# Feedback data project

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The data contains measurement results of an electrical potential measured by an electromyograph (EMG) device, in the biceps muscles. The subjects in the control group did not receive encouragement before measuring their electrical potential, while those in the treatment groups received positive reinforcement ("you are looking great") or negative ("you are not trying hard"). I am interested to find if there is an effect of positive or negative reinforcement on the electrical potential measured in the biceps muscle.

```
# loading data
feed <- read.csv('d:/Users/shalhevet/Downloads/feedback_df_bi.csv', h = T)
#install.packages('lmerTest')
library(lmerTest)
```

```
## Warning: package 'lmerTest' was built under R version 4.0.5

## Loading required package: lme4

## Warning: package 'lme4' was built under R version 4.0.5

## Loading required package: Matrix

## Warning: The package `vctrs` (>= 0.3.8) is required as of rlang 1.0.0.

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'tibble'

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'pillar'

##
## Attaching package: 'lmerTest'

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

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

it looks like Linear Mixed Model is the most suitable model for both fixed and random effects where samples are clustered into groups of dependent observations. The specific model Im using here is a Random-Intercept Linear regression.

```
model_a <- lmer(performance ~(1|id) + gender, data = feed)
summary(model_a)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: performance ~ (1 | id) + gender
##    Data: feed
```

```
##
## REML criterion at convergence: 6170.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4407 -0.4590 -0.0056  0.3728  4.6852
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  84.59    9.197
##  Residual             131.28   11.458
## Number of obs: 792, groups:  id, 22
##
## Fixed effects:
##             Estimate Std. Error     df t value Pr(>|t|)
## (Intercept)   93.185      6.333 20.000  14.714 3.43e-12 ***
## gender        -1.064      4.005 20.000  -0.266    0.793
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##        (Intr)
## gender -0.949
```

```r
#P-value for gender is 0.793, There is no evidence for effect of gender on perfromance


# from the above:
# Beta_0 for intercept = 93.185
# Beta for gender = -1.064
# sigma_a = 9.197
# sigma_eps = 11.458

# confidence interval
confint(model_a)
```

```
## Computing profile confidence intervals ...
```

```
##                 2.5 %     97.5 %
## .sig01       6.571680  12.281426
## .sigma      10.908391  12.054634
## (Intercept) 80.814130 105.555775
## gender      -8.887814   6.760177
```

now same as above but with feedback who has three levels instead of two.

```r
model_b <- lmer(performance ~(1|id) + feedback, data = feed)
summary(model_b)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: performance ~ (1 | id) + feedback
##    Data: feed
##
## REML criterion at convergence: 6119.1
##
```

```
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4058 -0.4546 -0.0217  0.4058  5.0225
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  80.92    8.995
##  Residual             122.87   11.085
## Number of obs: 792, groups:  id, 22
##
## Fixed effects:
##                        Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)             95.7091     2.0356  24.5328  47.019  < 2e-16 ***
## feedbackno feedback     -6.2064     0.9648 768.0000  -6.433  2.2e-10 ***
## feedbackpositive        -6.1532     0.9648 768.0000  -6.378  3.1e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) fdbckf
## fdbcknfdbck -0.237
## feedbckpstv -0.237  0.500
```

```r
#P-value for no feedback and positive is statistically significant (lower then 0.05)


# from the above:
# Beta_0 for intercept (negative) = 95.7091
# Beta for no feedback = -6.2064
# Beta for positive = -6.1532
# sigma_a = 8.995
# sigma_eps = 11.085

# confidence interval
confint(model_b)
```

```
## Computing profile confidence intervals ...
```

```
##                         2.5 %    97.5 %
## .sig01               6.602662 12.313431
## .sigma              10.539466 11.646941
## (Intercept)         91.652670 99.765507
## feedbackno feedback -8.097255 -4.315556
## feedbackpositive    -8.044036 -4.262336
```

here I mixed both to try get more info

```r
model_c <- lmer(performance ~(1|id) + feedback + gender, data = feed)
summary(model_c)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: performance ~ (1 | id) + feedback + gender
##    Data: feed
##
## REML criterion at convergence: 6114.5
```

```
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4078 -0.4562 -0.0243  0.4025  5.0205
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  84.82    9.21
##  Residual             122.87   11.08
## Number of obs: 792, groups:  id, 22
##
## Fixed effects:
##                       Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)            97.3048     6.3575  20.3106  15.306 1.28e-12 ***
## feedbackno feedback   -6.2064     0.9648 768.0000  -6.433 2.20e-10 ***
## feedbackpositive      -6.1532     0.9648 768.0000  -6.378 3.10e-10 ***
## gender                -1.0638     4.0054  20.0000  -0.266    0.793
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) fdbckf fdbckp
## fdbcknfdbck -0.076
## feedbckpstv -0.076  0.500
## gender      -0.945  0.000  0.000
```

```
# I dont see anything new with the p-v, no new information


# from the above:
# Beta_0 for intercept (negative) = 97.3048
# Beta for no feedback = -6.2064
# Beta for positive = -6.1532
# Beta for gender =-1.0638
# sigma_a = 9.21
# sigma_eps = 11.08

# confidence interval
confint(model_c)
```

```
## Computing profile confidence intervals ...
```

```
##                         2.5 %     97.5 %
## .sig01               6.590137  12.291286
## .sigma              10.539466  11.646941
## (Intercept)         84.889988 109.719644
## feedbackno feedback -8.097255  -4.315556
## feedbackpositive    -8.044036  -4.262336
## gender              -8.887795   6.760158
```

lets try add some interaction

```
model_d <- lmer(performance ~(1|id) + feedback*gender, data = feed)
summary(model_d)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
```

