

## hw7-Linear Mixed Effects model case study

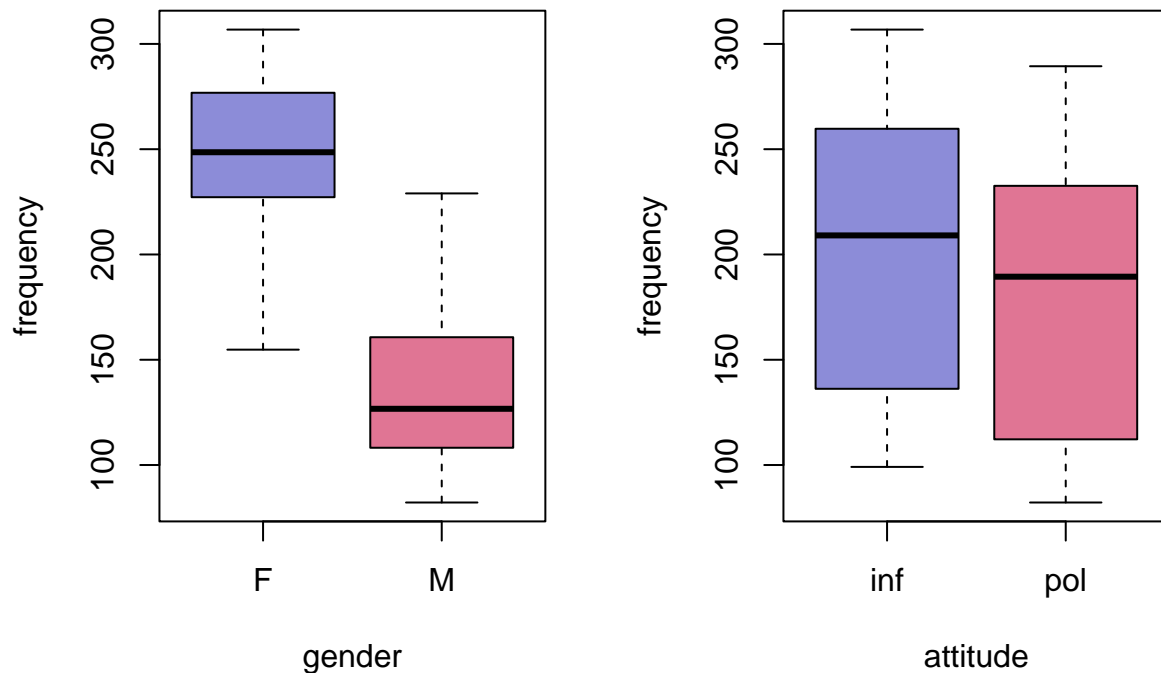
Cary Ni

```
# load dataset and modify variable types
data_df = read_csv("../data/HW7-politeness_data.csv", show_col_types = FALSE)
data_df[, c(1:4)] = lapply(data_df[, c(1:4)], as.factor)
```

(a)

```
# simple visualization of the categorical data
par(mfrow=c(1,2))
myColors = c(rgb(0.1,0.1,0.7,0.5) , rgb(0.8,0.1,0.3,0.6))

boxplot(frequency ~ gender, data = data_df, xlab = "gender", col = myColors)
boxplot(frequency ~ attitude, data = data_df, xlab = "attitude", col = myColors)
```



The boxplots show that female is associated with remarkably higher frequency than male while the informal register has a frequency that is only slightly higher than formal register.

(b)

```
model_1 = lme(frequency ~ gender + attitude, random = ~1 | subject, data = data_df)
summary(model_1)
```

```
## Linear mixed-effects model fit by REML
##   Data: data_df
##       AIC      BIC    logLik
##   806.0805 818.0527 -398.0402
##
## Random effects:
##   Formula: ~1 | subject
##           (Intercept) Residual
## StdDev:    24.45803 29.11537
##
## Fixed effects: frequency ~ gender + attitude
##               Value Std.Error DF   t-value p-value
## (Intercept)  256.98690 15.154986 77 16.957251  0.0000
## genderM      -108.79762 20.956235  4 -5.191659  0.0066
## attitudepol  -20.00238  6.353495 77 -3.148248  0.0023
## Correlation:
##           (Intr) gendrM
## genderM      -0.691
## attitudepol -0.210  0.000
##
## Standardized Within-Group Residuals:
##           Min           Q1           Med           Q3           Max
## -2.3564422 -0.5658319 -0.2011979  0.4617895  3.2997610
##
## Number of Observations: 84
## Number of Groups: 6
```

