Lab 4: Multilevel Logistic Regression

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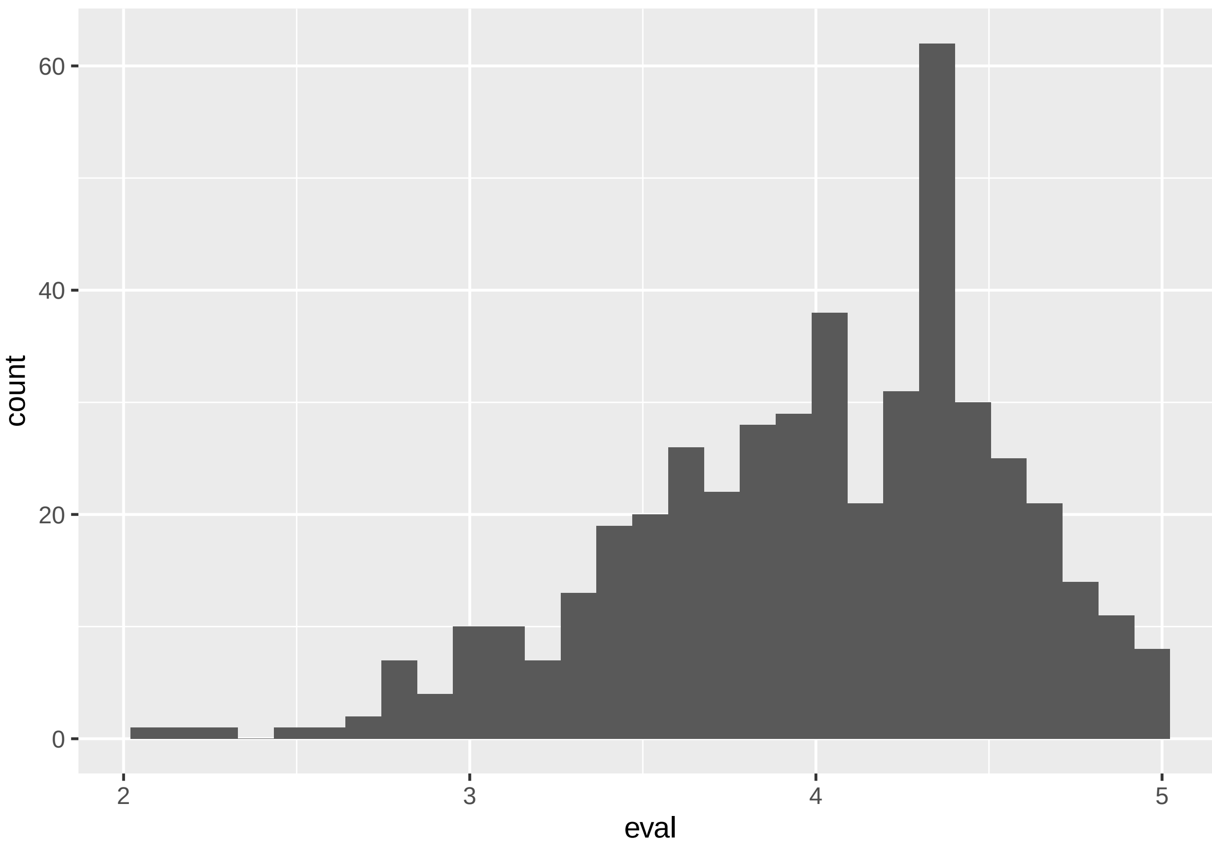
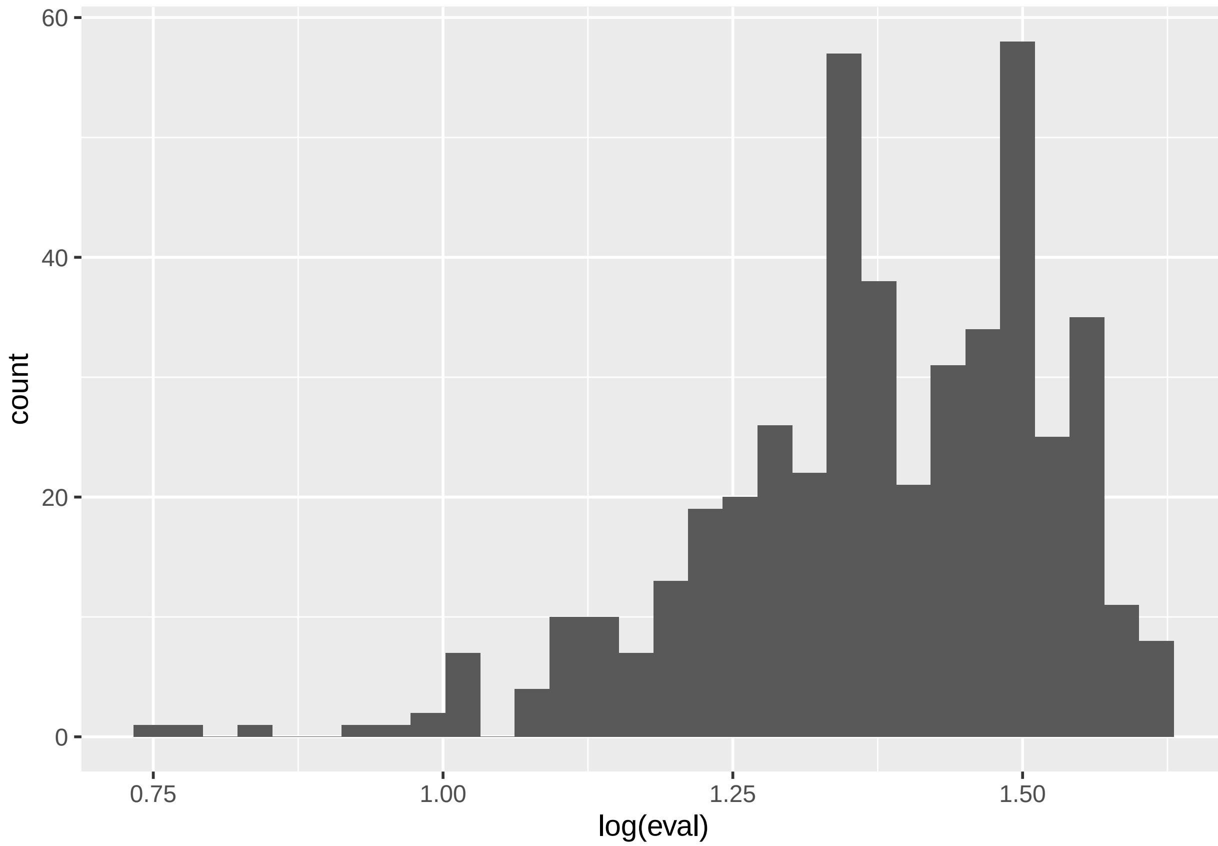
Exercise 1

