LEARN Center
EPFL

Analysis of Exam Scores

Data for Only "New" Students (Year 1 & Year 2)

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Flipped Classroom Project

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1 Background and Rationale

In this document, we will do the following :

1. Importing data of volunteers' normalized scores from Year 1 and Year 2.
2. Retain only the **new** volunteers (filtering out the Repeaters, Ex-CMS, and Ex-MAN). Also, we only retain the French and Swiss students.
3. Visualize and analyze the differences in normalized score across `Gender` and `Background`. Initially, we assess the differences across the different course parts.
4. Visualize and analyze the Gender and Background differences on volunteers' score. For this part, we removed the questions corresponding to the first 4 weeks (non-flipped) of the semester.
5. Analyze the relationship of independence between Gender, Condition, and Background.
6. Linear / Mixed Effect modelling to assess the impact of Gender, Condition, and Background on students' score.

2 R Package Imports

In this section, we will import all the required packages for importing, cleaning, and pre-processing the data. Please note that some or all of these packages may have to be installed before this script could be run.

```
library(readxl)
library(dplyr)
library(tidyr)
library(ggplot2)
library(scales)
library(gridExtra)
library(gplots)
library(RColorBrewer)
library(FactoMineR)
library(factoextra)
library(nlme)
library(rcompanion)
library(here)
library(RMariaDB)
library(keyringr)
library(ggalluvial)
library(wesanderson)
library(ggpubr)
```

3 Data Import and Pre-Processing

3.0.1 Data Import

First, we will load the data which we have previously cleaned and normalized in "`01-Data-Pre-Processing.Rnw`" project :

```
# Setting the path.
path = paste(here(), "/Data/Scores/Normalized-Volunteer-Data/", sep = "")

# Year1
dt.y1 = read.csv(paste(path, "Year1-Normalized-Score-DI-Filtered.csv", sep = ""), header = TRUE)
dt.y1$X = NULL

# Year2
dt.y2 = read.csv(paste(path, "Year2-Normalized-Score-DI-Filtered.csv", sep = ""), header = TRUE)
dt.y2$X = NULL

# Convert ID.Anon to Character
dt.y1$ID.Anon = as.character(dt.y1$ID.Anon)
dt.y2$ID.Anon = as.character(dt.y2$ID.Anon)

# Clean-up the path variable.
rm(path)
```

3.0.2 Data Summary

Secondly, we will produce a small summary of data, i.e. how many students are **new** and how many are **repeating**.

```
# Summarize.
# Year1
dt.y1 %>% group_by(Code.BA, Condition) %>%
  summarise(N = n()) %>%
  spread(Condition, N)

## # A tibble: 4 x 3
## # Groups:   Code.BA [4]
##   Code.BA   Control Flipped
##   <fct>       <int>   <int>
## 1 Ex-CMS         10      NA
## 2 Ex-MAN         36       8
## 3 New           302      75
## 4 Repeating      34       6
```

... also for Year2

```
# Summarize.
# Year2
dt.y2 %>% group_by(Code.BA, Condition) %>%
  summarise(N = n()) %>%
  spread(Condition, N)

## # A tibble: 4 x 3
## # Groups:   Code.BA [4]
##   Code.BA   Control Flipped
##   <fct>       <int>   <int>
## 1 Ex-CMS          3       4
## 2 Ex-MAN         15      18
## 3 New           100     102
## 4 Repeating       8      10
```

3.0.3 Data Filtering

After a joint discussion within the group, we discussed to retain only the **New** students for the analysis, which we will do next.

We will filter out only the **New** students.

```
# Year1
dt.y1 = dt.y1 %>% filter(Code.BA == "New")

# Year2
dt.y2 = dt.y2 %>% filter(Code.BA == "New")
```

... We will also filter out the Category of **Etranger.Autres** because this is one category with very small nunmber of students and could add noise to our analysis.

```
# Filter out Etranger.Autres
# Year1
dt.y1 = dt.y1 %>% filter(!(Category == "Etranger.Autres"))

# Year2
dt.y2 = dt.y2 %>% filter(!(Category == "Etranger.Autres"))
```

With all this filtering, we have in total 351 volunteers for Year1 and 196 volunteers for Year2.

... some summary for demographics (New students only) :

```
# Year 1
# Category
dt.y1 %>% group_by(Condition, Category) %>%
  summarise(N = n())
```

```
## # A tibble: 6 x 3
## # Groups:   Condition [2]
##   Condition Category          N
##   <fct>     <fct>         <int>
## 1 Control   France          168
## 2 Control   Suisse.Autres    54
## 3 Control   Suisse.PAM       59
## 4 Flipped   France           39
## 5 Flipped   Suisse.Autres    16
## 6 Flipped   Suisse.PAM       15

# Gender
dt.y1 %>% group_by(Category, Gender) %>%
  summarise(N = n())

## # A tibble: 6 x 3
## # Groups:   Category [3]
##   Category      Gender     N
##   <fct>         <fct>  <int>
## 1 France        F         63
## 2 France        M        144
## 3 Suisse.Autres F         36
## 4 Suisse.Autres M         34
## 5 Suisse.PAM    F         16
## 6 Suisse.PAM    M         58

# Year 2
# Category
dt.y2 %>% group_by(Condition, Category) %>%
  summarise(N = n())

## # A tibble: 6 x 3
## # Groups:   Condition [2]
##   Condition Category          N
##   <fct>     <fct>         <int>
## 1 Control   France           53
## 2 Control   Suisse.Autres    20
## 3 Control   Suisse.PAM       24
## 4 Flipped   France           50
## 5 Flipped   Suisse.Autres    25
## 6 Flipped   Suisse.PAM       24

# Gender
dt.y2 %>% group_by(Category, Gender) %>%
  summarise(N = n())

## # A tibble: 6 x 3
## # Groups:   Category [3]
##   Category      Gender     N
##   <fct>         <fct>  <int>
## 1 France        F         38
## 2 France        M         65
## 3 Suisse.Autres F         20
## 4 Suisse.Autres M         25
## 5 Suisse.PAM    F         12
## 6 Suisse.PAM    M         36
```

... some summary including the **mean** and **standard deviation** values.

```
# Year 1 -- Summary of Normalized Score
t.stat = dt.y1 %>% group_by(Condition) %>%
  summarise(N = n(),
            m = mean(Nor.Score),
            sd = sd(Nor.Score))
```

```
t.stat

## # A tibble: 2 x 4
##   Condition     N       m    sd
##   <fct>     <int>   <dbl> <dbl>
## 1 Control     281 -0.118  0.982
## 2 Flipped      70 -0.0701 0.939

# Year 1 -- Summary of Total Score
t.stat = dt.y1 %>% group_by(Condition) %>%
  summarise(N = n(),
            m = mean(Total.Score),
            sd = sd(Total.Score))
t.stat

## # A tibble: 2 x 4
##   Condition     N     m    sd
##   <fct>     <int> <dbl> <dbl>
## 1 Control     281  31.0  15.6
## 2 Flipped      70  31.7  15.0

# Year 2 -- Summary of Normalized Score
t.stat = dt.y2 %>% group_by(Condition) %>%
  summarise(N = n(),
            m = mean(Nor.Score),
            sd = sd(Nor.Score))
t.stat

## # A tibble: 2 x 4
##   Condition     N      m    sd
##   <fct>     <int>  <dbl> <dbl>
## 1 Control      97 -0.191 1.01
## 2 Flipped      99 -0.269 0.951

# Year 2 -- Summary of Total Score
t.stat = dt.y2 %>% group_by(Condition) %>%
  summarise(N = n(),
            m = mean(Total.Score),
            sd = sd(Total.Score))
t.stat

## # A tibble: 2 x 4
##   Condition     N     m    sd
##   <fct>     <int> <dbl> <dbl>
## 1 Control      97  33.2  17.5
## 2 Flipped      99  31.9  16.5
```

3.0.4 Difference in Score Across Condition

We will also perform the `t-test` on the `Total.Score` to examine the difference in students' `Total.Score` across `Condition`.

```
# T-Test
# Year 1
t.test(dt.y1$Total.Score~dt.y1$Condition)

##
##  Welch Two Sample t-test
##
## data:  dt.y1$Total.Score by dt.y1$Condition
## t = -0.37557, df = 109.67, p-value = 0.708
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -4.751855  3.237772
```

```
## sample estimates:
## mean in group Control mean in group Flipped
##                30.97153                31.72857

# Year 2
t.test(dt.y2$Total.Score~dt.y2$Condition)

##
##  Welch Two Sample t-test
##
## data:  dt.y2$Total.Score by dt.y2$Condition
## t = 0.55408, df = 192.77, p-value = 0.5802
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -3.450507  6.146539
## sample estimates:
## mean in group Control mean in group Flipped
##                33.22680                31.87879
```

3.0.5 Preparing Data For Visualization

In order to visualize the scores across the different `Course.Parts` we will have to accumulate the `Score.A`, `Score.B`, and `Score.C` columns (gathering operation), so that the data is more long than wide.

Year1 :

```
# Gathering the score variables
temp.y1 = gather(dt.y1,
              "Nor.Score.A", "Nor.Score.B", "Nor.Score.C",
              key = "Course.Parts",
              value = "Score.Parts")
```

Year2 :

```
# Gathering the score variables
temp.y2 = gather(dt.y2,
              "Nor.Score.A", "Nor.Score.B", "Nor.Score.C",
              key = "Course.Parts",
              value = "Score.Parts")
```

Now, that the data is ready, we can start analyzing and visualizing it.

4 Gender Differences

Let us summarize the data first, for Year1 :

```
# Year1
dt.y1 %>% group_by(Condition, Gender) %>%
  summarise(N = n()) %>%
  spread(Gender, N)

## # A tibble: 2 x 3
## # Groups:   Condition [2]
##   Condition     F     M
##   <fct>     <int> <int>
## 1 Control      92   189
## 2 Flipped      23    47

# With Mean and SD of Normalized Score.
dt.y1 %>% group_by(Condition, Gender) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score),
            SD = sd(Nor.Score))
```

```
## # A tibble: 4 x 5
## # Groups:   Condition [2]
##   Condition Gender     N    Mean    SD
##   <fct>     <fct>  <int>   <dbl> <dbl>
## 1 Control   F         92 -0.281  0.954
## 2 Control   M        189 -0.0381 0.988
## 3 Flipped   F         23 -0.0339 0.784
## 4 Flipped   M         47 -0.0878 1.01
```

... also for YEAR2 :

```
# Year2
dt.y2 %>% group_by(Condition, Gender) %>%
  summarise(N = n()) %>%
  spread(Gender, N)
```

```
## # A tibble: 2 x 3
## # Groups:   Condition [2]
##   Condition     F     M
##   <fct>     <int> <int>
## 1 Control      35    62
## 2 Flipped      35    64
```

```
# With Mean and SD of Normalized Score.
dt.y2 %>% group_by(Condition, Gender) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score),
            SD = sd(Nor.Score))
```

```
## # A tibble: 4 x 5
## # Groups:   Condition [2]
##   Condition Gender     N   Mean    SD
##   <fct>     <fct>  <int>  <dbl> <dbl>
## 1 Control   F         35 -0.332 0.913
## 2 Control   M         62 -0.111 1.06
## 3 Flipped   F         35 -0.224 0.911
## 4 Flipped   M         64 -0.293 0.978
```

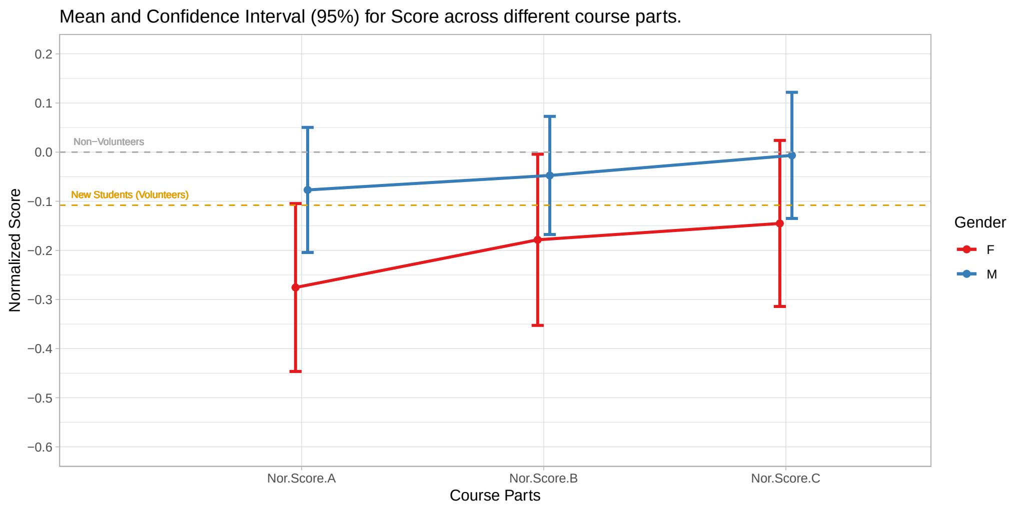
4.1 Visualizing Scores across Different Course Parts

Before we continue with the visualizations, we have to compute the **mean** value of the scores :

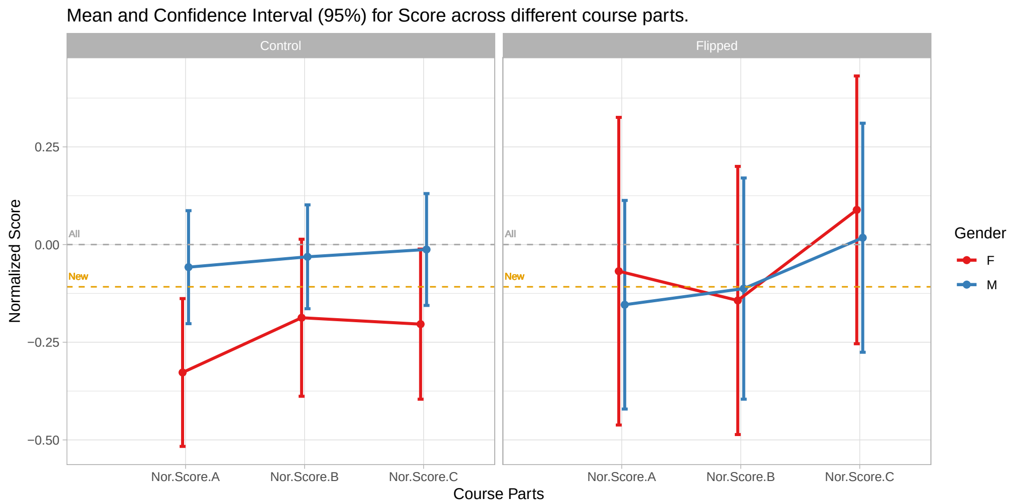
```
# Year1
# For Total Score
y1.mean = mean(dt.y1$Nor.Score)
# For Score.BC
y1.mean.bc = mean(dt.y1$Nor.Score.BC)

# Year2
# For Total Score
y2.mean = mean(dt.y2$Nor.Score)
# For Score.BC
y2.mean.bc = mean(dt.y2$Nor.Score.BC)
```