Covariance Matrix for Yi

```
extract.lme.cov2(model_1, data_df)$V[[1]]
```

```
##           [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## [1,] 1445.9002  598.1953  598.1953  598.1953  598.1953  598.1953  598.1953
## [2,]  598.1953 1445.9002  598.1953  598.1953  598.1953  598.1953  598.1953
## [3,]  598.1953  598.1953 1445.9002  598.1953  598.1953  598.1953  598.1953
## [4,]  598.1953  598.1953  598.1953 1445.9002  598.1953  598.1953  598.1953
## [5,]  598.1953  598.1953  598.1953  598.1953 1445.9002  598.1953  598.1953
## [6,]  598.1953  598.1953  598.1953  598.1953  598.1953 1445.9002  598.1953
## [7,]  598.1953  598.1953  598.1953  598.1953  598.1953  598.1953 1445.9002
## [8,]  598.1953  598.1953  598.1953  598.1953  598.1953  598.1953  598.1953
## [9,]  598.1953  598.1953  598.1953  598.1953  598.1953  598.1953  598.1953
```

```
## [10,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [11,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [12,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [13,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [14,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
##      [,8]      [,9]      [,10]      [,11]      [,12]      [,13]      [,14]
## [1,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [2,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [3,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [4,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [5,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [6,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [7,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [8,] 1445.9002 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953
## [9,] 598.1953 1445.9002 598.1953 598.1953 598.1953 598.1953 598.1953
## [10,] 598.1953 598.1953 1445.9002 598.1953 598.1953 598.1953 598.1953
## [11,] 598.1953 598.1953 598.1953 1445.9002 598.1953 598.1953 598.1953
## [12,] 598.1953 598.1953 598.1953 598.1953 1445.9002 598.1953 598.1953
## [13,] 598.1953 598.1953 598.1953 598.1953 598.1953 1445.9002 598.1953
## [14,] 598.1953 598.1953 598.1953 598.1953 598.1953 598.1953 1445.9002
```

#### Covariance matrix of fixed effects

```
vcov(model_1)
```

```
##      (Intercept)      genderM      attitudepol
## (Intercept)  229.67362 -2.195819e+02 -2.018345e+01
## genderM      -219.58189  4.391638e+02  6.451438e-15
## attitudepol  -20.18345   6.451438e-15  4.036690e+01
```

#### BLUP for intercepts

```
random.effects(model_1)
```

```
##      (Intercept)
## F1  -13.575831
## F2   10.170522
## F3   3.405309
## M3  27.960288
## M4   4.739325
## M7 -32.699613
```

