# Portfolio Assignment 1, Methods 3, 2021, autumn semester

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## Note

All work was done collectively as part of the study group, but for assessment purposes, student initials have been added to various sections indicating the person who worked on that section.

# Portfolio Assignment 1: Using mixed effects modelling to model hierarchical data

In this assignment we will be investigating the *politeness* dataset of Winter and Grawunder (2012) and apply basic methods of multilevel modelling.

```
#this is the dataset we will be exploring in this exercise
politeness <- read.csv('politeness.csv') ## read in data
```

# Exercise 1 - describing the dataset and making some initial plots

1. Describe the dataset, such that someone who happened upon this dataset could understand the variables and what they contain

## Exercise 1, part 1 – (EH)

The politeness dataset contains the data obtained from the study of Korean formal and informal speech (https://doi.org/10.1016/j.wocn.2012.08.006) which investigated the fundamental frequency of male and female participants’ speech in a variety of formal and informal scenarios.

The following table describes the variables in the dataset:

| Variable | Description |
|---|---|
| `subject` | participant ID |
| `gender` | participant’s gender |
| `scenario` | the experimental scenario from 1 to 7 such as “asking a favour” |
| `attitude` | either ‘inf’ for informal stimuli or ‘pol’ for formal stimuli |
| `total_duration` | duration of participant’s response in seconds |

| Variable | Description |
|---|---|
| `f0mn` | mean fundamental frequency (f0) of the participant’s speech |
| `hiss_count` | number of times the participants made a noisy breath intake |

Remark: The `gender` , `scenario` and `attitude` variables should be encoded as factors as they show a categorical function withing this dataset . In addition, these variables have non-unique values across participants, and are not ordered.

```
#Encoding some of the variables as factors (gender, attitude, and scenario)

politeness$attitude <- as.factor(politeness$attitude)
politeness$gender <- as.factor(politeness$gender)
politeness$scenario <- as.factor(politeness$scenario)
```

# Exercise 1, part 2–(EH)

2. Create a new data frame that just contains the subject *F1* and run two linear models; one that expresses *f0mn* as dependent on *scenario* as an integer; and one that expresses *f0mn* as dependent on *scenario* encoded as a factor
   i. Include the model matrices, $X$ from the General Linear Model, for these two models in your report and describe the different interpretations of *scenario* that these entail
   ii. Which coding of *scenario*, as a factor or not, is more fitting?

```
# Create a subset dataframe for subject F1 only
pf1 <- politeness[politeness$subject == "F1", ]
pf1
```

```
##    subject gender scenario attitude total_duration  f0mn hiss_count
## 1       F1      F        1      pol         18.392 214.6          2
## 2       F1      F        1      inf         13.551 210.9          0
## 3       F1      F        2      pol          5.217 284.7          0
## 4       F1      F        2      inf          4.247 265.6          0
## 5       F1      F        3      pol          6.791 210.6          0
## 6       F1      F        3      inf          4.126 285.6          0
## 7       F1      F        4      pol          6.244 251.5          1
## 8       F1      F        4      inf          3.245 281.5          0
## 9       F1      F        5      pol          5.625 229.6          1
## 10      F1      F        5      inf          3.950 250.5          0
## 11      F1      F        6      pol         28.508 181.1          1
## 12      F1      F        6      inf         55.159 229.3          0
## 13      F1      F        7      inf         60.309 219.8          2
## 14      F1      F        7      pol         40.825 175.8          0
```

```
# make model predicting f0mn by scenario (integer)
m1<- lm(f0mn ~ as.integer(scenario), data = pf1)

# get model matrix
mm1 <- model.matrix(m1)

# make model predicting f0mn by scenario (factor)
m2 <- lm(f0mn ~ as.factor(scenario), data = pf1)

# get model matrix
mm2 <- model.matrix(m2)
```

```
Here is the model using "scenario" encoded as an integer
```

```
summary(m1)
```

```
## 
## Call:
## lm(formula = f0mn ~ as.integer(scenario), data = pf1)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -44.836 -36.807   6.686  20.918  46.421 
## 
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)    
## (Intercept)           262.621     20.616  12.738 2.48e-08 ***
## as.integer(scenario)   -6.886      4.610  -1.494    0.161    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 34.5 on 12 degrees of freedom
## Multiple R-squared:  0.1568, Adjusted R-squared:  0.0865 
## F-statistic: 2.231 on 1 and 12 DF,  p-value: 0.1611
```

```
mm1
```

```
##    (Intercept) as.integer(scenario)
## 1            1                    1
## 2            1                    1
## 3            1                    2
## 4            1                    2
## 5            1                    3
## 6            1                    3
## 7            1                    4
## 8            1                    4
## 9            1                    5
## 10           1                    5
## 11           1                    6
## 12           1                    6
## 13           1                    7
## 14           1                    7
## attr(,"assign")
## [1] 0 1
```

And here is the model using “scenario” encoded as a factor

```
summary(m2)
```

```
## 
## Call:
## lm(formula = f0mn ~ as.factor(scenario), data = pf1)
## 
## Residuals:
##    Min     1Q Median     3Q    Max 
## -37.50 -13.86   0.00  13.86  37.50 
## 
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)    
## (Intercept)            212.75      20.35  10.453  1.6e-05 ***
## as.factor(scenario)2    62.40      28.78   2.168   0.0668 .  
## as.factor(scenario)3    35.35      28.78   1.228   0.2591    
## as.factor(scenario)4    53.75      28.78   1.867   0.1041    
## as.factor(scenario)5    27.30      28.78   0.948   0.3745    
## as.factor(scenario)6    -7.55      28.78  -0.262   0.8006    
## as.factor(scenario)7   -14.95      28.78  -0.519   0.6195    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 28.78 on 7 degrees of freedom
## Multiple R-squared:  0.6576, Adjusted R-squared:  0.364 
## F-statistic:  2.24 on 6 and 7 DF,  p-value: 0.1576
```

```
mm2
```

```
##    (Intercept) as.factor(scenario)2 as.factor(scenario)3 as.factor(scenario)4
## 1            1                    0                    0                    0
## 2            1                    0                    0                    0
## 3            1                    1                    0                    0
## 4            1                    1                    0                    0
## 5            1                    0                    1                    0
## 6            1                    0                    1                    0
## 7            1                    0                    0                    1
## 8            1                    0                    0                    1
## 9            1                    0                    0                    0
## 10           1                    0                    0                    0
## 11           1                    0                    0                    0
## 12           1                    0                    0                    0
## 13           1                    0                    0                    0
## 14           1                    0                    0                    0
##    as.factor(scenario)5 as.factor(scenario)6 as.factor(scenario)7
## 1                     0                    0                    0
## 2                     0                    0                    0
## 3                     0                    0                    0
## 4                     0                    0                    0
## 5                     0                    0                    0
## 6                     0                    0                    0
## 7                     0                    0                    0
## 8                     0                    0                    0
## 9                     1                    0                    0
## 10                    1                    0                    0
## 11                    0                    1                    0
## 12                    0                    1                    0
## 13                    0                    0                    1
## 14                    0                    0                    1
## attr(,"assign")
## [1] 0 1 1 1 1 1 1
## attr(,"contrasts")
## attr(,"contrasts")$`as.factor(scenario)`
## [1] "contr.treatment"
```