4.1.1 Year1

Gender differences for all the volunteers :



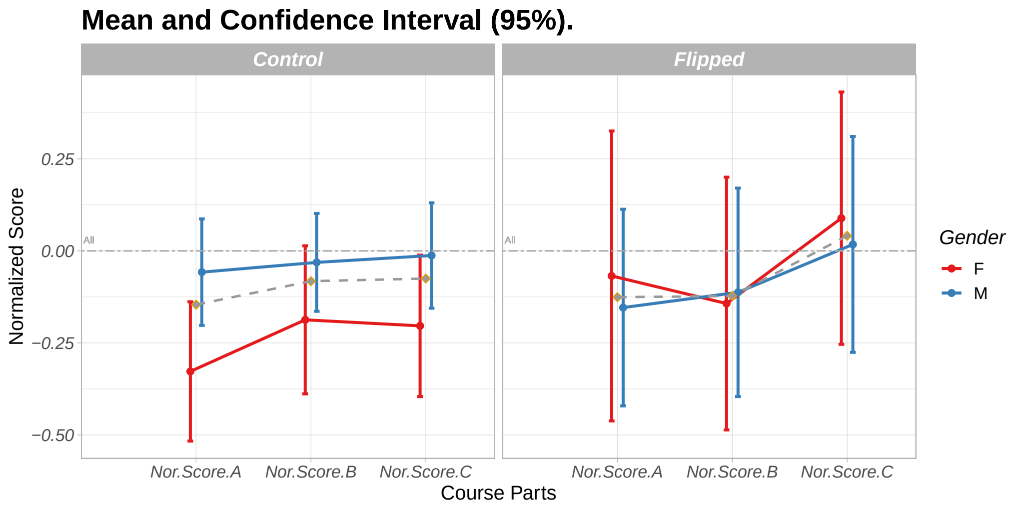
Gender differences across the Condition :



Tabular summary of both CONDITION and GENDER :

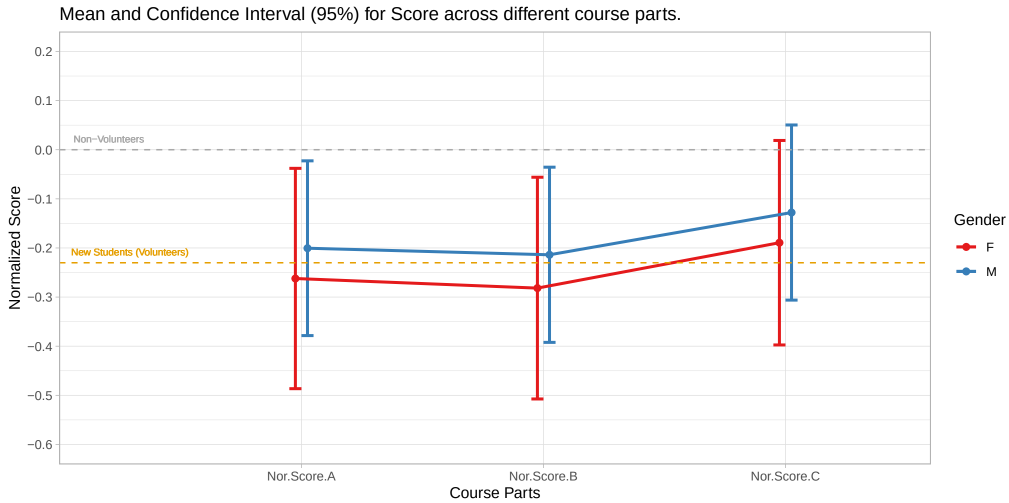
```
# Table (Year 1)
dt.y1 %>% group_by(Condition, Gender) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score),
            SD = sd(Nor.Score))

## # A tibble: 4 x 5
## # Groups:   Condition [2]
##   Condition Gender     N    Mean    SD
##   <fct>     <fct>  <int>   <dbl> <dbl>
## 1 Control   F         92 -0.281  0.954
## 2 Control   M        189 -0.0381 0.988
## 3 Flipped   F         23 -0.0339 0.784
## 4 Flipped   M         47 -0.0878 1.01
```

Gender differences across the Condition (with weighted mean) and faceting (Condition) :

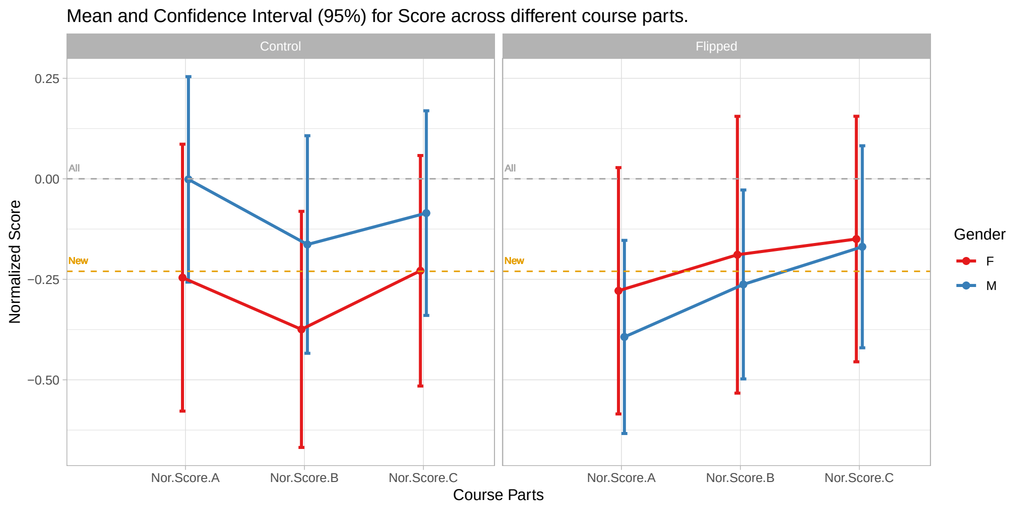


4.1.2 Year2

Gender differences for all the volunteers :



Gender differences across the Condition :

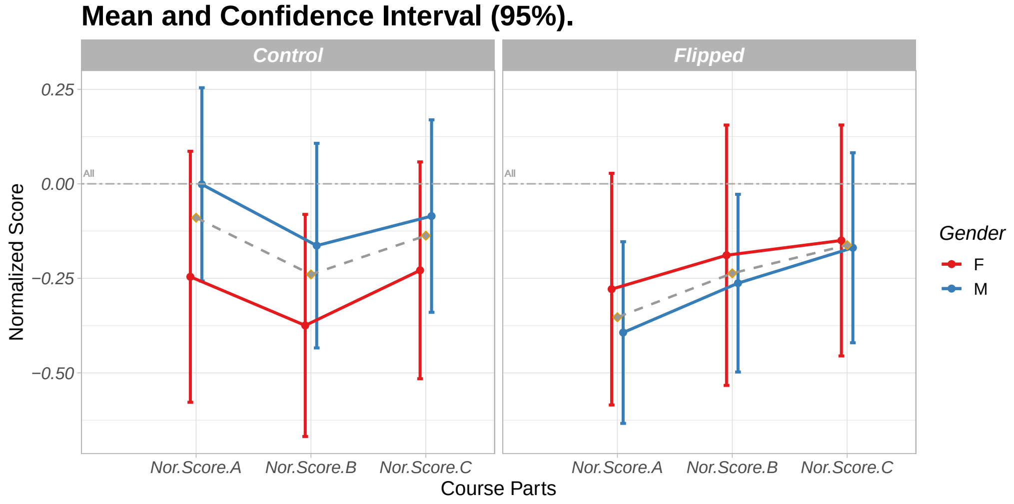


Tabular summary of both CONDITION and GENDER :

```
# Table (Year 2)
dt.y2 %>% group_by(Condition, Gender) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score),
            SD = sd(Nor.Score))

## # A tibble: 4 x 5
## # Groups:   Condition [2]
```

```
##   Condition Gender     N   Mean    SD
##   <fct>     <fct>  <int>  <dbl> <dbl>
## 1 Control   F         35 -0.332 0.913
## 2 Control   M         62 -0.111 1.06
## 3 Flipped   F         35 -0.224 0.911
## 4 Flipped   M         64 -0.293 0.978
```

Gender differences across the Condition (with weighted mean) and with faceting (Condition) :



4.2 Examining Gender Differences Across Course Parts

Now, we will examine if there is a statistical difference between `Gender` across the different `Course.Parts`. In order to do so, we will examine the Gender differences separately for the Control and Flipped condition, and also separately for the different course parts. To examine differences, we will use ANOVA.

4.2.1 Year1

Control Condition :

```
# Data for analysis
t.stat = dt.y1 %>% filter(Condition == "Control")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Gender
## F = 4.9238, num df = 1.00, denom df = 196.07, p-value = 0.02764

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Gender
## F = 1.6098, num df = 1.00, denom df = 172.05, p-value = 0.2062

# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Gender
## F = 2.4428, num df = 1.00, denom df = 191.55, p-value = 0.1197
```

Flipped Condition :

```
# Data for analysis
t.stat = dt.y1 %>% filter(Condition == "Flipped")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Gender
## F = 0.12521, num df = 1.000, denom df = 42.573, p-value = 0.7252

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Gender
## F = 0.017979, num df = 1.000, denom df = 50.865, p-value = 0.8939

# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Gender
## F = 0.096138, num df = 1.000, denom df = 52.523, p-value = 0.7577
```

4.2.2 Year2

Control Condition :

```
# Data for analysis
t.stat = dt.y2 %>% filter(Condition == "Control")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Gender
## F = 1.3076, num df = 1.000, denom df = 72.122, p-value = 0.2566

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Gender
## F = 1.074, num df = 1.000, denom df = 82.927, p-value = 0.3031

# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Gender
## F = 0.5381, num df = 1.000, denom df = 80.752, p-value = 0.4653
```

Flipped Condition :

```r
# Data for analysis
t.stat = dt.y2 %>% filter(Condition == "Flipped")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Gender
## F = 0.33415, num df = 1.000, denom df = 73.635, p-value = 0.565

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Gender
## F = 0.12076, num df = 1.000, denom df = 65.402, p-value = 0.7293

# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Gender
## F = 0.0091348, num df = 1.000, denom df = 76.657, p-value = 0.9241
```

5 Background Differences (Category)

Similar to the previous section, here, we will analyze the differences in `Nor.Score` (normalized total score) across the students' background (Swiss vs. French).

Let us summarize the data first, for Year1 :

```r
# Year1
dt.y1 %>% group_by(Category, Condition) %>%
  summarise(N = n()) %>%
  spread(Condition, N)

## # A tibble: 3 x 3
## # Groups:   Category [4]
##   Category      Control Flipped
##   <fct>           <int>   <int>
## 1 France            168      39
## 2 Suisse.Autres      54      16
## 3 Suisse.PAM         59      15

# Summary with the mean and sd values
dt.y1 %>% group_by(Category, Condition) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score),
            SD = sd(Nor.Score))

## # A tibble: 6 x 5
## # Groups:   Category [3]
##   Category      Condition     N  Mean    SD
##   <fct>         <fct>     <int> <dbl> <dbl>
## 1 France        Control     168 0.104 0.866
## 2 France        Flipped      39 0.201 0.861
```

```
## 3 Suisse.Autres Control      54 -0.808 0.975
## 4 Suisse.Autres Flipped      16 -0.654 0.985
## 5 Suisse.PAM    Control      59 -0.118 1.02
## 6 Suisse.PAM    Flipped      15 -0.154 0.831
```

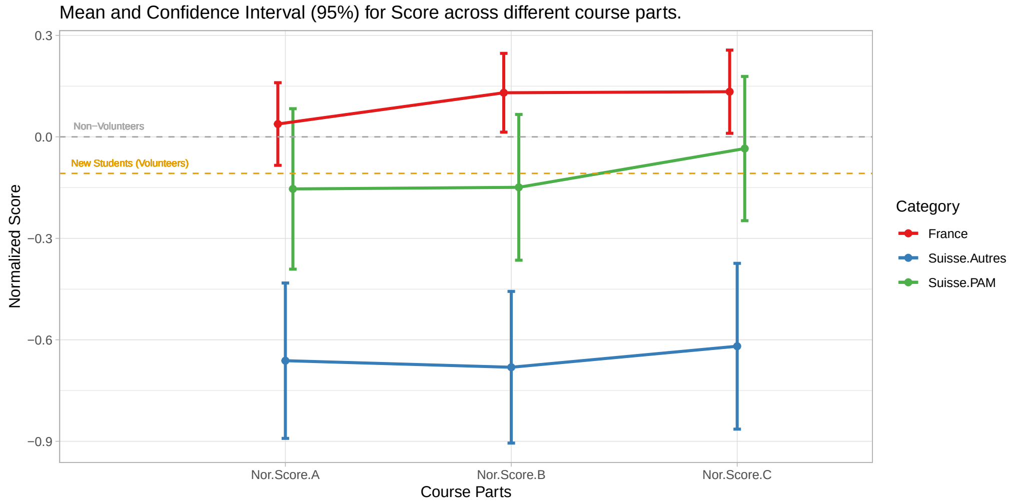
... also for YEAR2 :

```
# Year2
dt.y2 %>% group_by(Category, Condition) %>%
  summarise(N = n()) %>%
  spread(Condition, N)

## # A tibble: 3 x 3
## # Groups:   Category [4]
##   Category      Control Flipped
##   <fct>           <int>   <int>
## 1 France             53      50
## 2 Suisse.Autres      20      25
## 3 Suisse.PAM         24      24

# Summary with the mean and sd values
dt.y2 %>% group_by(Category, Condition) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score),
            SD = sd(Nor.Score))

## # A tibble: 6 x 5
## # Groups:   Category [3]
##   Category      Condition     N    Mean    SD
##   <fct>         <fct>     <int>   <dbl> <dbl>
## 1 France        Control      53  0.0155 0.803
## 2 France        Flipped      50 -0.137  0.853
## 3 Suisse.Autres Control      20 -1.08   0.996
## 4 Suisse.Autres Flipped      25 -0.598  1.06
## 5 Suisse.PAM    Control      24  0.0960 1.05
## 6 Suisse.PAM    Flipped      24 -0.199  0.981
```