- `eval` looks roughly normal, except for a gap right where the peak should be - however, neither log nor sqrt transformations seem to help:

```
## Loading required package: Matrix

##
## Attaching package: 'lmerTest'

## The following object is masked from 'package:lme4':
##
##     lmer

## The following object is masked from 'package:stats':
##
##     step
```




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




```
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```
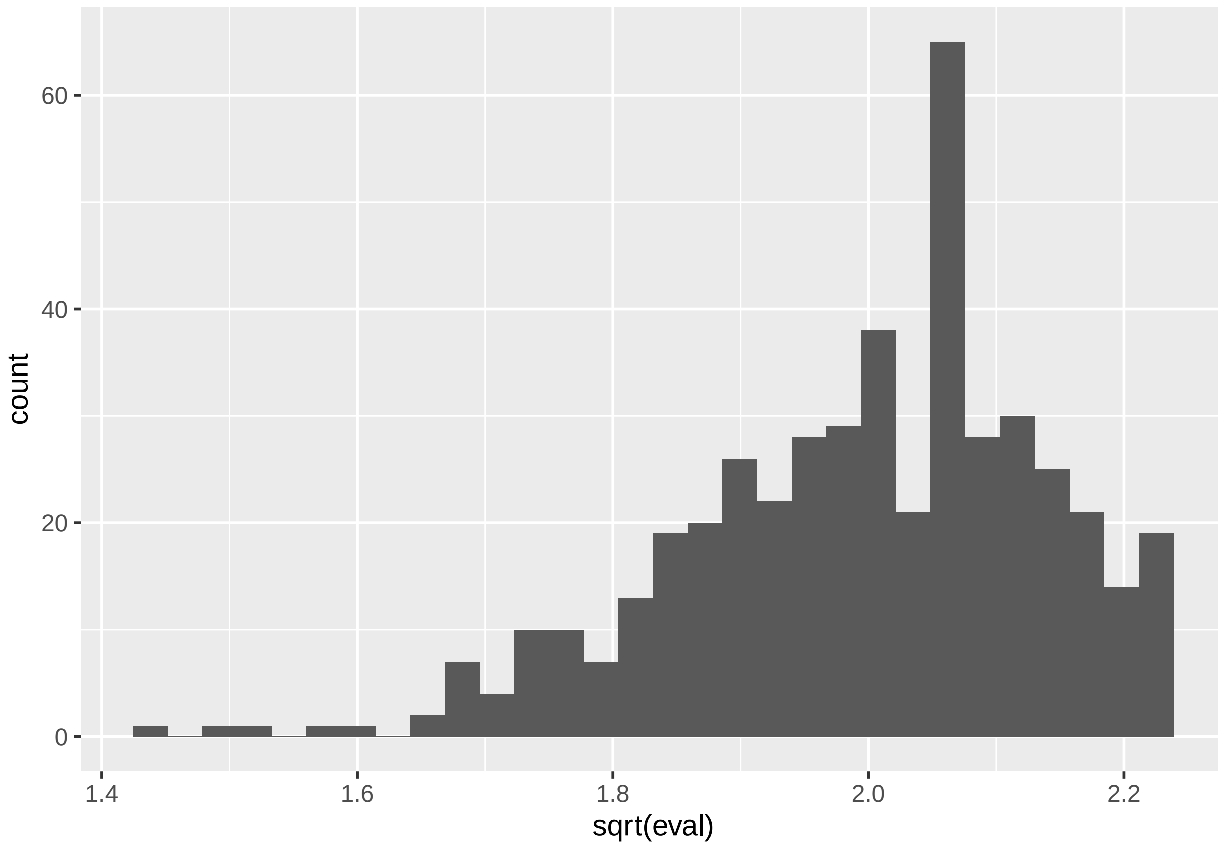
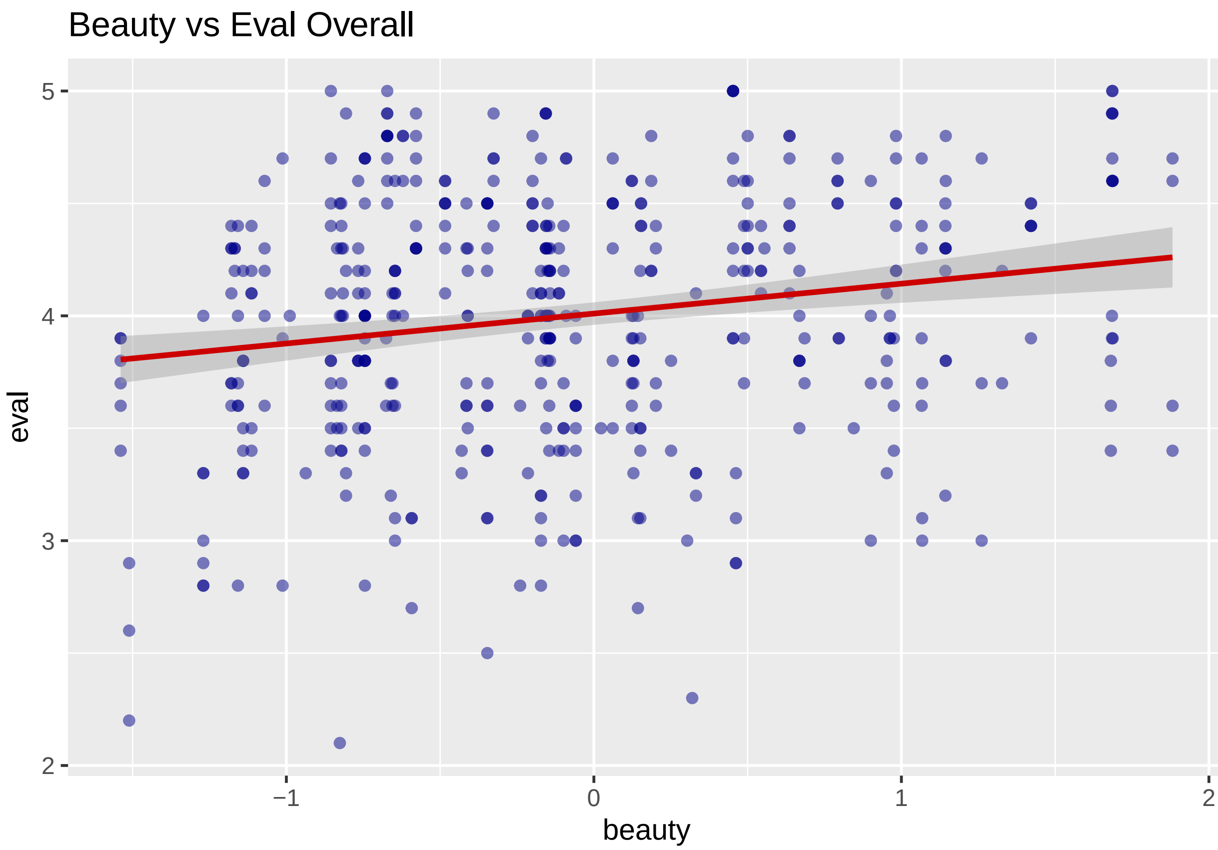
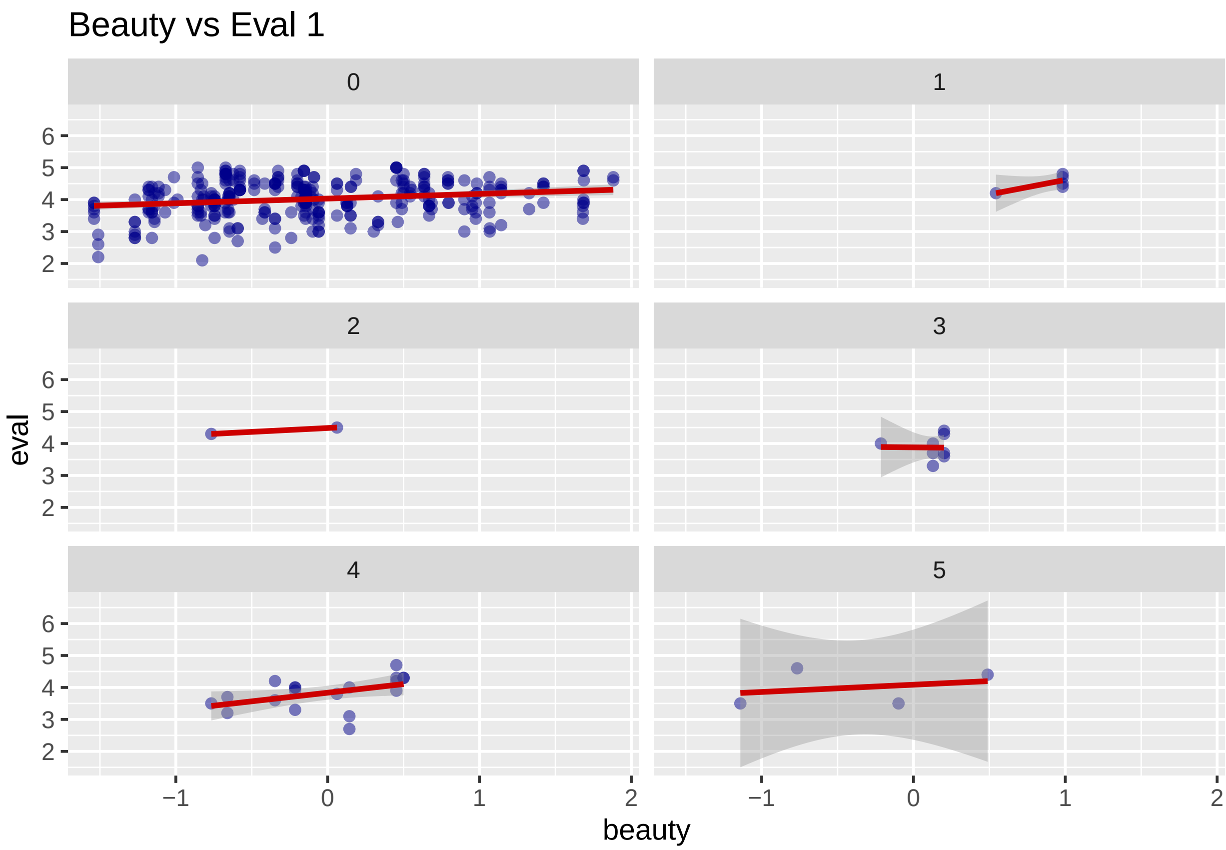



Exercise 2

- The relationship overall visually appears to be a mildly positive correlation.
- When separated by courseID, many of the courseIDs have no discernible relationship because they have almost no data. The two courseIDs with more data - courseID 1 and courseID 4 - appear to have positive relationships between `beauty` and `eval`.
- Fitting a linear model between `eval` and `beauty` shows a very weak value for R^2: `0.035`




