

For_Jim_toPDF

rwoo

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Data Cleaning and Formatting

Import data and clean from after intervention

```
setwd("C:/Users/rwoo/Documents/Thesis_Data_Analysis")
raw_post <- read.csv("Post.csv", stringsAsFactors = FALSE)
colnames(raw_post) <- c("Timestamp", "PID", "Desirability_List", "CC1_post", "CC2_post", "CC3_post", "CC4_post", "CC5_post", "CC6_post")
raw_post$PID = toupper(raw_post$PID) #Change all to uppercase
good_PID <- c("P21", "P3", "P4", "P64", "P9", "P68", "P66", "P60", "P70", "P81", "P69", "P72", "P71", "P73", "P74", "P75", "P76", "P77", "P78", "P79", "P80", "P82", "P83", "P84", "P85", "P86", "P87", "P88", "P89", "P90", "P91", "P92", "P93", "P94", "P95", "P96", "P97", "P98", "P99", "P100")
```

Import data and clean from before intervention. I make column names etc.

```
raw_pre <- read.csv("Pre.csv", stringsAsFactors = FALSE)
colnames(raw_pre) <- c("Timestamp", "PID", "Gender", "Sex", "Age", "Education", "College_Or_Uni", "Waterloo_Community", "Desirability_List", "CC1_pre", "CC2_pre", "CC3_pre", "CC4_pre", "CC5_pre", "CC6_pre")
#Only take good PID from pre
pre_Filtered <- raw_pre[which(raw_pre$PID %in% good_PID), ] #NOT WORK, only gives 16
```

Community Connectedness Analysis

CC1 You feel you are a part of the Waterloo community CC2 Participating in the Waterloo community is a positive thing for you. CC3 You feel a bond with the Waterloo community.

CC4 You are proud of the Waterloo community.

CC5 It is important for you to be aware of issues others face in your community

CC6 I feel aware of issues that others face in my community

Get change in community connectedness

```
#Pre
cc_pre <- pre_Filtered %>% select(PID, CC1_pre, CC2_pre, CC3_pre, CC4_pre, CC5_pre, CC6_pre)
#Post
cc_post <- raw_post %>% select(PID, CC1_post, CC2_post, CC3_post, CC4_post, CC5_post, CC6_post)
#Merge pre and post
cc <- merge(cc_pre, cc_post, by = "PID")
#Get delta cc NOTE: THIS METHOD SEEMS INEFFICIENT INVESTIGATE REGEX
cc <- mutate(cc, CC1_delta = CC1_post - CC1_pre)
cc <- mutate(cc, CC2_delta = CC2_post - CC2_pre)
cc <- mutate(cc, CC3_delta = CC3_post - CC3_pre)
cc <- mutate(cc, CC4_delta = CC4_post - CC4_pre)
cc <- mutate(cc, CC5_delta = CC5_post - CC5_pre)
cc <- mutate(cc, CC6_delta = CC6_post - CC6_pre)
```

#Only take delta columns

```
cc_delta <- cc %>% select(CC1_delta, CC2_delta, CC3_delta, CC4_delta, CC5_delta, CC6_delta)
summary(cc_delta) #Probably of most note for meeting
```

```
##      CC1_delta      CC2_delta      CC3_delta      CC4_delta
## Min.   :-1.00000   Min.    :-2.0000   Min.    :-1.0000   Min.    :-1.0000
## 1st Qu.: 0.00000   1st Qu.: 0.0000   1st Qu.: 0.0000   1st Qu.: 0.0000
## Median : 0.00000   Median : 0.0000   Median : 0.0000   Median : 0.0000
## Mean   :-0.05882   Mean    :-0.1176   Mean     0.3529   Mean    :-0.1765
## 3rd Qu.: 0.00000   3rd Qu.: 0.0000   3rd Qu.: 1.0000   3rd Qu.: 0.0000
## Max.    : 1.00000   Max.     : 2.0000   Max.     : 2.0000   Max.     : 1.0000
##      CC5_delta      CC6_delta
## Min.   :-1.0000   Min.    :-1.0000
## 1st Qu.: 0.0000   1st Qu.: 0.0000
## Median : 0.0000   Median : 0.0000
## Mean    : 0.5294   Mean     : 0.7647
## 3rd Qu.: 1.0000   3rd Qu.: 2.0000
## Max.    : 3.0000   Max.     : 3.0000
```

```
summary(cc_pre)
```

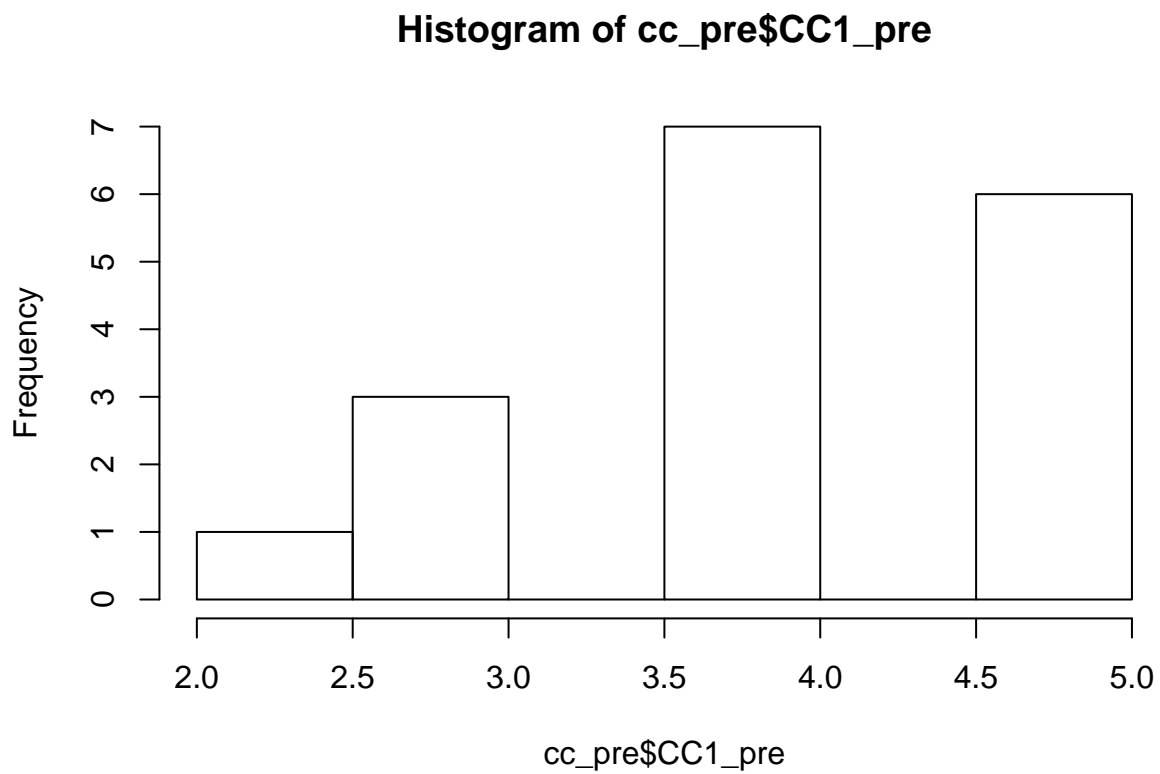
```
##      PID      CC1_pre      CC2_pre      CC3_pre
## Length:17   Min.    :2.000   Min.    :2.000   Min.    :1.000
## Class :character 1st Qu.:4.000   1st Qu.:4.000   1st Qu.:3.000
## Mode  :character Median :4.000   Median :4.000   Median :4.000
##              Mean  :4.059   Mean  :4.294   Mean  :3.706
##              3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:4.000
##              Max.   :5.000   Max.   :5.000   Max.   :5.000
##      CC4_pre      CC5_pre      CC6_pre
## Min.    :3.000   Min.    :2   Min.    :2
## 1st Qu.:4.000   1st Qu.:3   1st Qu.:2
## Median :5.000   Median :4   Median :3
## Mean    :4.471   Mean    :4   Mean    :3
## 3rd Qu.:5.000   3rd Qu.:5   3rd Qu.:3
## Max.    :5.000   Max.    :5   Max.    :5
```

```
summary(cc_post)
```

```
##      PID      CC1_post      CC2_post      CC3_post      CC4_post
## Length:17   Min.     :3   Min.     :2.000   Min.     :3.000   Min.     :3.000
## Class :character 1st Qu.:4   1st Qu.:4.000   1st Qu.:3.000   1st Qu.:4.000
## Mode  :character Median :4   Median :4.000   Median :4.000   Median :4.000
##              Mean  :4   Mean  :4.176   Mean  :4.059   Mean  :4.294
##              3rd Qu.:4   3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:5.000
##              Max.   :5   Max.   :5.000   Max.   :5.000   Max.   :5.000
##      CC5_post      CC6_post
## Min.    :4.000   Min.    :2.000
## 1st Qu.:4.000   1st Qu.:3.000
## Median :5.000   Median :4.000
## Mean    :4.529   Mean    :3.765
## 3rd Qu.:5.000   3rd Qu.:5.000
## Max.    :5.000   Max.    :5.000
```

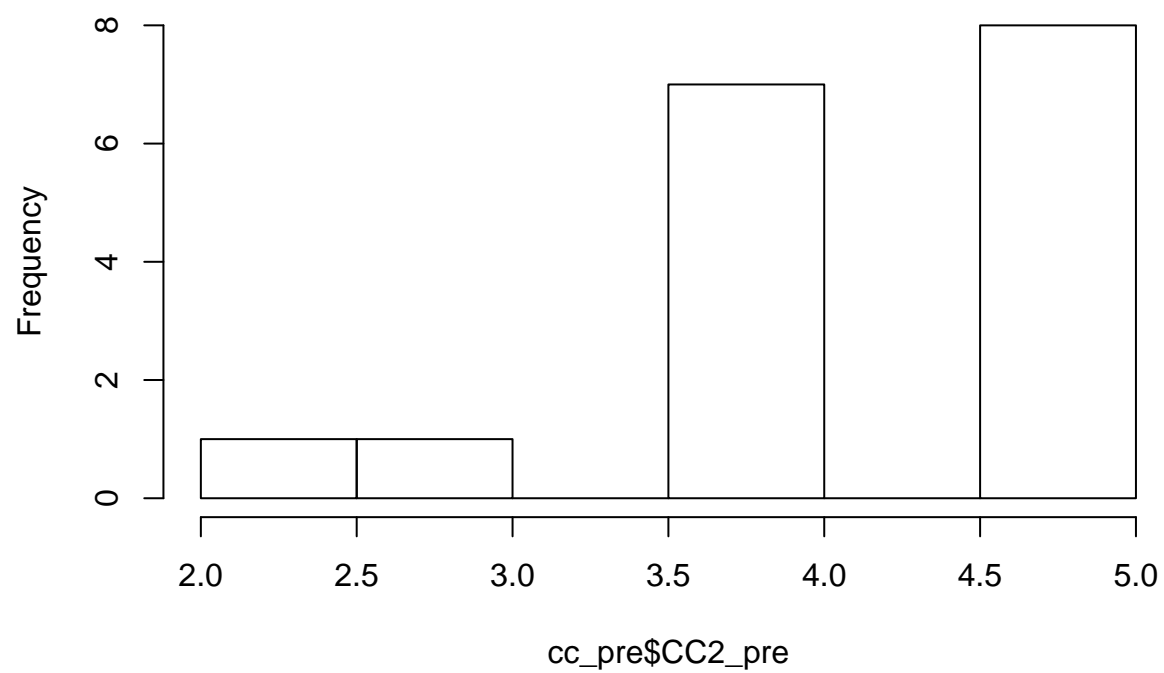
Check assumptions for CC

```
#Check shape before  
hist(cc_pre$CC1_pre)
```