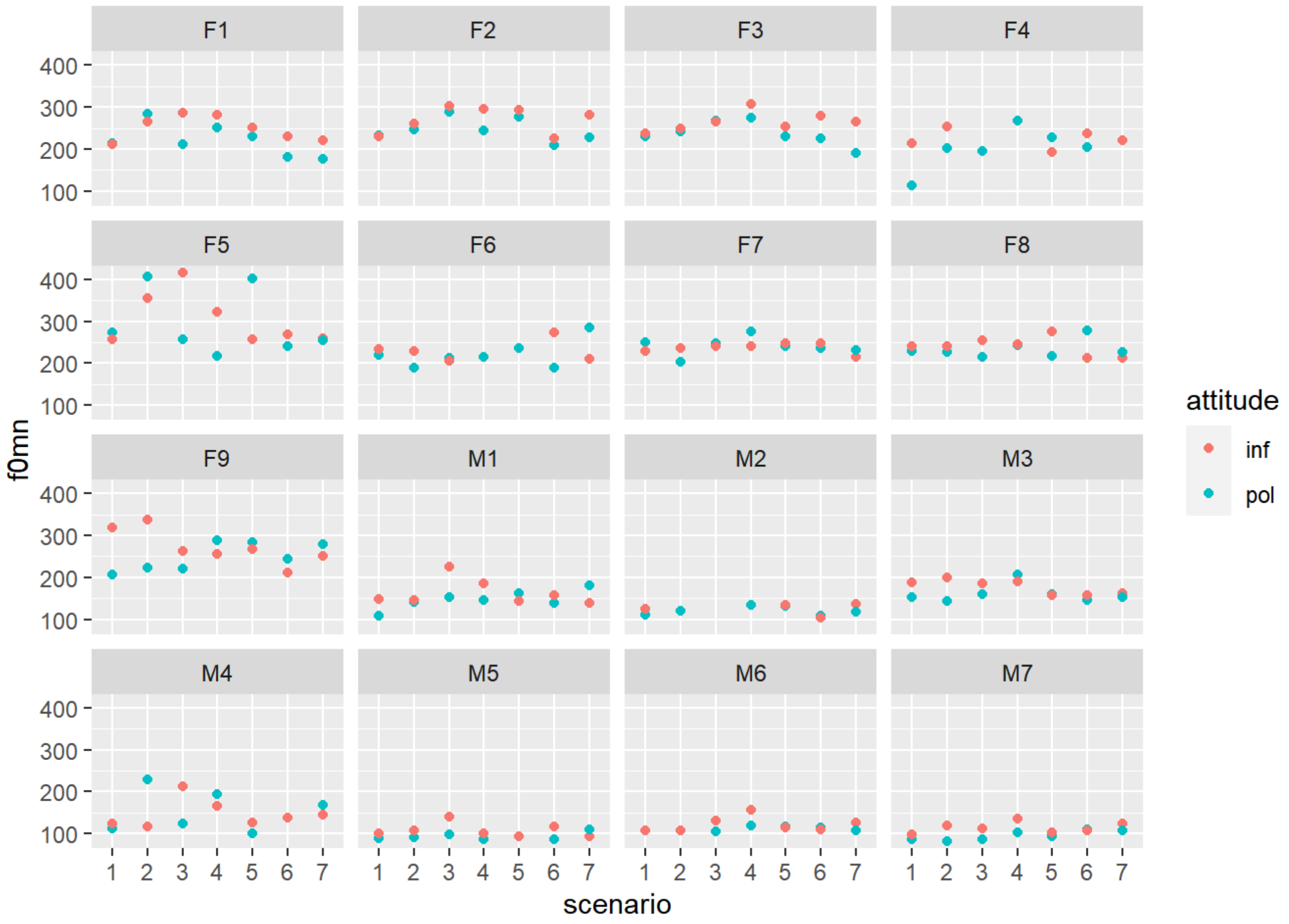
Conclusion: The above output shows the difference in model matrices between scenario encoded as an integer and factor. The integer version treats scenario as a continuous variable, whereas the factorized version creates a regression line per scenario.

For this dataset, scenario should be a factor, since the scenarios are not a continuous variable and depending on the prescribed scenario, the participants may have a different f0 (mean fundamental frequency of speech), and we are interested in following the trajectory of f0 across scenarios not as a variable that consistently decreases or increases, but a separate regression line showing the changes in f0 between the 7 different scenarios. And in order, to be able to see that crucial difference we need to consider the ‘scenario’ variable as a factor when we run a model predicting f0 across scenarios.

