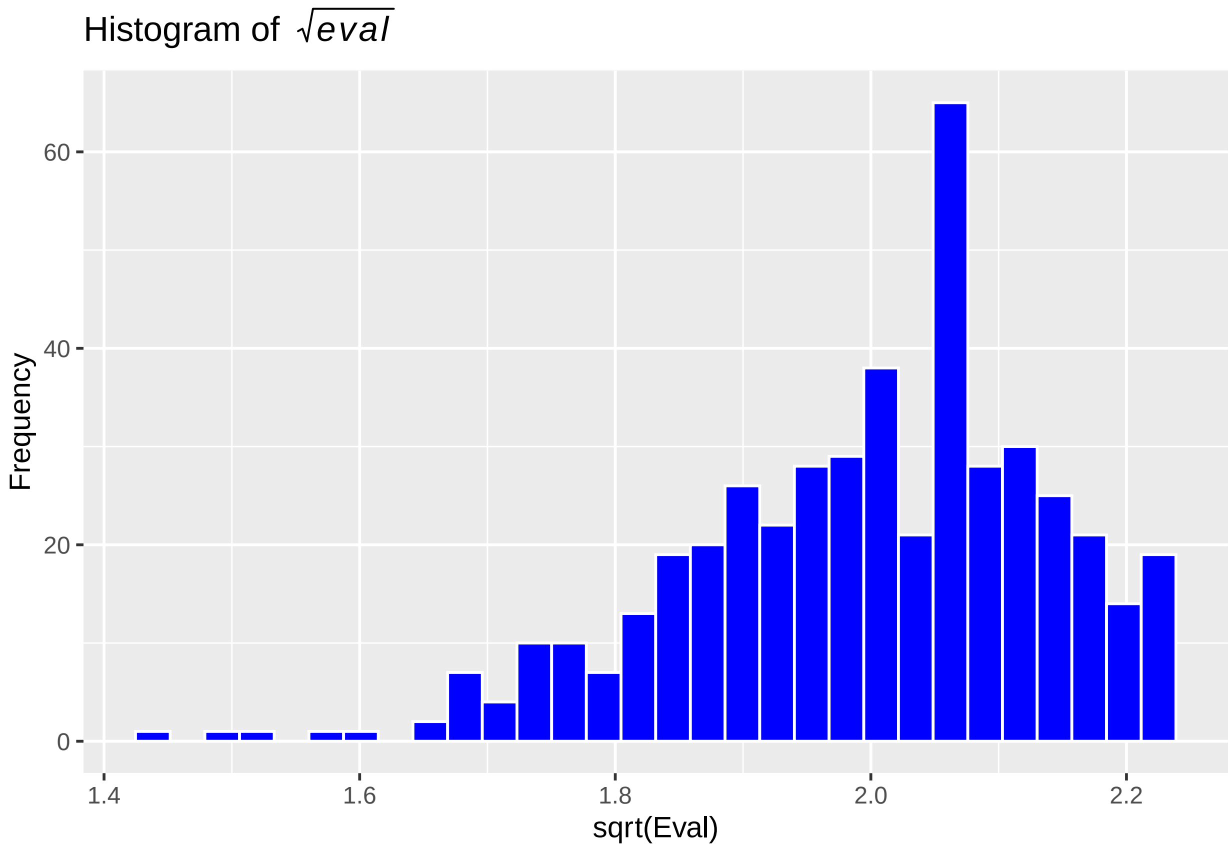

```r
# Shapiro test for normality

shapiro.test(log(Beauty$eval))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  log(Beauty$eval)
## W = 0.94882, p-value = 0.00000000001452
```

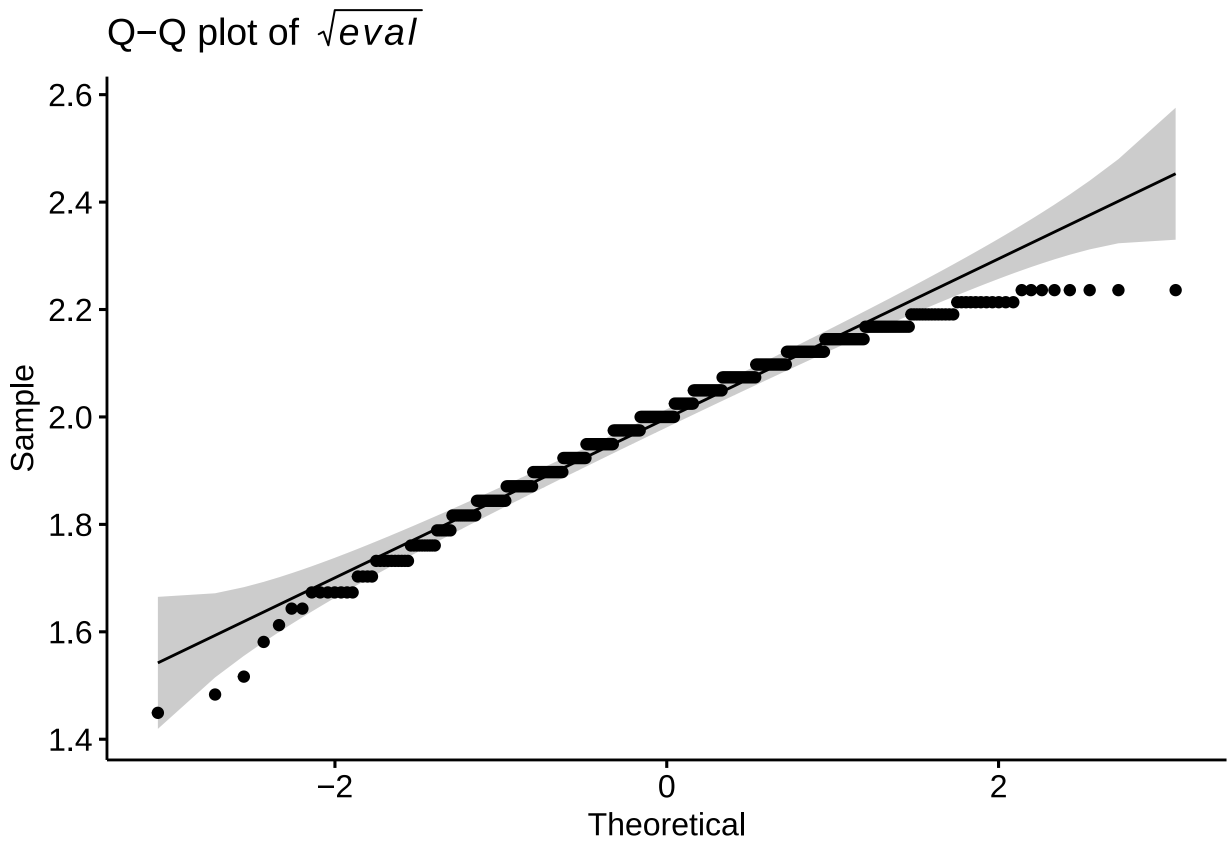
- The log transformation actually worsens the normality of *eval*

```r
# Histogram of eval, as it is
hist_sqrt.eval <- ggplot(Beauty, aes(x = sqrt(eval))) + geom_histogram(color = "white",
    fill = "blue") + labs(title = "Histogram of " ~ italic(sqrt(eval)),
    x = "sqrt(Eval)", y = "Frequency")

hist_sqrt.eval
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
# Q-Q plot on eval, as it is

ggqqplot(sqrt(Beauty$eval)) + labs(title = "Q-Q plot of " ~ italic(sqrt(eval)))
```