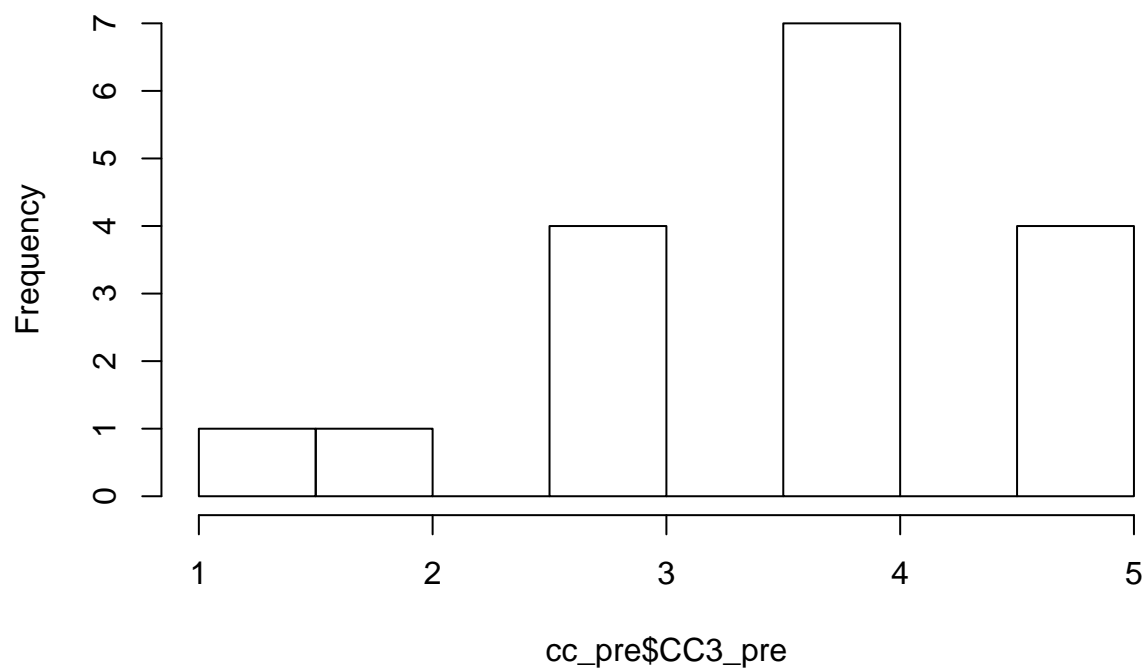
```
hist(cc_pre$CC2_pre)
```

Histogram of cc_pre\$CC2_pre



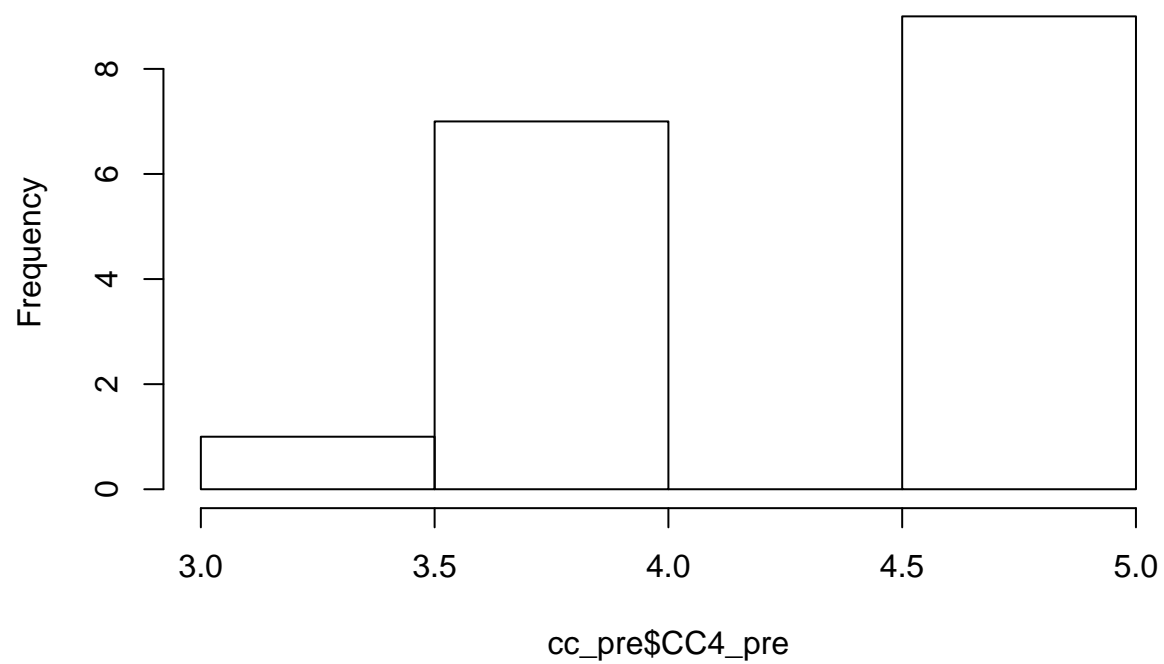
```
hist(cc_pre$CC3_pre)
```

Histogram of cc_pre\$CC3_pre



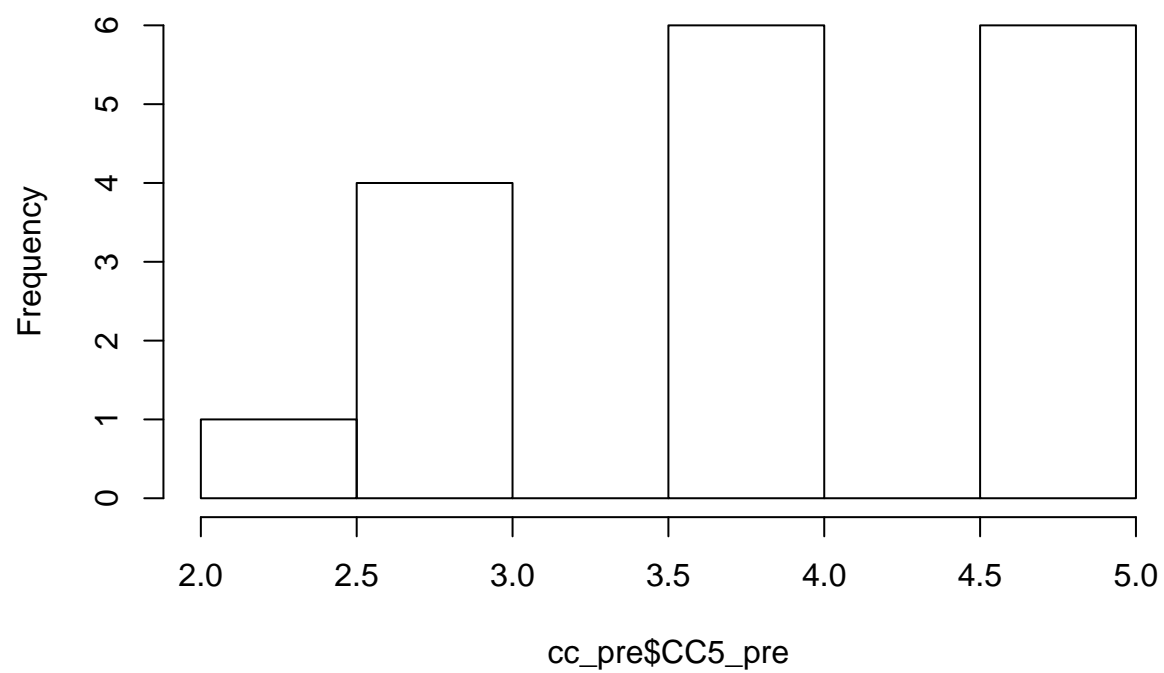
```
hist(cc_pre$CC4_pre)
```

Histogram of cc_pre\$CC4_pre

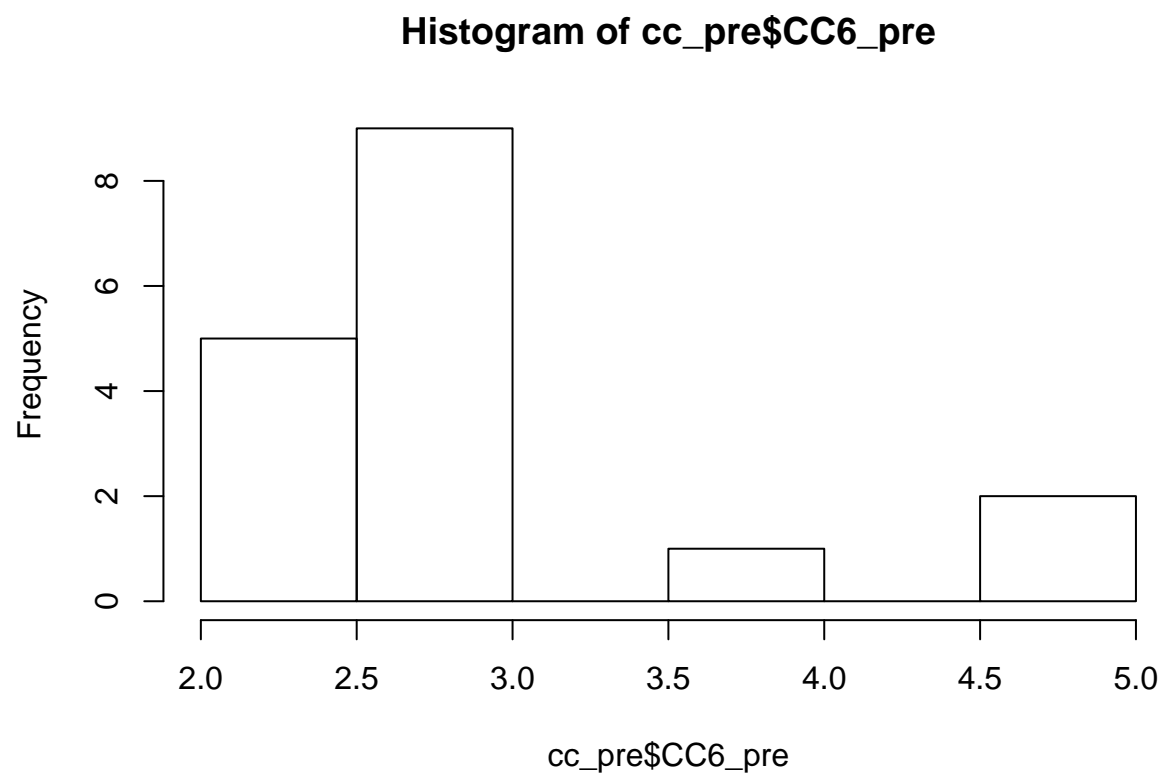


```
hist(cc_pre$CC5_pre)
```

Histogram of cc_pre\$CC5_pre

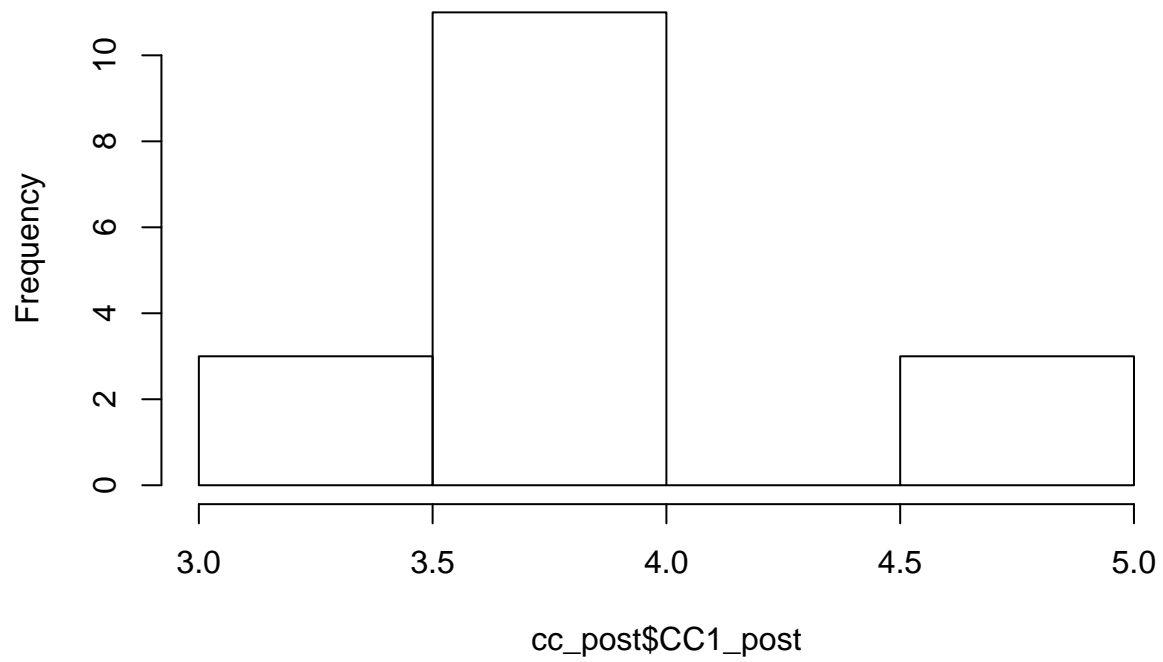


```
hist(cc_pre$CC6_pre)
```



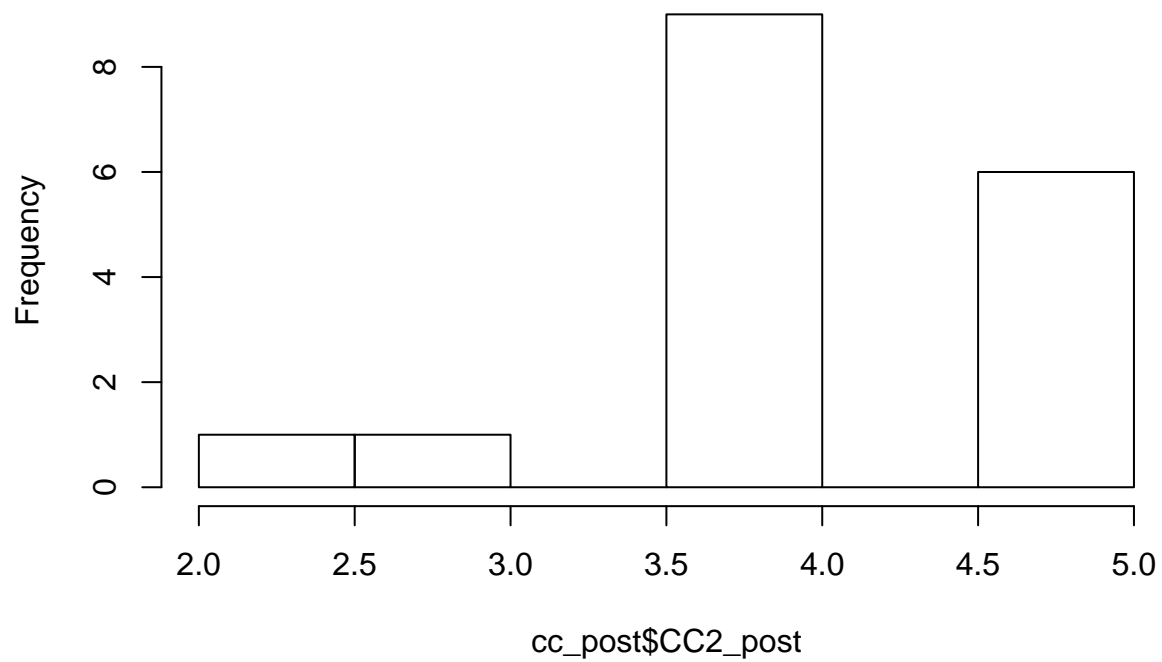
```
#Check shape after  
hist(cc_post$CC1_post)
```