# Exercise 1, part 3 – (EH)

3. Make a plot that includes a subplot for each subject that has *scenario* on the x-axis and *f0mn* on the y-axis and where points are colour coded according to *attitude*
    i. Describe the differences between subjects

```
politeness %>% ggplot(aes(scenario, f0mn, color = attitude)) +
    geom_point() +
    facet_wrap(vars(subject))
```



…

We can visually observe that there are baseline differences between the male and female subjects’ mean fundamental frequency of speech, where the males’ f0 is consistently lower, across scenario and attitude. Between the different scenarios there is variability in the f0 values for both male and female subjects depending on both the scenario type and the attitude (informal or formal). There is a consistent tendency across scenario type and gender for the mean fundamental frequency of speech to be slightly higher when the attitude is informal as opposed to formal. This visual information inerpreted from this plot is consistent with the results of Winter and Grawunder (2012)

# Exercise 2 - comparison of models

```
mixed.model <- lmer(formula=..., data=...)
example.formula <- formula(dep.variable ~ first.level.variable + (1 | second.level.va
riable))
```

## Exercise 2, Part 1 – (VK)

1. Build four different models and do some comparisons

```
# the single level model
m3 <- lm(formula = f0mn ~ gender, data = politeness)

# a two-level model where each scenario has a unique intercept
m4 <- lmer(formula = f0mn ~ gender + (1 | scenario), data = politeness)
# a two-level model that has models subject as intercept
m5 <- lmer(formula = f0mn ~ gender + (1 | subject), data = politeness)

# a two-level model that incorporate intercepts for both subject and scenario
m6 <- lmer(formula = f0mn ~ gender +
            (1 | subject) + (1 | scenario), data = politeness)

#comparing AIC and Deviance values for all the models
AIC(m3)
```

```
## [1] 2163.971
```

```
AIC(m4)
```

```
## [1] 2152.314
```

```
AIC(m5)
```

```
## [1] 2099.626
```

```
AIC(m6)
```

```
## [1] 2092.482
```

```
deviance(m3)
```

```
## [1] 327033.6
```

```
deviance(m4)
```

```
## [1] 2144.314
```

```
deviance(m5)
```

```
## [1] 2091.626
```

```
deviance(m6)
```

```
## [1] 2082.482
```

```
anova(m4, m5, m6)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: politeness
## Models:
## m4: f0mn ~ gender + (1 | scenario)
## m5: f0mn ~ gender + (1 | subject)
## m6: f0mn ~ gender + (1 | subject) + (1 | scenario)
##    npar    AIC    BIC  logLik deviance   Chisq Df Pr(>Chisq)
## m4    4 2162.3 2175.7 -1077.1   2154.3
## m5    4 2112.1 2125.5 -1052.0   2104.1 50.2095  0
## m6    5 2105.2 2122.0 -1047.6   2095.2  8.8725  1   0.002895 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
piecewiseSEM::rsquared(c(m4, m5, m6))
```

```
##   Response   family     link method  Marginal Conditional
## 1     f0mn gaussian identity   none 0.6779555   0.6967788
## 2     f0mn gaussian identity   none 0.6681651   0.7899229
## 3     f0mn gaussian identity   none 0.6677206   0.8077964
```

The single level model performs the worst and this makes sense as we do not expect all participants to have the same f0 as their voices have naturally occurring differences (not just ones predicted by gender). There are differences that might be explained by the scenario or individual subject (as we observed in the plot above), however, neither of those are taken into account when using a single level model.

So then using two-level models that explain variance by either taking scenario or subject as random intercepts, is definitely an improvement to help explain more of the scenario/attitude based differences, not just the gender differences.

Consequently, Of the three multi-level models,it is model m6, which includes random intercepts for both subject and scenario,that has the most explained variance with for the entire model $R^2 \approx 0.81$ or 81%.

Additionally, we see that model m6 has the lowest AIC and deviance.

# Exercise 2, part 2 and 3 – (LR)

2. Why is our single-level model bad?
    i. create a new data frame that has three variables, *subject*, *gender* and *f0mn*, where *f0mn* is the average of all responses of each subject, i.e. averaging across *attitude* and_scenario_
    ii. build a single-level model that models *f0mn* as dependent on *gender* using this new dataset
    iii. make Quantile-Quantile plots, comparing theoretical quantiles to the sample quantiles) using `qqnorm` and `qqline` for the new single-level model and compare it to the old single-level model (from 1).i). Which model's residuals ($\epsilon$) fulfil the assumptions of the General Linear Model better?)
    iv. Also make a quantile-quantile plot for the residuals of the multilevel model with two intercepts. Does it look alright?
3. Plotting the two-intercepts model
    i. Create a plot for each subject, (similar to part 3 in Exercise 1), this time also indicating the fitted value for each of the subjects for each for the scenarios (hint use `fixef` to get the "grand effects" for each gender and `ranef` to get the subject- and scenario-specific effects)