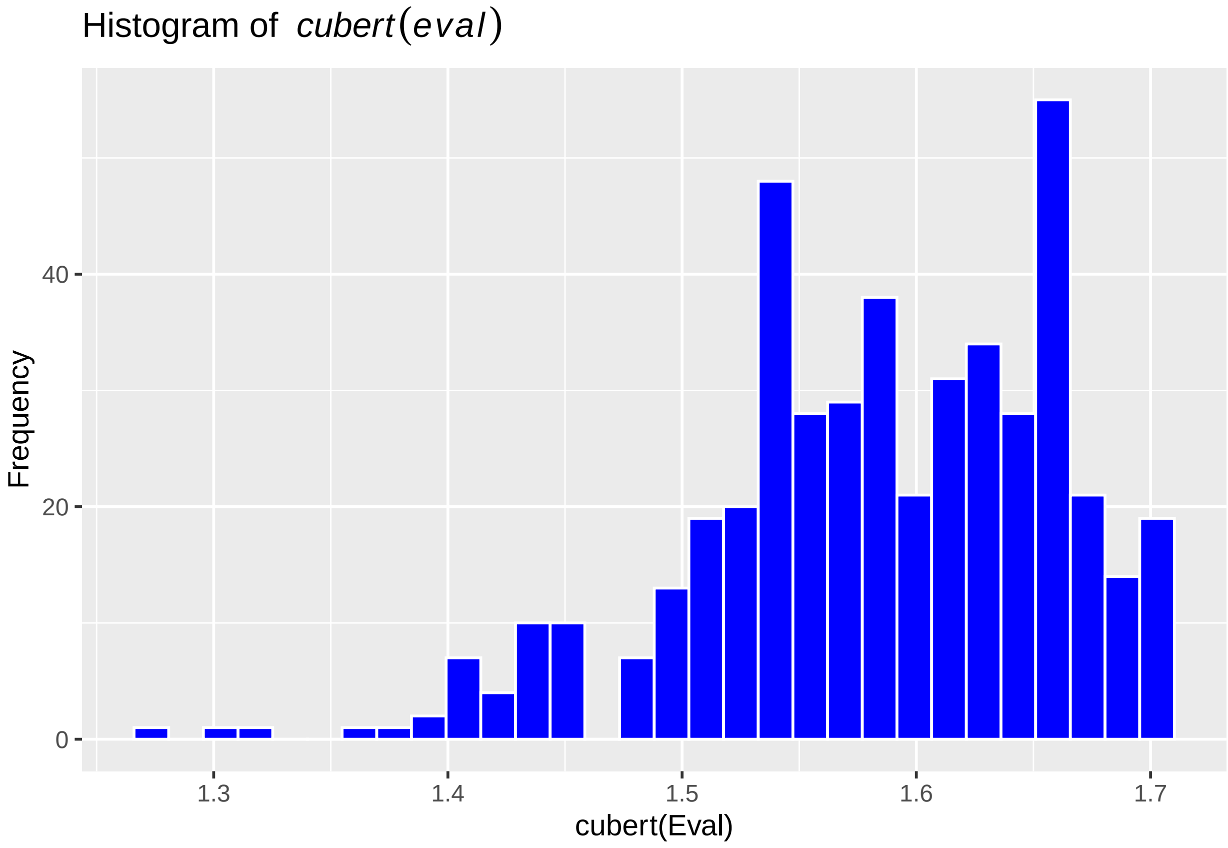

```r
# Shapiro test for normality

shapiro.test(sqrt(Beauty$eval))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  sqrt(Beauty$eval)
## W = 0.96583, p-value = 0.000000006578
```

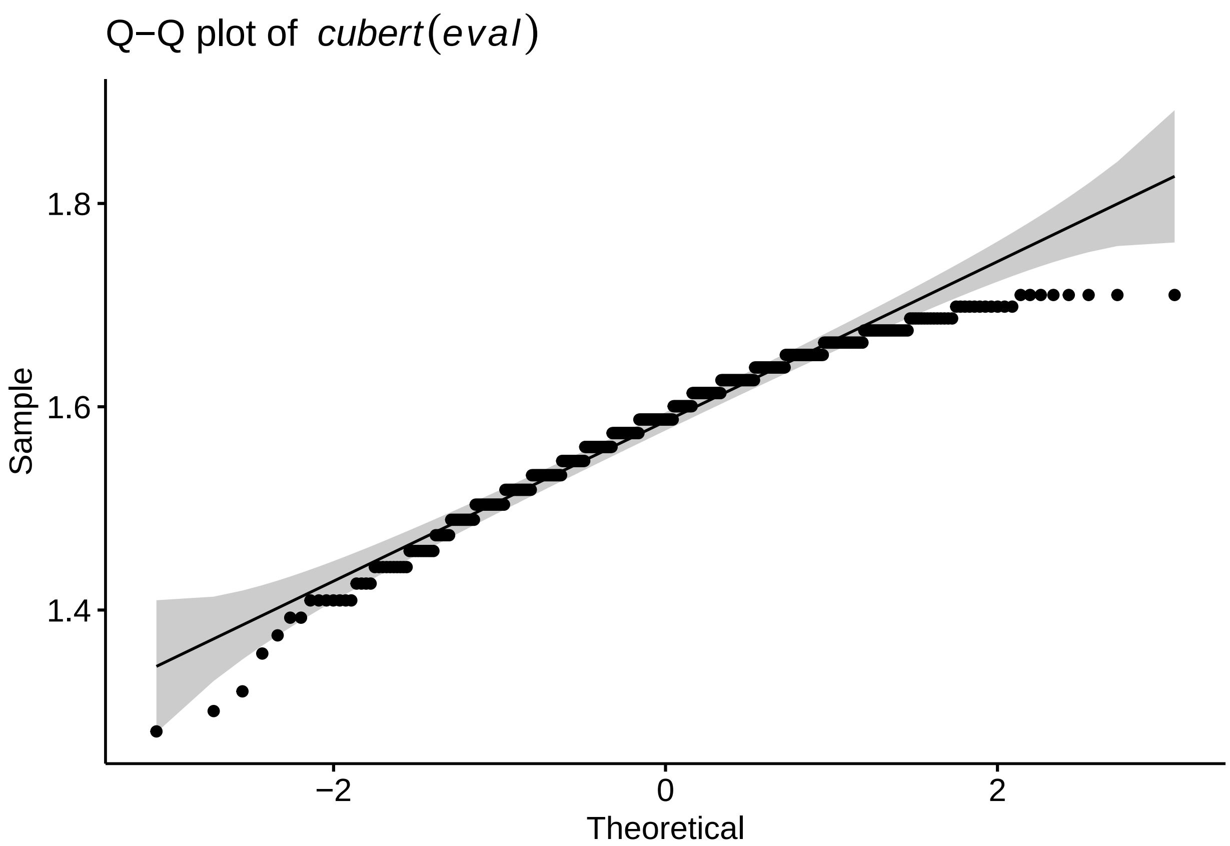
- As for the square root transformation it also decreases the normality of *eval*

```r
# Histogram of eval, as it is
hist_cube.eval <- ggplot(Beauty, aes(x = (eval)^(1/3))) + geom_histogram(color = "white",
    fill = "blue") + labs(title = "Histogram of " ~ italic(cubert(eval)),
    x = "cubert(Eval)", y = "Frequency")

hist_cube.eval
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
# Q-Q plot on eval, as it is

ggqqplot((Beauty$eval)^(1/3)) + labs(title = "Q-Q plot of " ~
    italic(cubert(eval)))
```




```
# Shapiro test for normality

shapiro.test((Beauty$eval)^(1/3))
```