Histogram of cc_post\$CC1_post

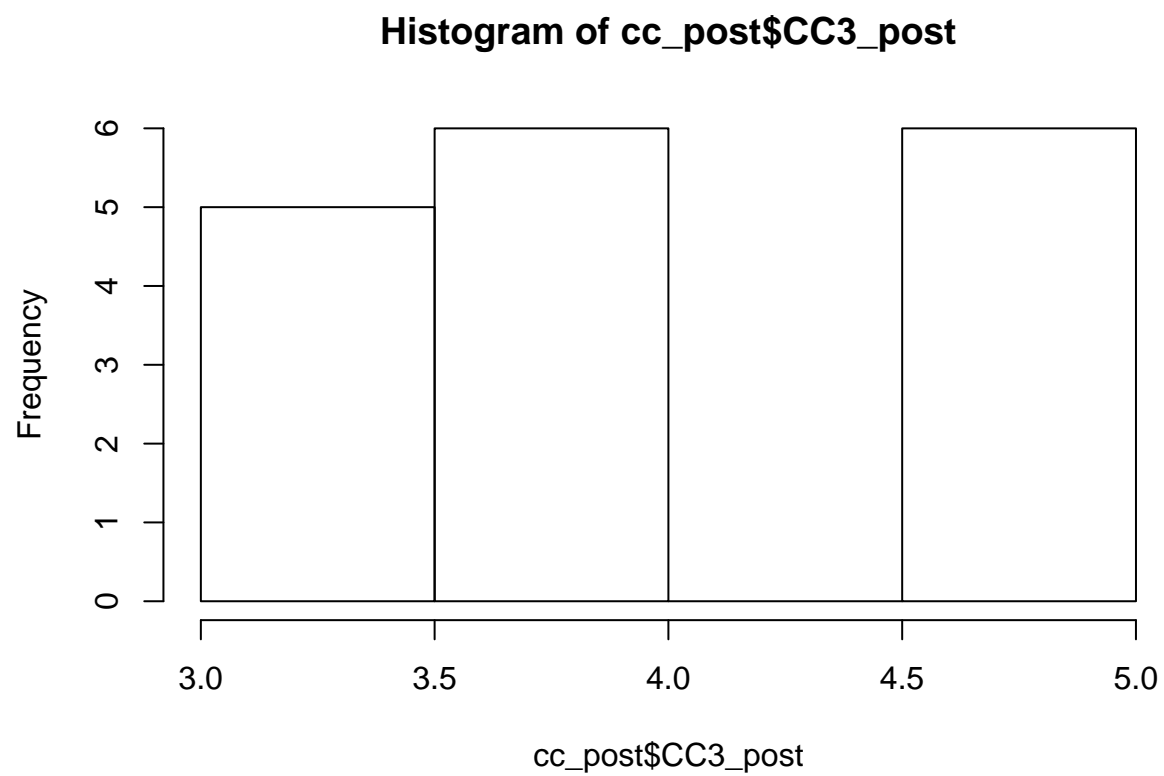


```
hist(cc_post$CC2_post)
```

Histogram of cc_post\$CC2_post

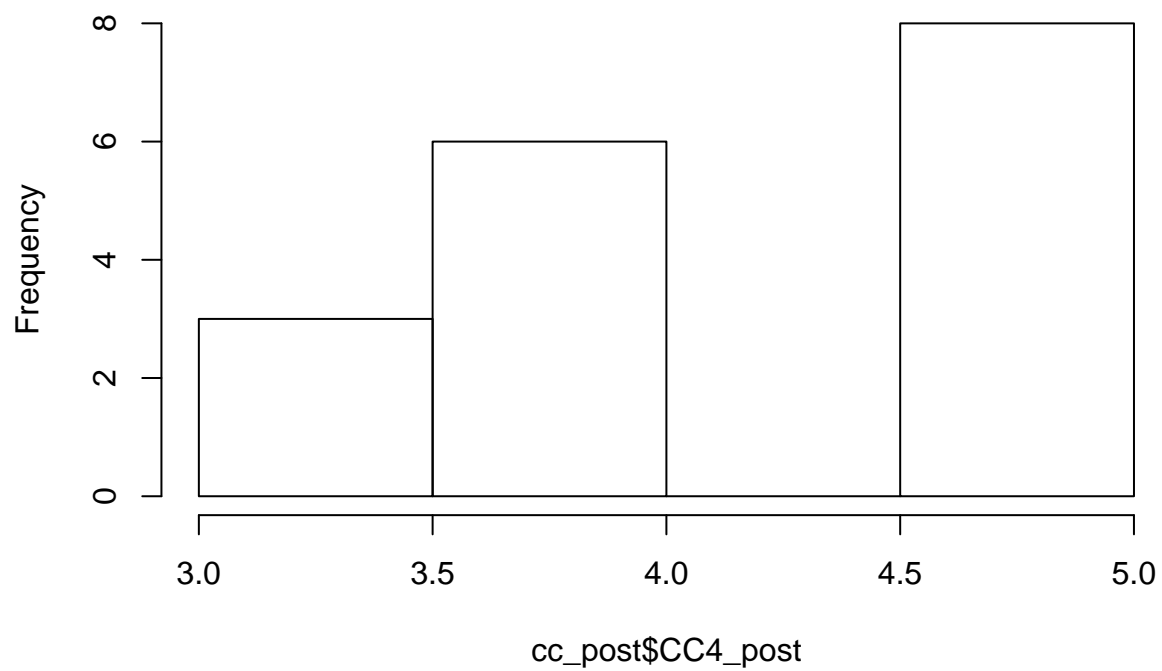


```
hist(cc_post$CC3_post)
```



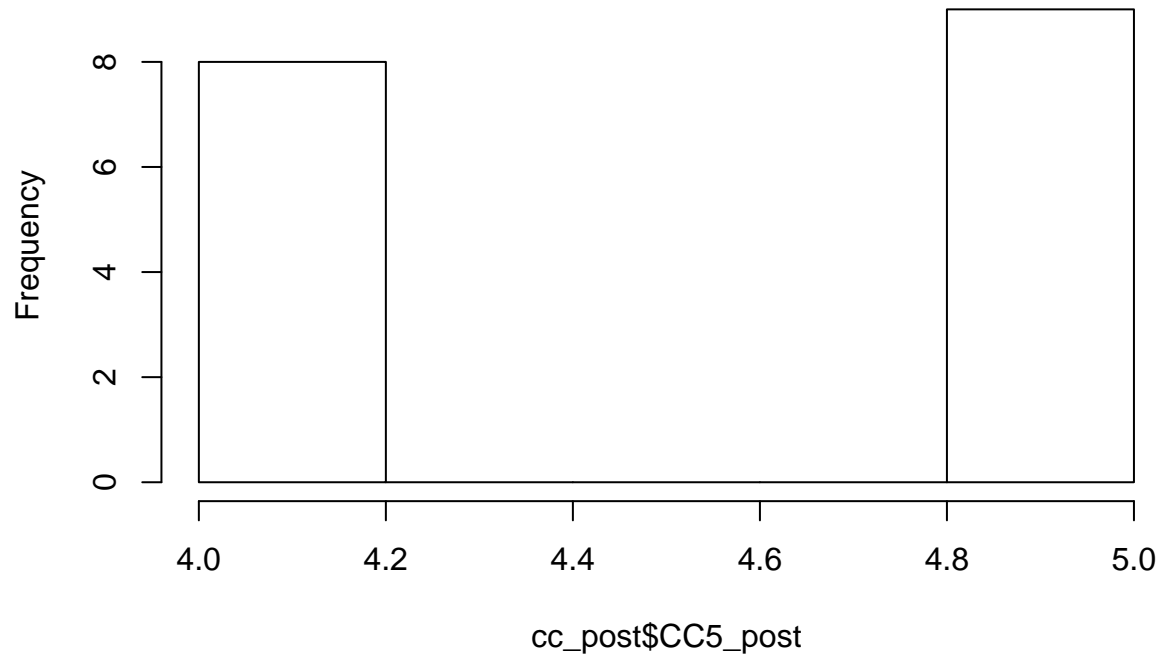
```
hist(cc_post$CC4_post)
```

Histogram of cc_post\$CC4_post

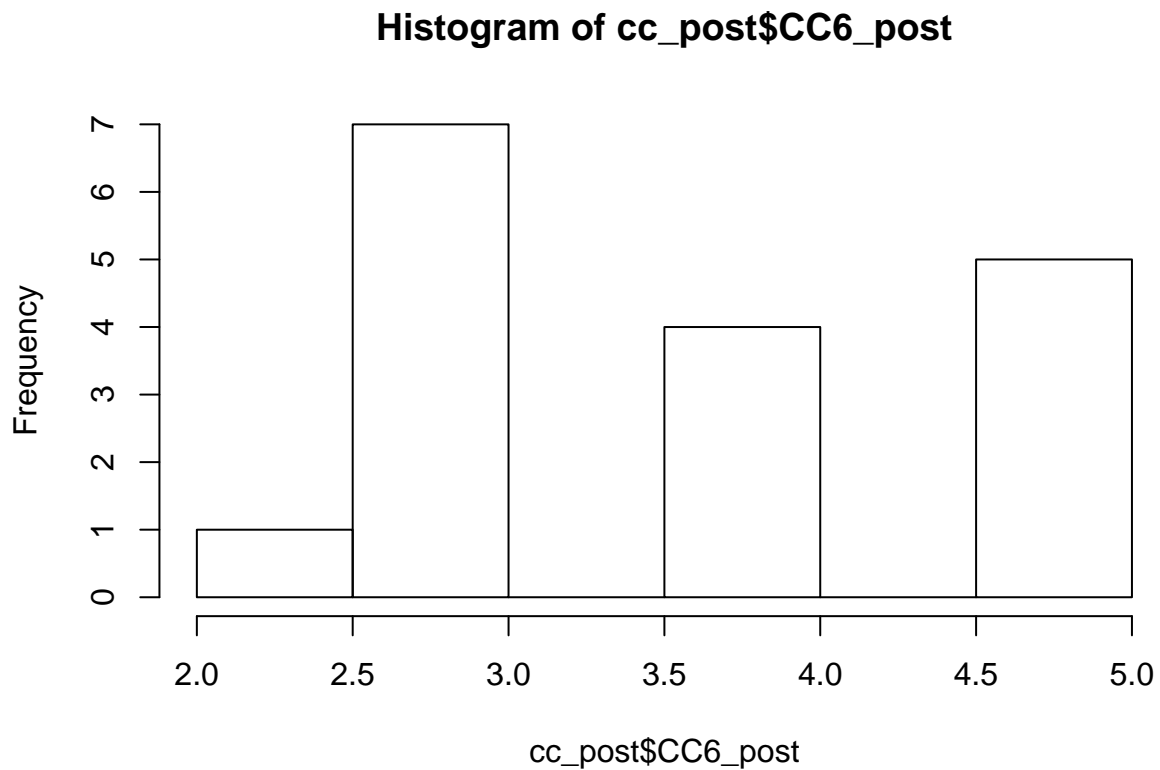


```
hist(cc_post$CC5_post)
```

Histogram of cc_post\$CC5_post



```
hist(cc_post$CC6_post)
```



#Inconclusive

Paired t-test Reading: https://www.jmp.com/en_ca/statistics-knowledge-portal/t-test/paired-t-test.html

```
t.test(cc_pre$CC1_pre, cc_post$CC1_post, paired = TRUE, alternative = "two.sided")
```

```
##
## Paired t-test
##
## data: cc_pre$CC1_pre and cc_post$CC1_post
## t = 0.22291, df = 16, p-value = 0.8264
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.5005932 0.6182403
## sample estimates:
## mean of the differences
## 0.05882353
```

```
t.test(cc_pre$CC2_pre, cc_post$CC2_post, paired = TRUE, alternative = "two.sided")
```

```
##
## Paired t-test
##
## data: cc_pre$CC2_pre and cc_post$CC2_post
```

```

## t = 0.46035, df = 16, p-value = 0.6515
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.4241180 0.6594122
## sample estimates:
## mean of the differences
## 0.1176471

t.test(cc_pre$CC3_pre, cc_post$CC3_post, paired = TRUE, alternative = "two.sided")

##
## Paired t-test
##
## data: cc_pre$CC3_pre and cc_post$CC3_post
## t = -1.4606, df = 16, p-value = 0.1635
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.8652000 0.1593176
## sample estimates:
## mean of the differences
## -0.3529412

t.test(cc_pre$CC4_pre, cc_post$CC4_post, paired = TRUE, alternative = "two.sided")

##
## Paired t-test
##
## data: cc_pre$CC4_pre and cc_post$CC4_post
## t = 0.82416, df = 16, p-value = 0.422
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.2774454 0.6303866
## sample estimates:
## mean of the differences
## 0.1764706

t.test(cc_pre$CC5_pre, cc_post$CC5_post, paired = TRUE, alternative = "two.sided")

##
## Paired t-test
##
## data: cc_pre$CC5_pre and cc_post$CC5_post
## t = -2.4962, df = 16, p-value = 0.02386
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.9790251 -0.0797984
## sample estimates:
## mean of the differences
## -0.5294118

```

```
t.test(cc_pre$CC6_pre, cc_post$CC6_post, paired = TRUE, alternative = "two.sided")
```

```
##
## Paired t-test
##
## data: cc_pre$CC6_pre and cc_post$CC6_post
## t = -2.6264, df = 16, p-value = 0.01833
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -1.3819409 -0.1474708
## sample estimates:
## mean of the differences
## -0.7647059
```

Shapiro-Wilk normality test for the differences. IM CRYING, violates assumption of normality (prob due to limited scope and small sample size)

```
d1 <- with(cc, CC1_post - CC1_pre)
shapiro.test(d1)
```

```
##
## Shapiro-Wilk normality test
##
## data: d1
## W = 0.79848, p-value = 0.001934
```

```
d2 <- with(cc, CC2_post - CC2_pre)
shapiro.test(d2)
```

```
##
## Shapiro-Wilk normality test
##
## data: d2
## W = 0.85696, p-value = 0.01372
```

```
d3 <- with(cc, CC3_post - CC3_pre)
shapiro.test(d3)
```

```
##
## Shapiro-Wilk normality test
##
## data: d3
## W = 0.85594, p-value = 0.01323
```

```
d4 <- with(cc, CC4_post - CC4_pre)
shapiro.test(d4)
```

```
##
## Shapiro-Wilk normality test
##
## data: d4
## W = 0.70335, p-value = 0.0001262
```



```
d5 <- with(cc, CC5_post - CC5_pre)
shapiro.test(d5)
```

```
##
## Shapiro-Wilk normality test
##
## data: d5
## W = 0.88688, p-value = 0.04117
```

```
d6 <- with(cc, CC6_post - CC6_pre)
shapiro.test(d6)
```

```
##
## Shapiro-Wilk normality test
##
## data: d6
## W = 0.89158, p-value = 0.04921
```

Do Wilcoxon (paired) signed-rank test <http://www.sthda.com/english/wiki/paired-samples-wilcoxon-test-in-r> <https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/assumptions-of-the-wilcox-sign-test/>

```
wilcox.test(cc_pre$CC1_pre, cc_post$CC1_post, paired = TRUE, alternative = "two.sided")
```

```