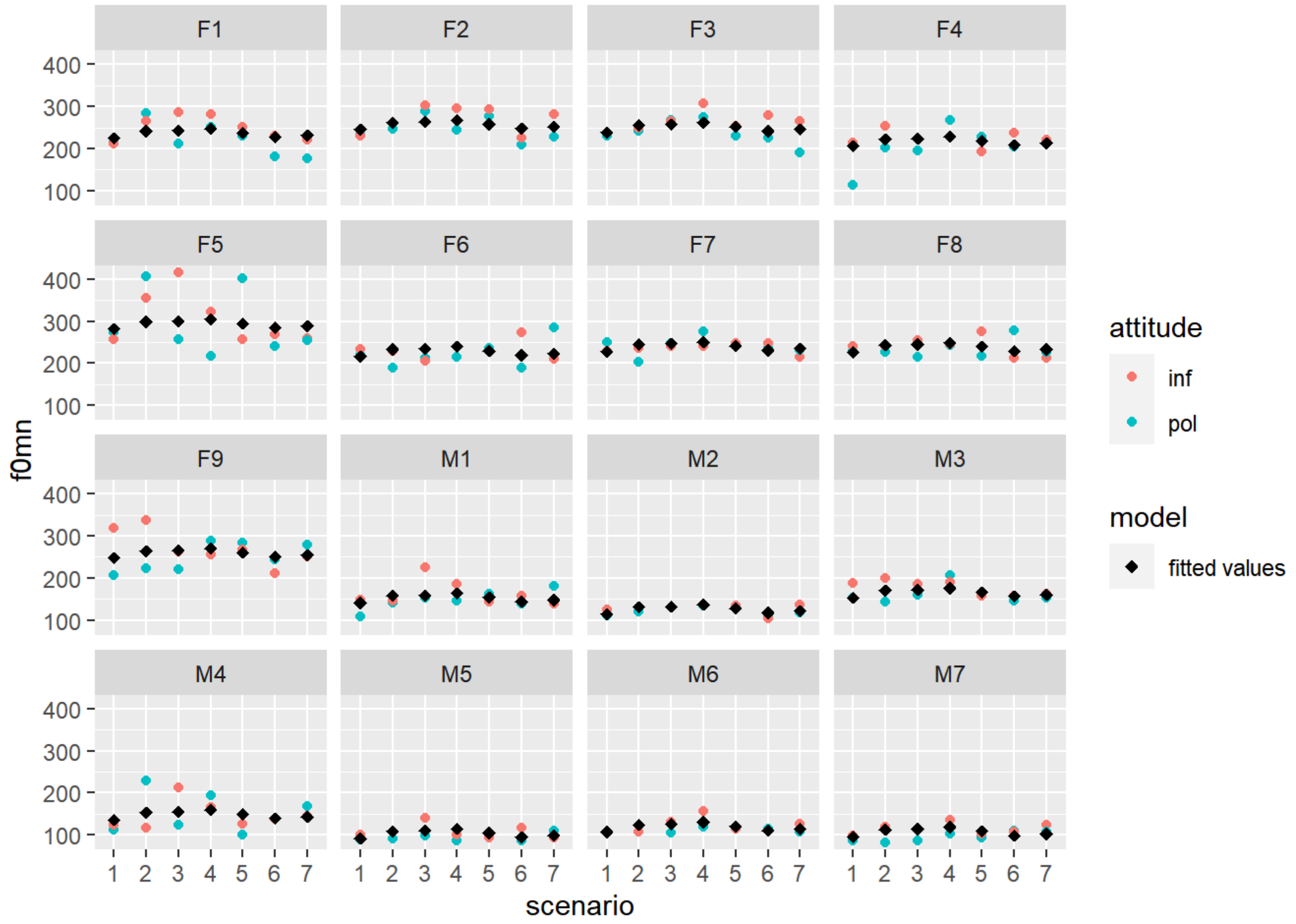
```
# scenario x f0mn y, attitude = color
ff <- fixef(m6)
ff
```

```
## (Intercept)     genderM
##    246.7650   -115.1746
```

```
rf <- ranef(m6)
rf <- as.data.frame(rf)
rf
```

```
##      grpvar        term grp    condval   condsd
## 1   subject (Intercept)  F1 -10.490356 8.280794
## 2   subject (Intercept)  F2  10.251809 8.280794
## 3   subject (Intercept)  F3   3.795129 8.280794
## 4   subject (Intercept)  F4 -29.495270 9.095403
## 5   subject (Intercept)  F5  47.093999 8.280794
## 6   subject (Intercept)  F6 -18.396273 8.794359
## 7   subject (Intercept)  F7  -6.976691 8.280794
## 8   subject (Intercept)  F8  -8.521934 8.280794
## 9   subject (Intercept)  F9  12.739587 8.280794
## 10  subject (Intercept)  M1  21.052117 8.280794
## 11  subject (Intercept)  M2  -5.462358 9.453009
## 12  subject (Intercept)  M3  33.561535 8.280794
## 13  subject (Intercept)  M4  16.093337 8.524543
## 14  subject (Intercept)  M5 -28.267430 8.280794
## 15  subject (Intercept)  M6 -12.640202 8.794541
## 16  subject (Intercept)  M7 -24.336998 8.280794
## 17 scenario (Intercept)   1 -11.595496 5.488728
## 18 scenario (Intercept)   2   5.321218 5.532205
## 19 scenario (Intercept)   3   6.795658 5.586194
## 20 scenario (Intercept)   4  11.348815 5.578013
## 21 scenario (Intercept)   5   1.411037 5.488705
## 22 scenario (Intercept)   6  -8.622136 5.489258
## 23 scenario (Intercept)   7  -4.659096 5.488058
```

```
politeness$effect_gender <- 0.0
politeness[politeness$gender == "F", ]$effect_gender <- ff[1]
politeness[politeness$gender == "M", ]$effect_gender <- ff[1] + ff[2]
politeness$intercept_subject <- left_join(politeness, rf, by = c("subject" = "grp"),
 copy = TRUE, keep = FALSE)$condval
politeness$intercept_scenario <- left_join(politeness, rf, by = c("scenario" = "grp"
), copy = TRUE, keep = FALSE)$condval
politeness$predicted <- politeness$effect_gender + politeness$intercept_subject + pol
iteness$intercept_scenario
politeness %>% ggplot(aes(scenario, f0mn, color = attitude)) +
    geom_point() +
    geom_point(aes(y = predicted, shape = "fitted values"), color = "black", size = 2
) +
    scale_shape_manual(name = "model", values = c(18)) +
    facet_wrap(vars(subject))
```



```
deviance(m3)
```

```
## [1] 327033.6
```

```
deviance(m4, REML = FALSE)
```

```
## [1] 2154.33
```

```
deviance(m5, REML = FALSE)
```

```
## [1] 2104.175
```