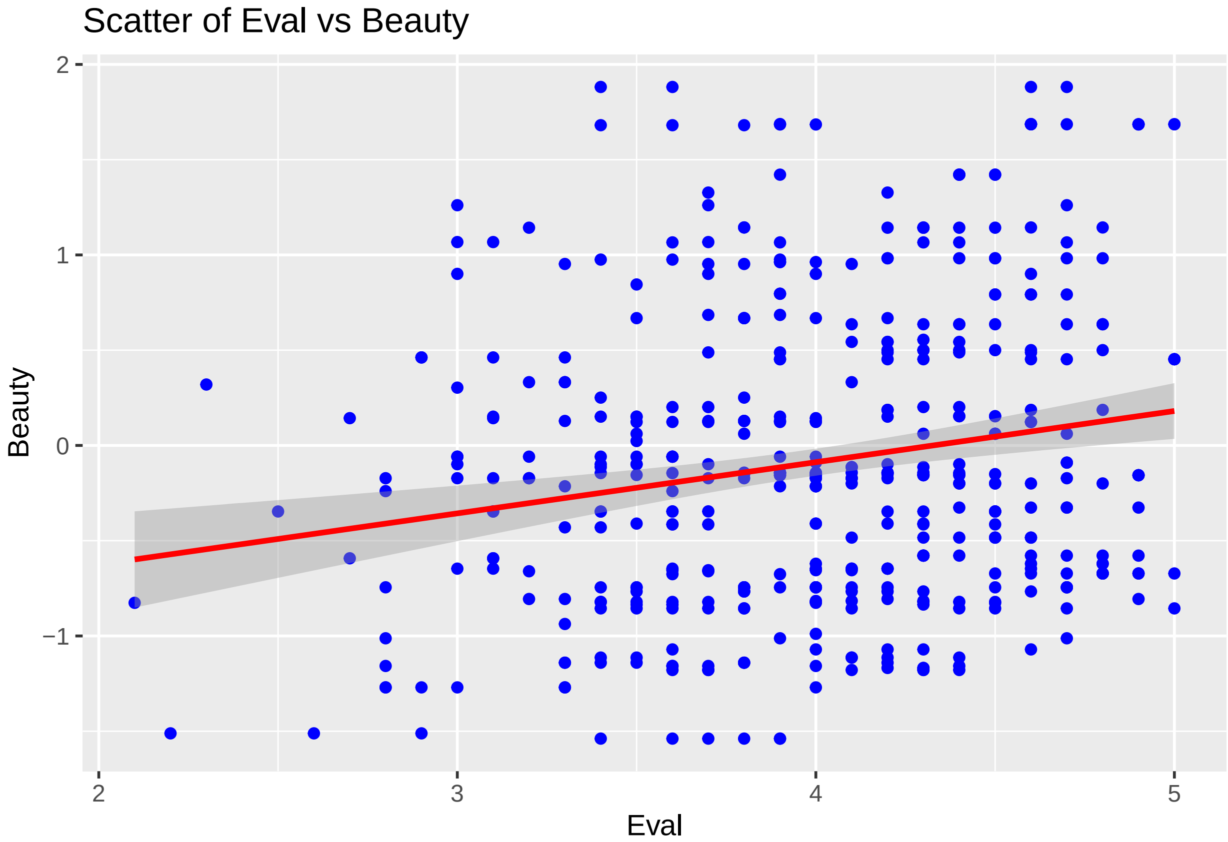
```
##
##  Shapiro-Wilk normality test
##
## data:  (Beauty$eval)^(1/3)
## W = 0.96078, p-value = 0.0000000009063
```

- Moreover, the cube root transformation does not enhance the normality of *eval* either.

We will be using the variable *eval* as it is, given the results of our transformations analysis.

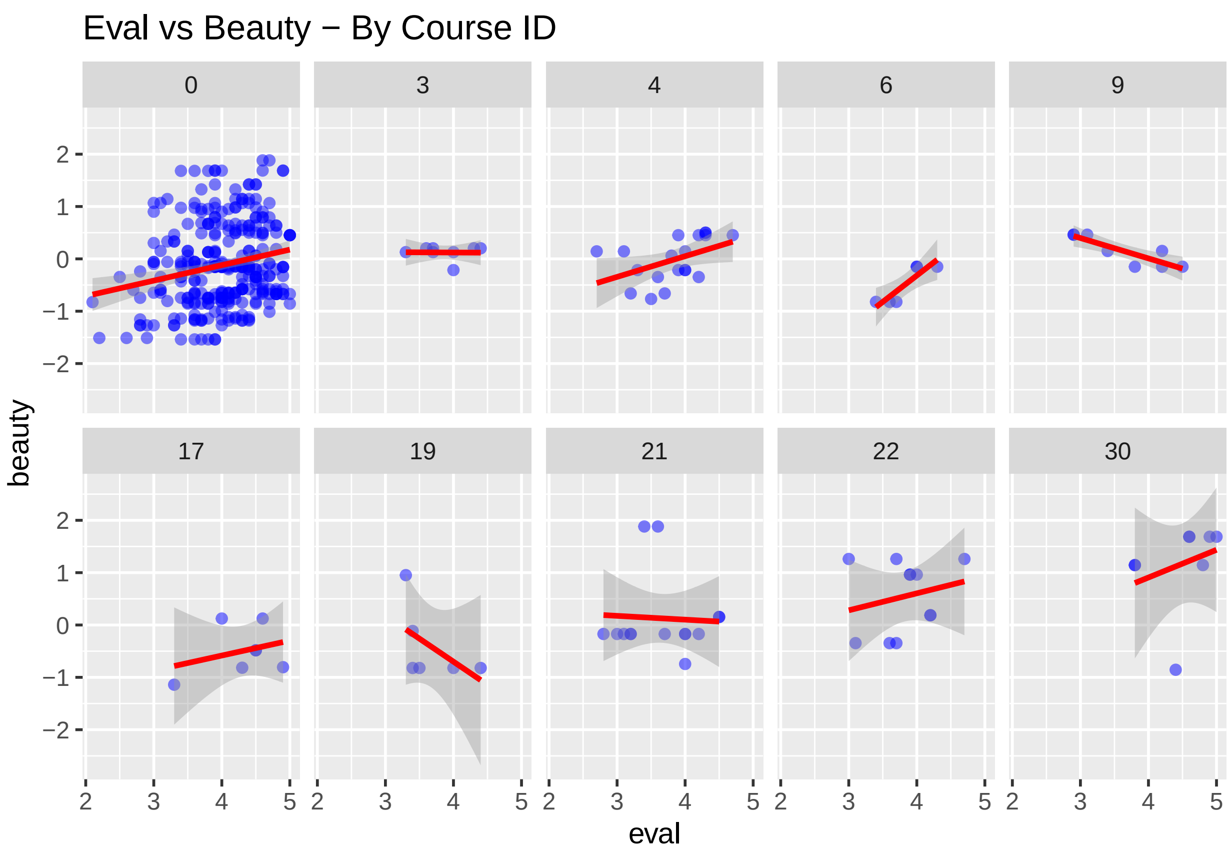
Exercise 2

```
# Histogram of eval, as it is
ggplot(Beauty, aes(x = eval, y = beauty)) + geom_point(color = "blue") +
    labs(title = "Scatter of Eval vs Beauty", x = "Eval", y = "Beauty") +
    stat_smooth(method = "lm", col = "red")
```



- The main effect appears to be a positive relation between *eval* and *beauty*

```
# Histogram of eval vs beauty by courseID
ggplot(Beauty[which(Beauty$courseID %in% c(0, 4, 21, 22, 30,
    19, 17, 9, 3, 6)), ], aes(x = eval, y = beauty)) + # ggplot(Beauty,aes(x=eval, y=beauty)) +
geom_point(alpha = 0.5, colour = "blue") + geom_smooth(method = "lm",
    col = "red") + labs(title = "Eval vs Beauty - By Course ID") +
    facet_wrap(~courseID, ncol = 5)
```



- Comparing the relation between *eval* and *beauty* by Courses shows that the majority of courses have the same positive correlation. However, there are courses for which this relation changes to negative (3, 9, 19, 21). There is also evidence that could lead us to think that there might be different intensities of the relation (the slopes may differ by courses)

Exercise 3

- It is not meaningful since every professor has only one beauty score which is the average of the beauty scores made by the graduate students.