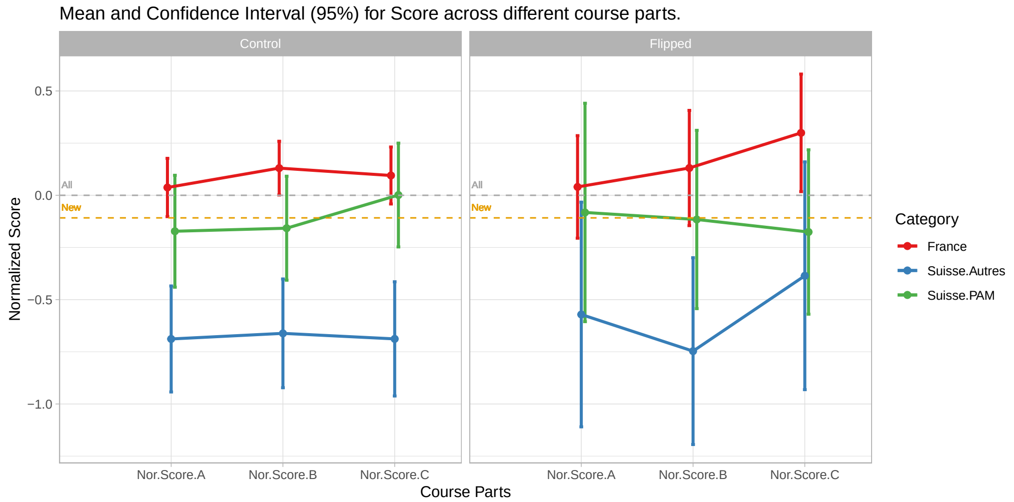
5.1 Visualizing Scores

5.1.1 Year1

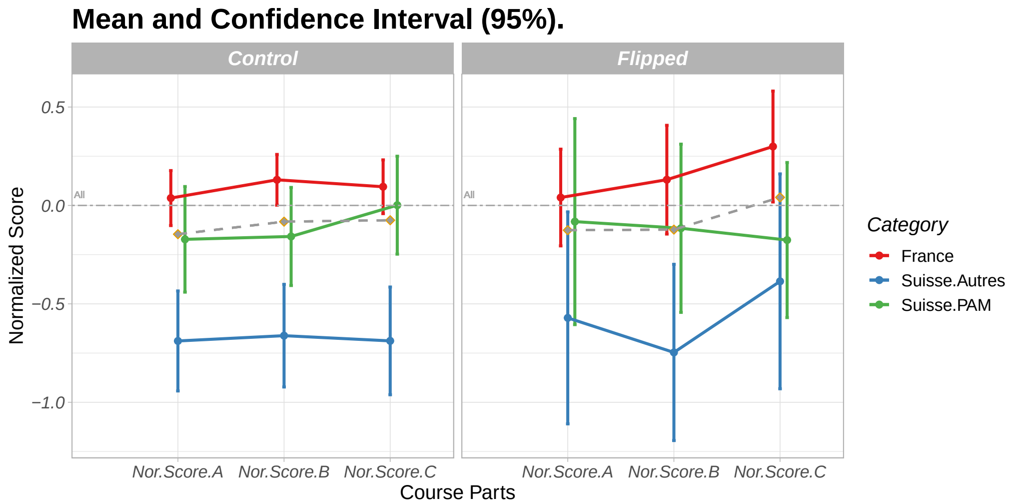
Category differences for all the volunteers :



Category differences across the Condition :

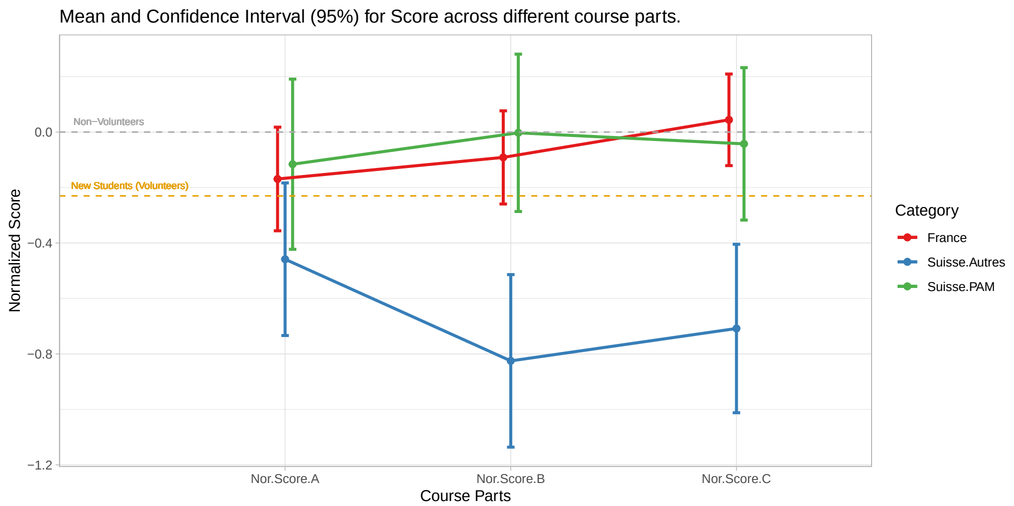


Category differences across the Condition (with weighted mean) and faceting :

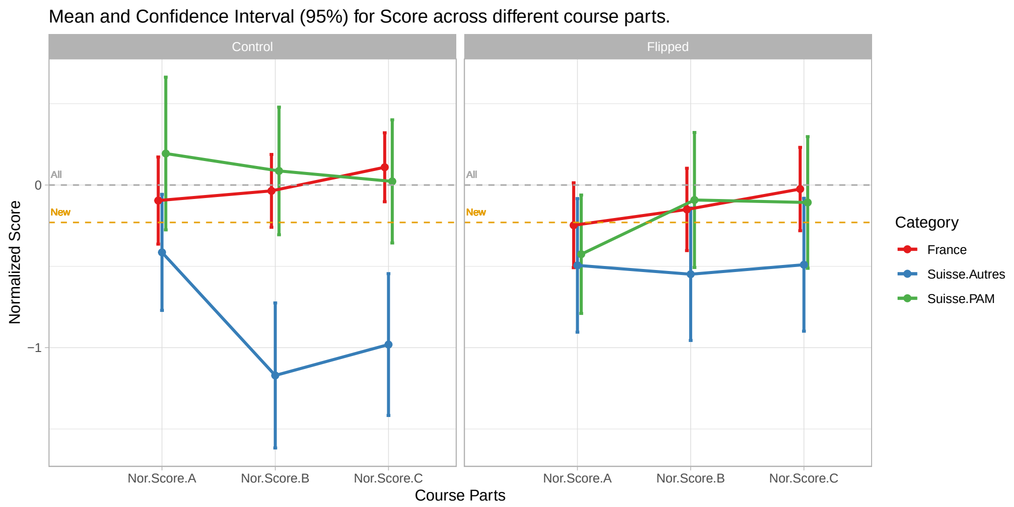


5.1.2 Year2

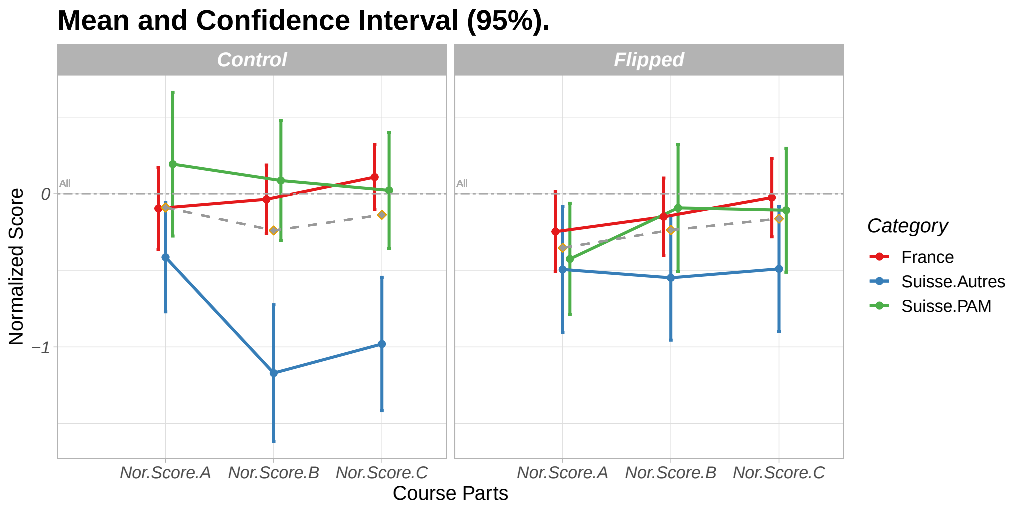
Category differences for all the volunteers :



Category differences across the Condition :



Category differences across the Condition (with weighted mean) and faceting :



5.2 Examining Background Differences Across Course Parts

Now, we will examine if there is statistical differences between different `Categories` across the `Course.Parts`. In order to do so, we will examine the Background differences separately for the Control and Flipped condition, and also separately for the different course parts. To examine differences, we will use ANOVA.

5.2.1 Year1

CONTROL Condition :

```
# Data for analysis
t.stat = dt.y1 %>% filter(Condition == "Control")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Category
## F = 12.014, num df = 2, denom df = 107, p-value = 1.964e-05

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Category
## F = 14.611, num df = 2.00, denom df = 104.03, p-value = 2.557e-06
```

```
# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Category
## F = 12.615, num df = 2.00, denom df = 105.63, p-value = 1.222e-05
```

FLIPPED Condition :

```
# Data for analysis
t.stat = dt.y1 %>% filter(Condition == "Flipped")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Category
## F = 2.0011, num df = 2.000, denom df = 26.115, p-value = 0.1554

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Category
## F = 5.2339, num df = 2.000, denom df = 30.054, p-value = 0.01121

# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Category
## F = 3.2824, num df = 2.000, denom df = 29.807, p-value = 0.05148
```

5.2.2 Year2

CONTROL Condition :

```
# Data for analysis
t.stat = dt.y2 %>% filter(Condition == "Control")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Category
## F = 2.1246, num df = 2.000, denom df = 44.476, p-value = 0.1314

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Category
## F = 10.974, num df = 2.000, denom df = 39.726, p-value = 0.0001605
```

```r
# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Category
## F = 9.7029, num df = 2.000, denom df = 39.281, p-value = 0.0003763
```

Flipped Condition :

```r
# Data for analysis
t.stat = dt.y2 %>% filter(Condition == "Flipped")

# Part A
oneway.test(t.stat$Nor.Score.A~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.A and t.stat$Category
## F = 0.60892, num df = 2.000, denom df = 49.432, p-value = 0.548

# Part B
oneway.test(t.stat$Nor.Score.B~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.B and t.stat$Category
## F = 1.5552, num df = 2.000, denom df = 47.454, p-value = 0.2217

# Part C
oneway.test(t.stat$Nor.Score.C~t.stat$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  t.stat$Nor.Score.C and t.stat$Category
## F = 1.7859, num df = 2.000, denom df = 47.939, p-value = 0.1786
```

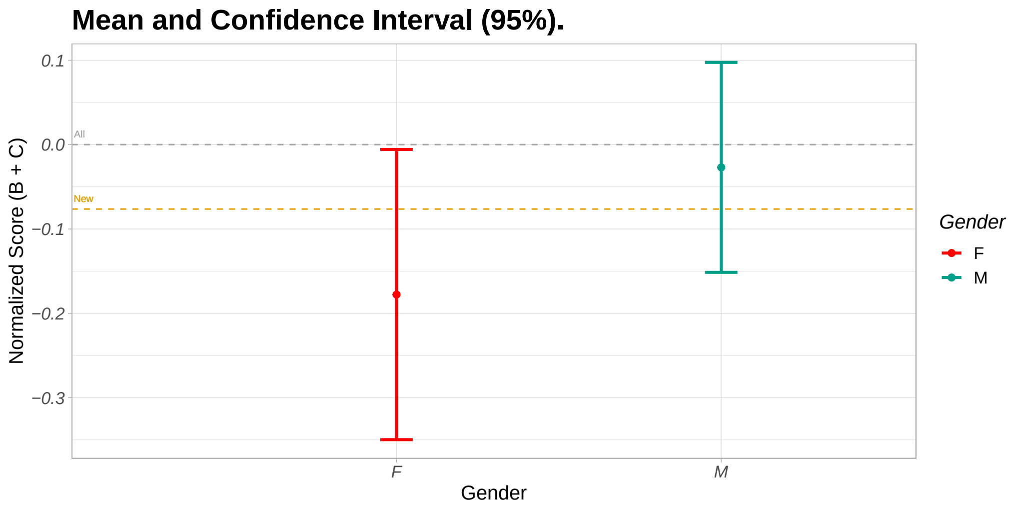
6 Gender Differences on Aggregated Parts BC

In this section, we will only analyze gender differences across the combined score of Parts B and C. In this way, we are removing the questions that belong to the Part A (the first 4 weeks).

6.1 Visualizing Scores

6.1.1 Year1

Gender differences for all the volunteers :



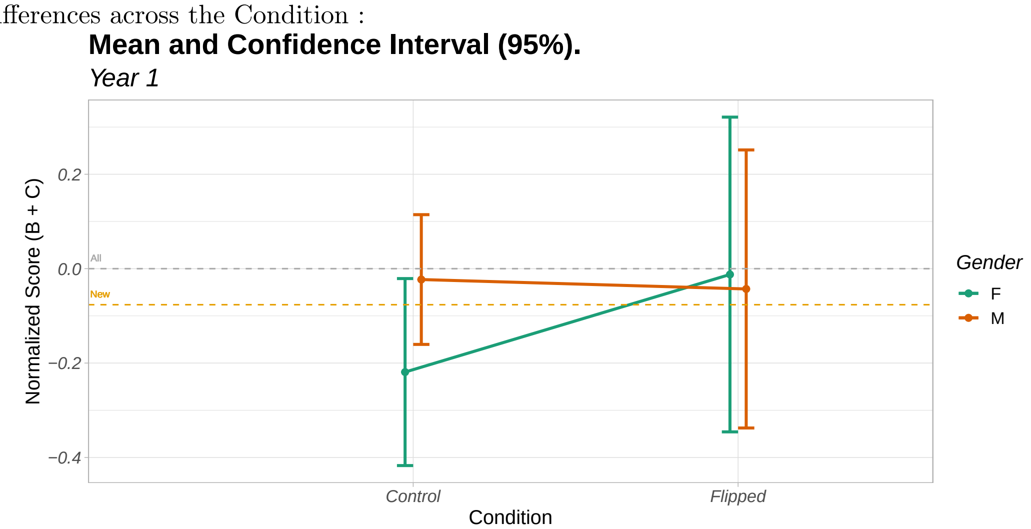
... and the ANOVA :

```
oneway.test(dt.y1$Nor.Score.BC~dt.y1$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  dt.y1$Nor.Score.BC and dt.y1$Gender
## F = 1.9365, num df = 1.00, denom df = 233.57, p-value = 0.1654
```