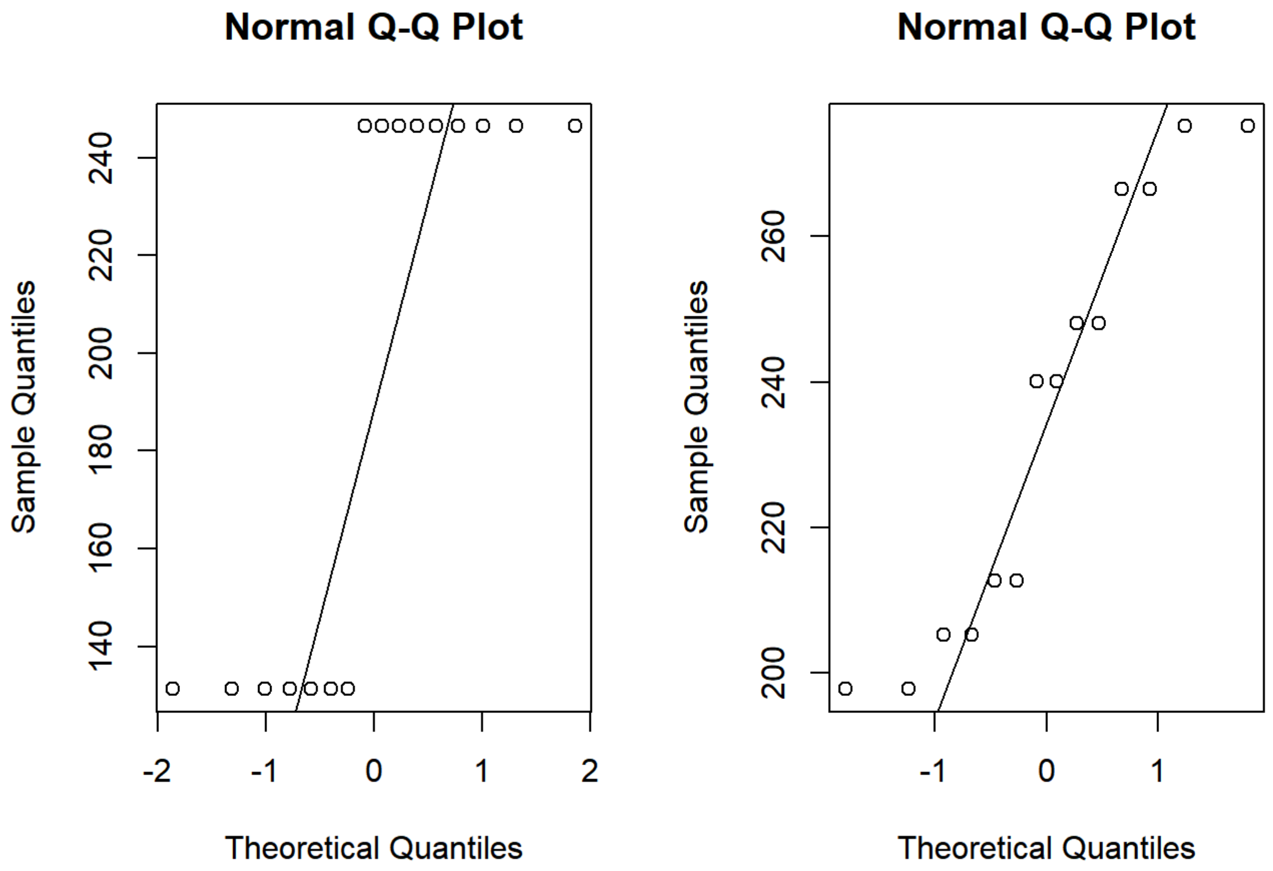
```
deviance(m6, REML = FALSE)
```

```
## [1] 2095.279
```

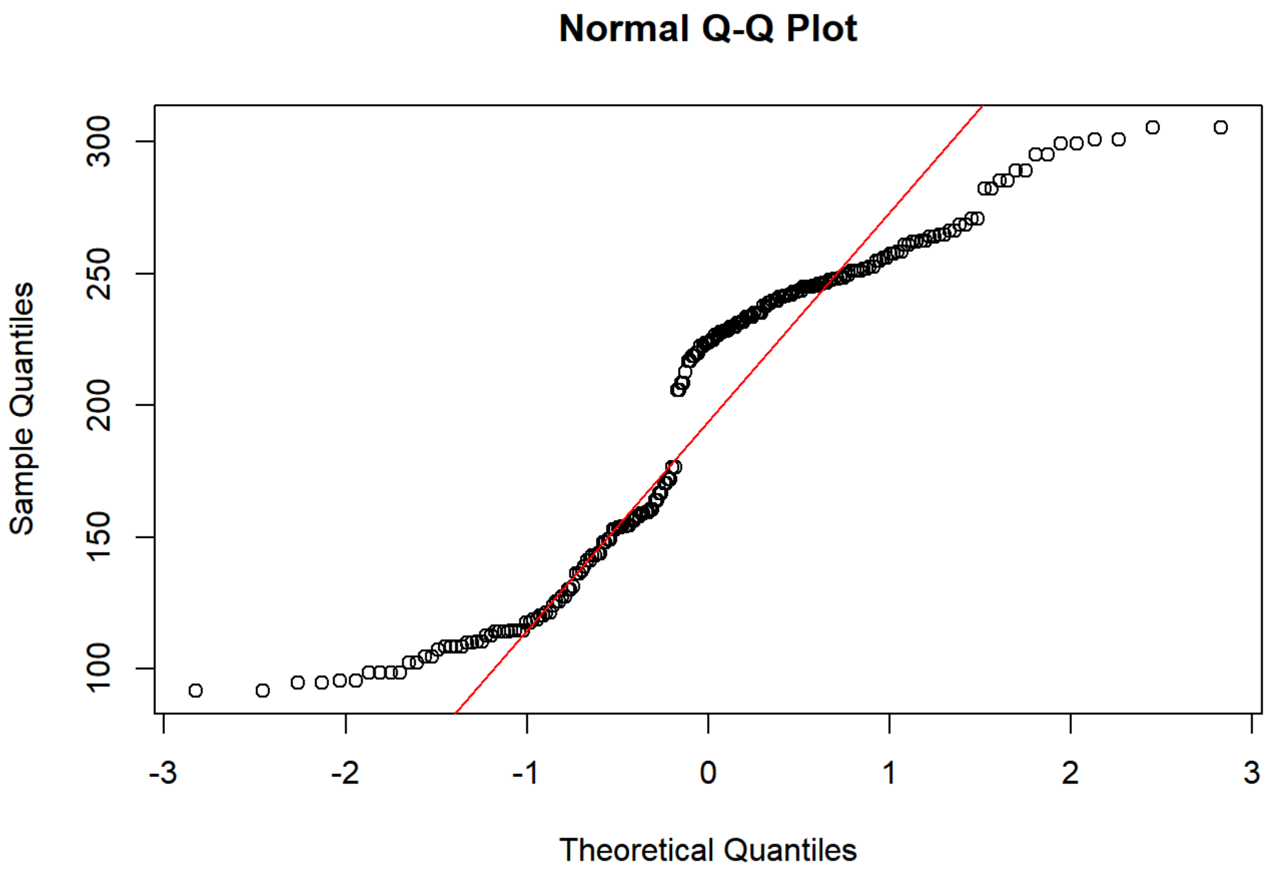
```
politeness_aggregated <- politeness[!is.na(politeness$f0mn), ] %>% group_by(subject)
%>% summarize(subject = subject[1], gender = gender[1], f0mn = mean(f0mn))
politeness_aggregated
```

```
## # A tibble: 16 x 3
##    subject gender  f0mn
##    <chr>   <fct>  <dbl>
##  1 F1      F       235.
##  2 F2      F       258.
##  3 F3      F       251.
##  4 F4      F       212.
##  5 F5      F       299.
##  6 F6      F       225.
##  7 F7      F       239.
##  8 F8      F       237.
##  9 F9      F       261.
## 10 M1      M       155.
## 11 M2      M       122.
## 12 M3      M       169.
## 13 M4      M       150.
## 14 M5      M       100.
## 15 M6      M       118.
## 16 M7      M       104.
```

```
m7 <- lm(f0mn ~ gender, data = politeness_aggregated)
par(mfrow=c(1,2))
qqnorm(fitted.values(m7))
qqline(fitted.values(m7))
qqnorm(fitted.values(m2))
qqline(fitted.values(m2))
```



```
par(mfrow=c(1,1))
qqnorm(fitted.values(m6))
qqline(fitted.values(m6), col = "red")
```