Exercise 4

```
Beauty$courseID <- as.factor(Beauty$courseID)
Beauty$tenured <- factor(Beauty$tenured, levels = c(0, 1), labels = c("Not tenured",
    "Tenured"))
Beauty$minority <- factor(Beauty$minority, levels = c(0, 1),
    labels = c("Not minority", "Minority"))
```

```r
Beauty$female <- factor(Beauty$female, levels = c(0, 1), labels = c("Male",
    "Female"))
Beauty$formal <- factor(Beauty$formal, levels = c(0, 1), labels = c("Not formal",
    "Formal"))
Beauty$lower <- factor(Beauty$lower, levels = c(0, 1), labels = c("Not lower course",
    "Lower course"))
Beauty$multipleclass <- factor(Beauty$multipleclass, levels = c(0,
    1), labels = c("Not multiple class", "Multiple class"))
Beauty$nonenglish <- factor(Beauty$nonenglish, levels = c(0,
    1), labels = c("English education", "Non-english education"))
Beauty$onecredit <- factor(Beauty$onecredit, levels = c(0, 1),
    labels = c("Not one credit course", "One credit course"))
Beauty$tenuretrack <- factor(Beauty$tenuretrack, levels = c(0,
    1), labels = c("Not tenure track", "Tenure track"))
summary(Beauty)
```

```
##    profnumber        beauty              eval          courseID
##  Min.   : 1.00   Min.   :-1.53884   Min.   :2.100   0      :306
##  1st Qu.:20.00   1st Qu.:-0.74462   1st Qu.:3.600   4      : 19
##  Median :44.00   Median :-0.15636   Median :4.000   21     : 14
##  Mean   :45.43   Mean   :-0.08835   Mean   :3.998   22     : 11
##  3rd Qu.:70.50   3rd Qu.: 0.45725   3rd Qu.:4.400   3      :  8
##  Max.   :94.00   Max.   : 1.88167   Max.   :5.000   9      :  8
##                                                     (Other): 97
##         tenured            minority        age         didevaluation
##  Not tenured:210   Not minority:399   Min.   :29.00   Min.   :  5.00
##  Tenured    :253   Minority    : 64   1st Qu.:42.00   1st Qu.: 15.00
##                                       Median :48.00   Median : 23.00
##                                       Mean   :48.37   Mean   : 36.62
##                                       3rd Qu.:57.00   3rd Qu.: 40.00
##                                       Max.   :73.00   Max.   :380.00
##
##     female           formal                 lower
##  Male  :268   Not formal:386   Not lower course:306
##  Female:195   Formal    : 77   Lower course    :157
##
##
##
##
##
##             multipleclass                 nonenglish
##  Not multiple class:306   English education    :435
##  Multiple class    :157   Non-english education: 28
##
##
##
##
##
##                  onecredit   percentevaluating profevaluation
##  Not one credit course:436   Min.   : 10.42    Min.   :2.300
##  One credit course    : 27   1st Qu.: 62.70    1st Qu.:3.800
##                              Median : 76.92    Median :4.300
##                              Mean   : 74.43    Mean   :4.175
##                              3rd Qu.: 87.25    3rd Qu.:4.600
##                              Max.   :100.00    Max.   :5.000
##
##     students                 tenuretrack
##  Min.   :  8.00   Not tenure track:102
##  1st Qu.: 19.00   Tenure track    :361
##  Median : 29.00
##  Mean   : 55.18
##  3rd Qu.: 60.00
##  Max.   :581.00
##
```

```r
# hist(Beauty$beauty)
```

Main EDA findings:

- *students* and *didevaluation* are highly correlated (0.97), this could cause problems in the final model due to multicollinearity.
- It seems that the higher the age of a professor the lower the average beauty score, an expected result.
- As seen in the previous items, *beauty* and *eval* show a positive relation, leading us to think that the prettier the professor the higher is going to be his eval score.
- As expected, tenured professors tend to be older than the ones that are not.
- It seems that female professors might have slightly higher beauty scores.
- It appears that formally dressed professors tend to have higher beauty scores.
- Evaluation might be lower for professors that are on a tenure track.
- It seems that female professors might have slightly lower profevaluation scores.
- Lower level courses tend to have higher professor evaluations.
- one-credit courses tend to have higher professor evaluations.
- one-credit courses tend to have a higher percentage of students evaluating.

- Professors that have been educated in a non-English speaking country tend to have lower professor evaluations and course evaluation.
- The percentage of students evaluating seems to have a positive relationship with the evaluation of the professor.
- Profesor evaluation is highly correlated with the course evaluation.

Why not include profevaluation?:

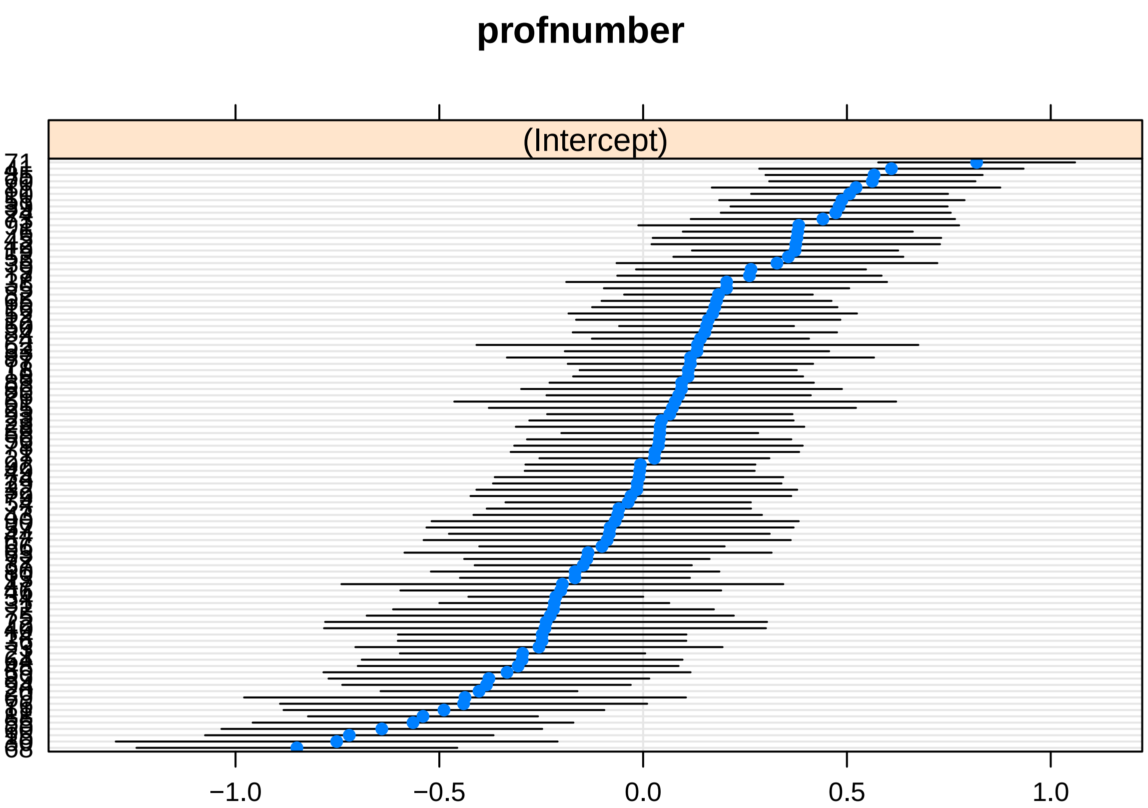
- *profevaluation* and *eval* are simultaneously determined variables. Simultaneity happens when the explanatory variable (in this case profevaluation) is jointly determined with the dependent variable (in this case eval). When a professor receives a high professor evaluation this causes that the course receives a high evaluation as well, at the same time, when a course receives a high evaluation is very likely that the professor receives a high professor evaluation. In simpler terms, X causes Y but Y also causes X. This brings the problem of endogeneity in our model and consequently, our model will depict unexpected results due to this simultaneity bias.

Exercise 5

```r
lmer_beauty <- lmer(eval ~ beauty + (1 | profnumber), data = Beauty)
summary(lmer_beauty)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: eval ~ beauty + (1 | profnumber)
##    Data: Beauty
##
## REML criterion at convergence: 643.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.6897 -0.6200  0.0688  0.5724  2.4529
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  profnumber (Intercept) 0.1387   0.3724
##  Residual               0.1705   0.4129
## Number of obs: 463, groups:  profnumber, 94
##
## Fixed effects:
##             Estimate Std. Error       df t value            Pr(>|t|)
## (Intercept)  3.93893    0.04420 84.83439  89.125 <0.0000000000000002 ***
## beauty       0.11566    0.05387 86.85890   2.147              0.0346 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##        (Intr)
## beauty 0.022
```

```r
dotplot(ranef(lmer_beauty, condVar = TRUE))$profnumber
```




```r
gammas <- as.data.frame(ranef(lmer_beauty)$profnumber)
# rownames(gammas) <- NULL
gammas$j <- 1:94
gammas <- gammas[, c(2, 1)]
colnames(gammas) <- c("j", "gamma_0")
rows <- seq_len(nrow(gammas)%/%2)
kable(list(gammas[rows, 1:2], matrix(numeric(), nrow = 0, ncol = 1),
    gammas[-rows, 1:2]), caption = "This is the caption.", label = "tables",
    format = "latex", booktabs = TRUE, row.names = FALSE) %>%
    kable_styling(latex_options = "HOLD_position")
```

Table 1: This is the caption.