```
## Warning in qt((1 - level)/2, df): NaNs produced
```

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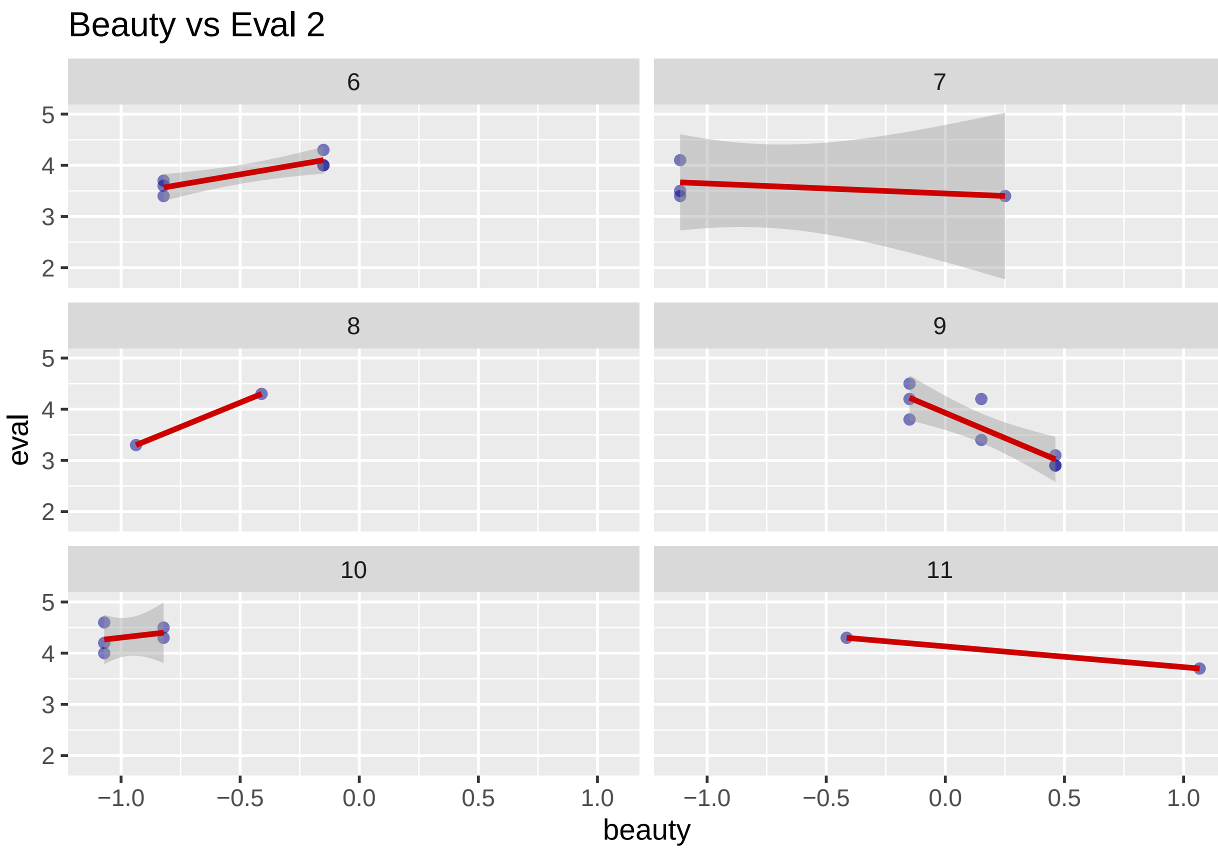


Exercise 3

- No, this does not make sense - because there is only one beauty value for each professor, this would be the same as including a random intercept - there can be no concept of slope with respect to beauty within a single professor's data, because the beauty value doesn't change.

Exercise 4

- `profevaluation` is very highly correlated with `eval` - this variable is the professor's average rating, so this makes intuitive sense. We should not include both in the model as they are not independent.
- `female` seems to have a mild negative relationship with `eval`.
- `onecredit` seems to have a mild positive relationship with `eval`.
- `percentevaluating` seems to have a mild positive relationship with `eval`.

Exercise 5