## Warning in wilcox.test.default(cc_pre$CC1_pre, cc_post$CC1_post, paired =
## TRUE, : cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(cc_pre$CC1_pre, cc_post$CC1_post, paired =
## TRUE, : cannot compute exact p-value with zeroes
```

```
##
## Wilcoxon signed rank test with continuity correction
##
## data: cc_pre$CC1_pre and cc_post$CC1_post
## V = 30, p-value = 0.8319
## alternative hypothesis: true location shift is not equal to 0
```

```
wilcox.test(cc_pre$CC2_pre, cc_post$CC2_post, paired = TRUE, alternative = "two.sided")
```

```
## Warning in wilcox.test.default(cc_pre$CC2_pre, cc_post$CC2_post, paired =
## TRUE, : cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(cc_pre$CC2_pre, cc_post$CC2_post, paired =
## TRUE, : cannot compute exact p-value with zeroes
```

```
##
## Wilcoxon signed rank test with continuity correction
##
## data: cc_pre$CC2_pre and cc_post$CC2_post
## V = 26.5, p-value = 0.6675
## alternative hypothesis: true location shift is not equal to 0
```

```
wilcox.test(cc_pre$CC3_pre, cc_post$CC3_post, paired = TRUE, alternative = "two.sided")
```

```
## Warning in wilcox.test.default(cc_pre$CC3_pre, cc_post$CC3_post, paired =  
## TRUE, : cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(cc_pre$CC3_pre, cc_post$CC3_post, paired =  
## TRUE, : cannot compute exact p-value with zeroes
```

```
##  
## Wilcoxon signed rank test with continuity correction  
##  
## data: cc_pre$CC3_pre and cc_post$CC3_post  
## V = 22.5, p-value = 0.179  
## alternative hypothesis: true location shift is not equal to 0
```

```
wilcox.test(cc_pre$CC4_pre, cc_post$CC4_post, paired = TRUE, alternative = "two.sided")
```

```
## Warning in wilcox.test.default(cc_pre$CC4_pre, cc_post$CC4_post, paired =  
## TRUE, : cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(cc_pre$CC4_pre, cc_post$CC4_post, paired =  
## TRUE, : cannot compute exact p-value with zeroes
```

```
##  
## Wilcoxon signed rank test with continuity correction  
##  
## data: cc_pre$CC4_pre and cc_post$CC4_post  
## V = 35, p-value = 0.4374  
## alternative hypothesis: true location shift is not equal to 0
```

```
wilcox.test(cc_pre$CC5_pre, cc_post$CC5_post, paired = TRUE, alternative = "two.sided")
```

```
## Warning in wilcox.test.default(cc_pre$CC5_pre, cc_post$CC5_post, paired =  
## TRUE, : cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(cc_pre$CC5_pre, cc_post$CC5_post, paired =  
## TRUE, : cannot compute exact p-value with zeroes
```

```
##  
## Wilcoxon signed rank test with continuity correction  
##  
## data: cc_pre$CC5_pre and cc_post$CC5_post  
## V = 10, p-value = 0.03301  
## alternative hypothesis: true location shift is not equal to 0
```

```
wilcox.test(cc_pre$CC6_pre, cc_post$CC6_post, paired = TRUE, alternative = "two.sided")
```

```
## Warning in wilcox.test.default(cc_pre$CC6_pre, cc_post$CC6_post, paired =  
## TRUE, : cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(cc_pre$CC6_pre, cc_post$CC6_post, paired =
## TRUE, : cannot compute exact p-value with zeroes
```

```
##
## Wilcoxon signed rank test with continuity correction
##
## data: cc_pre$CC6_pre and cc_post$CC6_post
## V = 15, p-value = 0.03082
## alternative hypothesis: true location shift is not equal to 0
```

CC total

```
tot_pre <- cc_pre %>%
  mutate(CC_tot_pre = (CC1_pre + CC2_pre + CC3_pre + CC4_pre + CC5_pre + CC6_pre)/6)
tot_post <- cc_post %>%
  mutate(CC_tot_post = (CC1_post + CC2_post + CC3_post + CC4_post + CC5_post + CC6_post)/6)
wilcox.test(tot_pre$CC_tot_pre, tot_post$CC_tot_post, paired = TRUE, alternative = "two.sided")
```

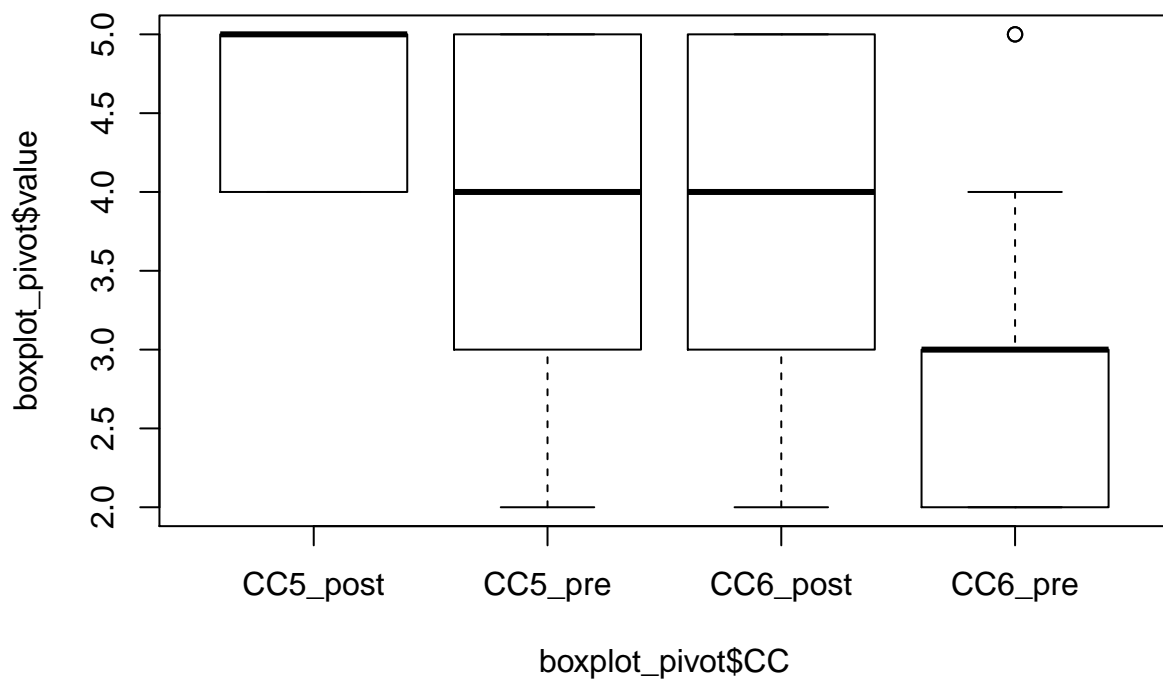
```
## Warning in wilcox.test.default(tot_pre$CC_tot_pre, tot_post$CC_tot_post, :
## cannot compute exact p-value with ties
```

```
## Warning in wilcox.test.default(tot_pre$CC_tot_pre, tot_post$CC_tot_post, :
## cannot compute exact p-value with zeroes
```

```
##
## Wilcoxon signed rank test with continuity correction
##
## data: tot_pre$CC_tot_pre and tot_post$CC_tot_post
## V = 30, p-value = 0.09344
## alternative hypothesis: true location shift is not equal to 0
```

