Thesis Stuff

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I'm joking, none of the mtg sites will let me scrape more, so im moving on :)

```
library(rvest)
library(skimr)
library(glue)
library(tidyverse)
library(usethis)
library(stringi)
library(robotstxt)
```

Lets filter some data!!

For my thesis, I'm interested in counterfactuals and moral thinking. This study was basic, as I only asked students to either come up with a counterfactual after thinking about a negative event, or not! The counterfactual were split between upward and downward counterfactuals.

This is RAW data so lets clean it up!

```
library(haven)
Personal_Experiences_Assessment_Study_May_15_2023_19_29 <- read_sav("~/Documents/GitHub/Project-1/Porfol
View(Personal_Experiences_Assessment_Study_May_15_2023_19_29)
```

First, lets delete some columns that are unneeded

```
Thesis_Data <- Personal_Experiences_Assessment_Study_May_15_2023_19_29

Thesis_Data = subset(Thesis_Data, select = -c(StartDate, EndDate, Status, IPAddress, Progress, Finished
```

Now we need to add the number of counterfactuals for each condition

```
UP_Coun_Num = c(0, 0, 5, 0, 5, 0, 0, 5, 0, 0, 0, 2, 0, 4, 0, 0, 3, 0, 0, 2, 0, 0, 0, 2, 0, 0, 0, 0, 3, 

DOWN_Coun_Num = c(0, 0, 0, 4, 0, 0, 0, 0, 2, 0, 4, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 2, 0, 5, 0

#adding to data frame
```

```r
Thesis_Data <- data.frame(Thesis_Data, UP_Coun_Num, DOWN_Coun_Num)

# Now we need to set the individuals that are not in that condition as 0

Thesis_Data <- Thesis_Data %>% mutate(FL_18_DO_UP_CTP = ifelse(is.na(FL_18_DO_UP_CTP), 0, FL_18_DO_UP_C

Thesis_Data <- Thesis_Data %>% mutate(FL_18_DO_DW_CFTP = ifelse(is.na(FL_18_DO_DW_CFTP), 0, FL_18_DO_DW_

Thesis_Data <- Thesis_Data %>% mutate(FL_18_DO_WT = ifelse(is.na(FL_18_DO_WT), 0, FL_18_DO_WT))


# Rename these

colnames(Thesis_Data)[colnames(Thesis_Data) == "FL_18_DO_DW_CFTP"] ="Downward_Participants"

colnames(Thesis_Data)[colnames(Thesis_Data) == "FL_18_DO_UP_CTP"] ="Upward_Participants"

colnames(Thesis_Data)[colnames(Thesis_Data) == "FL_18_DO_WT"] ="Control_Participants"


# Recode and Merge

Thesis_Data$Participants[Thesis_Data$Upward_Participants=="1"] <- "1"
Thesis_Data$Participants[Thesis_Data$Downward_Participants=="1"] <- "2"
Thesis_Data$Participants[Thesis_Data$Control_Participants=="1"] <- "3"


#Now we need to add for the number of Counterfactuals

Thesis_Data <- Thesis_Data %>% mutate(Count_Num = UP_Coun_Num + DOWN_Coun_Num)

#Need to Multiply for CP

Thesis_Data <- Thesis_Data %>% mutate(CF_1 = CTR_IF1 * CTR_TH1)

Thesis_Data <- Thesis_Data %>% mutate(CF_2 = CTR_IF2 * CTR_TH2)

Thesis_Data <- Thesis_Data %>% mutate(CF_3 = CTR_IF3 * CTR_TH3)

Thesis_Data <- Thesis_Data %>% mutate(CF_4 = CTR_IF4 * CTR_TH4)

Thesis_Data <- Thesis_Data %>% mutate(CF_5 = CRT_IF5 * CTR_TH5)

#Divide for Total

Thesis_Data <- Thesis_Data %>% mutate(CF_1_Tot = CF_1 / Count_Num)

Thesis_Data <- Thesis_Data %>% mutate(CF_2_Tot = CF_2 / Count_Num)

Thesis_Data <- Thesis_Data %>% mutate(CF_3_Tot = CF_3 / Count_Num)

Thesis_Data <- Thesis_Data %>% mutate(CF_4_Tot = CF_4 / Count_Num)
```

```r
Thesis_Data <- Thesis_Data %>% mutate(CF_5_Tot = CF_5 / Count_Num)

#Add All

Thesis_Data <- Thesis_Data %>% mutate(CF_Tot = CF_5 + CF_4 + CF_3 + CF_4 + CF_5)

Thesis_Data <- Thesis_Data %>% mutate(CF_Tot_All = CF_Tot / 5)

# Affect Total

Thesis_Data <- Thesis_Data %>% mutate(Postitive_Affect = PANAS_1 + PANAS_3 + PANAS_5 + PANAS_9 + PANAS_

Thesis_Data <- Thesis_Data %>% mutate(Negative_Affect = PANAS_2 + PANAS_4 + PANAS_6 + PANAS_7 + PANAS_8
```