```
## 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   <2e-16 ***
## 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
```

- The intercept listed for profnumber is the baseline level, without taking into account the profnumber. The random effects given by `ranef` are gamma values which denote the professor's difference from the overall baseline level.
- The intercept and beauty coefficient represent the baseline level for a hypothetical professor with a beauty of zero (oh no!) and the increase in expected `eval` per point of beauty increase.
- Beauty is significant in the model, indicating what our EDA would suggest - that more beautiful professors are rated more highly.

Exercise 6

- Based on our EDA, we chose `female`, `tenuretrack` and `nonenglish`.

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## eval ~ beauty + female + tenuretrack + nonenglish + (1 | profnumber)
##    Data: Beauty
##
## REML criterion at convergence: 636.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7663 -0.6090  0.0854  0.5502  2.4437
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  profnumber (Intercept) 0.1207   0.3474
##  Residual               0.1698   0.4121
## Number of obs: 463, groups:  profnumber, 94
##
## Fixed effects:
##             Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)  4.24463    0.10933 71.45689  38.826  < 2e-16 ***
## beauty       0.13681    0.05187 84.91999   2.638  0.00993 **
## female      -0.22306    0.08646 82.95211  -2.580  0.01165 *
```

```
## tenuretrack -0.22690    0.11094 72.67664  -2.045  0.04445 *
## nonenglish  -0.31512    0.16542 91.13033  -1.905  0.05994 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) beauty female tnrtrc
## beauty       0.093
## female      -0.420 -0.168
## tenuretrack -0.855 -0.037  0.105
## nonenglish   0.007  0.037 -0.014 -0.129
```