```
## lmerModLmerTest]
## Formula: performance ~ (1 | id) + feedback * gender
##    Data: feed
##
## REML criterion at convergence: 6086
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5657 -0.5251  0.0072  0.4470  4.9436
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  84.91    9.215
##  Residual             119.63   10.938
## Number of obs: 792, groups:  id, 22
##
## Fixed effects:
##                             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)                  105.128      6.567  23.123  16.008 5.26e-14 ***
## feedbackno feedback          -17.192      3.010 766.000  -5.711 1.61e-08 ***
## feedbackpositive             -18.638      3.010 766.000  -6.191 9.74e-10 ***
## gender                        -6.280      4.153  23.123  -1.512  0.14411
## feedbackno feedback:gender     7.324      1.904 766.000   3.847  0.00013 ***
## feedbackpositive:gender        8.323      1.904 766.000   4.371 1.40e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) fdbckf fdbckp gender ffdbc:
## fdbcknfdbck -0.229
## feedbckpstv -0.229  0.500
## gender      -0.949  0.217  0.217
## fdbckfdbck:  0.217 -0.949 -0.474 -0.229
## fdbckpstv:g  0.217 -0.474 -0.949 -0.229  0.500
```

```
#II

# The effect of gender is statistically non-significant and negative (p = 0.131)

# The effect of no feedback compared to a negative feedback is statistically significant and negative (p

# The effect of positive feedback compared to a negative feedback is statistically significant and nega

# The interaction effect of no feedback on gender is statistically significant and positive (pv < .001)

# The interaction effect of positive feedback on gender is statistically significant and positive (pv <



# no feedback (Main, Fixed)= -17.192
# positive feedback (Main, Fixed) =-18.638
# Gender(Main, Fixed)= -6.280
# Gender X no feedback (Interaction, Fixed)= 7.324
# Gender X positive feedback (Interaction, Fixed)= 8.323
```

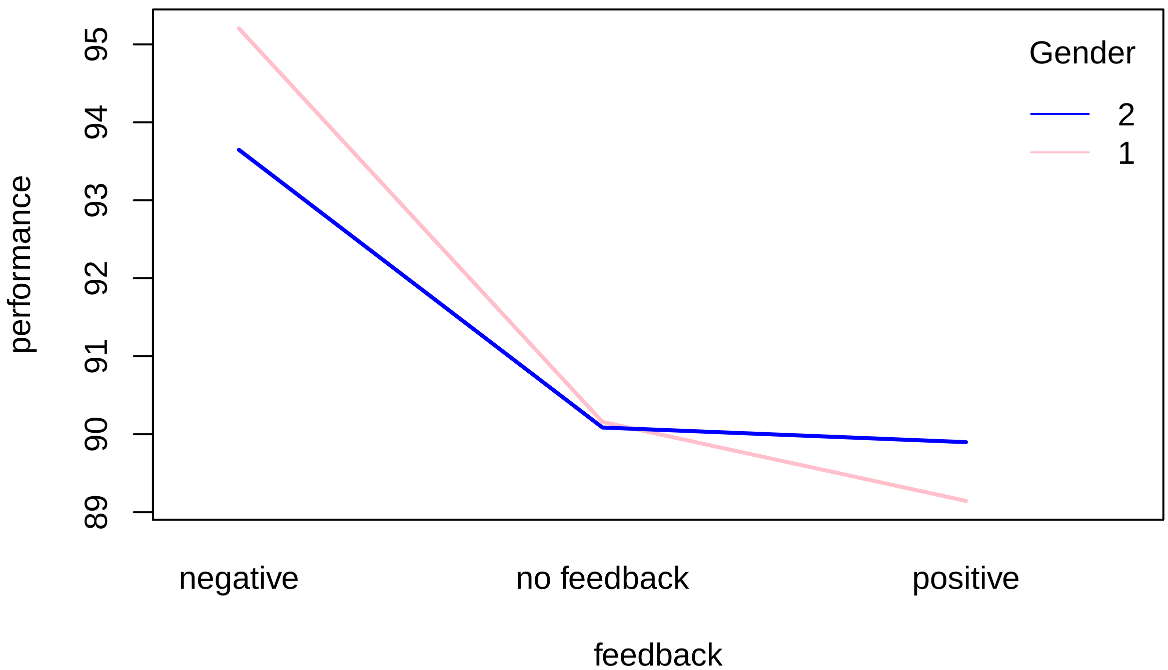
```r
# Sigma_a (Id, Random) =9.215
# Sigma_eps (Random)= 10.938


# confidence interval
confint(model_d)
```

```
## Computing profile confidence intervals ...
```

```
##                                  2.5 %     97.5 %
## .sig01                        6.597596  12.295277
## .sigma                       10.386109  11.477468
## (Intercept)                  92.334423 117.922361
## feedbackno feedback         -23.084710 -11.299937
## feedbackpositive            -24.530381 -12.745608
## gender                      -14.371152   1.812081
## feedbackno feedback:gender    3.597273  11.050618
## feedbackpositive:gender       4.596533  12.049878
```

```r
# interaction plot
interaction.plot(x.factor = feed$feedback, #x-axis variable
                 trace.factor = feed$gender, #variable for lines
                 response = feed$performance, #y-axis variable
                 fun = median, #metric to plot
                 ylab = "performance",
                 xlab = "feedback",
                 col = c("pink", "blue"),
                 lty = 1, #line type
                 lwd = 2, #line width
                 trace.label = "Gender")
```




The full model adapted in the end is the chosen model.

Although the gender is not significant, the interaction between gender and feedback is significant, as can also be seen from the interaction graph.

This model explains the most of the variance (the percentage of explained variance increases as my model grew)