Now, Lets view some data.

```r
mean(Thesis_Data$CF_Tot_All, na.rm = T)
```

```
## [1] 32.14375
```

```r
mean_culp_all <- mean(Thesis_Data$CF_Tot_All)
mean_culp_all
```

```
## [1] NA
```

Mean CP is 32.14- meaning that CP is fairly normal overall (0-60 range)

```r
mean(Thesis_Data$Postitive_Affect, na.rm = T)
```

```
## [1] 27.25
```

```r
mean_pos_Affect <- mean(Thesis_Data$Postitive_Affect)
mean_pos_Affect
```

```
## [1] NA
```

```r
mean(Thesis_Data$Negative_Affect, na.rm = T)
```

```
## [1] 20.8172
```

```r
mean_neg_Affect <- mean(Thesis_Data$Negative_Affect)
mean_neg_Affect
```

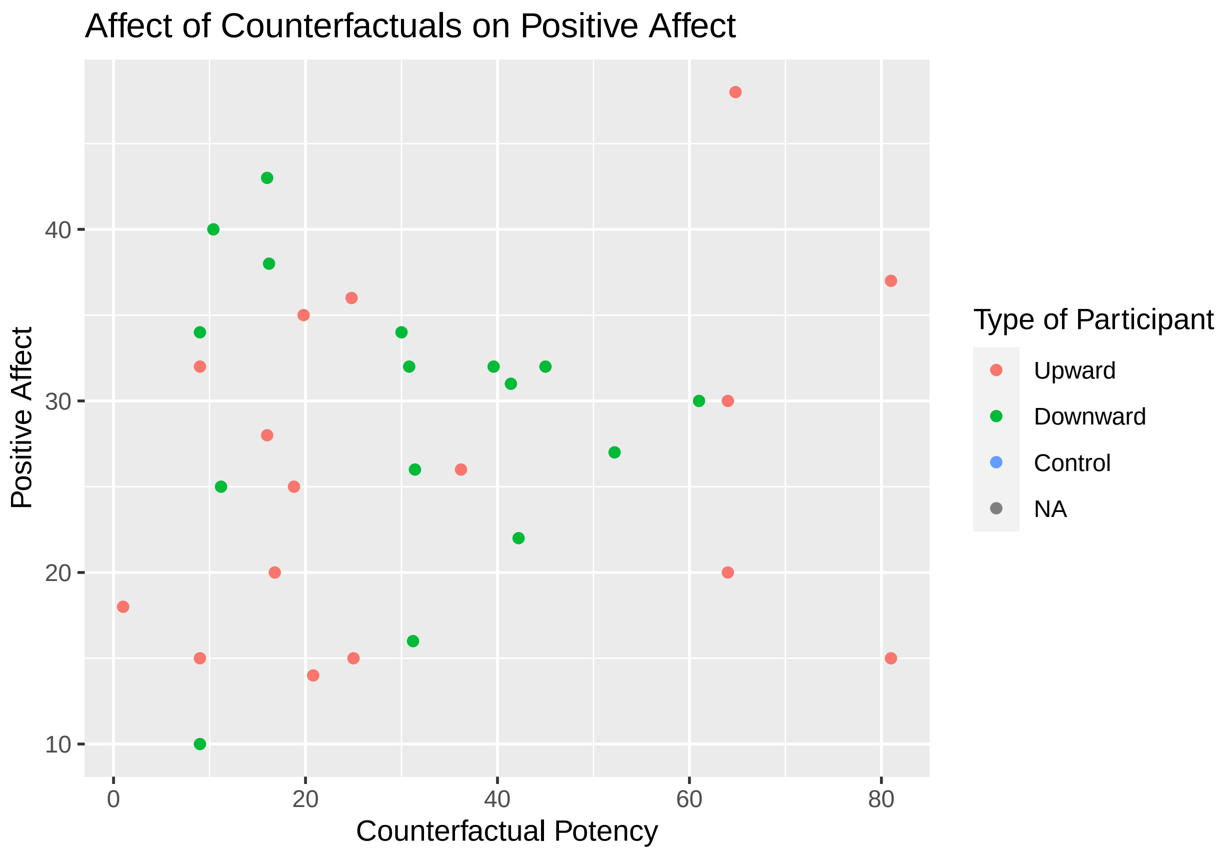
```
## [1] NA
```

Postitive affect overall is higher than negative affect, which is good :)