- All the predictors (possible exception `nonenglish` depending on where you set the cutoff) are significant in the model.
- As before, the intercept for profnumber is the baseline intercept without taking profnumber into account.
- The intercept and coefficients listed under Fixed effects are the baseline level for a hypothetical male professor with beauty of zero, who is not on a tenure track and got their undergraduate degree in an english speaking country.

Exercise 7

The two values are roughly equal - this means that the tau^2 value and the *average* sigma^2j value are roughly equal in the equation for estimated group mean. For constant values of n, this would mean that were considering the group's information and the overall information (from tau^2 and grand mean) roughly evenly.

Exercise 8

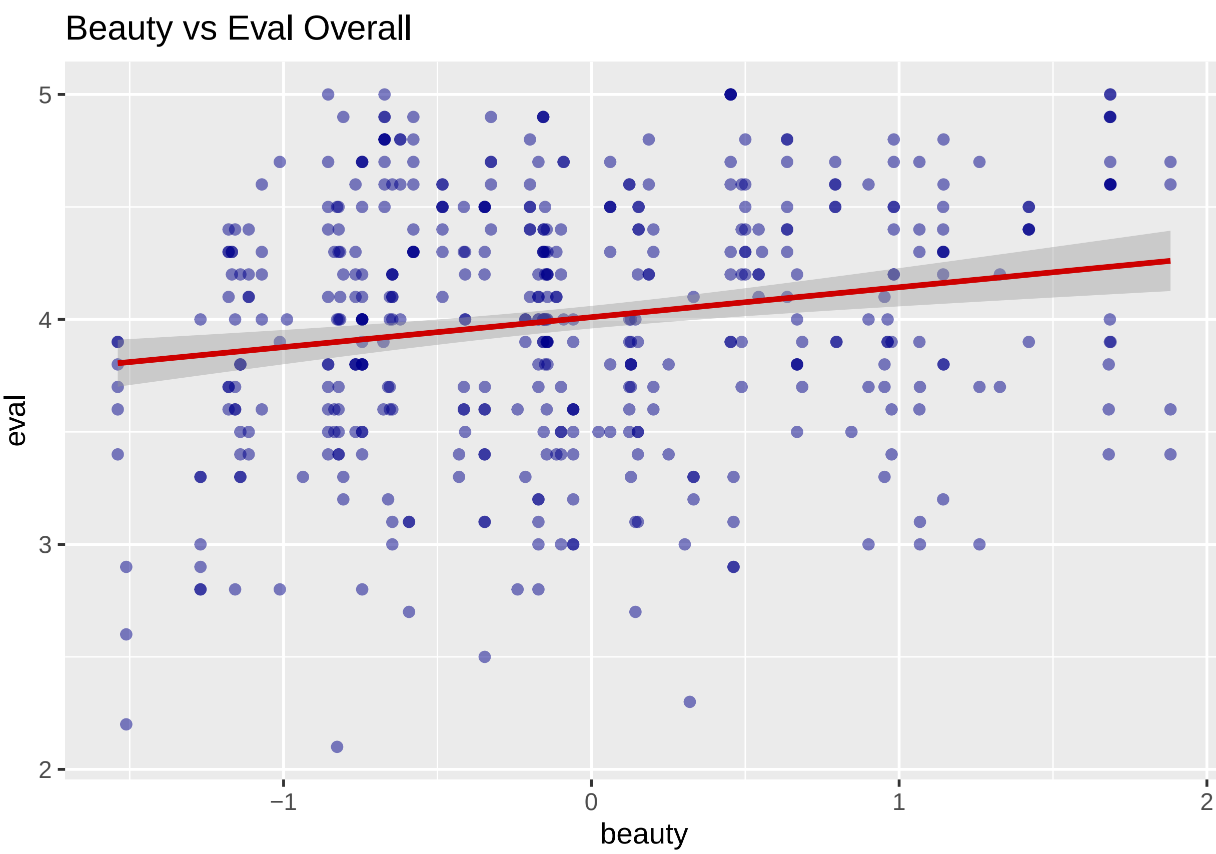
```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## eval ~ beauty + female + tenuretrack + nonenglish + (1 | profnumber) +
##     (beauty | courseID)
##    Data: Beauty
##
## REML criterion at convergence: 622.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9599 -0.6028  0.0664  0.5628  2.4661
##
## Random effects:
##  Groups     Name        Variance Std.Dev. Corr
##  profnumber (Intercept) 0.117023 0.34209
##  courseID   (Intercept) 0.069497 0.26362
##             beauty      0.003582 0.05985  0.01
##  Residual               0.152904 0.39103
## Number of obs: 463, groups:  profnumber, 94; courseID, 31
##
## Fixed effects:
##             Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)  4.23904    0.12382 87.85082  34.236  < 2e-16 ***
## beauty       0.12048    0.06274  6.46862   1.920  0.09972 .
## female      -0.23108    0.08564 84.92313  -2.698  0.00841 **
```

```
## tenuretrack -0.21201    0.10988 74.25688  -1.929  0.05750 .
## nonenglish  -0.30766    0.16519 93.72753  -1.862  0.06568 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) beauty female tnrtrc
## beauty       0.072
## female      -0.355 -0.127
## tenuretrack -0.752 -0.006  0.095
## nonenglish  -0.010  0.026 -0.021 -0.124
```