j	gamma_0	j	gamma_0
1	0.0288845	48	-0.3066174
2	-0.2199410	49	-0.0084593
3	-0.2555255	50	0.1555810
4	0.1406063	51	0.4876141
5	0.2047280	52	0.1707482
6	0.3794508	53	0.3562948
7	-0.0595070	54	-0.0367454
8	0.1103515	55	-0.5644793
9	0.2646540	56	0.0393320
10	0.5064797	57	-0.0811566
11	-0.4886437	58	0.0408514
12	0.1597388	59	-0.3339714
13	-0.1672810	60	-0.6410968
14	-0.2476834	61	0.0787140
15	-0.7208642	62	0.1332051
16	0.1757917	63	-0.1351341
17	0.2608092	64	-0.2968288
18	0.1105881	65	0.1800783
19	0.3727067	66	-0.1010191
20	-0.4026259	67	-0.0882319
21	-0.2958135	68	-0.8494574
22	-0.2380139	69	-0.4369727
23	0.0450181	70	0.5622881
24	0.4725966	71	0.8182285
25	0.0718047	72	-0.1379673
26	0.0871067	73	0.4410103
27	0.0276640	74	-0.0100856
28	0.0415352	75	-0.2279099
29	-0.0145054	76	-0.4405032
30	-0.7518581	77	0.1160708
31	-0.2178495	78	0.0376451
32	-0.0154929	79	-0.0300295
33	0.1321162	80	-0.1668323
34	-0.2141746	81	0.5223706
35	0.3283189	82	0.1848001
36	-0.2479250	83	0.0945468
37	-0.1469429	84	0.1514883
38	0.2048705	85	0.5665309
39	0.4806786	86	0.0942557
40	-0.2407623	87	0.1161234
41	0.6090786	88	-0.5400706
42	0.3744441	89	-0.3783620
43	-0.0623957	90	-0.0686170
44	-0.0829487	91	0.3817684
45	0.3773718	92	-0.0066919
46	-0.2020202	93	0.0654568
47	-0.1981179	94	-0.3842642

$$\hat{eval}_{i,j} = (\hat{\beta}_0 + \hat{\gamma}_{0,j}) + \hat{\beta}_1 beauty_{i,j}$$

- We have an overall "average" regression line for all professors (rows across profnumbers), which has slope 0.11566 and intercept 3.93893.
- The slope value indicates that the evaluation of a professor increases by 0.11566 for every unit increase of the average beauty score.
- For any distinct professor the baseline eval value can be estimated using both the overall average intercept of 3.93893 plus the random effect gamma for the corresponding profnumber.
- For instance, for professor 1, we have the same slope value of 0.11566, but the resulting intercept value is equal to the sum of the fixed intercept plus the random effect intercept: $3.93893 + 0.0288845 = 3.967815$. We could repeat this same process to calculate the intercept for every other profnumber.

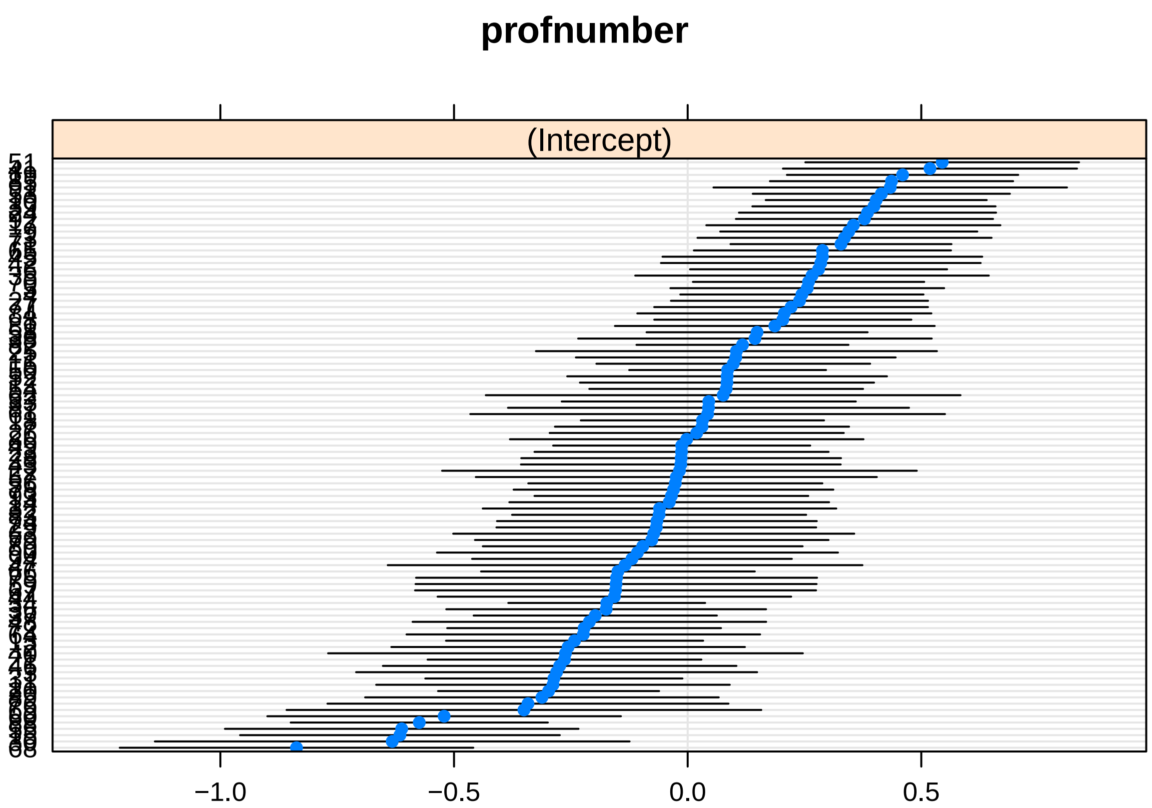
Exercise 6

```
lmer_beauty2 <- lmer(eval ~ beauty + female + onecredit + nonenglish +
    (1 | profnumber), data = Beauty)
summary(lmer_beauty2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## eval ~ beauty + female + onecredit + nonenglish + (1 | profnumber)
##    Data: Beauty
##
## REML criterion at convergence: 626.2
##
```

```
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8148 -0.5997  0.0866  0.5589  2.4318
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  profnumber (Intercept) 0.1122   0.3349
##  Residual               0.1673   0.4091
## Number of obs: 463, groups:  profnumber, 94
##
## Fixed effects:
##                                Estimate Std. Error        df t value
## (Intercept)                     4.03261    0.05531  82.74588  72.905
## beauty                          0.14074    0.05040  83.39414   2.793
## femaleFemale                   -0.20229    0.08352  80.97599  -2.422
## onecreditOne credit course      0.46495    0.12009 443.74520   3.872
## nonenglishNon-english education -0.35460    0.15949  89.12627  -2.223
##                                           Pr(>|t|)
## (Intercept)                    < 0.0000000000000002 ***
## beauty                                    0.006480 **
## femaleFemale                              0.017671 *
## onecreditOne credit course                0.000124 ***
## nonenglishNon-english education           0.028721 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) beauty fmlFml oncOcc
## beauty       0.113
## femaleFemal -0.639 -0.164
## oncrdtOncrc -0.101  0.039  0.005
## nnnglshNn-e -0.202  0.032  0.000  0.007
```

```r
dotplot(ranef(lmer_beauty2, condVar = TRUE))$profnumber
```




```r
gammas <- as.data.frame(ranef(lmer_beauty2)$profnumber)
# rownames(gammas) <- NULL
gammas$j <- 1:94
gammas <- gammas[, c(2, 1)]
colnames(gammas) <- c("j", "gamma_0")
rows <- seq_len(nrow(gammas)%/%2)
kable(list(gammas[rows, 1:2], matrix(numeric(), nrow = 0, ncol = 1),
    gammas[-rows, 1:2]), caption = "This is the caption.", label = "tables",
    format = "latex", booktabs = TRUE, row.names = FALSE) %>%
    kable_styling(latex_options = "HOLD_position")
```

Table 2: This is the caption.