Now lets compare CP to Positive Affect and Negative Affect for each condition

```
Thesis_Data %>%
  ggplot(Thesis_Data, mapping = aes(x = CF_Tot_All, y= Postitive_Affect, color= Participants))+ geom_poi
```

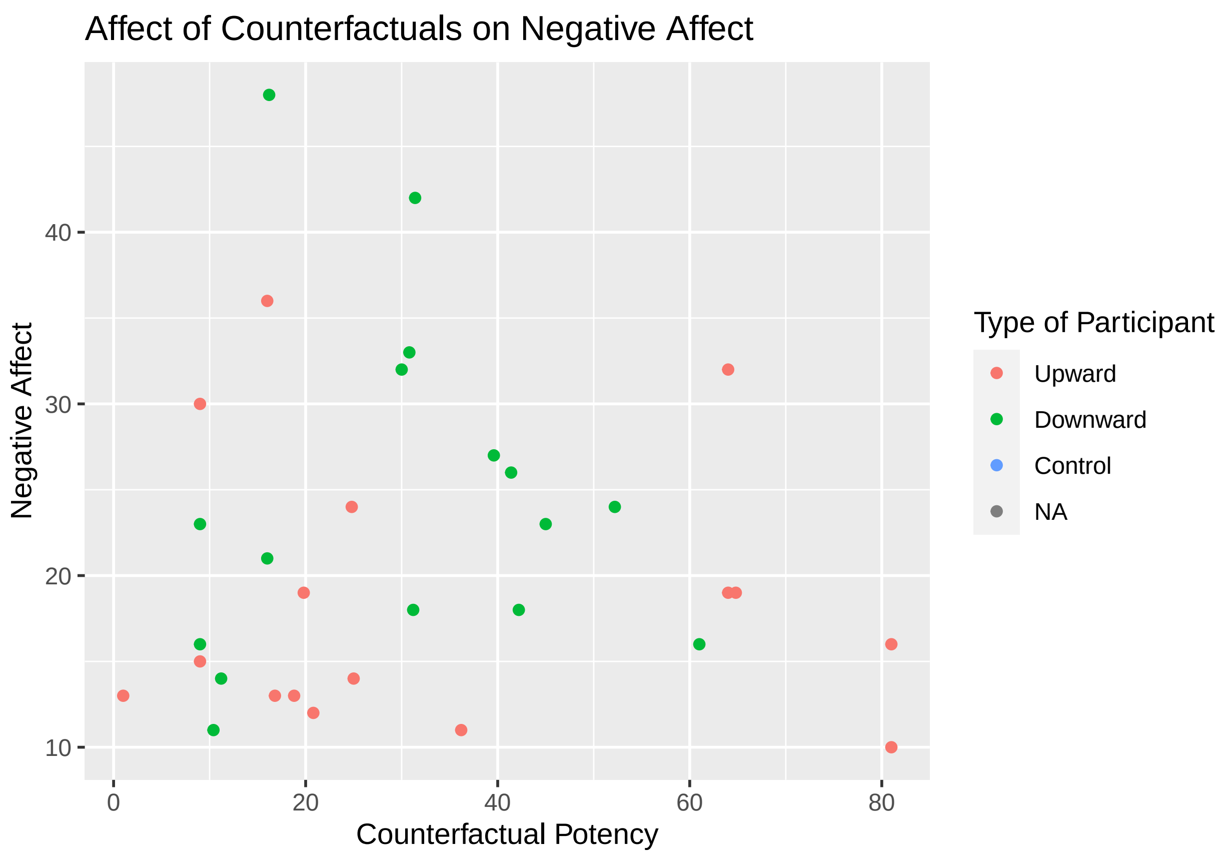
```
## Warning: Removed 65 rows containing missing values (`geom_point()`).
```



It seems as if those with higher positive affect had lower CP scores, meaning that those who felt alright about the situation afterwards believed their own counterfactuals less.

```
Thesis_Data %>%
  ggplot(Thesis_Data, mapping = aes(x = CF_Tot_All, y= Negative_Affect, color= Participants))+ geom_poin
```

```
## Warning: Removed 65 rows containing missing values (`geom_point()`).
```



The affect seems to have shift just a liiitttllleee bit here. It seems fairly average on both sides. Average NEgative Affect= Average CP.

I believe this has helped me look at my data a little bit (especially after the clean up)!

Lets save it.

```
write.csv(Thesis_Data, "/Users/Awesh/Documents/GitHub/Project-1/Porfolio 9\\Thesis Data.csv", row.names=
```