Assessing the QQ-plots of the single-level models it seems that the aggregated model m7's residuals are worse off than those of model m2. The residuals of model m2 are better dispersed along the line - however it still doesn't look fantastic. The QQ-plot of the multilevel model m6 looks better than any of the single level ones, with data points closer to the line and more evenly dispersed on both sides of the line.

Looking at the plot for the observed and the fitted values it looks as if the model m6 performs reasonably as well.

# Exercise 3 - now with attitude

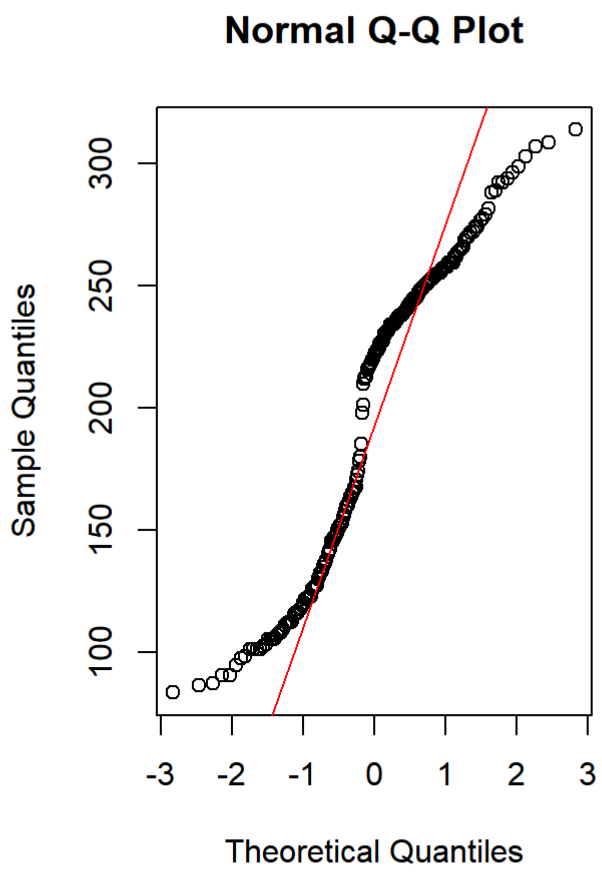
## Exercise 3, part 1 –(VK)

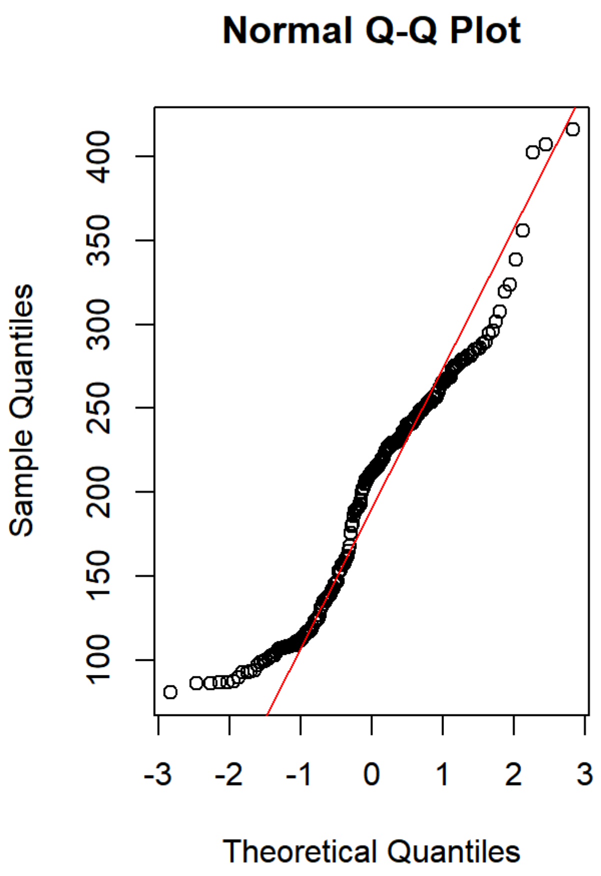
1. Carry on with the model with the two unique intercepts fitted (*scenario* and *subject*) but now build a new model that has *attitude* as a main effect besides *gender*. After create a separate model that besides the main effects of *attitude* and *gender* also include their interaction

```
#making a model with two unicue intercepts and having attitude and gender as main eff
ects
m8 <- lmer(formula = f0mn ~ gender + attitude + (1 | subject) + (1 | scenario), data
 = politeness)
summary(m8)
```