MAKE BOXPLOTS CC

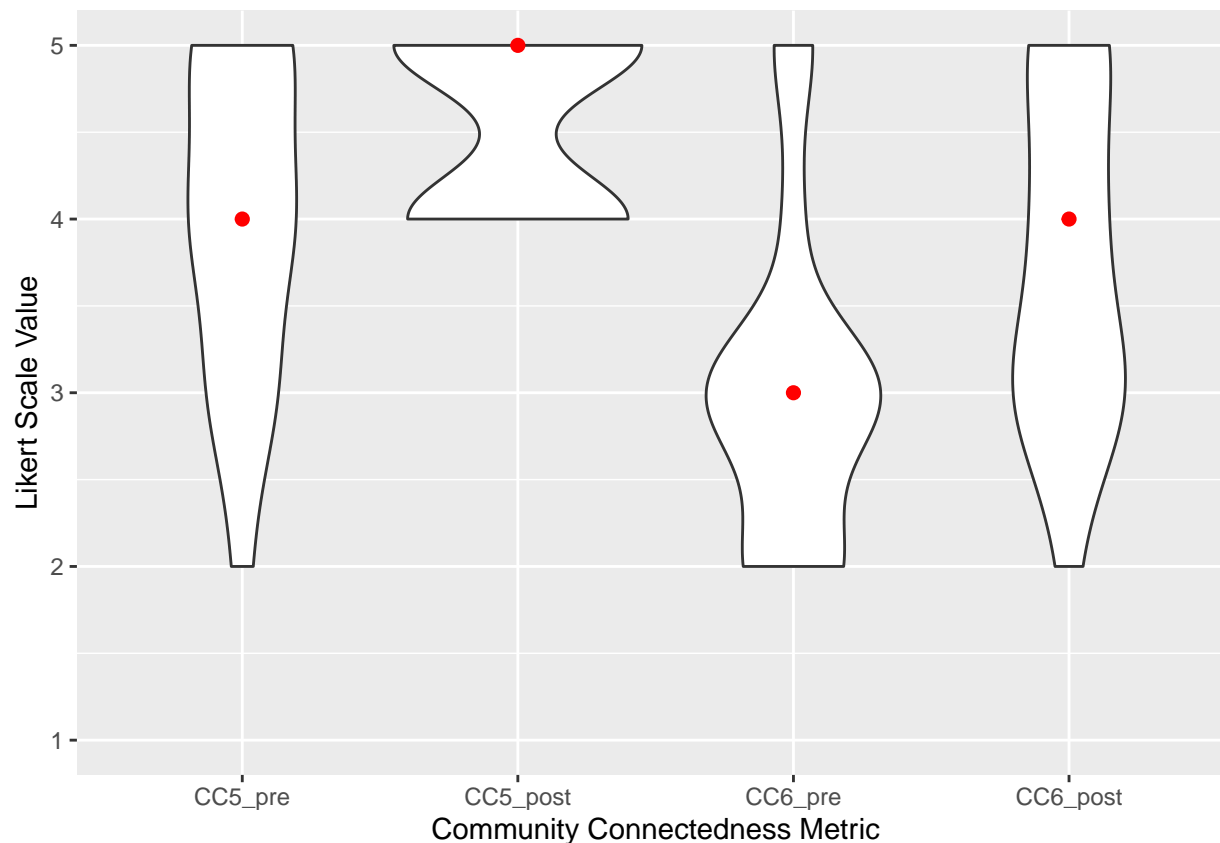
```
cc_sig <- cc %>% select(CC5_pre, CC6_pre, CC5_post, CC6_post)
boxplot_pivot <- cc_sig %>%
  pivot_longer(
    cols = starts_with("CC"),
    names_to = "CC",
    values_to = "value",
    values_drop_na = TRUE
  )
boxplot(boxplot_pivot$value ~ boxplot_pivot$CC)
```



Format and make violin plot

```
#Change order
boxplot_pivot <- boxplot_pivot %>%
  mutate( CC=factor(CC,levels=c("CC5_pre", "CC5_post", "CC6_pre", "CC6_post"))) )

# Basic violin plot
p <- ggplot(boxplot_pivot, aes(x=CC, y=value)) +
  geom_violin(position=position_dodge(1)) + coord_cartesian(ylim = c(1, 5)) + xlab("Community Connected")
# violin plot with median points
p + stat_summary(fun=median, geom="point", size=2, color="red")
```



CC5 and CC6 are significant. Others are not

Reflection Inventory Analysis

RI1 The experience gives me ideas on how to overcome challenges

RI2 I learned from exploring the data

RI3 I enjoyed exploring the data

RI4 I reflected on my own experiences with mental health and accessing resources

RI5 The app would help me discuss mental health and resources with others

```
ri <- raw_post %>% select(PID, RI1, RI2, RI3, RI4, RI5)
summary(ri)
```

```
##      PID      RI1      RI2      RI3
## Length:17    Min.   :1.000    Min.   :2.000    Min.   :3.000
## Class :character 1st Qu.:3.000    1st Qu.:4.000    1st Qu.:4.000
## Mode  :character Median :4.000    Median :5.000    Median :5.000
##              Mean  :3.647    Mean  :4.471    Mean  :4.588
##              3rd Qu.:5.000    3rd Qu.:5.000    3rd Qu.:5.000
##              Max.   :5.000    Max.   :5.000    Max.   :5.000
##      RI4      RI5
## Min.   :2.000    Min.   :2.000
## 1st Qu.:4.000    1st Qu.:3.000
## Median :5.000    Median :4.000
## Mean   :4.235    Mean   :3.824
```

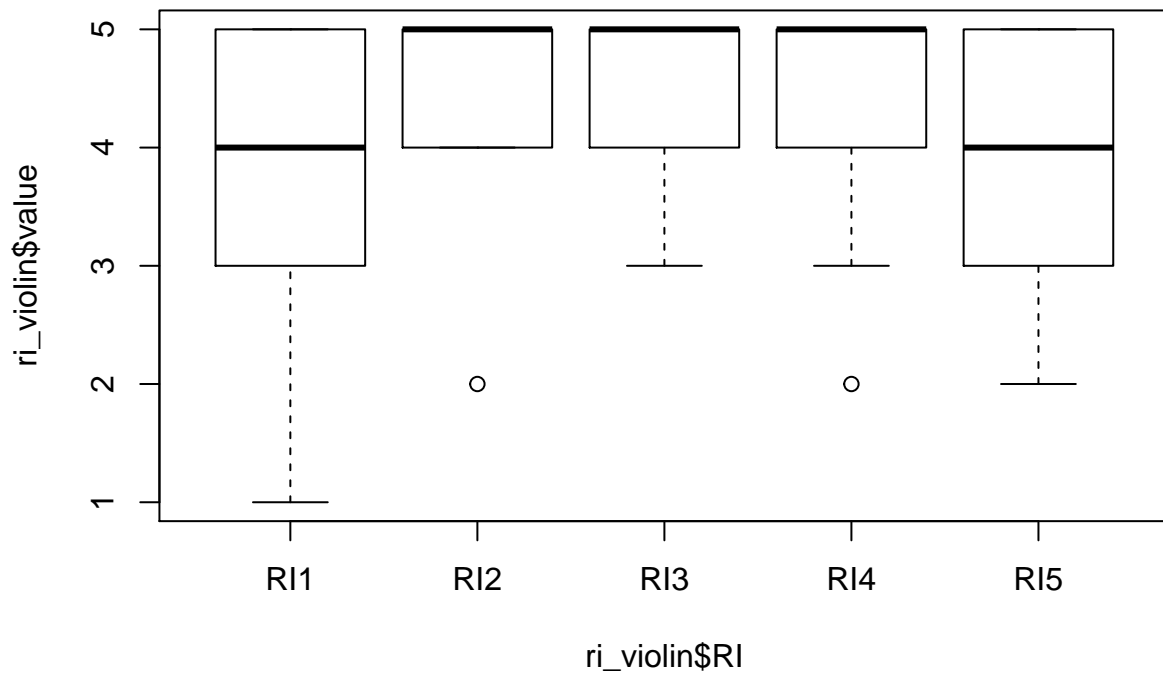
```
## 3rd Qu.:5.000 3rd Qu.:5.000
## Max. :5.000 Max. :5.000
```

```
ri
```

```
##      PID RI1 RI2 RI3 RI4 RI5
## 1    P4   3   4   5   3   4
## 2   P21   1   5   3   4   2
## 3    P3   2   4   4   2   2
## 4   P64   3   4   4   3   3
## 5    P9   5   5   5   5   5
## 6   P68   3   4   3   5   3
## 7   P66   5   5   5   5   5
## 8   P60   4   5   5   5   5
## 9   P70   5   5   5   5   5
## 10  P81   3   4   5   4   3
## 11  P69   4   5   5   4   4
## 12  P72   4   5   5   5   5
## 13  P71   5   5   5   5   5
## 14  P77   4   5   5   5   4
## 15  P75   3   2   4   3   2
## 16  P74   5   4   5   5   3
## 17  P82   3   5   5   4   5
```

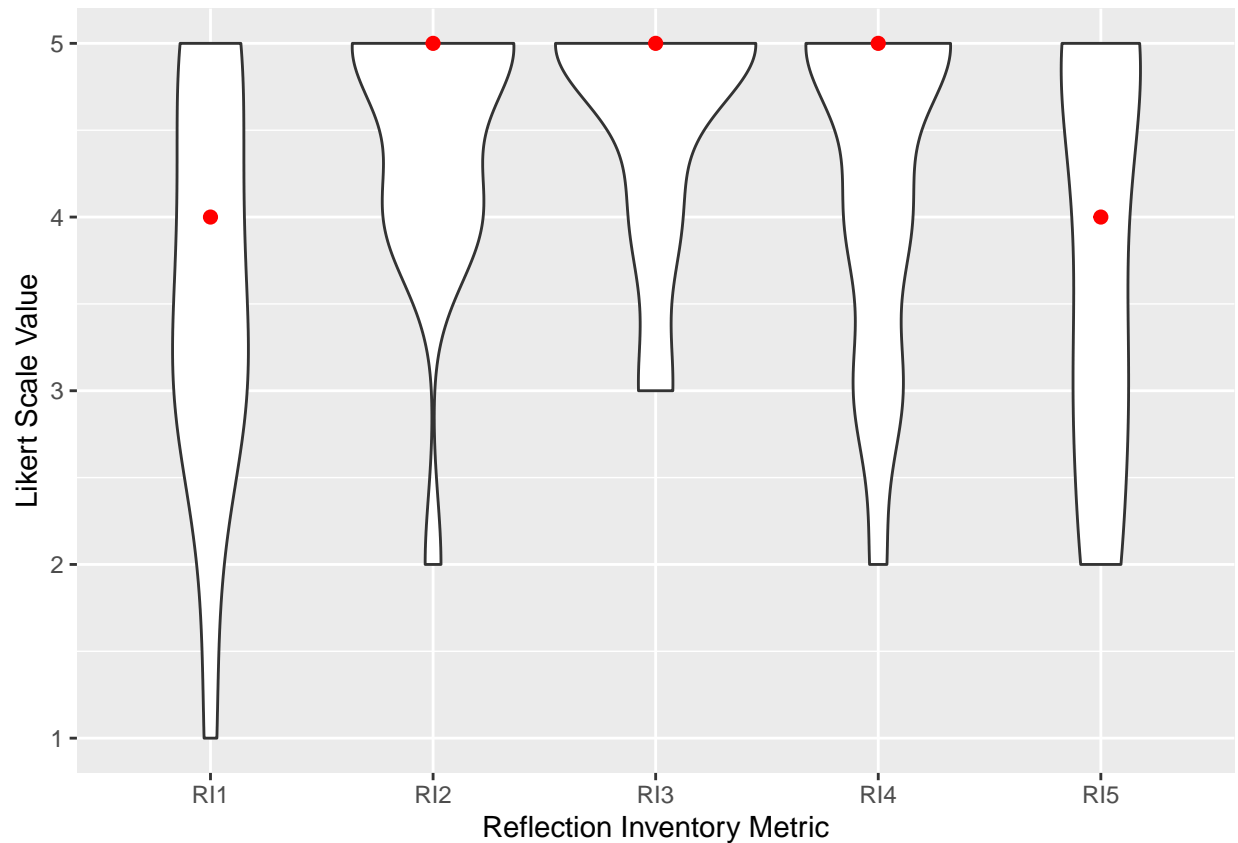
```
ri_sig <- ri %>% select(RI1, RI2, RI3, RI4, RI5)
ri_violin <- ri_sig %>%
  pivot_longer(
    cols = starts_with("RI"),
    names_to = "RI",
    values_to = "value",
    values_drop_na = TRUE
  )

boxplot(ri_violin$value ~ ri_violin$RI)
```