#### Residuals

```
data_df$frequency-fitted(model_1)
```

```
##          F1          F1          F1          F1          F1          F1
## -10.1086926 -38.9110735  61.6913074  16.2889265 -19.5086926  43.4889265
##          F1          F1          F1          F1          F1          F1
##  27.3913074  33.3889265   8.4913074   8.9889265 -42.2086926 -12.7110735
##          F1          F1          F3          F3          F3          F3
## -26.9110735 -68.6086926 -10.6898326 -23.0922136  -3.5898326  -9.3922136
##          F3          F3          F3          F3          F3          F3
##  26.6101674   5.6077864  35.0101674  46.4077864  -7.7898326  -7.8922136
##          F3          F3          F3          F3          M4          M4
## -13.8898326  18.4077864   4.0077864 -54.8898326 -22.2262298 -29.3286108
##          M4          M4          M4          M4          M4          M4
##  96.0737702 -38.0286108 -20.7262298  60.6713892  60.4737702   9.9713892
##          M4          M4          M4          M4          M4          M4
## -31.1262298 -26.0286108 -22.9262298 -16.7286108  -6.9286108  -6.4262298
##          M7          M7          M7          M7          M7          M7
##  -9.3872916 -16.3896725 -13.2872916 -11.1896725  -9.5872916  -5.2896725
##          M7          M7          M7          M7          M7          M7
##   1.6127084   4.5103275  -1.7872916 -12.5896725  13.3127084  -7.2896725
##          M7          M7          F2          F2          F2          F2
##   8.9103275  12.1127084 -14.4550462 -35.8574271  -0.8550462  -7.4574271
##          F2          F2          F2          F2          F2          F2
##  42.2449538  34.6425729  -3.9550462  29.0425729  30.5449538  27.0425729
##          F2          F2          F2          F2          M3          M3
## -39.1550462 -41.2574271  13.8425729 -19.9550462  -2.3471929  12.6504261
##          M3          M3          M3          M3          M3          M3
## -13.7471929  23.5504261   4.0528071   9.9504261  51.3528071  14.7504261
##          M3          M3          M3          M3          M3          M3
##   4.5528071 -19.6495739  -9.4471929 -18.1495739 -15.0495739  -2.8471929
## attr("label")
## [1] "Fitted values"
```

```
model_1$residuals
```

```
##          fixed      subject
## 1  -23.6845238 -10.1086926
## 2  -52.4869048 -38.9110735
## 3   48.1154762  61.6913074
## 4    2.7130952  16.2889265
## 5  -33.0845238 -19.5086926
## 6   29.9130952  43.4889265
## 7   13.8154762  27.3913074
## 8   19.8130952  33.3889265
## 9   -5.0845238   8.4913074
## 10  -4.5869048   8.9889265
## 11 -55.7845238 -42.2086926
## 12 -26.2869048 -12.7110735
## 13 -40.4869048 -26.9110735
## 14 -82.1845238 -68.6086926
## 15  -7.2845238 -10.6898326
## 16 -19.6869048 -23.0922136
## 17  -0.1845238  -3.5898326
## 18  -5.9869048  -9.3922136
## 19  30.0154762  26.6101674
## 20   9.0130952   5.6077864
```

```

## 21 38.4154762 35.0101674
## 22 49.8130952 46.4077864
## 23 -4.3845238 -7.7898326
## 24 -4.4869048 -7.8922136
## 25 -10.4845238 -13.8898326
## 26 21.8130952 18.4077864
## 27 7.4130952 4.0077864
## 28 -51.4845238 -54.8898326
## 29 -17.4869048 -22.2262298
## 30 -24.5892857 -29.3286108
## 31 100.8130952 96.0737702
## 32 -33.2892857 -38.0286108
## 33 -15.9869048 -20.7262298
## 34 65.4107143 60.6713892
## 35 65.2130952 60.4737702
## 36 14.7107143 9.9713892
## 37 -26.3869048 -31.1262298
## 38 -21.2892857 -26.0286108
## 39 -18.1869048 -22.9262298
## 40 -11.9892857 -16.7286108
## 41 -2.1892857 -6.9286108
## 42 -1.6869048 -6.4262298
## 43 -42.0869048 -9.3872916
## 44 -49.0892857 -16.3896725
## 45 -45.9869048 -13.2872916
## 46 -43.8892857 -11.1896725
## 47 -42.2869048 -9.5872916
## 48 -37.9892857 -5.2896725
## 49 -31.0869048 1.6127084
## 50 -28.1892857 4.5103275
## 51 -34.4869048 -1.7872916
## 52 -45.2892857 -12.5896725
## 53 -19.3869048 13.3127084
## 54 -39.9892857 -7.2896725
## 55 -23.7892857 8.9103275
## 56 -20.5869048 12.1127084
## 57 -4.2845238 -14.4550462
## 58 -25.6869048 -35.8574271
## 59 9.3154762 -0.8550462
## 60 2.7130952 -7.4574271
## 61 52.4154762 42.2449538
## 62 44.8130952 34.6425729
## 63 6.2154762 -3.9550462
## 64 39.2130952 29.0425729
## 65 40.7154762 30.5449538
## 66 37.2130952 27.0425729
## 67 -28.9845238 -39.1550462
## 68 -31.0869048 -41.2574271
## 69 24.0130952 13.8425729
## 70 -9.7845238 -19.9550462
## 71 25.6130952 -2.3471929
## 72 40.6107143 12.6504261
## 73 14.2130952 -13.7471929
## 74 51.5107143 23.5504261