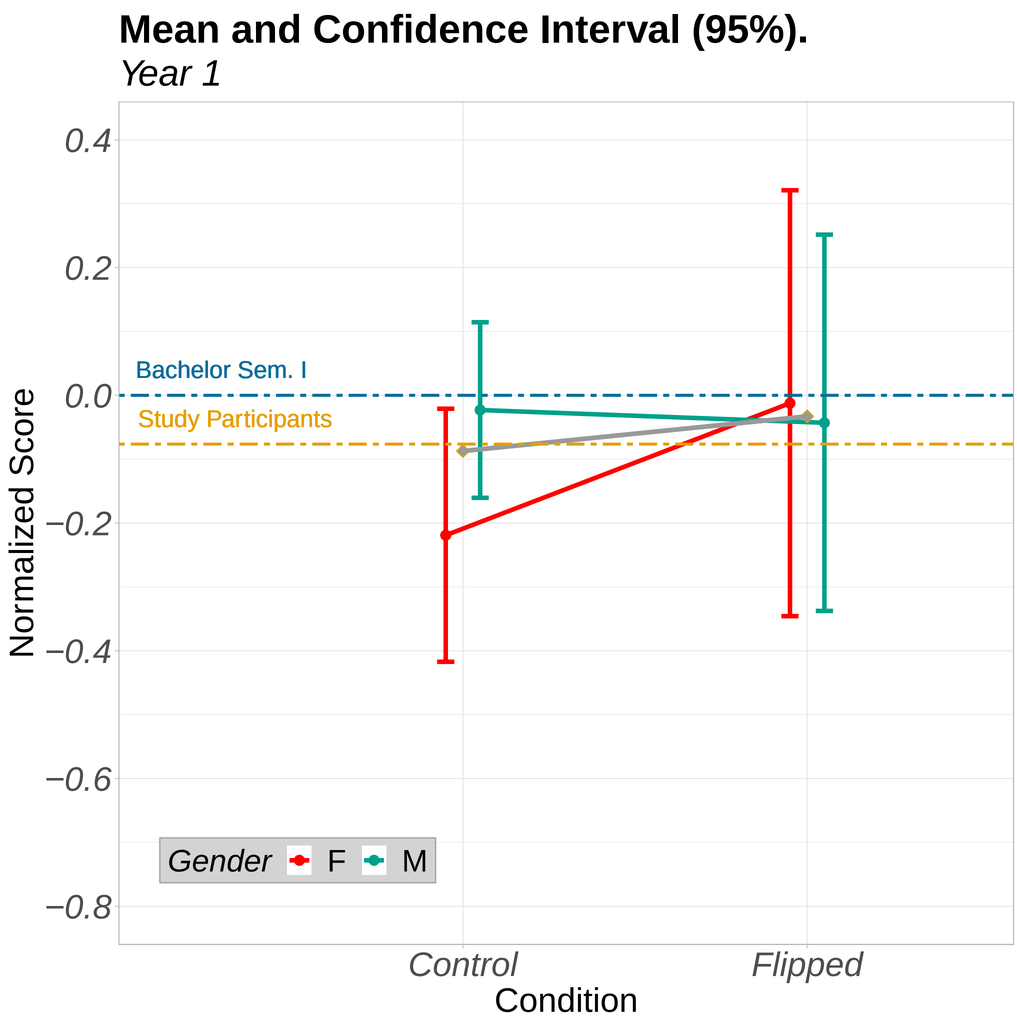
... and the Kruskal-Wallis :

```
kruskal.test(dt.y1$Nor.Score.BC~dt.y1$Gender)

##
##  Kruskal-Wallis rank sum test
##
## data:  dt.y1$Nor.Score.BC by dt.y1$Gender
## Kruskal-Wallis chi-squared = 2.133, df = 1, p-value = 0.1442

epsilonSquared(x = dt.y1$Nor.Score.BC,
               g = dt.y1$Gender)

## epsilon.squared
##         0.00609
```

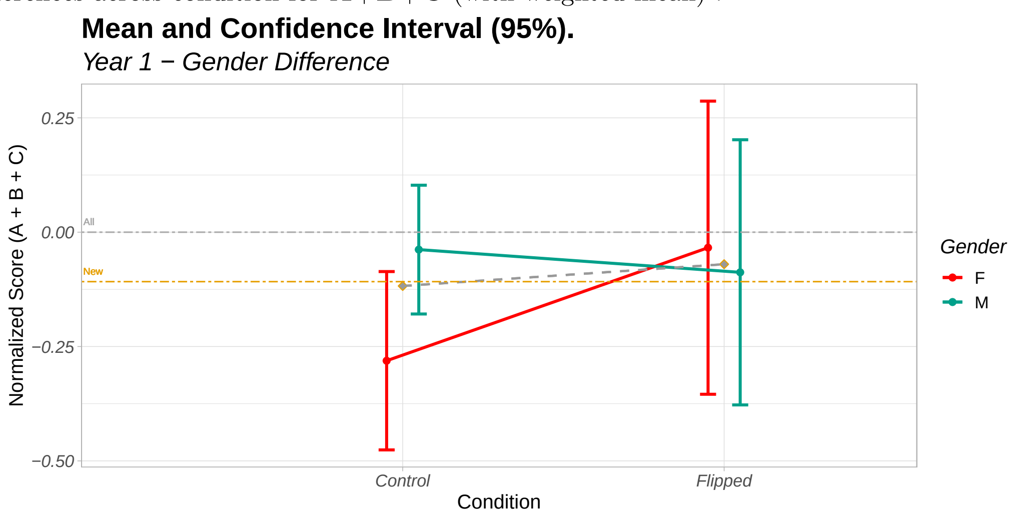
Gender differences across the Condition :



Gender differences across condition (with weighted mean) – Plot used for JEE Paper :

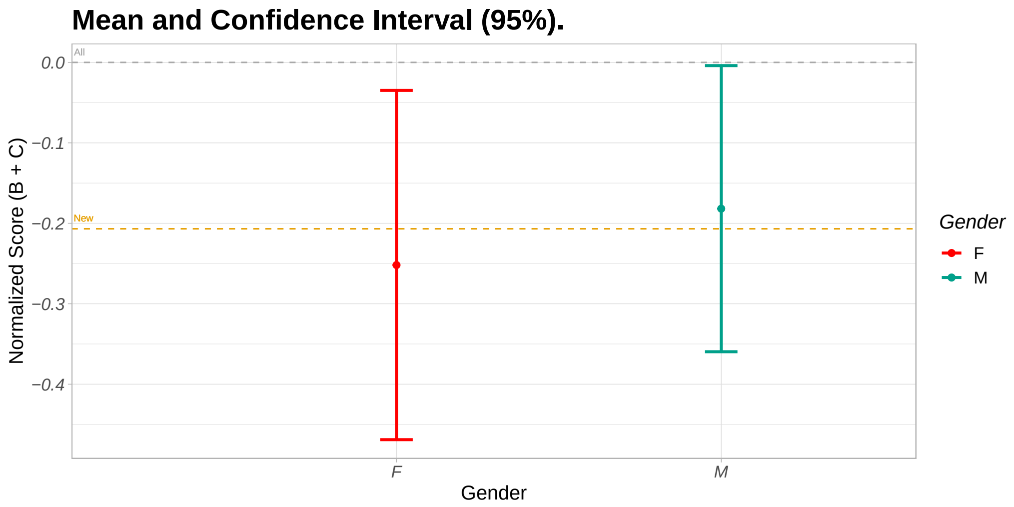


Gender differences across condition for **A+B+C** (with weighted mean) :



6.1.2 Year2

Gender differences for all the volunteers :



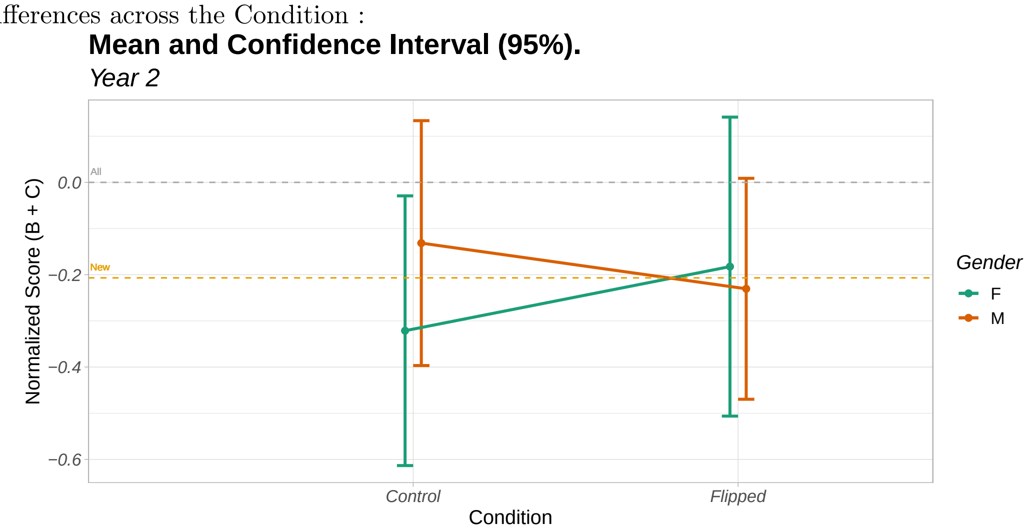
... and the ANOVA :

```
oneway.test(dt.y2$Nor.Score.BC~dt.y2$Gender)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  dt.y2$Nor.Score.BC and dt.y2$Gender
## F = 0.23961, num df = 1.00, denom df = 154.32, p-value = 0.6252
```

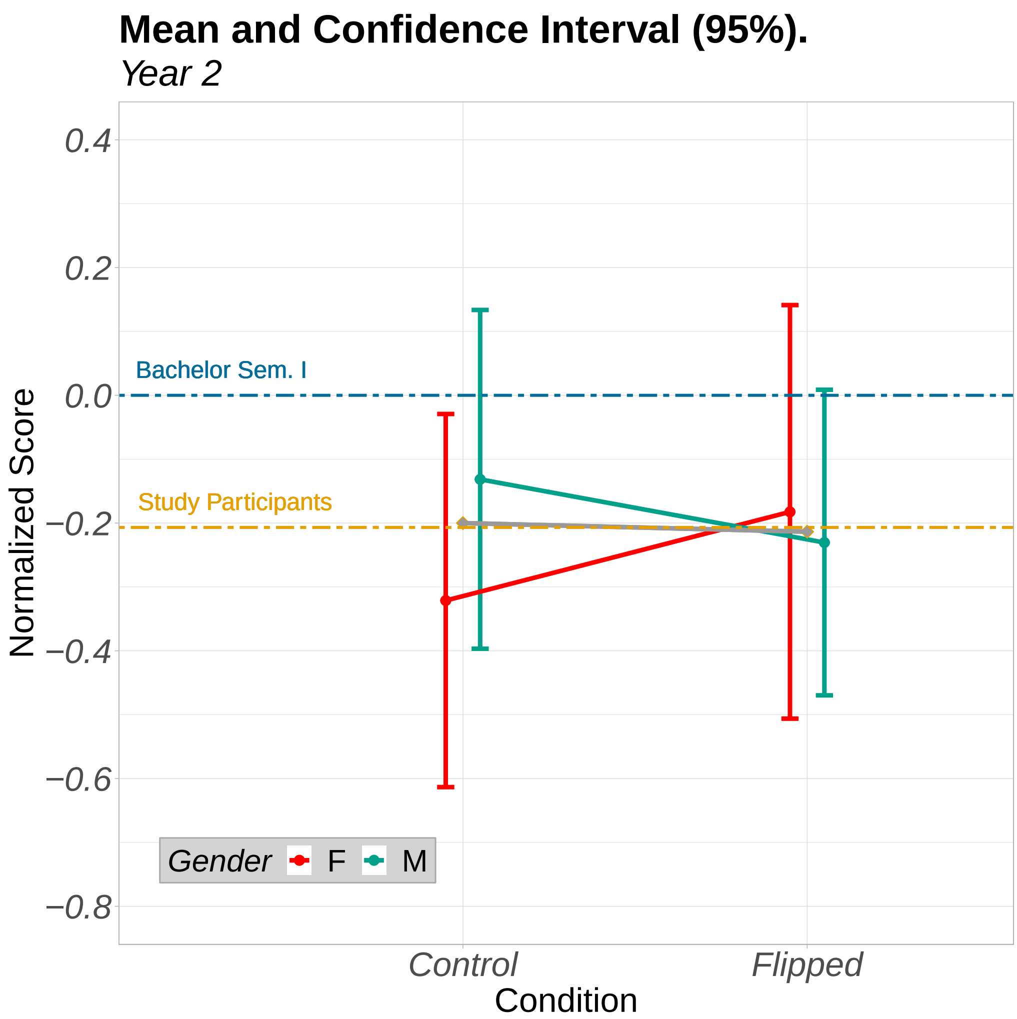
... and the Kruskal-Wallis :

```
kruskal.test(dt.y2$Nor.Score.BC~dt.y2$Gender)

##
##  Kruskal-Wallis rank sum test
##
## data:  dt.y2$Nor.Score.BC by dt.y2$Gender
## Kruskal-Wallis chi-squared = 0.46197, df = 1, p-value = 0.4967

epsilonSquared(x = dt.y2$Nor.Score.BC,
               g = dt.y2$Gender)

## epsilon.squared
##         0.00237
```

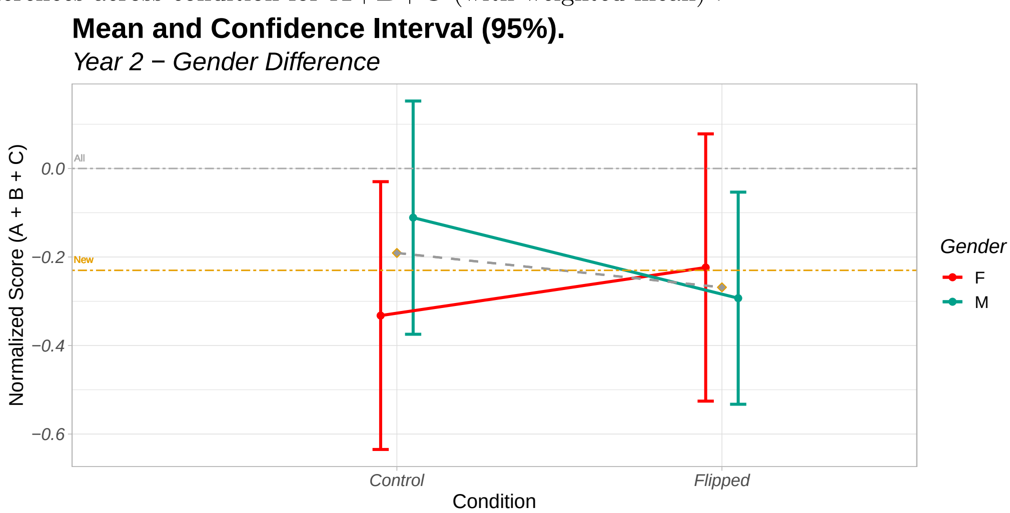
Gender differences across the Condition :



Gender differences across condition (with weighted mean) – Plot used for the JEE Paper :



Gender differences across condition for **A+B+C** (with weighted mean) :



7 Background Differences on Aggregated Parts BC

In this section, we will only analyze background differences across the combined score of Parts B and C. In this way, we are removing the questions that belong to the Part A (the first 4 weeks).