Violin Plot

```
p <- ggplot(ri_violin, aes(x=RI, y=value)) +
  geom_violin(position=position_dodge(1)) + coord_cartesian(ylim = c(1, 5)) + xlab("Reflection Inventory")
# violin plot with median points
p + stat_summary(fun=median, geom="point", size=2, color="red")
```



Initial RI analysis shows that most reflection is around a 4 or 5 for both mean and median

Demographics

Parse and clean data

```
full_demo_phone <- pre_Filtered %>% select(PID, Gender, Sex, Age, Education, College_Or_Uni, Waterloo_R
```

In this section I just print all demographics summaries (Data exploration)

```
#Gender
full_demo_phone %>%
  group_by(Gender) %>%
  summarise(gender_count=n())
```

```
## # A tibble: 3 x 2
##   Gender      gender_count
## * <chr>          <int>
## 1 Man              5
## 2 Non-binary       1
## 3 Woman           11
```

```
#Sex
full_demo_phone %>%
  group_by(Sex) %>%
  summarise(sex_count=n())
```



```
## # A tibble: 3 x 2
##   Sex                sex_count
## * <chr>              <int>
## 1 Female              11
## 2 Male                5
## 3 Prefer not to disclose 1
```

#Age

```
summary(full_demo_phone$Age)
```

```
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  20.00  23.00   25.00   25.53  26.00   44.00
```

#Education

```
full_demo_phone %>%
  group_by(Education) %>%
  summarise(education_count=n())
```

```
## # A tibble: 4 x 2
##   Education                education_count
## * <chr>                    <int>
## 1 Bachelorâs degree          9
## 2 Graduated high school or less    2
## 3 Post-graduate degree            3
## 4 Some college, no degree          3
```

###NOTE: I STRONGLY SUSPECT SOME PEOPLE FILLED THIS IN WRONG

#College_Or_Uni

```
full_demo_phone %>%
  group_by(College_Or_Uni) %>%
  summarise(college_or_uni_count=n())
```

```
## # A tibble: 1 x 2
##   College_Or_Uni college_or_uni_count
## * <chr>          <int>
## 1 Yes            17
```

#Everyone went to college or uni which makes sense give the population. I will exclude this from the re

#Waterloo_Relation

```
full_demo_phone %>%
  group_by(Waterloo_Relation) %>%
  summarise(waterloo_relation_count=n())
```

```
## # A tibble: 5 x 2
##   Waterloo_Relation                waterloo_relation_count
## * <chr>                    <int>
## 1 Former Undergraduate Student    1
## 2 Graduate Student                10
## 3 Undergraduate Student           4
## 4 Undergraduate Student, Graduate Student 1
## 5 Undergraduate Student, Graduate Student, Faculty 1
```

```
#Majority grad students
```

```
#Community years
```

```
summary(as.integer(full_demo_phone$Community_Years))
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.000   1.000   2.000   2.706   3.000   7.000
```

```
#Agerage is 2.7
```

```
#Occupation
```

```
full_demo_phone %>%
  group_by(Occupation) %>%
  summarise(occupation_count=n())
```

```
## # A tibble: 13 x 2
##   Occupation                occupation_count
##   * <chr>                  <int>
## 1 "Agile delivery manager"           1
## 2 "Engineer"                       1
## 3 "Game Developer / Temporary Associate" 1
## 4 "grad student"                   1
## 5 "Graduate student"               1
## 6 "Graduate Student"               1
## 7 "PhD Student"                    1
## 8 "Registered nurse"               1
## 9 "Software Developer"              1
## 10 "student"                       1
## 11 "Student"                       4
## 12 "Student "                     2
## 13 "Supervisor at Peel Public Health for Vaccine Clinics" 1
```

```
#Mostly students, I need to just count manually because of case/whitespace/alternative words issues
```

```
#Headset_Expereince
```

```
full_demo_phone %>%
  group_by(Headset_Expereince) %>%
  summarise(Headset_Expereince_count=n())
```

```
## # A tibble: 2 x 2
##   Headset_Expereince Headset_Expereince_count
##   * <chr>                <int>
## 1 No                    10
## 2 Yes                    7
```

```
# Around half in each category
```

```
#MobileAR_Expereince
```

```
full_demo_phone %>%
  group_by(MobileAR_Expereince) %>%
  summarise(MobileAR_Expereincee_count=n())
```

```
## # A tibble: 2 x 2
##   MobileAR_Expereince MobileAR_Expereincee_count
## * <chr>                                <int>
## 1 No                                10
## 2 Yes                                7
```

#Interestingly almost exactly the same as the headset! TODO: check if there is significant overlap betw

```
#Phone
full_demo_phone %>%
  group_by(Phone) %>%
  summarise(phone_count=n())
```

```
## # A tibble: 15 x 2
##   Phone                phone_count
## * <chr>                <int>
## 1 Google Pixel 2        1
## 2 Huawei honor 8x       1
## 3 I phone 13 pro max    1
## 4 iphone                1
## 5 iPhone 11             2
## 6 Iphone 11             1
## 7 Iphone 12 pro max     1
## 8 Iphone 13 pro         2
## 9 iPhone XR             1
## 10 Iphone XR            1
## 11 iPhone Xs            1
## 12 Pixel 6              1
## 13 Samsung 7            1
## 14 Samsung Galaxy M21   1
## 15 Samsung Galaxy S9    1
```

#Good mix, seems to be mostly iphones

Desirability Toolkit Analysis

I am cleaning the data because it is messy as it was people inputted

```
#TODO: make desirability graph
Desirability_List <- raw_post$Desirability_List
Desirability_List <- gsub('[â€¢]', '', Desirability_List) #Use regex to remove special characters
Desirability_List
```

```
## [1] " Compelling, Creative, Easy to use, Engaging, High quality, Meaningful"
## [2] " Annoying, Not Valuable, Overwhelming"
## [3] " Creative, High quality, Innovative, Useful"
## [4] " Annoying, Confusing, Creative, Cutting edge, Engaging, Hard to Use, Innovative, Meaningful"
## [5] " Creative, Easy to use, Engaging, Innovative, Meaningful, Overwhelming, Useful"
## [6] " Annoying, Boring, Slow, Useful"
## [7] " Confusing, Creative, Cutting edge, Easy to use, Empowering, Engaging, Innovative, Meaningful"
## [8] " Creative, Engaging, High quality, Irrelevant"
```

```
## [9] " Creative, Cutting edge, Hard to Use, High quality, Innovative, Meaningful, Useful"
## [10] " Compelling, Creative, Cutting edge, Easy to use, Innovative, Overwhelming, Too Technical"
## [11] " Confusing, Engaging, High quality, Innovative, Meaningful, Relevant, Useful"
## [12] " Creative, Cutting edge, Meaningful"
## [13] " Engaging, High quality, Innovative, Meaningful, Useful"
## [14] " Creative, Easy to use, Engaging, Innovative, Relevant"
## [15] " Compelling, Creative, Cutting edge, Empowering, Engaging, Innovative, Overwhelming, Pe
## [16] " Creative, Cutting edge, Easy to use, Engaging, Innovative, Meaningful, Useful"
## [17] " Confusing, Creative, Engaging, Hard to Use, Innovative, Meaningful"
```

Compiled words agnostic of participant

```
all_DT_words <- list()
for (participant in Desirability_List) {
  split <- as.list(strsplit(participant, ","))
  all_DT_words <- c(all_DT_words, split[[1]])
}
all_DT_words2 <- list()
for (item in all_DT_words) {
  trimmed <- trimws(item)
  all_DT_words2 <- c(all_DT_words2, trimmed)
}
all_DT_words2
```

```
## [[1]]
## [1] "Compelling"
##
## [[2]]
## [1] "Creative"
##
## [[3]]
## [1] "Easy to use"
##
## [[4]]
## [1] "Engaging"
##
## [[5]]
## [1] "High quality"
##
## [[6]]
## [1] "Meaningful"
##
## [[7]]
## [1] "Annoying"
##
## [[8]]
## [1] "Not Valuable"
##
## [[9]]
## [1] "Overwhelming"
##
## [[10]]
## [1] "Creative"
```

```

##
## [[11]]
## [1] "High quality"
##
## [[12]]
## [1] "Innovative"
##
## [[13]]
## [1] "Useful"
##
## [[14]]
## [1] "Annoying"
##
## [[15]]
## [1] "Confusing"
##
## [[16]]
## [1] "Creative"
##
## [[17]]
## [1] "Cutting edge"
##
## [[18]]
## [1] "Engaging"
##
## [[19]]
## [1] "Hard to Use"
##
## [[20]]
## [1] "Innovative"
##
## [[21]]
## [1] "Meaningful"
##
## [[22]]
## [1] "Overwhelming"
##
## [[23]]
## [1] "Poor quality"
##
## [[24]]
## [1] "Creative"
##
## [[25]]
## [1] "Easy to use"
##
## [[26]]
## [1] "Engaging"
##
## [[27]]
## [1] "Innovative"
##
## [[28]]
## [1] "Meaningful"

```

```
##
## [[29]]
## [1] "Overwhelming"
##
## [[30]]
## [1] "Useful"
##
## [[31]]
## [1] "Annoying"
##
## [[32]]
## [1] "Boring"
##
## [[33]]
## [1] "Slow"
##
## [[34]]
## [1] "Useful"
##
## [[35]]
## [1] "Confusing"
##
## [[36]]
## [1] "Creative"
##
## [[37]]
## [1] "Cutting edge"
##
## [[38]]
## [1] "Easy to use"
##
## [[39]]
## [1] "Empowering"
##
## [[40]]
## [1] "Engaging"
##
## [[41]]
## [1] "Innovative"
##
## [[42]]
## [1] "Meaningful"
##
## [[43]]
## [1] "Relevant"
##
## [[44]]
## [1] "Creative"
##
## [[45]]
## [1] "Engaging"
##
## [[46]]
## [1] "High quality"
```

```

##
## [[47]]
## [1] "Irrelevant"
##
## [[48]]
## [1] "Creative"
##
## [[49]]
## [1] "Cutting edge"
##
## [[50]]
## [1] "Hard to Use"
##
## [[51]]
## [1] "High quality"
##
## [[52]]
## [1] "Innovative"
##
## [[53]]
## [1] "Meaningful"
##
## [[54]]
## [1] "Useful"
##
## [[55]]
## [1] "Compelling"
##
## [[56]]
## [1] "Creative"
##
## [[57]]
## [1] "Cutting edge"
##
## [[58]]
## [1] "Easy to use"
##
## [[59]]
## [1] "Innovative"
##
## [[60]]
## [1] "Overwhelming"
##
## [[61]]
## [1] "Too Technical"
##
## [[62]]
## [1] "Confusing"
##
## [[63]]
## [1] "Engaging"
##
## [[64]]
## [1] "High quality"

```

```

##
## [[65]]
## [1] "Innovative"
##
## [[66]]
## [1] "Meaningful"
##
## [[67]]
## [1] "Relevant"
##
## [[68]]
## [1] "Useful"
##
## [[69]]
## [1] "Creative"
##
## [[70]]
## [1] "Cutting edge"
##
## [[71]]
## [1] "Meaningful"
##
## [[72]]
## [1] "Engaging"
##
## [[73]]
## [1] "High quality"
##
## [[74]]
## [1] "Innovative"
##
## [[75]]
## [1] "Meaningful"
##
## [[76]]
## [1] "Useful"
##
## [[77]]
## [1] "Creative"
##
## [[78]]
## [1] "Easy to use"
##
## [[79]]
## [1] "Engaging"
##
## [[80]]
## [1] "Innovative"
##
## [[81]]
## [1] "Relevant"
##
## [[82]]
## [1] "Compelling"

```



```

##
## [[83]]
## [1] "Creative"
##
## [[84]]
## [1] "Cutting edge"
##
## [[85]]
## [1] "Empowering"
##
## [[86]]
## [1] "Engaging"
##
## [[87]]
## [1] "Innovative"
##
## [[88]]
## [1] "Overwhelming"
##
## [[89]]
## [1] "Personal"
##
## [[90]]
## [1] "Useful"
##
## [[91]]
## [1] "Creative"
##
## [[92]]
## [1] "Cutting edge"
##
## [[93]]
## [1] "Easy to use"
##
## [[94]]
## [1] "Engaging"
##
## [[95]]
## [1] "Innovative"
##
## [[96]]
## [1] "Meaningful"
##
## [[97]]
## [1] "Useful"
##
## [[98]]
## [1] "Confusing"
##
## [[99]]
## [1] "Creative"
##
## [[100]]
## [1] "Engaging"