- The intercept, coefficients and their significance levels changed for the fixed effects. This is because some information that could be explained by courseID was accounted for by the fixed effects - once we split courseID out into its own grouping variable, it became clear that within a specific courseID, the other predictors were not as significant.

Exercise 9

- In the EDA plot below, it appears that beauty is likely to be a significant predictor. In fact, before separating by profnumber and courseID, it is statistically significant - however, after fitting the hierarchical model, we found that beauty was not significant.



Exercise 10

- Based on EDA, `onecredit` looks like a reasonable candidate.

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: eval ~ beauty + female + tenuretrack + nonenglish + onecredit +
##     (1 | profnumber) + (beauty | courseID)
##    Data: Beauty
##
## REML criterion at convergence: 618.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9561 -0.5982  0.0840  0.5809  2.4703
##
## Random effects:
##  Groups     Name        Variance Std.Dev. Corr
##  profnumber (Intercept) 0.109642 0.3311
##  courseID   (Intercept) 0.055465 0.2355
##             beauty      0.003956 0.0629   0.02
##  Residual               0.153620 0.3919
## Number of obs: 463, groups:  profnumber, 94; courseID, 31
##
## Fixed effects:
##              Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)   4.17187    0.12197  87.64415  34.204  < 2e-16 ***
## beauty        0.12203    0.06212   6.37994   1.964  0.09425 .
## female       -0.22326    0.08357  82.52677  -2.671  0.00910 **
## tenuretrack  -0.15642    0.10911  75.99022  -1.434  0.15578
## nonenglish   -0.31581    0.16121  91.28202  -1.959  0.05317 .
## onecredit     0.34823    0.13028 355.09878   2.673  0.00787 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) beauty female tnrtrc nnngls
## beauty       0.064
## female      -0.357 -0.123
## tenuretrack -0.770  0.001  0.100
## nonenglish  -0.004  0.025 -0.022 -0.126
## onecredit   -0.208  0.027  0.030  0.195 -0.021
```

- Fitting the model shows that `onecredit` is significant. According to the coefficient, we would expect a one-credit course to have an average eval of 0.348 higher than a course that is not one-credit.