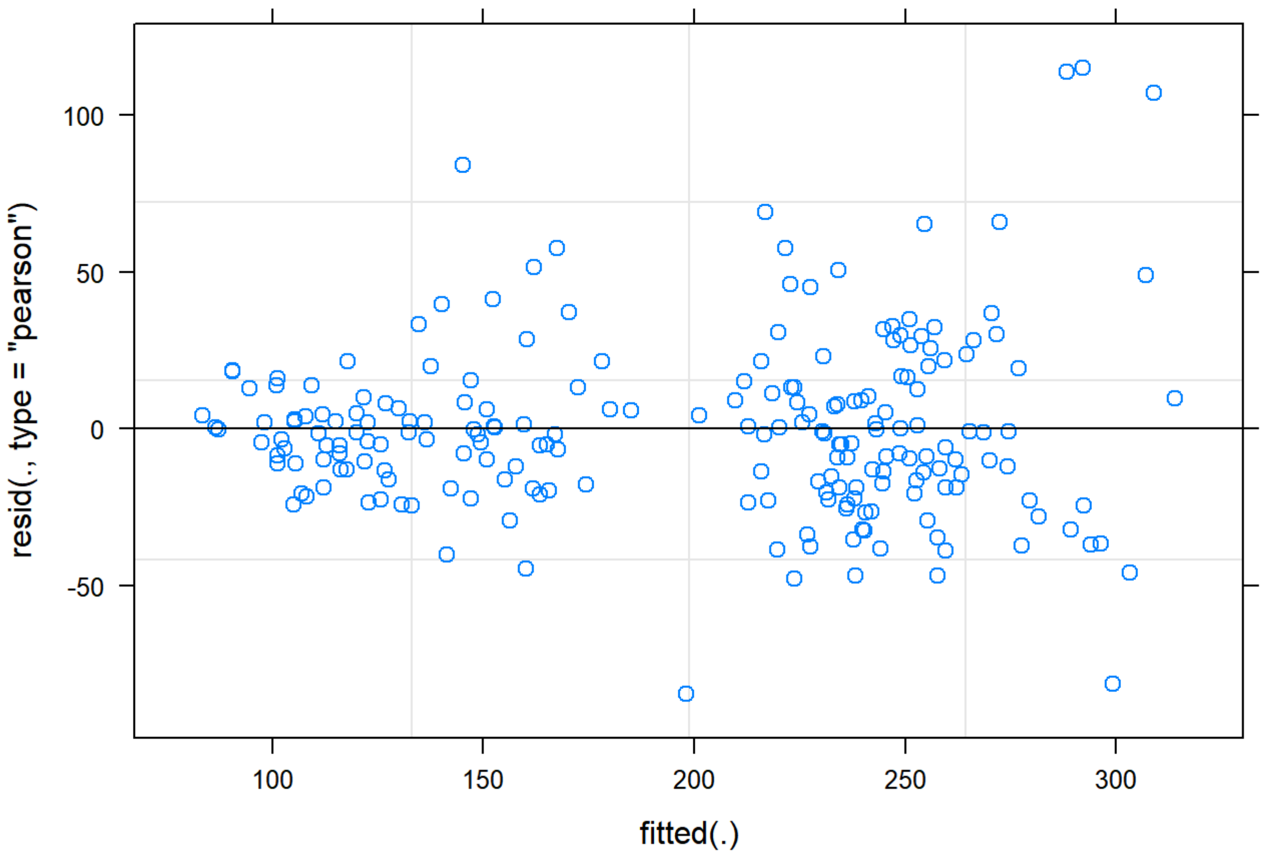
```
## Linear mixed model fit by REML ['lmerMod']
## Formula: f0mn ~ gender + attitude + (1 | subject) + (1 | scenario)
##    Data: politeness
##
## REML criterion at convergence: 2065.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8511 -0.6081 -0.0602  0.4329  3.8745
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subject  (Intercept) 585.6    24.20
##  scenario (Intercept) 106.7    10.33
##  Residual             882.7    29.71
## Number of obs: 212, groups:  subject, 16; scenario, 7
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  254.398      9.597  26.507
## genderM     -115.437     12.881  -8.962
## attitudepol  -14.819      4.096  -3.618
##
## Correlation of Fixed Effects:
##             (Intr) gendrM
## genderM     -0.587
## attitudepol -0.220  0.006
```

```
par(mfrow=c(1,2))
qqnorm(fitted.values(m8))
qqline(fitted.values(m8), col = "red")
qqnorm(politeness$f0mn)
qqline(politeness$f0mn, col = "red")
```


Normal Q-Q Plot
Sample Quantiles
100
150
200
250
300
-3
-2
-1
0
1
2
3
Theoretical Quantiles


Normal Q-Q Plot
Sample Quantiles
100
150
200
250
300
350
400
-3
-2
-1
0
1
2
3
Theoretical Quantiles

```
plot(m8)
```


resid(., type = "pearson")
100
50
0
-50
100
150
200
250
300
fitted(.)

```
#a model that additionally includes the interaction between the main effects (attitud
e and gender)
m9 <- lmer(formula = f0mn ~ gender + attitude + gender:attitude + (1 | subject) + (1
 | scenario), data = politeness)
summary(m9)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: f0mn ~ gender + attitude + gender:attitude + (1 | subject) +
##     (1 | scenario)
##    Data: politeness
##
## REML criterion at convergence: 2058.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8120 -0.5884 -0.0645  0.4014  3.9100
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subject  (Intercept) 584.4    24.17
##  scenario (Intercept) 106.4    10.32
##  Residual             885.5    29.76
## Number of obs: 212, groups:  subject, 16; scenario, 7
##
## Fixed effects:
##                      Estimate Std. Error t value
## (Intercept)           255.618      9.761  26.186
## genderM              -118.232     13.531  -8.738
## attitudepol           -17.192      5.423  -3.170
## genderM:attitudepol     5.544      8.284   0.669
##
## Correlation of Fixed Effects:
##             (Intr) gendrM atttdp
## genderM     -0.606
## attitudepol -0.286  0.206
## gndrM:tttdp  0.187 -0.309 -0.654
```

The model m9 can be read as following: The intercept for women/inf are $\approx 256Hz$, when we look at men with the same attitude their pitch drops by $\approx 118Hz$. Overall a polite attitude will result in a drop in pitch by $\approx 17Hz$, however for men it will only be $-17.2 + 5.5 \approx 11.6Hz$. Korean women's relative drop in pitch is therefore larger than male's in a polite situation according to this sample.