j	gamma_0	j	gamma_0
1	0.1029262	48	-0.2103566
2	-0.2558183	49	-0.0127837
3	-0.2804848	50	0.0854741
4	0.2444510	51	0.5447250
5	0.2559812	52	0.0844165
6	0.2801460	53	0.4144892
7	0.0306899	54	0.0824315
8	0.2036298	55	-0.6119323
9	0.3447281	56	-0.0264139
10	0.4035039	57	-0.0242838
11	-0.2882051	58	0.1485382
12	0.0841127	59	-0.1532244
13	-0.2419942	60	-0.5211546
14	-0.0394517	61	0.0427718
15	-0.6157267	62	0.0759832
16	0.0976180	63	-0.0726054
17	0.3545908	64	-0.2232789
18	0.0315819	65	0.2884050
19	0.4599052	66	-0.1492610
20	-0.2976320	67	-0.1543266
21	-0.2635618	68	-0.8370530
22	-0.0175914	69	-0.3503857
23	-0.0130945	70	0.2587105
24	0.3848765	71	0.3280749
25	0.1043759	72	-0.2215873
26	0.0193478	73	0.3357038
27	0.2393446	74	-0.0658799
28	-0.0139666	75	-0.1521674
29	-0.0670525	76	-0.3417217
30	-0.6322487	77	0.2213447
31	-0.2863039	78	-0.0303188
32	-0.0602039	79	-0.0768583
33	0.0451801	80	-0.0962009
34	-0.1731672	81	0.1864995
35	0.2661134	82	0.1173040
36	-0.1743650	83	-0.0610849
37	-0.1977334	84	0.2069065
38	0.1439897	85	0.4362560
39	0.3986424	86	-0.0020497
40	-0.2614932	87	0.0445872
41	0.5185807	88	-0.5743429
42	0.2848919	89	-0.3118630
43	-0.0146798	90	-0.1074140
44	-0.1567966	91	0.4334965
45	0.2882841	92	0.3783550
46	-0.2739057	93	-0.0348287
47	-0.1338838	94	-0.1192270

$$\hat{eval}_{i,j} = (\hat{\beta}_0 + \hat{\gamma}_{0,j}) + \hat{\beta}_1 beauty_{i,j} + \hat{\beta}_2 female_{i,j} + \hat{\beta}_3 onecredit_{i,j} + \hat{\beta}_4 nonenglish_{i,j}$$

- We have an overall "average" regression line for all professors (rows across profnumbers), which has a baseline intercept of 4.03261 and slope values of 0.14074 for beauty, -0.20229 for female, 0.46495 for one-credit, and -0.35460 for nonenglish.
- For beauty, the slope value indicates that the evaluation of a professor increases by 0.14074 for every unit increase of the average beauty score.
- For female, the slope value indicates that the evaluation of a professor decreases by 0.20229 if they are female.
- For one-credit, the slope value indicates that the evaluation of a professor increases by 0.46495 if the course is a one-credit course.
- For nonenglish, the slope value indicates that the evaluation of a professor decreases by 0.35460 if the professor received an undergraduate education from a non-English speaking country.
- For any distinct professor the baseline eval value can be estimated using both the overall average intercept of 4.03261 plus the random effect gamma for the corresponding profnumber.
- For instance, for professor 1, we have the same slope values for the predictors, but the resulting intercept value is equal to the sum of the fixed intercept plus the random effect intercept: $4.03261 + 0.1029262 = 4.135536$. We could repeat this same process to calculate the intercept for every other profnumber.

Exercise 7

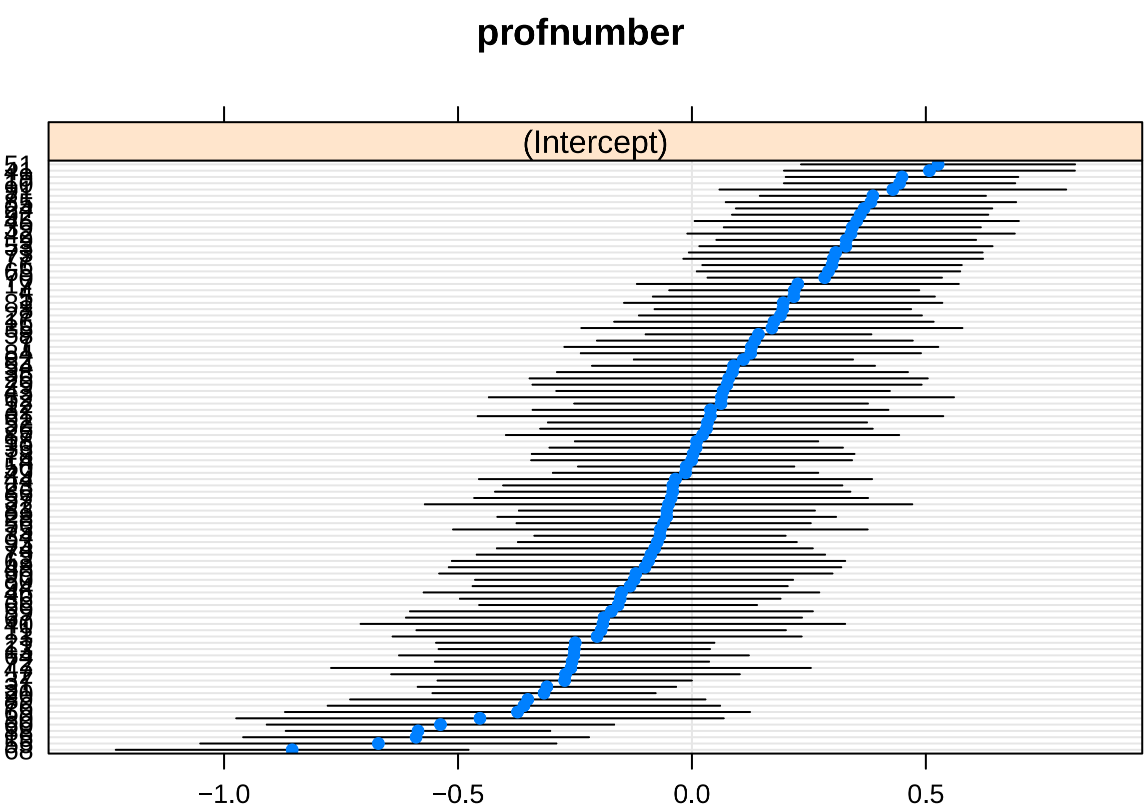
- We can see from the regression report in exercise 5, that the variance across professors has a value of 0.4129, while the variation for different scores for the same professor is 0.3724. This is expected, since a professor will teach with the same quality even if he teaches many different courses, however, the higher variance across multiple different professors is very likely given the differences of styles, preparation, and teaching quality.