```

```
##
## [[101]]
## [1] "Hard to Use"
##
## [[102]]
## [1] "Innovative"
##
## [[103]]
## [1] "Meaningful"
```

```
#Get frequencies of words
sort(table(unlist(all_DT_words2)), decreasing = T)
```

```
##
##      Creative      Innovative      Engaging      Meaningful      Useful
##      13           12           11           10           8
## Cutting edge    Easy to use    High quality    Overwhelming    Confusing
##      7           6           6           5           4
##      Annoying    Compelling    Hard to Use      Relevant      Empowering
##      3           3           3           3           2
##      Boring      Irrelevant    Not Valuable    Personal    Poor quality
##      1           1           1           1           1
##
##      Slow Too Technical
##      1           1
```

Make graph object, this is all edges in

```
#Add vertices
toVert <- unique(all_DT_words2)
g <- make_empty_graph(directed = FALSE) %>%
  add_vertices(1, name="Compelling", color = "green") %>%
  add_vertices(1, name="Creative", color = "green") %>%
  add_vertices(1, name="Easy to use", color = "green") %>%
  add_vertices(1, name="Engaging", color = "green") %>%
  add_vertices(1, name="High quality", color = "green") %>%
  add_vertices(1, name="Meaningful", color = "green") %>%
  add_vertices(1, name="Innovative", color = "green") %>%
  add_vertices(1, name="Useful", color = "green") %>%
  add_vertices(1, name="Cutting edge", color = "green") %>%
  add_vertices(1, name="Empowering", color = "green") %>%
  add_vertices(1, name="Relevant", color = "green") %>%
  add_vertices(1, name="Personal", color = "green") %>%

  add_vertices(1, name="Annoying", color = "red") %>%
  add_vertices(1, name="Not Valuable", color = "red") %>%
  add_vertices(1, name="Overwhelming", color = "red") %>%
  add_vertices(1, name="Confusing", color = "red") %>%
  add_vertices(1, name="Hard to Use", color = "red") %>%
  add_vertices(1, name="Boring", color = "red") %>%
  add_vertices(1, name="Slow", color = "red") %>%
  add_vertices(1, name="Irrelevant", color = "red") %>%
  add_vertices(1, name="Too Technical", color = "red") %>%
  add_vertices(1, name="Poor quality", color = "red")
g
```

```
## IGRAPH 336e144 UN-- 22 0 --
## + attr: name (v/c), color (v/c)
## + edges from 336e144 (vertex names):

#### Add edges
#loop through participants
for (participant in Desirability_List) {

  #Split and trim
  split <- as.list(strsplit(participant, ","))
  split_trimmed <- c()
  for (word in split){
    trimmed <- trimws(word)
    split_trimmed <- c(split_trimmed, trimmed)
  }

  #adding edges
  for(i1 in 1:length(split_trimmed)){
    for(i2 in 1:length(split_trimmed)){
      if (i1 < i2){ #then add edge

        #print("new edge")
        #print(are_adjacent(g, split_trimmed[i1], split_trimmed[i2]))
        #Check if there is an edge there already
        if (are_adjacent(g, split_trimmed[i1], split_trimmed[i2])) {
          #If there is an edge already increment
          ei <- get.edge.ids(g, c(split_trimmed[i1], split_trimmed[i2]))
          E(g)[ei]$weight = (E(g)[ei]$weight + 1)
        }
        else{
          g <- g + edge(split_trimmed[i1], split_trimmed[i2], color = "blue", weight=1)
        }
      }
    }
  }
}
}
```

Plot the graph

```
V(g)[[]]
```

```
## + 22/22 vertices, named, from 33a16e8:
##           name color
## 1    Compelling green
## 2    Creative green
## 3    Easy to use green
## 4    Engaging green
## 5    High quality green
## 6    Meaningful green
## 7    Innovative green
```

```

## 8      Useful green
## 9  Cutting edge green
## 10     Empowering green
## 11      Relevant green
## 12     Personal green
## 13     Annoying  red
## 14 Not Valuable  red
## 15 Overwhelming  red
## 16     Confusing  red
## 17   Hard to Use  red
## 18        Boring  red
## 19        Slow   red
## 20   Irrelevant  red
## 21 Too Technical  red
## 22 Poor quality  red

```

E(g)[[]]

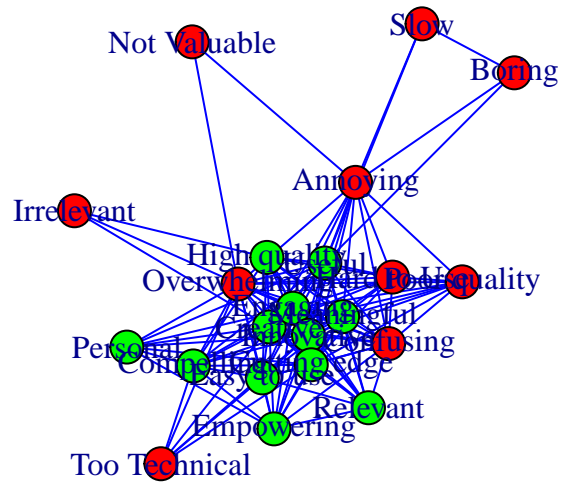
```
## + 124/124 edges from 33a16e8 (vertex names):
```

##	tail	head	tid	hid	color	weight
## 1	Compelling	Creative	1	2	blue	3
## 2	Compelling	Easy to use	1	3	blue	2
## 3	Compelling	Engaging	1	4	blue	2
## 4	Compelling	High quality	1	5	blue	1
## 5	Compelling	Meaningful	1	6	blue	1
## 6	Creative	Easy to use	2	3	blue	6
## 7	Creative	Engaging	2	4	blue	9
## 8	Creative	High quality	2	5	blue	4
## 9	Creative	Meaningful	2	6	blue	8
## 10	Easy to use	Engaging	3	4	blue	5
## 11	Easy to use	High quality	3	5	blue	1
## 12	Easy to use	Meaningful	3	6	blue	4
## 13	Engaging	High quality	4	5	blue	4
## 14	Engaging	Meaningful	4	6	blue	8
## 15	High quality	Meaningful	5	6	blue	4
## 16	Annoying	Not Valuable	13	14	blue	1
## 17	Annoying	Overwhelming	13	15	blue	2
## 18	Not Valuable	Overwhelming	14	15	blue	1
## 19	Creative	Innovative	2	7	blue	10
## 20	Creative	Useful	2	8	blue	5
## 21	High quality	Innovative	5	7	blue	4
## 22	High quality	Useful	5	8	blue	4
## 23	Innovative	Useful	7	8	blue	7
## 24	Annoying	Confusing	13	16	blue	1
## 25	Creative	Annoying	2	13	blue	1
## 26	Cutting edge	Annoying	9	13	blue	1
## 27	Engaging	Annoying	4	13	blue	1
## 28	Annoying	Hard to Use	13	17	blue	1
## 29	Innovative	Annoying	7	13	blue	1
## 30	Meaningful	Annoying	6	13	blue	1
## 31	Annoying	Poor quality	13	22	blue	1
## 32	Creative	Confusing	2	16	blue	3
## 33	Cutting edge	Confusing	9	16	blue	2
## 34	Engaging	Confusing	4	16	blue	4

## 35	Confusing	Hard to Use	16	17	blue	2
## 36	Innovative	Confusing	7	16	blue	4
## 37	Meaningful	Confusing	6	16	blue	4
## 38	Overwhelming	Confusing	15	16	blue	1
## 39	Confusing	Poor quality	16	22	blue	1
## 40	Creative	Cutting edge	2	9	blue	7
## 41	Creative	Hard to Use	2	17	blue	3
## 42	Creative	Overwhelming	2	15	blue	4
## 43	Creative	Poor quality	2	22	blue	1
## 44	Engaging	Cutting edge	4	9	blue	4
## 45	Cutting edge	Hard to Use	9	17	blue	2
## 46	Innovative	Cutting edge	7	9	blue	6
## 47	Meaningful	Cutting edge	6	9	blue	5
## 48	Cutting edge	Overwhelming	9	15	blue	3
## 49	Cutting edge	Poor quality	9	22	blue	1
## 50	Engaging	Hard to Use	4	17	blue	2
## 51	Engaging	Innovative	4	7	blue	9
## 52	Engaging	Overwhelming	4	15	blue	3
## 53	Engaging	Poor quality	4	22	blue	1
## 54	Innovative	Hard to Use	7	17	blue	3
## 55	Meaningful	Hard to Use	6	17	blue	3
## 56	Overwhelming	Hard to Use	15	17	blue	1
## 57	Hard to Use	Poor quality	17	22	blue	1
## 58	Meaningful	Innovative	6	7	blue	8
## 59	Innovative	Overwhelming	7	15	blue	4
## 60	Innovative	Poor quality	7	22	blue	1
## 61	Meaningful	Overwhelming	6	15	blue	2
## 62	Meaningful	Poor quality	6	22	blue	1
## 63	Overwhelming	Poor quality	15	22	blue	1
## 64	Easy to use	Innovative	3	7	blue	5
## 65	Easy to use	Overwhelming	3	15	blue	2
## 66	Easy to use	Useful	3	8	blue	2
## 67	Engaging	Useful	4	8	blue	5
## 68	Meaningful	Useful	6	8	blue	5
## 69	Useful	Overwhelming	8	15	blue	2
## 70	Annoying	Boring	13	18	blue	1
## 71	Annoying	Slow	13	19	blue	1
## 72	Useful	Annoying	8	13	blue	1
## 73	Boring	Slow	18	19	blue	1
## 74	Useful	Boring	8	18	blue	1
## 75	Useful	Slow	8	19	blue	1
## 76	Easy to use	Confusing	3	16	blue	1
## 77	Empowering	Confusing	10	16	blue	1
## 78	Relevant	Confusing	11	16	blue	2
## 79	Creative	Empowering	2	10	blue	2
## 80	Creative	Relevant	2	11	blue	2
## 81	Easy to use	Cutting edge	3	9	blue	3
## 82	Cutting edge	Empowering	9	10	blue	2
## 83	Cutting edge	Relevant	9	11	blue	1
## 84	Easy to use	Empowering	3	10	blue	1
## 85	Easy to use	Relevant	3	11	blue	2
## 86	Engaging	Empowering	4	10	blue	2
## 87	Innovative	Empowering	7	10	blue	2
## 88	Meaningful	Empowering	6	10	blue	1

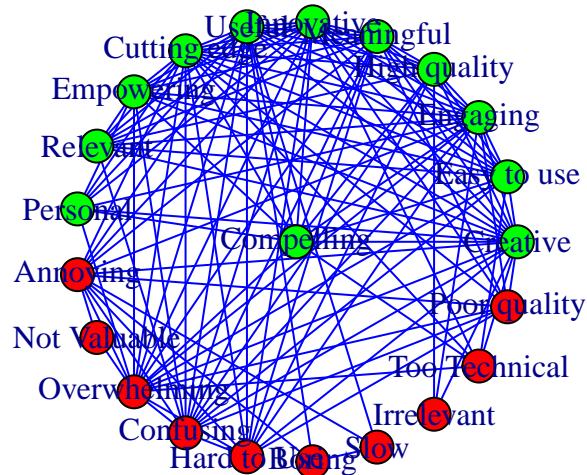
## 89	Empowering	Relevant	10	11	blue	1
## 90	Engaging	Relevant	4	11	blue	3
## 91	Innovative	Relevant	7	11	blue	3
## 92	Meaningful	Relevant	6	11	blue	2
## 93	Creative	Irrelevant	2	20	blue	1
## 94	Engaging	Irrelevant	4	20	blue	1
## 95	High quality	Irrelevant	5	20	blue	1
## 96	High quality	Cutting edge	5	9	blue	1
## 97	Useful	Cutting edge	8	9	blue	3
## 98	High quality	Hard to Use	5	17	blue	1
## 99	Useful	Hard to Use	8	17	blue	1
## 100	Compelling	Cutting edge	1	9	blue	2
## 101	Compelling	Innovative	1	7	blue	2
## 102	Compelling	Overwhelming	1	15	blue	2
## 103	Compelling	Too Technical	1	21	blue	1
## 104	Creative	Too Technical	2	21	blue	1
## 105	Cutting edge	Too Technical	9	21	blue	1
## 106	Easy to use	Too Technical	3	21	blue	1
## 107	Innovative	Too Technical	7	21	blue	1
## 108	Overwhelming	Too Technical	15	21	blue	1
## 109	High quality	Confusing	5	16	blue	1
## 110	Useful	Confusing	8	16	blue	1
## 111	High quality	Relevant	5	11	blue	1
## 112	Useful	Relevant	8	11	blue	1
## 113	Compelling	Empowering	1	10	blue	1
## 114	Compelling	Personal	1	12	blue	1
## 115	Compelling	Useful	1	8	blue	1
## 116	Creative	Personal	2	12	blue	1
## 117	Cutting edge	Personal	9	12	blue	1
## 118	Empowering	Overwhelming	10	15	blue	1
## 119	Empowering	Personal	10	12	blue	1
## 120	Useful	Empowering	8	10	blue	1
## 121	Engaging	Personal	4	12	blue	1
## 122	Innovative	Personal	7	12	blue	1
## 123	Personal	Overwhelming	12	15	blue	1
## 124	Useful	Personal	8	12	blue	1

```
plot(g)
```