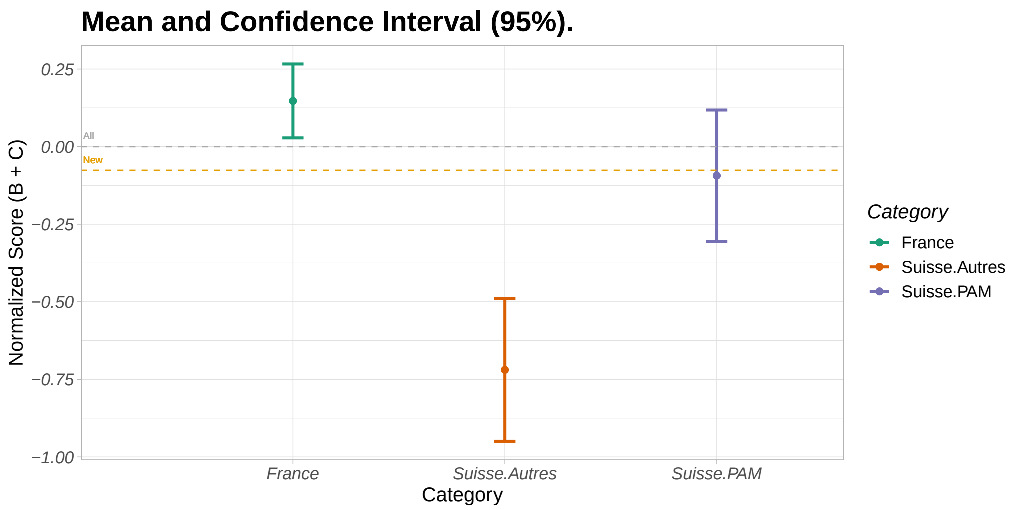
7.1 Visualizing Scores

7.1.1 Year1

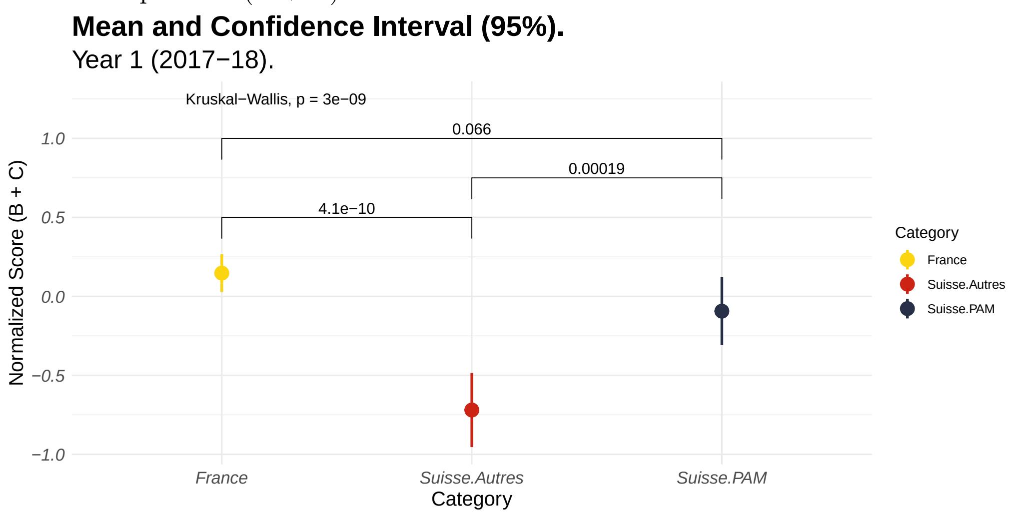
Summarizing the data first :

```
dt.y1 %>% group_by(Category, Condition) %>%
  summarise(N = n()) %>%
  spread(Condition, N)

## # A tibble: 3 x 3
## # Groups:   Category [4]
##   Category      Control Flipped
##   <fct>           <int>   <int>
## 1 France            168      39
## 2 Suisse.Autres      54      16
## 3 Suisse.PAM         59      15

# With the mean and sd values.
dt.y1 %>% group_by(Category, Condition) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score.BC),
            SD = sd(Nor.Score.BC))

## # A tibble: 6 x 5
## # Groups:   Category [3]
##   Category      Condition     N    Mean    SD
##   <fct>         <fct>     <int>   <dbl> <dbl>
## 1 France        Control     168  0.123  0.866
## 2 France        Flipped      39  0.253  0.916
## 3 Suisse.Autres Control      54 -0.754  0.983
## 4 Suisse.Autres Flipped      16 -0.603  1.00
## 5 Suisse.PAM    Control      59 -0.0749 0.972
## 6 Suisse.PAM    Flipped      15 -0.167  0.755
```

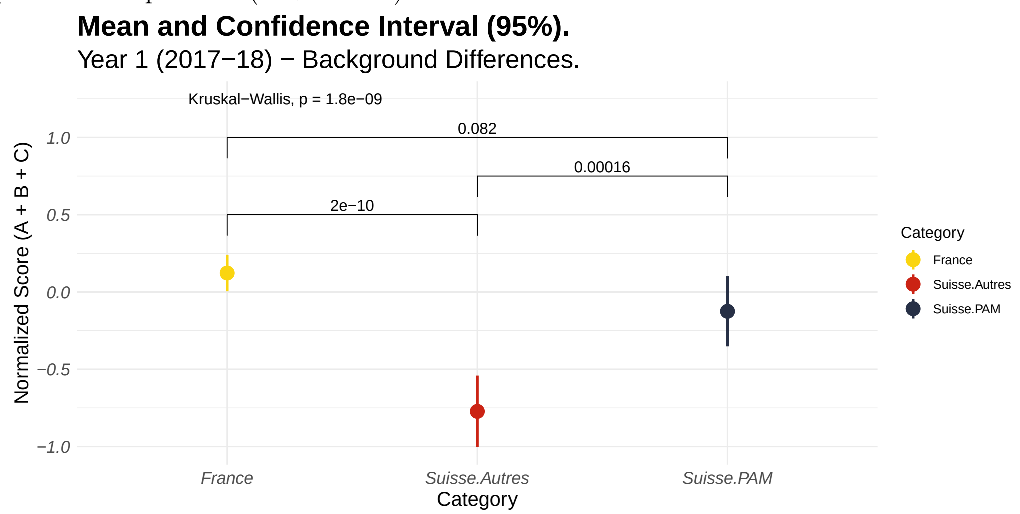
Category differences for all the volunteers :



Plot with pairwise comparisons (B + C) :



Plot with pairwise comparisons (A + B + C) :



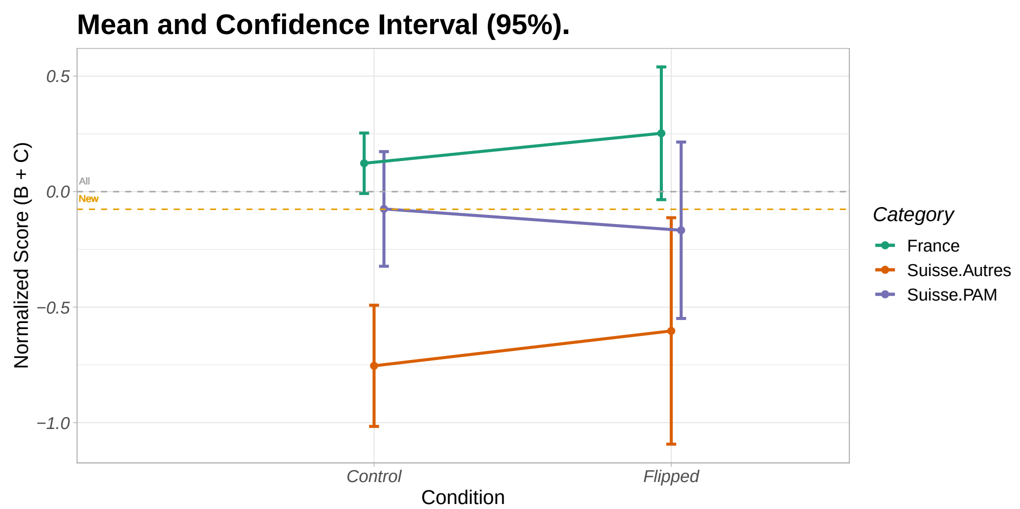
... and the ANOVA :

```
oneway.test(dt.y1$Nor.Score.BC~dt.y1$Category)

##
##  One-way analysis of means (not assuming equal variances)
##
## data:  dt.y1$Nor.Score.BC and dt.y1$Category
## F = 21.505, num df = 2.00, denom df = 137.23, p-value = 7.516e-09
```

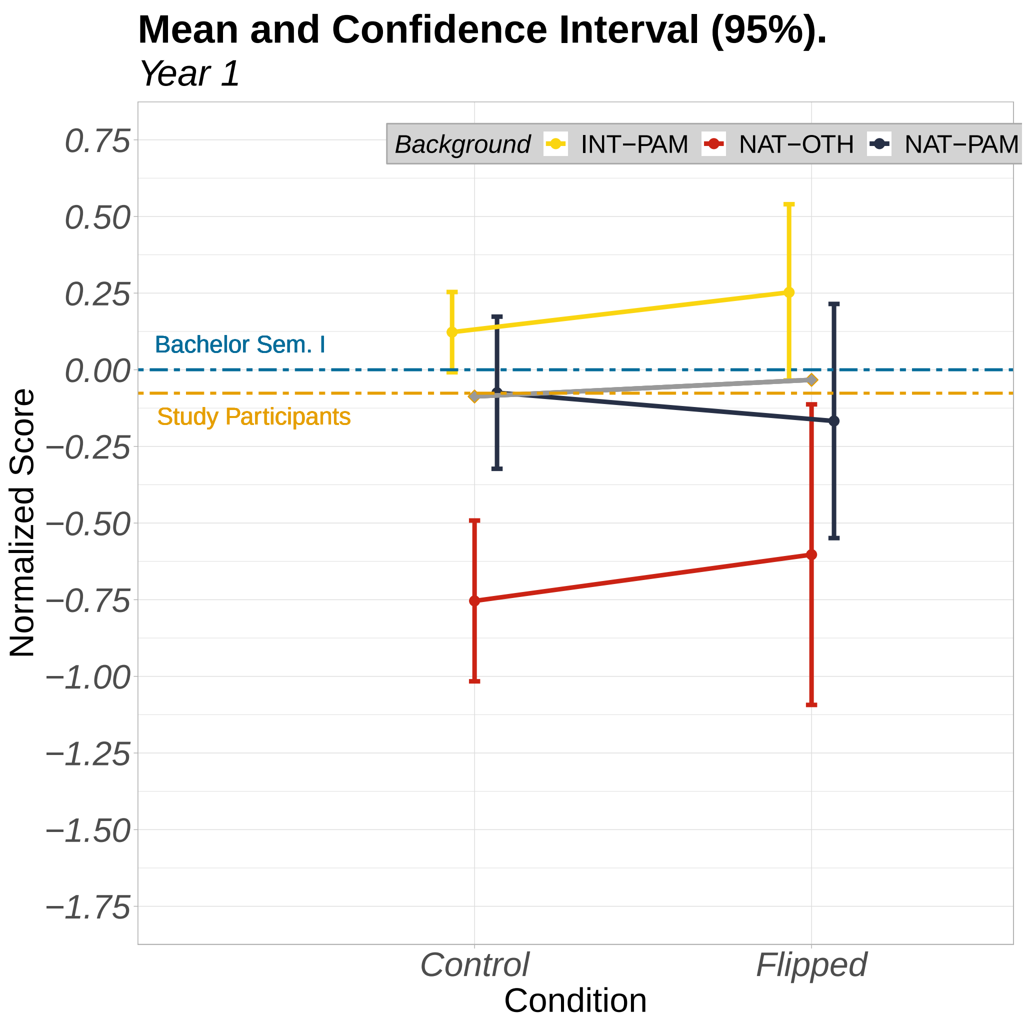
... and the Kruskal-Wallis :

```
kruskal.test(dt.y1$Nor.Score.BC~dt.y1$Category)

##
##  Kruskal-Wallis rank sum test
##
## data:  dt.y1$Nor.Score.BC by dt.y1$Category
## Kruskal-Wallis chi-squared = 39.282, df = 2, p-value = 2.952e-09

epsilonSquared(x = dt.y1$Nor.Score.BC,
               g = dt.y1$Category)

## epsilon.squared
##           0.112
```

Category differences across the Condition :



Category differences across condition (with weighted mean) – Plot for the JEE paper :



Y1 : Kruskal-Wallis for **Control** Condition :

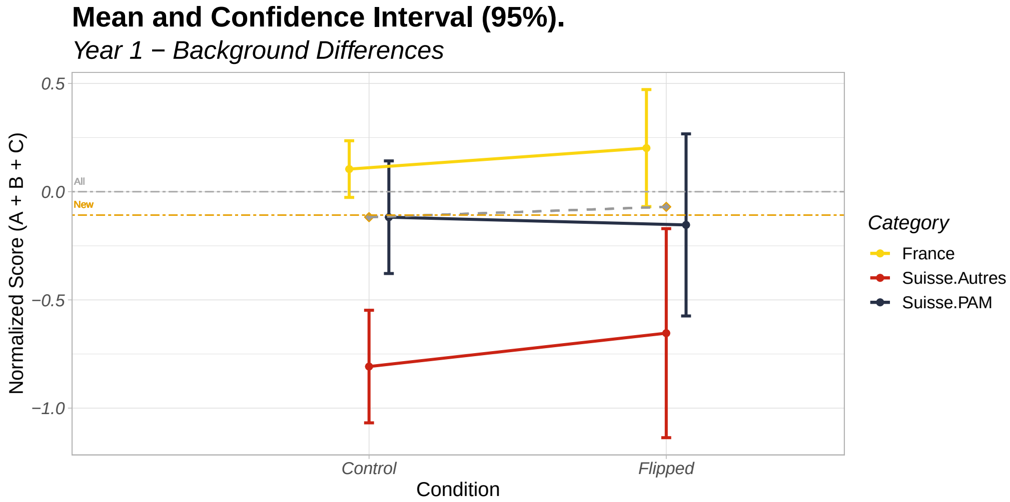
```
t.y1.c = dt.y1 %>% filter(Condition == "Control")
kruskal.test(t.y1.c$Nor.Score.BC~t.y1.c$Category)

##
##  Kruskal-Wallis rank sum test
##
## data:  t.y1.c$Nor.Score.BC by t.y1.c$Category
## Kruskal-Wallis chi-squared = 30.865, df = 2, p-value = 1.985e-07

epsilonSquared(x = t.y1.c$Nor.Score.BC,
               g = t.y1.c$Category)

## epsilon.squared
##            0.11

rm(t.y1.c)
```