Exercise 8

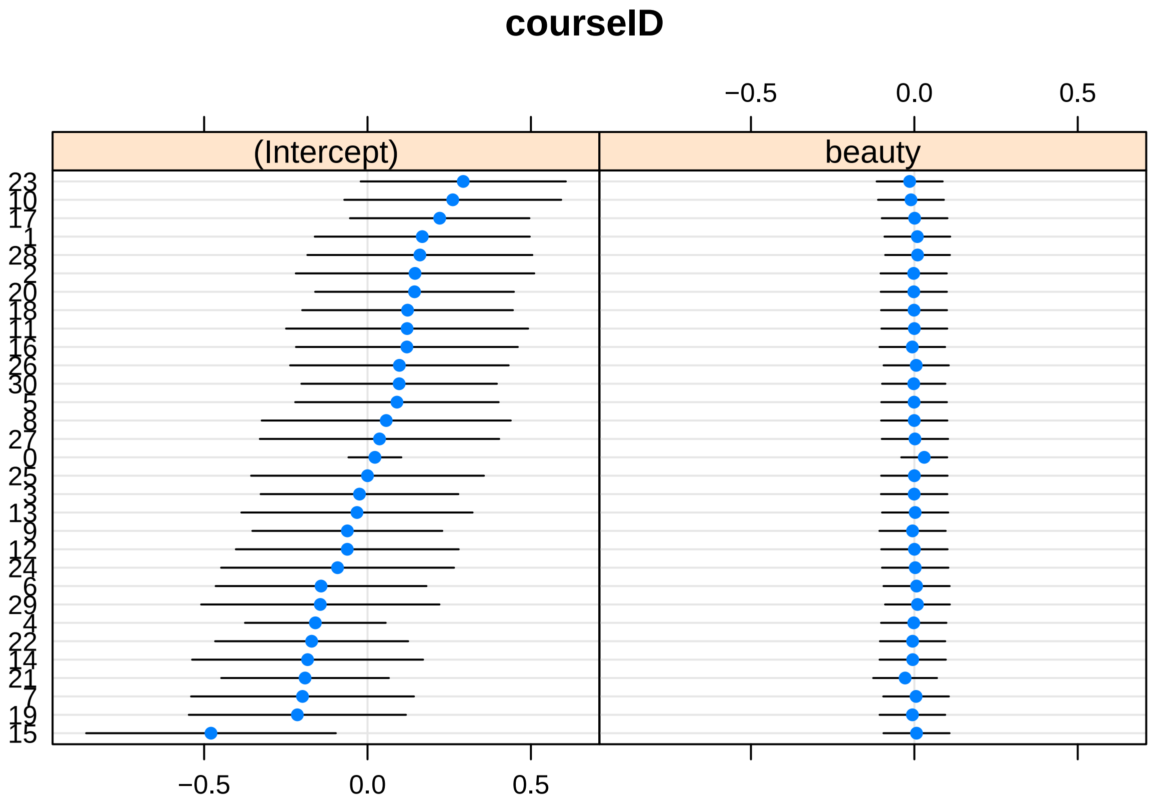
```r
lmer_beauty3 <- lmer(eval ~ beauty + female + onecredit + nonenglish +
    (1 | profnumber) + (beauty | courseID), data = Beauty)
summary(lmer_beauty3)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## eval ~ beauty + female + onecredit + nonenglish + (1 | profnumber) +
##     (beauty | courseID)
##    Data: Beauty
##
## REML criterion at convergence: 617.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9741 -0.6049  0.0883  0.5675  2.4562
##
## Random effects:
##  Groups     Name        Variance Std.Dev. Corr
##  profnumber (Intercept) 0.109394 0.33075
##  courseID   (Intercept) 0.056812 0.23835
##             beauty      0.002696 0.05192  0.01
##  Residual               0.154129 0.39259
## Number of obs: 463, groups:  profnumber, 94; courseID, 31
##
## Fixed effects:
##                                  Estimate Std. Error        df t value
## (Intercept)                       4.03818    0.07806  45.41462  51.729
## beauty                            0.12763    0.05967   4.32465   2.139
## femaleFemale                     -0.21094    0.08310  82.09509  -2.538
## onecreditOne credit course        0.38412    0.12802 344.74208   3.000
## nonenglishNon-english education  -0.34472    0.15989  90.61358  -2.156
##                                             Pr(>|t|)
## (Intercept)                     < 0.0000000000000002 ***
## beauty                                       0.09403 .
## femaleFemale                                 0.01302 *
## onecreditOne credit course                   0.00289 **
## nonenglishNon-english education              0.03374 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) beauty fmlFml oncOcc
## beauty       0.098
## femaleFemal -0.440 -0.130
## oncrdtOncrc -0.093  0.028  0.011
## nnnglshNn-e -0.160  0.025 -0.009  0.003
```

```r
dotplot(ranef(lmer_beauty3, condVar = TRUE))$profnumber
```



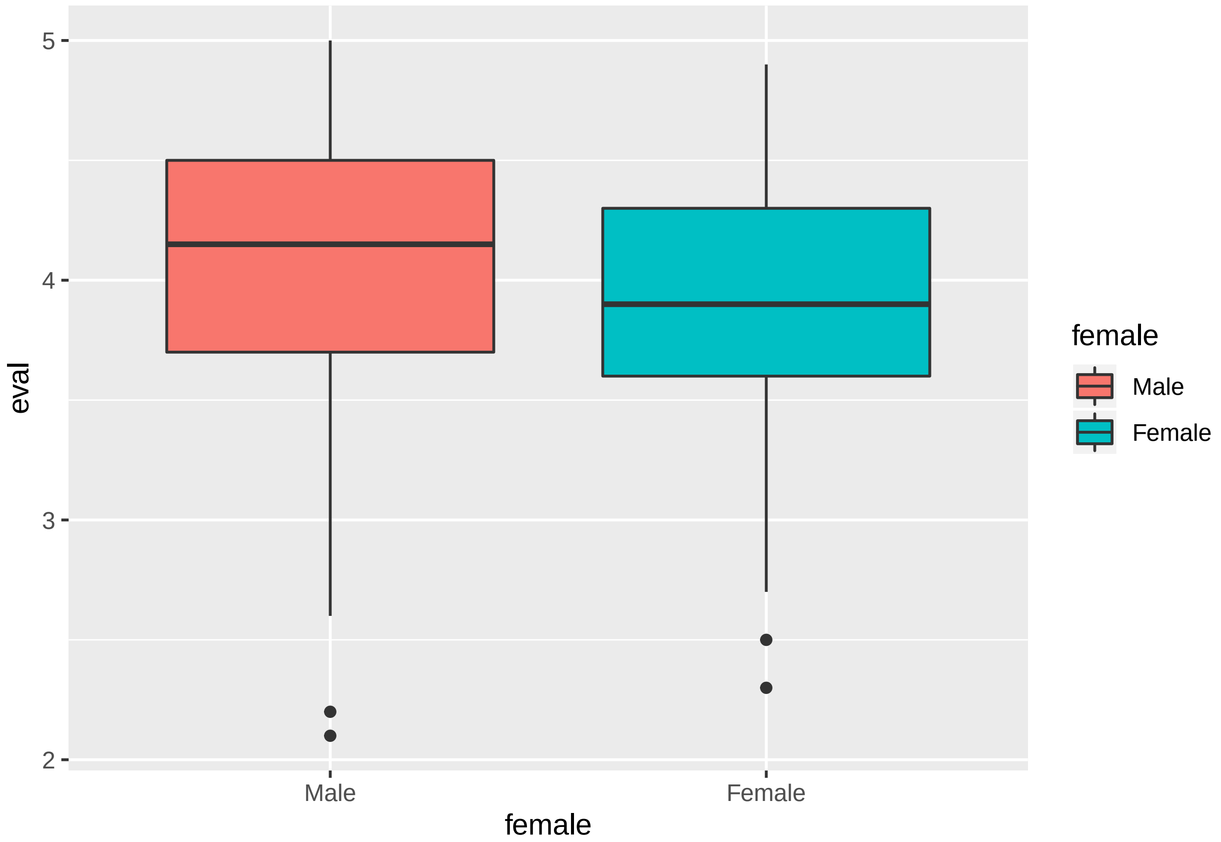

```r
dotplot(ranef(lmer_beauty3, condVar = TRUE))$courseID
```