# Exercise 3, part 2 –(KV)

2. Compare the three models (1. gender as a main effect; 2. gender and attitude as main effects; 3. gender and attitude as main effects and the interaction between them.

```
#comparing the models
anova(m6, m8, m9)
```

```
## refitting model(s) with ML (instead of REML)
## Data: politeness
## Models:
## m6: f0mn ~ gender + (1 | subject) + (1 | scenario)
## m8: f0mn ~ gender + attitude + (1 | subject) + (1 | scenario)
## m9: f0mn ~ gender + attitude + gender:attitude + (1 | subject) + (1 | scenario)
##    npar    AIC    BIC  logLik deviance   Chisq Df Pr(>Chisq)    
## m6    5 2105.2 2122.0 -1047.6   2095.2                          
## m8    6 2094.5 2114.6 -1041.2   2082.5 12.6868  1  0.0003683 ***
## m9    7 2096.0 2119.5 -1041.0   2082.0  0.4551  1  0.4998998    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
piecewiseSEM::rsquared(c(m6, m8, m9))
```

```
##   Response   family     link method  Marginal Conditional
## 1     f0mn gaussian identity   none 0.6677206   0.8077964
## 2     f0mn gaussian identity   none 0.6782542   0.8196777
## 3     f0mn gaussian identity   none 0.6782490   0.8192531
```

# Exercise 3, part 3 –(KV)

3. Choose the model that you think describe the data the best - and write a short report on the main findings based on this model.

This dataset consists of the basic demographic information of 16 Korean participants, and their observed pitch in different situations that require either an informal or polite(formal) attitude.

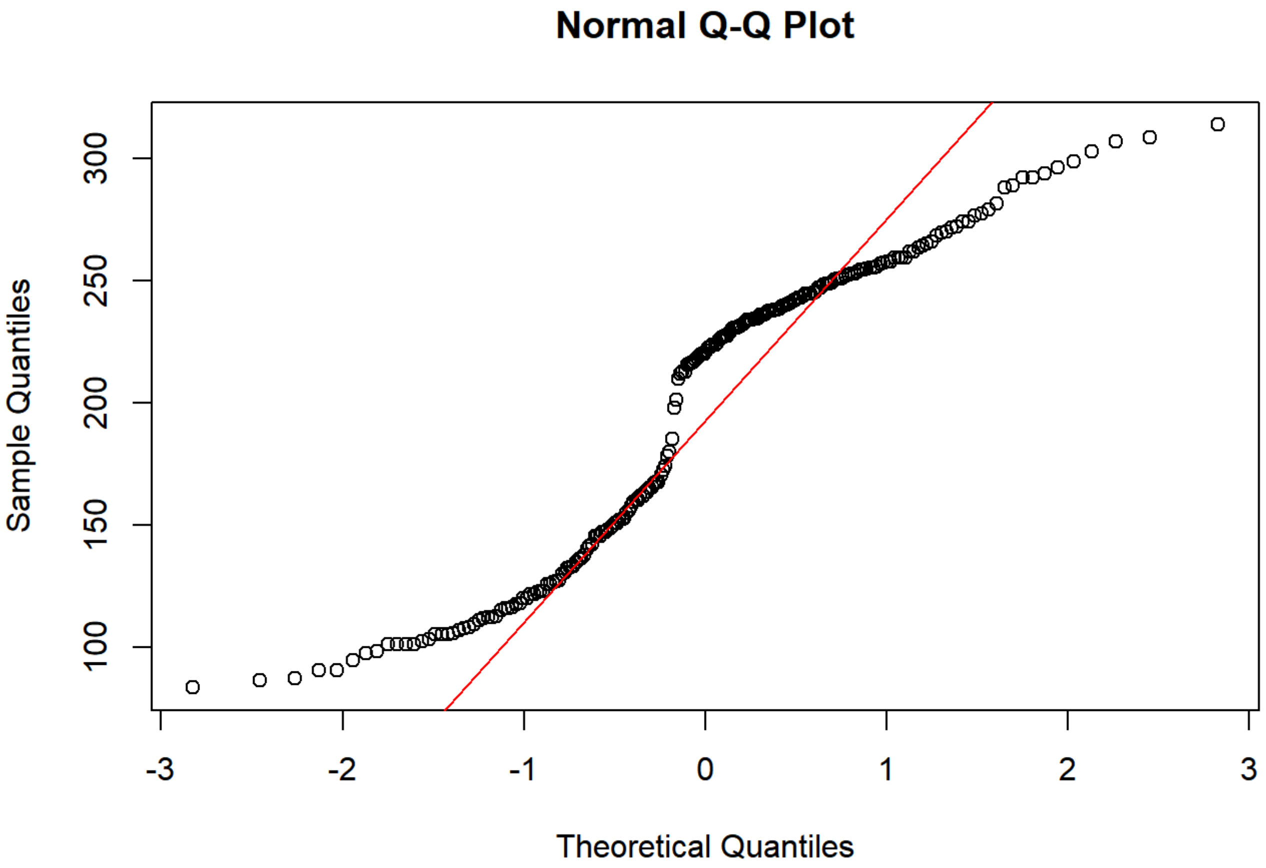
The model we chose as the best is m8. Consistent with the conclusions of the original oauthor’s study, this model showed that women on average have a higher pitch than men BUT it also suggested a negative relationship between *attitude* and pitch with p-values<0.001. It would seem that both Korean men’s and women’s frequency of voice drops when having a polite attitude.

Subjects and scenarios should have different intercepts because it would be assumed they would all have different baselines, (and therefore need different intercepts to account for this). Different subjects will naturally already speak at a different pitch level, so separate intercepts allows us to account for these differences. The different scenarios may also need separate intercepts as certain scenarios may result in participants lowering or raising their pitch to meet the appropriate ambiance of the scenario. Once again, by including separate intercepts for scenarios then we should be accounting for these differences in our models.

Furthermore the output of the summary function shows that more variance is explained by the random effect of the subject than that of the scenario, further strengthening the choice of multilevel modelling.

And here’s a QQ-plot of our chosen model

```
qqnorm(fitted.values(m8))
qqline(fitted.values(m8), col = "red")
```


Normal Q-Q Plot
Sample Quantiles
100
150
200
250
300
-3
-2
-1
0
1
2
3
Theoretical Quantiles