Y1 : Kruskal-Wallis for **Flipped** Condition :

```
t.y1.f = dt.y1 %>% filter(Condition == "Flipped")
kruskal.test(t.y1.f$Nor.Score.BC~t.y1.f$Category)

##
##  Kruskal-Wallis rank sum test
##
## data:  t.y1.f$Nor.Score.BC by t.y1.f$Category
## Kruskal-Wallis chi-squared = 9.9688, df = 2, p-value = 0.006844

epsilonSquared(x = t.y1.f$Nor.Score.BC,
               g = t.y1.f$Category)
```

```
## epsilon.squared
##            0.144

rm(t.y1.f)
```

Category differences across condition and **A** + **B** + **C** (with weighted mean) :

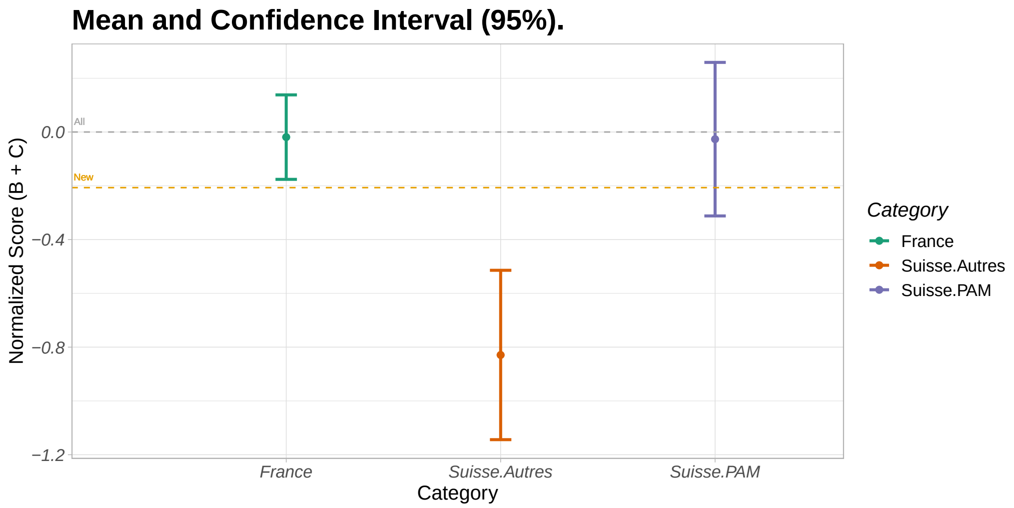


7.1.2 Year2

Summarizing the data first :

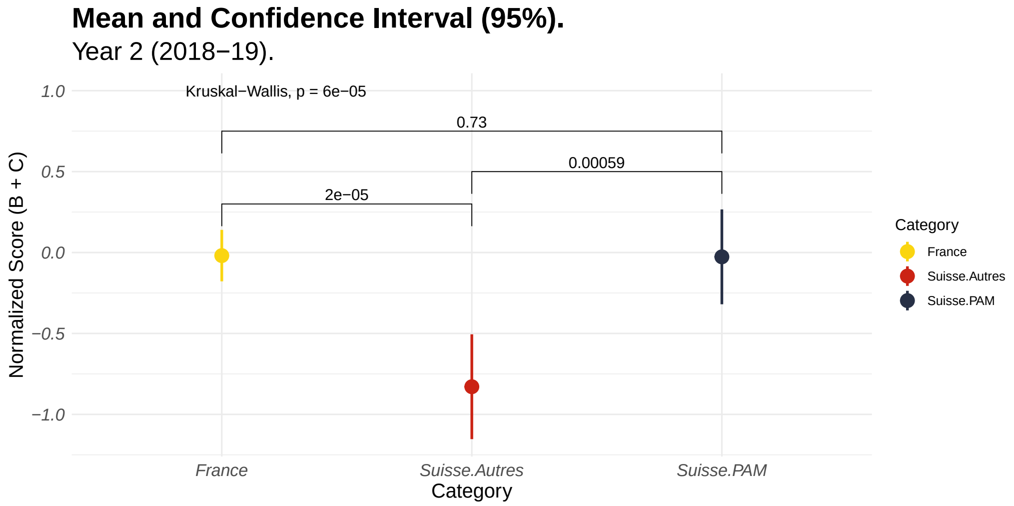
```
dt.y2 %>% group_by(Category, Condition) %>%
  summarise(N = n()) %>%
  spread(Condition, N)

## # A tibble: 3 x 3
## # Groups:   Category [4]
##   Category      Control Flipped
##   <fct>           <int>   <int>
## 1 France             53      50
## 2 Suisse.Autres      20      25
## 3 Suisse.PAM         24      24

# Summary with the mean and sd values.
dt.y2 %>% group_by(Category, Condition) %>%
  summarise(N = n(),
            Mean = mean(Nor.Score.BC),
            SD = sd(Nor.Score.BC))

## # A tibble: 6 x 5
## # Groups:   Category [3]
##   Category      Condition     N    Mean    SD
##   <fct>         <fct>     <int>   <dbl> <dbl>
## 1 France        Control      53  0.0471 0.757
## 2 France        Flipped      50 -0.0890 0.872
## 3 Suisse.Autres Control      20 -1.16   1.06
## 4 Suisse.Autres Flipped      25 -0.563  1.04
## 5 Suisse.PAM    Control      24  0.0561 0.982
## 6 Suisse.PAM    Flipped      24 -0.109  1.05
```

Category differences for all the volunteers :



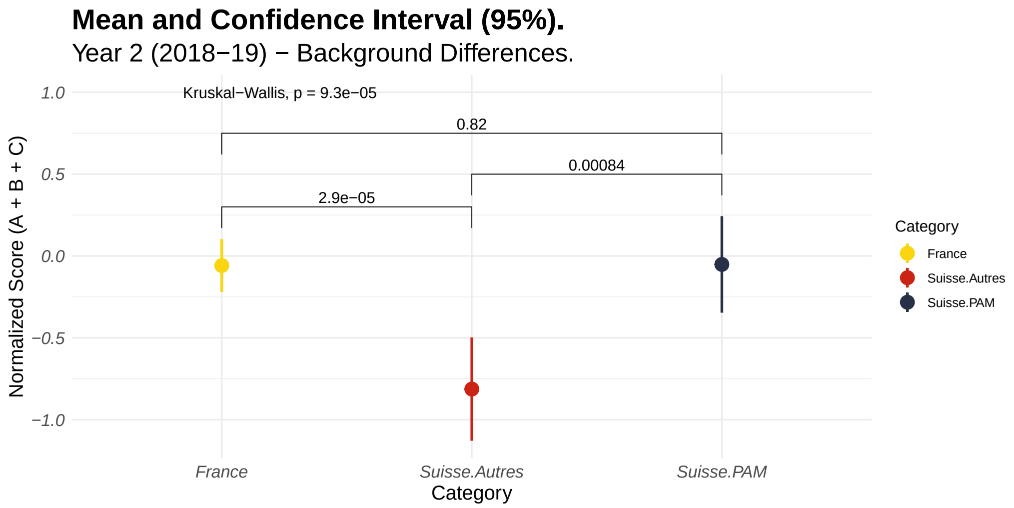
Plot with pairwise comparisons (B + C) :

```
## Warning in wilcox.test.default(c(-0.0123356589575437, -0.833688951103404, : cannot compute exact
p-value with ties
```



Plot with pairwise comparisons (A + B + C) :

```
## Warning in wilcox.test.default(c(0.0264149421745262, -1.01031095344588, : cannot compute exact p-value
with ties
```



Y2 : Kruskal-Wallis for **Control** Condition :

```
t.y2.c = dt.y2 %>% filter(Condition == "Control")
kruskal.test(t.y2.c$Nor.Score.BC~t.y2.c$Category)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  t.y2.c$Nor.Score.BC by t.y2.c$Category
## Kruskal-Wallis chi-squared = 18.252, df = 2, p-value = 0.0001088
```

```
epsilonSquared(x = t.y2.c$Nor.Score.BC,
               g = t.y2.c$Category)
```

```
## epsilon.squared
##            0.19
```

```
rm(t.y2.c)
```

Y2 : Kruskal-Wallis for **Flipped** Condition :

```
t.y2.f = dt.y2 %>% filter(Condition == "Flipped")
kruskal.test(t.y2.f$Nor.Score.BC~t.y2.f$Category)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  t.y2.f$Nor.Score.BC by t.y2.f$Category
## Kruskal-Wallis chi-squared = 4.0723, df = 2, p-value = 0.1305
```

```
epsilonSquared(x = t.y2.f$Nor.Score.BC,
               g = t.y2.f$Category)
```

```
## epsilon.squared
##          0.0416
```

```
rm(t.y2.f)
```

... and the ANOVA :

```
oneway.test(dt.y2$Nor.Score.BC~dt.y2$Category)
```

```
##
##  One-way analysis of means (not assuming equal variances)
##
## data:  dt.y2$Nor.Score.BC and dt.y2$Category
## F = 10.546, num df = 2.000, denom df = 85.898, p-value = 8.024e-05
```

... and the Kruskal-Wallis :

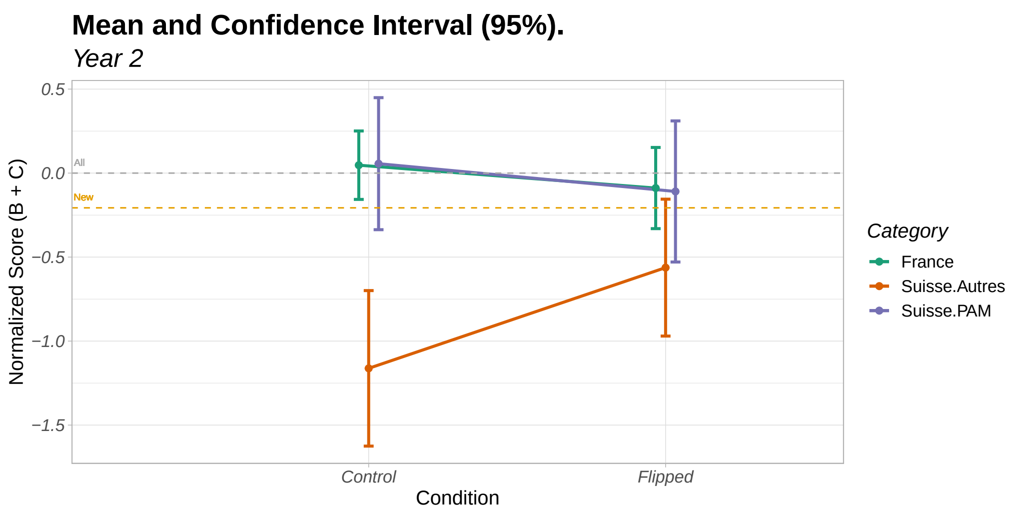
```
kruskal.test(dt.y2$Nor.Score.BC~dt.y2$Category)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  dt.y2$Nor.Score.BC by dt.y2$Category
## Kruskal-Wallis chi-squared = 19.432, df = 2, p-value = 6.03e-05
```

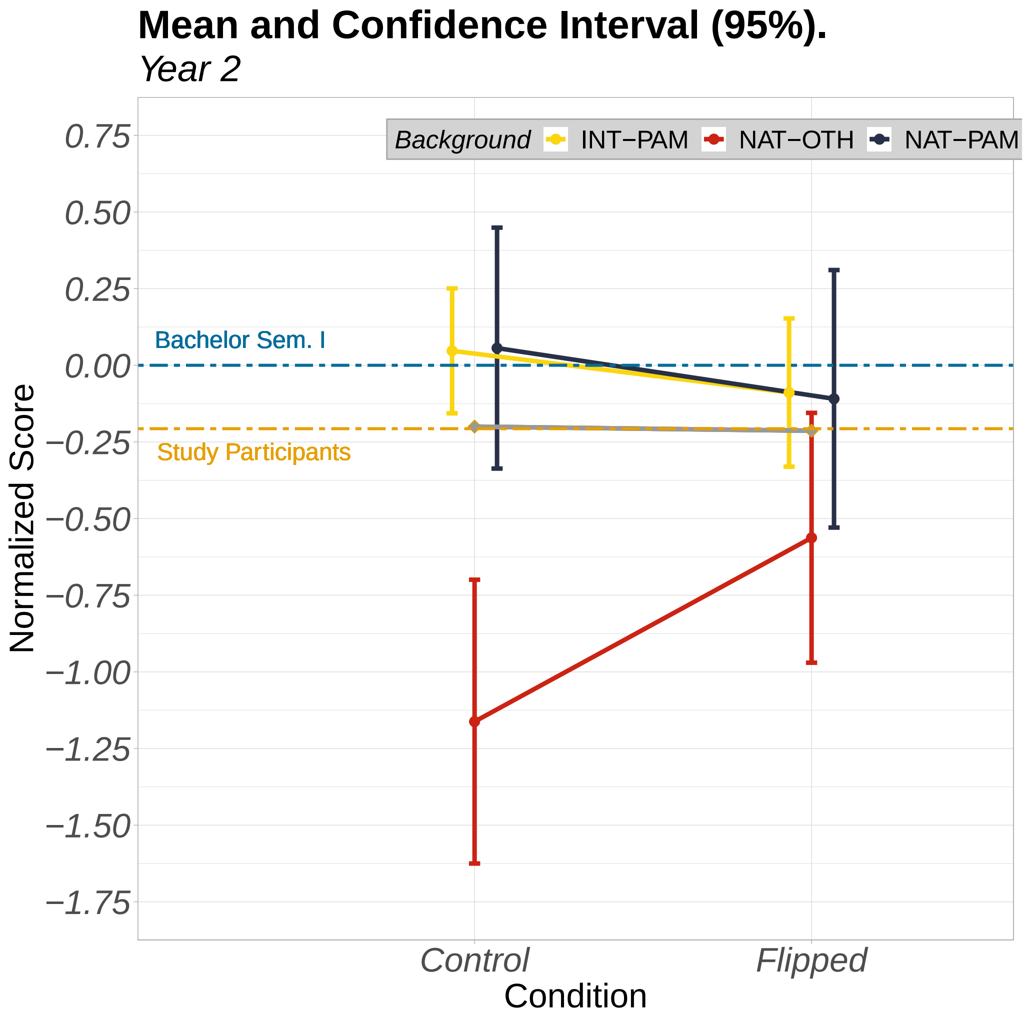
```
epsilonSquared(x = dt.y2$Nor.Score.BC,
               g = dt.y2$Category)
```

```
## epsilon.squared
##          0.0997
```

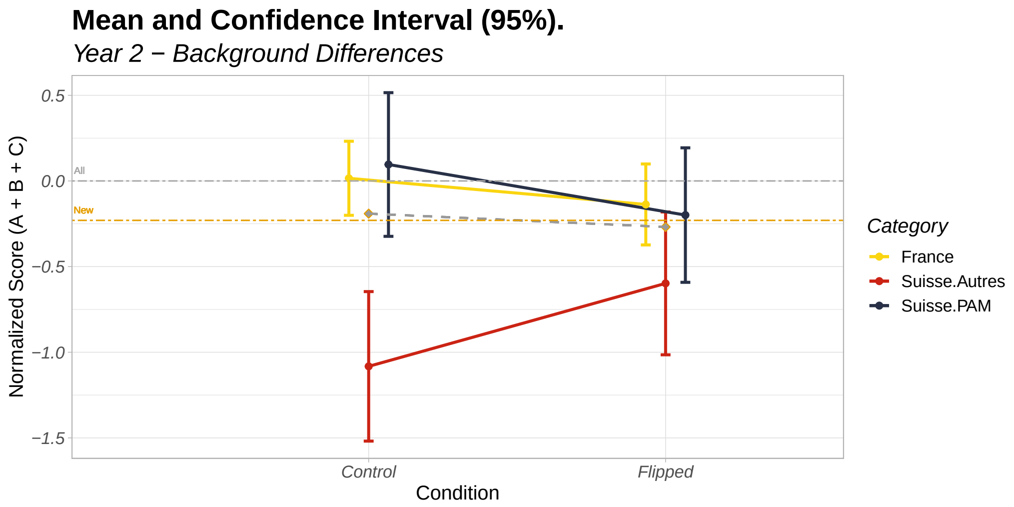
Category differences across the Condition :



Category differences across condition (with weighted mean) – Plot for the JEE Paper :



Category differences across condition and **A+B+C** (with weighted mean) :



8 Influence of Gender, Condition, and Category (Chi-Square and Linear Regression)

In this section, we will perform linear regression to understand the influence of `Gender`, `Condition`, and `Category` on the post-flipped scores (not the Grade).