```

```
## 75 32.0130952 4.0528071
## 76 37.9107143 9.9504261
## 77 79.3130952 51.3528071
## 78 42.7107143 14.7504261
## 79 32.5130952 4.5528071
## 80 8.3107143 -19.6495739
## 81 18.5130952 -9.4471929
## 82 9.8107143 -18.1495739
## 83 12.9107143 -15.0495739
## 84 25.1130952 -2.8471929
## attr(,"std")
## [1] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [9] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [17] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [25] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [33] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [41] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [49] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [57] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [65] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [73] 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537 29.11537
## [81] 29.11537 29.11537 29.11537 29.11537
```

(c)

```
# Rebuild the model_1 with ML
model_2 = lme(frequency ~ gender + attitude, random = ~1 | subject, data = data_df, method = "ML")
model_3 = lme(frequency ~ gender*attitude, random = ~1 | subject, data = data_df, method = "ML")
# Likelihood ratio test
anova(model_2, model_3)
```

```
##          Model df      AIC      BIC    logLik   Test  L.Ratio p-value
## model_2      1  5 825.6363 837.7904 -407.8182
## model_3      2  6 826.2508 840.8357 -407.1254 1 vs 2 1.385523 0.2392
```

The likelihood ratio test gives a p value of 0.239, which fails to reject the null hypothesis. Therefore, we will take the small model and believe that the interaction term between gender and attitude is not significantly associated with pitch.

(d)

**Mixed effects Model**

$$Y_{ij} = \beta_0 + X^T \beta_1 + b_i + b_m + \epsilon_{ij}$$

$$b_i \sim N(0, \sigma_i^2) b_m \sim N(0, \sigma_m^2) \epsilon_{ij} \sim N(0, \sigma^2)$$

Note:  $b_i$  is the random intercept introduced by **subjects**,  $b_m$  is the random intercept introduced by **scenarios** (m scenarios in total).  $X^T$  is the fixed effects of **gender** and **attitude**.

```
# Build the model
model_4 = lmer(frequency ~ gender + attitude + (1 | subject) + (1 | scenario), data = data_df)
summary(model_4)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: frequency ~ gender + attitude + (1 | subject) + (1 | scenario)
## Data: data_df
##
## REML criterion at convergence: 784.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.2690 -0.6331 -0.0878  0.5204  3.5326
##
## Random effects:
## Groups Name Variance Std.Dev.
## scenario (Intercept) 224.5 14.98
## subject (Intercept) 613.2 24.76
## Residual 637.8 25.25
## Number of obs: 84, groups: scenario, 7; subject, 6
##
## Fixed effects:
## Estimate Std. Error t value
## (Intercept) 256.987 16.101 15.961
## genderM -108.798 20.956 -5.192
## attitudepol -20.002 5.511 -3.630
##
## Correlation of Fixed Effects:
## (Intr) gendrM
## genderM -0.651
## attitudepol -0.171 0.000
```

Covariance Matrix for  $Y_i$

```
# get variance of random effects
VarCorr(model_4)
```

```
## Groups Name Std.Dev.
## scenario (Intercept) 14.983
## subject (Intercept) 24.763
## Residual 25.254
```

```
# build the covariance matrix for  $Y_i$ 
knitr::include_graphics("../data/corr matrix.png")
```

$$v\hat{a}r(y_i) = \begin{pmatrix} 1476 & \dots & 613 & 838 & \dots & 613 \\ \vdots & 1476 & \vdots & \vdots & 838 & \vdots \\ 613 & \dots & 1476 & 613 & \dots & 838 \\ 838 & \dots & 613 & 1476 & \dots & 613 \\ \vdots & 838 & \vdots & \vdots & 1476 & \vdots \\ 613 & \dots & 838 & 613 & \dots & 1476 \end{pmatrix}$$

### Coefficient of attitude

```
fixed.effects(model_4)
```

```
## (Intercept)      genderM attitudepol
##   256.98690  -108.79762   -20.00238
```

The coefficient of **attitude** indicates that talking in formal register is expected to have a 20 Hz decrease in frequency compared to informal register while holding gender fixed.