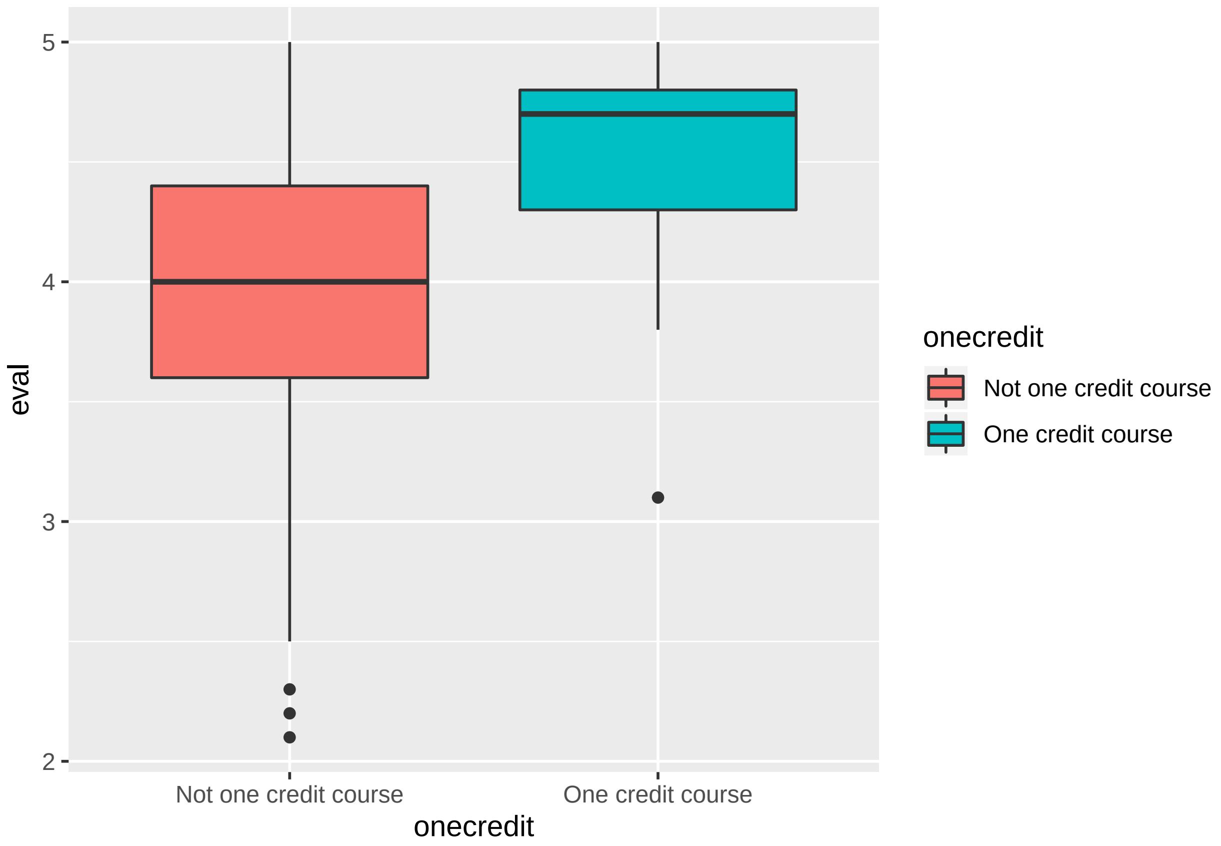
- All of the results for the fixed effects did change once we took into account a variation of the intercept and coefficient of beauty by courseID.
- The baseline intercept changed from 4.03261 to 4.03818, and slope values changed from 0.14074 to 0.12763 for beauty, from -0.20229 to -0.21094 for female, from 0.46495 to 0.38412 for onecredit, and from -0.35460 to -0.34472 for nonenglish. It is important to notice the coefficient for beauty became not statistically significant in the new model.
- These changes are due to the fact that the first model was not taking into account the variations in the effect of beauty that could differ by the different courses (courseID).

Exercise 9

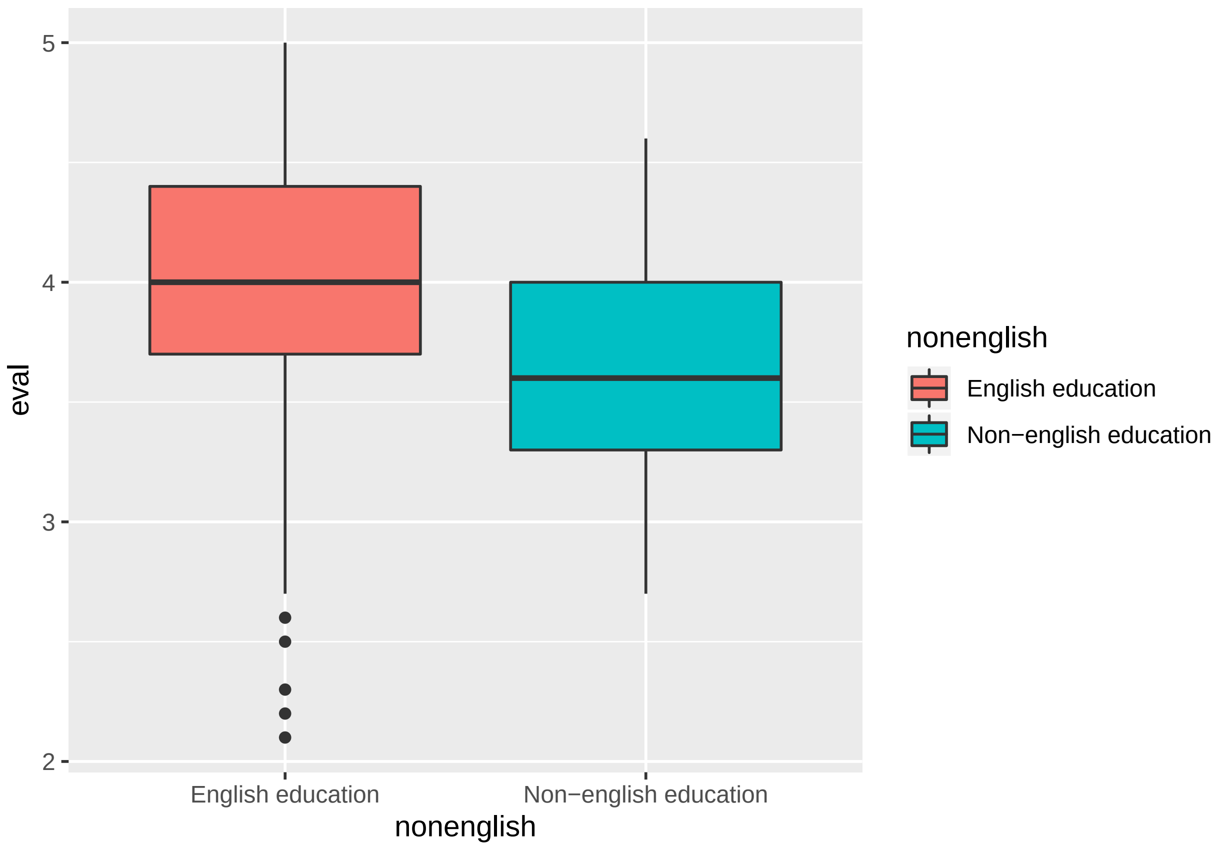
```r
ggplot(Beauty, aes(x = female, y = eval, fill = female)) + geom_boxplot()
```




```r
ggplot(Beauty, aes(x = onecredit, y = eval, fill = onecredit)) +
    geom_boxplot()
```




```r
ggplot(Beauty, aes(x = nonenglish, y = eval, fill = nonenglish)) +
    geom_boxplot()
```



- The first box plot shows that female professors appear to receive lower class evaluations.
- The second box plot shows that one credit classes seem to be better evaluated than the rest of the classes.
- The third box plot shows that professors who received education in a non-English speaking country seemed to receive lower class evaluations than the rest of the professors.

Exercise 10

```r
lmer_beauty3 <- lmer(eval ~ beauty + female + onecredit + nonenglish +
    lower + (1 | profnumber) + (beauty | courseID), data = Beauty)
summary(lmer_beauty3)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: eval ~ beauty + female + onecredit + nonenglish + lower + (1 |
##     profnumber) + (beauty | courseID)
##    Data: Beauty
##
## REML criterion at convergence: 619.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9959 -0.5726  0.1037  0.5719  2.2968
##
## Random effects:
##  Groups     Name        Variance Std.Dev. Corr
##  profnumber (Intercept) 0.113511 0.33691
```

```
##  courseID   (Intercept) 0.054389 0.23321
##             beauty      0.002669 0.05166  -0.05
##  Residual               0.153267 0.39149
## Number of obs: 463, groups:  profnumber, 94; courseID, 31
##
## Fixed effects:
##                                 Estimate Std. Error        df t value
## (Intercept)                      4.06137    0.08052  50.26874  50.439
## beauty                           0.13062    0.06009   4.58175   2.174
## femaleFemale                    -0.21721    0.08429  80.50241  -2.577
## onecreditOne credit course       0.41397    0.13076 359.11621   3.166
## nonenglishNon-english education  -0.35634    0.16210  88.58329  -2.198
## lowerLower course               -0.07710    0.06434 350.84397  -1.198
##                                            Pr(>|t|)
## (Intercept)                    < 0.0000000000000002 ***
## beauty                                      0.08674 .
## femaleFemale                                0.01179 *
## onecreditOne credit course                  0.00168 **
## nonenglishNon-english education             0.03054 *
## lowerLower course                           0.23158
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) beauty fmlFml oncOcc nnnN-e
## beauty       0.097
## femaleFemal -0.446 -0.134
## oncrdtOncrc -0.038  0.036 -0.001
## nnnglshNn-e -0.171  0.024 -0.006 -0.009
## lowerLwrcrs -0.249 -0.042  0.057 -0.201  0.060
```

- We decided to add the variable lower to the previous model. The resulting model's R output is shown above. lower turned out not to be significant since we cannot reject the hypothesis that it is equal to zero with 95% significance (its p-value is 0.23).