Initially, we will do this analysis individually for both YEAR 1 and YEAR 2.

8.1 What does Chi-Square test do ?

Before, we examine the relationship of the aforementioned categorical (nominal) variables on score using *linear regression*, we would look if there exists a relationship between the categorical variables themselves. We will use *Chi-square test of independence* to achieve that. Following is the description of what Chi-Square test does and how to interpret it :

The Chi-Square test of independence is used to determine if there is a significant relationship between two nominal (categorical) variables. The frequency of each category for one nominal variable is compared across the categories of the second nominal variable. The data can be displayed in a contingency table where each row represents a category for one variable and each column represents a category for the other variable. For example, say we to examine the relationship between gender (male vs. female) and background (French vs. Swiss). The chi-square test of independence can be used to examine this relationship. The null hypothesis for this test is that there is no relationship between gender and background (i.e. Knowing the value of one variable does not help to predict the value of the other variable). The alternative hypothesis is that there is a relationship between gender and background i.e. knowing the value of one variable helps to predict the value of the other variable.

The Chi-square test of independence works by comparing the observed frequencies (*the frequencies observed in our sample*) to the expected frequencies if there was no relationship between the two categorical variables (*the expected frequencies if the null hypothesis was true*).

Residuals helps us in interpreting the association and the direction of relationship between the two categorical variables. Positive values in cells specify an attraction (positive association) between the corresponding row and column variables. And, the negative values for residuals implies a repulsion (negative association) between the corresponding row and column variables.

8.2 Year1

8.2.1 Chi-Square Test of Independence

First, let's try the **Chi-Square Test of Independence** to examine the relationship between these variables :

```
# Chi-Square Test of Independence.
t = chisq.test(table(dt.y1$Gender, dt.y1$Category, exclude = "Etranger.Autres"))
t

##
##  Pearson's Chi-squared test
##
## data:  table(dt.y1$Gender, dt.y1$Category, exclude = "Etranger.Autres")
## X-squared = 15.75, df = 2, p-value = 0.0003801
```

```r
# ... we also show the residuals for different classes.
t$residuals

##
##         France Suisse.Autres Suisse.PAM
##   F -0.5853461     2.7282399 -1.6744809
##   M  0.4086068    -1.9044759  1.1688886

# ... the Observed values.
t$observed

##
##     France Suisse.Autres Suisse.PAM
##   F     63            36         16
##   M    144            34         58

# ... and the expected frequency corresponding to each class.
t$expected

##
##        France Suisse.Autres Suisse.PAM
##   F  67.82051      22.93447   24.24501
##   M 139.17949      47.06553   49.75499
```

We see that there is **Significant Relationship** between `Gender` and `Category`.
Next, we will perform the same test between `Condition` and `Category` :

```r
# Chi-Square Test of Independence.
t = chisq.test(table(dt.y1$Condition, dt.y1$Category, exclude = "Etranger.Autres"))
t

##
##  Pearson's Chi-squared test
##
## data:  table(dt.y1$Condition, dt.y1$Category, exclude = "Etranger.Autres")
## X-squared = 0.53487, df = 2, p-value = 0.7653

# ... we also show the residuals for different classes.
t$residuals

##
##                France Suisse.Autres  Suisse.PAM
##   Control  0.17727220   -0.27249421 -0.03146273
##   Flipped -0.35517694    0.54596075  0.06303772

# ... the Observed values.
t$observed

##
##           France Suisse.Autres Suisse.PAM
##   Control    168            54         59
##   Flipped     39            16         15

# ... and the expected frequency corresponding to each class.
t$expected

##
##               France Suisse.Autres Suisse.PAM
##   Control 165.71795      56.03989   59.24217
##   Flipped  41.28205      13.96011   14.75783
```

There is **NO Significant Relationship** between `Condition` and `Category`.
Finally, let's do the same for `Gender` and `Condition` :

```r
# Chi-Square Test of Independence.
t = chisq.test(table(dt.y1$Gender, dt.y1$Condition))
t

##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  table(dt.y1$Gender, dt.y1$Condition)
## X-squared = 1.0689e-30, df = 1, p-value = 1

# ... we also show the residuals for different classes.
t$residuals

##
##          Control      Flipped
##   F -0.006829237  0.013682843
##   M  0.004767219 -0.009551449

# ... the Observed values.
t$observed

##
##     Control Flipped
##   F      92      23
##   M     189      47

# ... and the expected frequency corresponding to each class.
t$expected

##
##       Control   Flipped
##   F  92.06553 22.93447
##   M 188.93447 47.06553
```

There is **NO Significant Relationship** between `Gender` and `Condition`.

8.2.2 Linear Regression

Linear regression :

```r
# Model fitting
m = lm(Nor.Score.BC ~ Gender * Category * Condition,
       data = dt.y1)

# Printing the model coefficients
print(m)

##
## Call:
## lm(formula = Nor.Score.BC ~ Gender * Category * Condition, data = dt.y1)
##
## Coefficients:
##                                    (Intercept)
##                                        0.10889
##                                        GenderM
##                                        0.02004
##                          CategorySuisse.Autres
##                                       -1.09555
##                             CategorySuisse.PAM
##                                       -0.04572
##                               ConditionFlipped
##                                        0.04453
##                  GenderM:CategorySuisse.Autres
##                                        0.44536
##                     GenderM:CategorySuisse.PAM
```

```
##                                      -0.19710
##                       GenderM:ConditionFlipped
##                                       0.11807
##         CategorySuisse.Autres:ConditionFlipped
##                                       0.67874
##            CategorySuisse.PAM:ConditionFlipped
##                                       0.02514
## GenderM:CategorySuisse.Autres:ConditionFlipped
##                                      -1.35975
##    GenderM:CategorySuisse.PAM:ConditionFlipped
##                                      -0.31601
```

```
# Next, we print the model summary
summary(m)
```

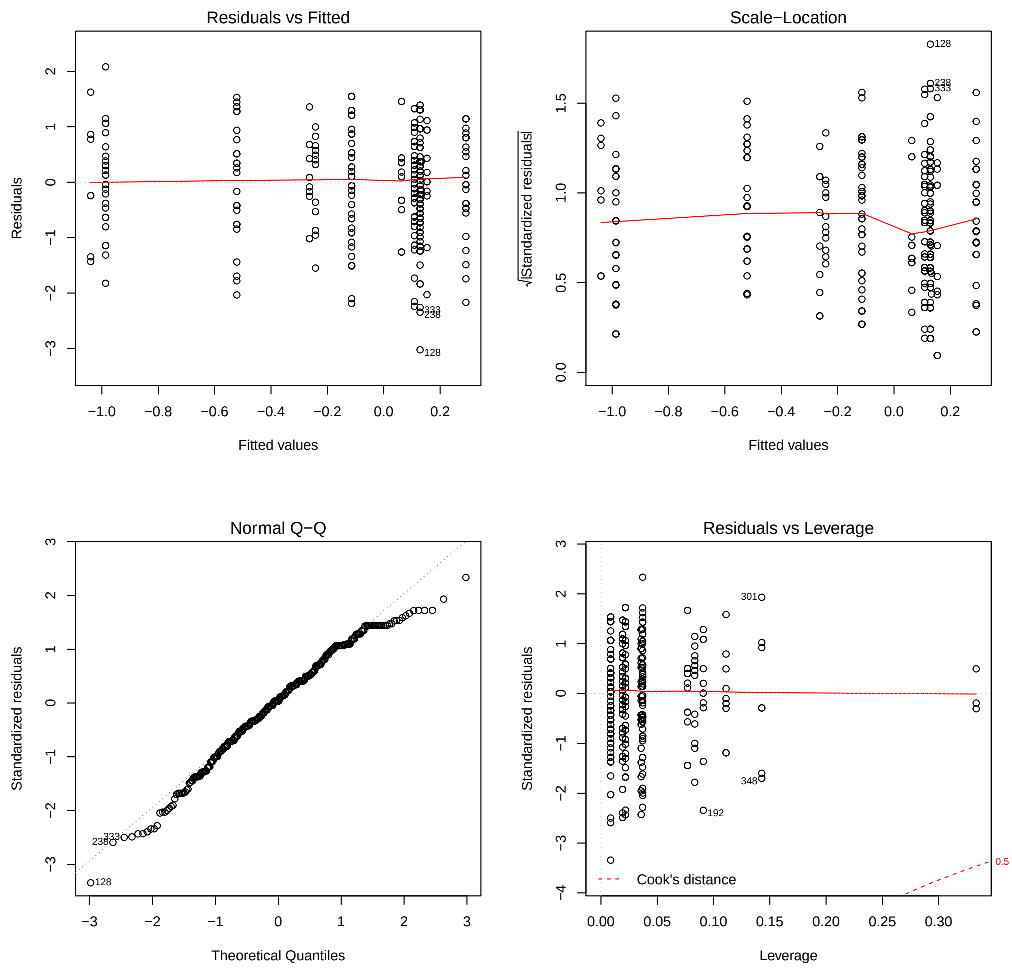
```
##
## Call:
## lm(formula = Nor.Score.BC ~ Gender * Category * Condition, data = dt.y1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.02440 -0.56213  0.03221  0.64659  2.08176
##
## Coefficients:
##                                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                                     0.10889    0.12602   0.864   0.3881
## GenderM                                         0.02004    0.15166   0.132   0.8949
## CategorySuisse.Autres                          -1.09555    0.21556  -5.082 6.17e-07 ***
## CategorySuisse.PAM                             -0.04572    0.28179  -0.162   0.8712
## ConditionFlipped                                0.04453    0.30158   0.148   0.8827
## GenderM:CategorySuisse.Autres                   0.44536    0.29012   1.535   0.1257
## GenderM:CategorySuisse.PAM                     -0.19710    0.32323  -0.610   0.5424
## GenderM:ConditionFlipped                        0.11807    0.35716   0.331   0.7412
## CategorySuisse.Autres:ConditionFlipped          0.67874    0.46184   1.470   0.1426
## CategorySuisse.PAM:ConditionFlipped             0.02514    0.65555   0.038   0.9694
## GenderM:CategorySuisse.Autres:ConditionFlipped -1.35975    0.63124  -2.154   0.0319 *
## GenderM:CategorySuisse.PAM:ConditionFlipped    -0.31601    0.74372  -0.425   0.6712
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9087 on 339 degrees of freedom
## Multiple R-squared:  0.1421,Adjusted R-squared:  0.1142
## F-statistic: 5.103 on 11 and 339 DF,  p-value: 2.107e-07
```

```
# We also show the ANOVA table
anova(m)
```

```
## Analysis of Variance Table
##
## Response: Nor.Score.BC
##                            Df  Sum Sq Mean Sq F value    Pr(>F)
## Gender                      1   1.757  1.7566  2.1271   0.14564
## Category                    2  37.633 18.8164 22.7857 5.191e-10 ***
## Condition                   1   0.422  0.4219  0.5109   0.47525
## Gender:Category             2   1.183  0.5913  0.7161   0.48941
## Gender:Condition            1   1.184  1.1838  1.4335   0.23203
## Category:Condition          2   0.318  0.1591  0.1927   0.82483
## Gender:Category:Condition   2   3.855  1.9274  2.3340   0.09847 .
## Residuals                 339 279.946  0.8258
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We will also plot the diagnostic plots for the regression analysis :

```r
# Diagnostic plots
layout(matrix(c(1,2,3,4), 2, 2))
plot(m)
```



The results from Year1 show that Suisse.Autres perform significantly badly overall. In addition, there is an *interaction effect* between `Gender` – particularly Male, `Category` – Suisse.Autres, and `Condition` – Flipped. This signifies that Male students belonging to Suisse.Autres and in the Flipped condition performed significantly worse (a drop of 2.7 points in `Nor.Score.BC`.

Furthermore, the ANOVA of the model shows that `Category` significantly influences the `Nor.Score.BC`, and there is an interaction effect between `Gender`, `Category`, and `Condition`.

8.3 Year2

8.3.1 Chi Square Test of Independence

First, let's try the **Chi-Square Test of Independence** to examine the relationship between these variables :

```r
# Chi-Square Test of Independence.
t = chisq.test(table(dt.y2$Gender, dt.y2$Category, exclude = "Etranger.Autres"))
t

##
##  Pearson's Chi-squared test
##
## data:  table(dt.y2$Gender, dt.y2$Category, exclude = "Etranger.Autres")
## X-squared = 3.9562, df = 2, p-value = 0.1383

# ... we also show the residuals for different classes.
t$residuals

##
##          France Suisse.Autres Suisse.PAM
```

```
##   F  0.2002079     0.9799579 -1.2421180
##   M -0.1492262    -0.7304175  0.9258201

# ... the Observed values.
t$observed

##
##     France Suisse.Autres Suisse.PAM
##   F     38            20         12
##   M     65            25         36

# ... and the expected frequency corresponding to each class.
t$expected

##
##       France Suisse.Autres Suisse.PAM
##   F 36.78571      16.07143   17.14286
##   M 66.21429      28.92857   30.85714
```

We see that there is **NO Significant Relationship** between `Gender` and `Category`.
Next, we will perform the same test between `Condition` and `Category` :

```
# Chi-Square Test of Independence.
t = chisq.test(table(dt.y2$Condition, dt.y2$Category, exclude = "Etranger.Autres"))
t

##
##  Pearson's Chi-squared test
##
## data:  table(dt.y2$Condition, dt.y2$Category, exclude = "Etranger.Autres")
## X-squared = 0.62259, df = 2, p-value = 0.7325

# ... we also show the residuals for different classes.
t$residuals

##
##                 France Suisse.Autres  Suisse.PAM
##   Control  0.28369912   -0.48110498  0.05024660
##   Flipped -0.28081885    0.47622054 -0.04973647

# ... the Observed values.
t$observed

##
##            France Suisse.Autres Suisse.PAM
##   Control     53            20         24
##   Flipped     50            25         24

# ... and the expected frequency corresponding to each class.
t$expected

##
##              France Suisse.Autres Suisse.PAM
##   Control 50.97449      22.27041    23.7551
##   Flipped 52.02551      22.72959    24.2449
```

There is **NO Significant Relationship** between `Condition` and `Category`.
Finally, let's do the same for `Gender` and `Condition` :

```
# Chi-Square Test of Independence.
t = chisq.test(table(dt.y2$Gender, dt.y2$Condition))
t

##
##  Pearson's Chi-squared test with Yates' continuity correction
```

```
##
## data:  table(dt.y2$Gender, dt.y2$Condition)
## X-squared = 0, df = 1, p-value = 1
```

```
# ... we also show the residuals for different classes.
t$residuals
```

```
##
##          Control     Flipped
##   F  0.06067854 -0.06006250
##   M -0.04522711  0.04476794
```

```
# ... the Observed values.
t$observed
```

```
##
##     Control Flipped
##   F      35      35
##   M      62      64
```

```
# ... and the expected frequency corresponding to each class.
t$expected
```

```
##
##      Control  Flipped
##   F 34.64286 35.35714
##   M 62.35714 63.64286
```

There is **NO Significant Relationship** between `Gender` and `Condition`.

8.3.2 Linear Regression

Linear regression :

```
# Model fitting
m = lm(Nor.Score.BC ~ Gender * Category * Condition,
       data = dt.y2)

# Printing the model coefficients
print(m)
```

```
##
## Call:
## lm(formula = Nor.Score.BC ~ Gender * Category * Condition, data = dt.y2)
##
## Coefficients:
##                                    (Intercept)
##                                       -0.05556
##                                        GenderM
##                                        0.15999
##                         CategorySuisse.Autres
##                                       -0.63363
##                            CategorySuisse.PAM
##                                       -0.51412
##                              ConditionFlipped
##                                        0.12969
##                 GenderM:CategorySuisse.Autres
##                                       -1.02006
##                    GenderM:CategorySuisse.PAM
##                                        0.72348
##                      GenderM:ConditionFlipped
##                                       -0.42308
##        CategorySuisse.Autres:ConditionFlipped
##                                       -0.30530
##           CategorySuisse.PAM:ConditionFlipped
```

```
##                                            0.78358
## GenderM:CategorySuisse.Autres:ConditionFlipped
##                                            1.82272
##    GenderM:CategorySuisse.PAM:ConditionFlipped
##                                           -1.03245
```

```r
# Next, we print the model summary
summary(m)
```

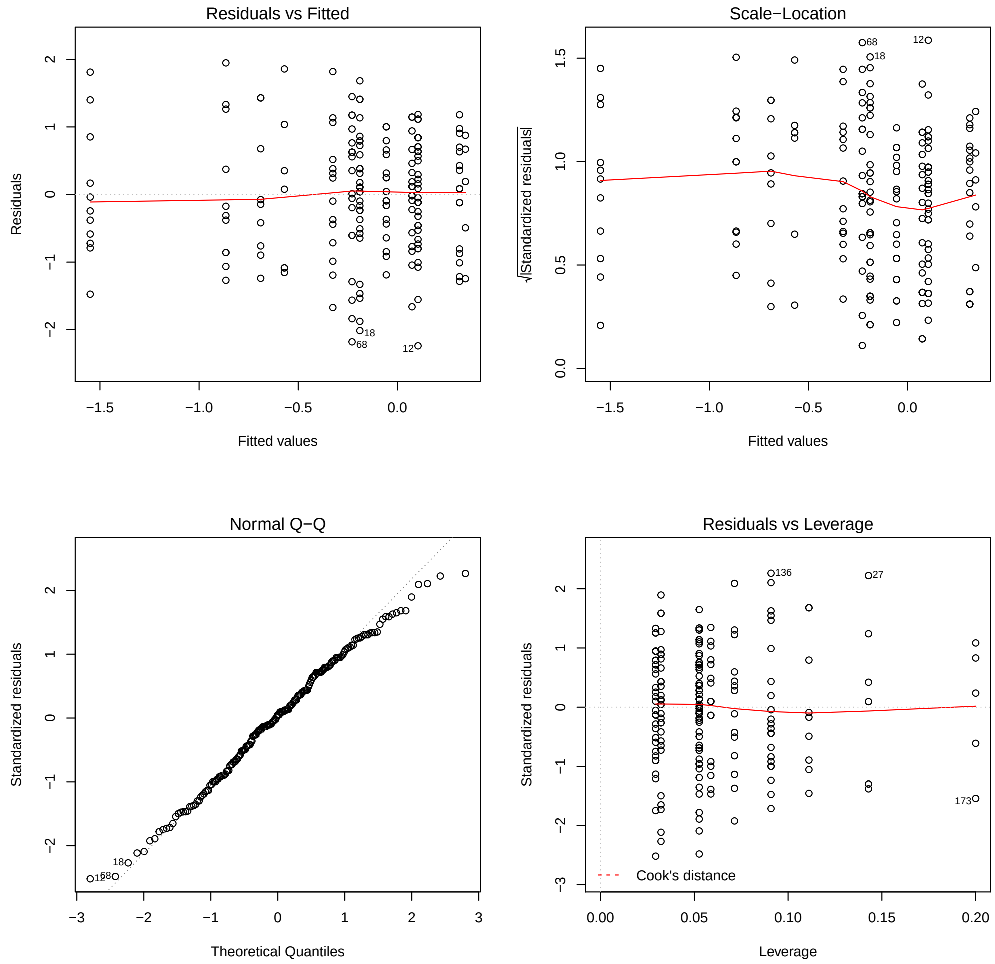
```
##
## Call:
## lm(formula = Nor.Score.BC ~ Gender * Category * Condition, data = dt.y2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.23859 -0.61421  0.03974  0.66105  1.94760
##
## Coefficients:
##                                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                                    -0.05556    0.20708  -0.268  0.78875
## GenderM                                         0.15999    0.25854   0.619  0.53681
## CategorySuisse.Autres                          -0.63363    0.36525  -1.735  0.08446 .
## CategorySuisse.PAM                             -0.51412    0.39909  -1.288  0.19929
## ConditionFlipped                                0.12969    0.29285   0.443  0.65840
## GenderM:CategorySuisse.Autres                  -1.02006    0.48108  -2.120  0.03532 *
## GenderM:CategorySuisse.PAM                      0.72348    0.48080   1.505  0.13410
## GenderM:ConditionFlipped                       -0.42308    0.36879  -1.147  0.25279
## CategorySuisse.Autres:ConditionFlipped         -0.30530    0.50036  -0.610  0.54251
## CategorySuisse.PAM:ConditionFlipped             0.78358    0.60424   1.297  0.19632
## GenderM:CategorySuisse.Autres:ConditionFlipped  1.82272    0.65793   2.770  0.00617 **
## GenderM:CategorySuisse.PAM:ConditionFlipped    -1.03245    0.71145  -1.451  0.14843
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9026 on 184 degrees of freedom
## Multiple R-squared:  0.2071,Adjusted R-squared:  0.1597
## F-statistic:  4.37 on 11 and 184 DF,  p-value: 8.11e-06
```

```r
# We also show the ANOVA table
anova(m)
```

```
## Analysis of Variance Table
##
## Response: Nor.Score.BC
##                            Df  Sum Sq Mean Sq F value   Pr(>F)
## Gender                      1   0.221  0.2210  0.2712 0.603140
## Category                    2  22.399 11.1996 13.7460 2.73e-06 ***
## Condition                   1   0.028  0.0283  0.0348 0.852266
## Gender:Category             2   0.528  0.2642  0.3243 0.723429
## Gender:Condition            1   0.648  0.6475  0.7948 0.373828
## Category:Condition          2   4.560  2.2798  2.7981 0.063518 .
## Gender:Category:Condition   2  10.783  5.3916  6.6174 0.001678 **
## Residuals                 184 149.915  0.8148
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We will also plot the diagnostic plots for the regression analysis :

```r
# Diagnostic plots
layout(matrix(c(1,2,3,4), 2, 2))
plot(m)
```



The results from YEAR2 show an *inverse* effect as compared to YEAR1. *Firstly*, MALES in `Category` SUISSE.AUTRES and FLIPPED `Condition` had a significant positive score (which was not the case in YEAR1). In addition, the analysis of ANOVA shows significant influence of `Category`, as well as significant interaction efffects between `Category` and `Condition`, and between `Gender`, `Category`, and `Condition`.

9 Linear Mixed Effect Models

In this section, we will perform "Linear Mixed-Effects Modelling" to assess the relationship of different variables on the `Nor.Score.BC`. In order to do so, we will combine the YEAR 1 and YEAR 2 datasets, and use the `Course.Year` as a random effect.

9.1 Preparing Data

First, we prepare the data by binding the YEAR 1 and YEAR 2 datasets.

```
# Select relevant columns.
cols = c("ID.Anon", "Gender", "Category",
         "Course.Year", "Condition", "Nor.Score.BC")
t.y1 = dt.y1 %>% select(one_of(cols))
t.y2 = dt.y2 %>% select(one_of(cols))

# Bind the two datasets.
dt = rbind(t.y1, t.y2)

# Clean up
rm(cols, t.y1, t.y2)
```

9.2 Null Model

We will create a **null** model.

```r
# Null model
m0 = lm(Nor.Score.BC ~ 1,
        data = dt)

# Summary
summary(m0)

##
## Call:
## lm(formula = Nor.Score.BC ~ 1, data = dt)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9008 -0.6421  0.1108  0.7088  1.6428
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.12314    0.04163  -2.958  0.00323 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9736 on 546 degrees of freedom
```

9.3 Mixed-Effect Model

We will create a mixed-effect model with `Condition, Gender, Category` as the fixed effects, and `Course.Year` as the random effect.

```r
# Mixed-Effect Model
m1 = lme(Nor.Score.BC ~ Condition * Gender * Category,
         random = ~1|Course.Year,
         data = dt)

# Summary
summary(m1)

## Linear mixed-effects model fit by REML
##  Data: dt
##        AIC     BIC    logLik
##   1497.189 1557.14 -734.5943
##
## Random effects:
##  Formula: ~1 | Course.Year
##         (Intercept)  Residual
## StdDev:  0.05718557 0.9172953
##
## Fixed effects: Nor.Score.BC ~ Condition * Gender * Category
##                                                   Value Std.Error  DF   t-value p-value
## (Intercept)                                   0.0520550 0.1169396 534  0.445144  0.6564
## ConditionFlipped                              0.0585062 0.2009129 534  0.291202  0.7710
## GenderM                                       0.0562379 0.1321610 534  0.425525  0.6706
## CategorySuisse.Autres                        -0.9781443 0.1876840 534 -5.211654  0.0000
## CategorySuisse.PAM                           -0.2186601 0.2322636 534 -0.941431  0.3469
## ConditionFlipped:GenderM                     -0.1263296 0.2445109 534 -0.516663  0.6056
## ConditionFlipped:CategorySuisse.Autres        0.2761804 0.3245898 534  0.850860  0.3952
## ConditionFlipped:CategorySuisse.PAM           0.3795556 0.4326407 534  0.877300  0.3807
## GenderM:CategorySuisse.Autres                 0.0394004 0.2509965 534  0.156976  0.8753
## GenderM:CategorySuisse.PAM                    0.0991871 0.2699882 534  0.367376  0.7135
## ConditionFlipped:GenderM:CategorySuisse.Autres  0.0679193 0.4330106 534  0.156854  0.8754
## ConditionFlipped:GenderM:CategorySuisse.PAM  -0.5280944 0.4975771 534 -1.061332  0.2890
##  Correlation:
##                                              (Intr) CndtnF GendrM CtgS.A CS.PAM CnF:GM
```

```
## ConditionFlipped                              -0.517
## GenderM                                       -0.765  0.444
## CategorySuisse.Autres                         -0.539  0.314  0.478
## CategorySuisse.PAM                            -0.439  0.256  0.386  0.272
## ConditionFlipped:GenderM                       0.416 -0.814 -0.540 -0.258 -0.209
## ConditionFlipped:CategorySuisse.Autres         0.314 -0.613 -0.276 -0.578 -0.157  0.503
## ConditionFlipped:CategorySuisse.PAM            0.236 -0.460 -0.207 -0.146 -0.537  0.377
## GenderM:CategorySuisse.Autres                  0.402 -0.233 -0.527 -0.748 -0.203  0.284
## GenderM:CategorySuisse.PAM                     0.376 -0.219 -0.489 -0.234 -0.860  0.265
## ConditionFlipped:GenderM:CategorySuisse.Autres -0.236  0.461  0.305  0.433  0.118 -0.565
## ConditionFlipped:GenderM:CategorySuisse.PAM    -0.206  0.401  0.265  0.127  0.467 -0.492
##                                               CF:CS.A CF:CS.P GM:CS.A GM:CS.P CF:GM:CS.A
## ConditionFlipped
## GenderM
## CategorySuisse.Autres
## CategorySuisse.PAM
## ConditionFlipped:GenderM
## ConditionFlipped:CategorySuisse.Autres
## ConditionFlipped:CategorySuisse.PAM            0.284
## GenderM:CategorySuisse.Autres                  0.432   0.109
## GenderM:CategorySuisse.PAM                     0.135   0.462   0.257
## ConditionFlipped:GenderM:CategorySuisse.Autres -0.750  -0.213  -0.579  -0.150
## ConditionFlipped:GenderM:CategorySuisse.PAM    -0.247  -0.870  -0.140  -0.543   0.278
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.30466331 -0.63070611  0.02752506  0.73675893  2.26236460
##
## Number of Observations: 547
## Number of Groups: 2
```

```
# ANOVA
anova(m1)
```

```
##                         numDF denDF  F-value p-value
## (Intercept)                 1   534  5.40080  0.0205
## Condition                   1   534  0.00025  0.9873
## Gender                      1   534  2.20029  0.1386
## Category                    2   534 35.43504  <.0001
## Condition:Gender            1   534  1.88602  0.1702
## Condition:Category          2   534  1.12429  0.3257
## Gender:Category             2   534  0.11791  0.8888
## Condition:Gender:Category   2   534  0.67371  0.5102
```