Plot the graph using a force directed layout

```
coords <- layout_(g, as_star())
plot(g, layout = coords)
```



Make a cluter using cluster walktrap From: https://igraph.org/r/doc/cluster_walktrap.html

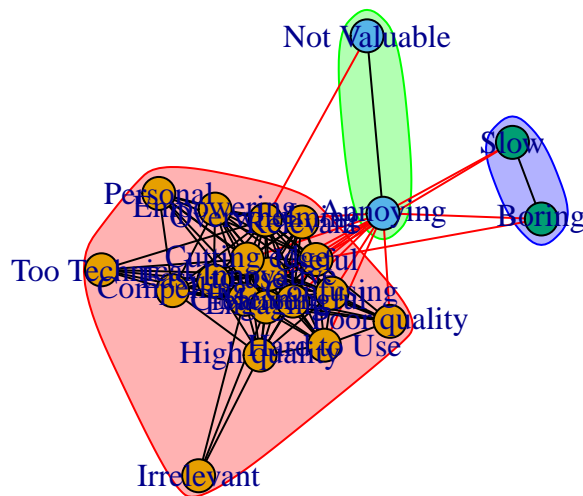
```
wc <- cluster_walktrap(g, steps=12)
modularity(wc)
```

```
## [1] 0.01805606
```

```
membership(wc)
```

```
##      Compelling      Creative  Easy to use      Engaging  High quality
##           1           1           1           1           1
##      Meaningful    Innovative      Useful  Cutting edge    Empowering
##           1           1           1           1           1
##      Relevant      Personal      Annoying  Not Valuable  Overwhelming
##           1           1           2           2           1
##      Confusing    Hard to Use      Boring      Slow      Irrelevant
##           1           1           3           3           1
##      Too Technical  Poor quality
##           1           1
```

```
plot(wc, g)
```

This is a new graph where I got rid of words that only happened once total.

```
once_list <- c("Boring", "Irrelevant", "Not Valuable", "Personal", "Poor quality", "Slow", "Too Technical")
toVert <- unique(all_DT_words2)
g <- make_empty_graph(directed = FALSE) %>%
  add_vertices(1, name="Compelling", color = "green") %>%
  add_vertices(1, name="Creative", color = "green") %>%
  add_vertices(1, name="Easy to use", color = "green") %>%
  add_vertices(1, name="Engaging", color = "green") %>%
  add_vertices(1, name="High quality", color = "green") %>%
  add_vertices(1, name="Meaningful", color = "green") %>%
  add_vertices(1, name="Innovative", color = "green") %>%
  add_vertices(1, name="Useful", color = "green") %>%
  add_vertices(1, name="Cutting edge", color = "green") %>%
  add_vertices(1, name="Empowering", color = "green") %>%
  add_vertices(1, name="Relevant", color = "green") %>%

  add_vertices(1, name="Annoying", color = "red") %>%
  add_vertices(1, name="Overwhelming", color = "red") %>%
  add_vertices(1, name="Confusing", color = "red") %>%
  add_vertices(1, name="Hard to Use", color = "red")
g
```

```
## IGRAPH 33cba92 UN-- 15 0 --
## + attr: name (v/c), color (v/c)
## + edges from 33cba92 (vertex names):
```

```

#### Add edges
#loop through participants
for (participant in Desirability_List) {

  #Split and trim
  split <- as.list(strsplit(participant, ","))
  split_trimmed <- c()
  for (word in split){
    trimmed <- trimws(word)
    split_trimmed <- c(split_trimmed, trimmed)
  }

  #adding edges
  for(i1 in 1:length(split_trimmed)){
    for(i2 in 1:length(split_trimmed)){
      if (i1 < i2){ #then add edge

        #Check if in once list
        if ( !(split_trimmed[i1] %in% once_list | split_trimmed[i2] %in% once_list) ){

          #Check if there is an edge there already
          if (are_adjacent(g, split_trimmed[i1], split_trimmed[i2])) {
            #If there is an edge already increment
            ei <- get.edge.ids(g, c(split_trimmed[i1], split_trimmed[i2]))
            E(g)[ei]$weight = (E(g)[ei]$weight + 1)
          }
          else{
            g <- g + edge(split_trimmed[i1], split_trimmed[i2], color = "blue", weight=1)
          }
        }
      }
    }
  }
}

```

Plot paired down graph

```
V(g)[[]]
```

```

## + 15/15 vertices, named, from 33fd8c8:
##           name color
## 1    Compelling green
## 2    Creative green
## 3    Easy to use green
## 4    Engaging green
## 5    High quality green
## 6    Meaningful green
## 7    Innovative green
## 8    Useful green

```

```

## 9 Cutting edge green
## 10 Empowering green
## 11 Relevant green
## 12 Annoying red
## 13 Overwhelming red
## 14 Confusing red
## 15 Hard to Use red

```

E(g)[[]]

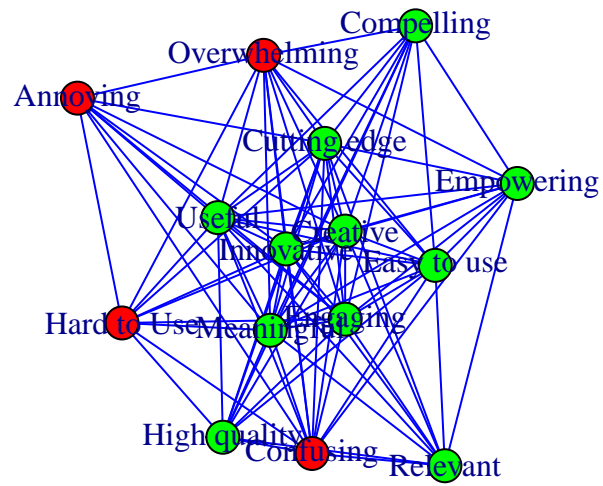
```

## + 91/91 edges from 33fd8c8 (vertex names):
##      tail      head tid hid color weight
## 1 Compelling Creative 1 2 blue 3
## 2 Compelling Easy to use 1 3 blue 2
## 3 Compelling Engaging 1 4 blue 2
## 4 Compelling High quality 1 5 blue 1
## 5 Compelling Meaningful 1 6 blue 1
## 6 Creative Easy to use 2 3 blue 6
## 7 Creative Engaging 2 4 blue 9
## 8 Creative High quality 2 5 blue 4
## 9 Creative Meaningful 2 6 blue 8
## 10 Easy to use Engaging 3 4 blue 5
## 11 Easy to use High quality 3 5 blue 1
## 12 Easy to use Meaningful 3 6 blue 4
## 13 Engaging High quality 4 5 blue 4
## 14 Engaging Meaningful 4 6 blue 8
## 15 High quality Meaningful 5 6 blue 4
## 16 Annoying Overwhelming 12 13 blue 2
## 17 Creative Innovative 2 7 blue 10
## 18 Creative Useful 2 8 blue 5
## 19 High quality Innovative 5 7 blue 4
## 20 High quality Useful 5 8 blue 4
## 21 Innovative Useful 7 8 blue 7
## 22 Annoying Confusing 12 14 blue 1
## 23 Creative Annoying 2 12 blue 1
## 24 Cutting edge Annoying 9 12 blue 1
## 25 Engaging Annoying 4 12 blue 1
## 26 Annoying Hard to Use 12 15 blue 1
## 27 Innovative Annoying 7 12 blue 1
## 28 Meaningful Annoying 6 12 blue 1
## 29 Creative Confusing 2 14 blue 3
## 30 Cutting edge Confusing 9 14 blue 2
## 31 Engaging Confusing 4 14 blue 4
## 32 Confusing Hard to Use 14 15 blue 2
## 33 Innovative Confusing 7 14 blue 4
## 34 Meaningful Confusing 6 14 blue 4
## 35 Overwhelming Confusing 13 14 blue 1
## 36 Creative Cutting edge 2 9 blue 7
## 37 Creative Hard to Use 2 15 blue 3
## 38 Creative Overwhelming 2 13 blue 4
## 39 Engaging Cutting edge 4 9 blue 4
## 40 Cutting edge Hard to Use 9 15 blue 2
## 41 Innovative Cutting edge 7 9 blue 6
## 42 Meaningful Cutting edge 6 9 blue 5

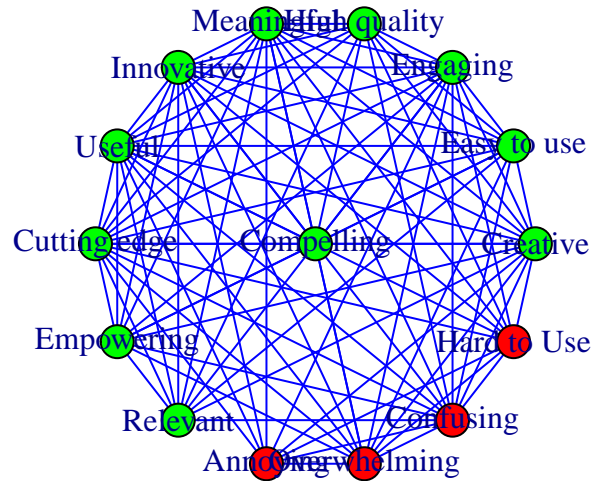
```

## 43	Cutting edge	Overwhelming	9	13	blue	3
## 44	Engaging	Hard to Use	4	15	blue	2
## 45	Engaging	Innovative	4	7	blue	9
## 46	Engaging	Overwhelming	4	13	blue	3
## 47	Innovative	Hard to Use	7	15	blue	3
## 48	Meaningful	Hard to Use	6	15	blue	3
## 49	Overwhelming	Hard to Use	13	15	blue	1
## 50	Meaningful	Innovative	6	7	blue	8
## 51	Innovative	Overwhelming	7	13	blue	4
## 52	Meaningful	Overwhelming	6	13	blue	2
## 53	Easy to use	Innovative	3	7	blue	5
## 54	Easy to use	Overwhelming	3	13	blue	2
## 55	Easy to use	Useful	3	8	blue	2
## 56	Engaging	Useful	4	8	blue	5
## 57	Meaningful	Useful	6	8	blue	5
## 58	Useful	Overwhelming	8	13	blue	2
## 59	Useful	Annoying	8	12	blue	1
## 60	Easy to use	Confusing	3	14	blue	1
## 61	Empowering	Confusing	10	14	blue	1
## 62	Relevant	Confusing	11	14	blue	2
## 63	Creative	Empowering	2	10	blue	2
## 64	Creative	Relevant	2	11	blue	2
## 65	Easy to use	Cutting edge	3	9	blue	3
## 66	Cutting edge	Empowering	9	10	blue	2
## 67	Cutting edge	Relevant	9	11	blue	1
## 68	Easy to use	Empowering	3	10	blue	1
## 69	Easy to use	Relevant	3	11	blue	2
## 70	Engaging	Empowering	4	10	blue	2
## 71	Innovative	Empowering	7	10	blue	2
## 72	Meaningful	Empowering	6	10	blue	1
## 73	Empowering	Relevant	10	11	blue	1
## 74	Engaging	Relevant	4	11	blue	3
## 75	Innovative	Relevant	7	11	blue	3
## 76	Meaningful	Relevant	6	11	blue	2
## 77	High quality	Cutting edge	5	9	blue	1
## 78	Useful	Cutting edge	8	9	blue	3
## 79	High quality	Hard to Use	5	15	blue	1
## 80	Useful	Hard to Use	8	15	blue	1
## 81	Compelling	Cutting edge	1	9	blue	2
## 82	Compelling	Innovative	1	7	blue	2
## 83	Compelling	Overwhelming	1	13	blue	2
## 84	High quality	Confusing	5	14	blue	1
## 85	Useful	Confusing	8	14	blue	1
## 86	High quality	Relevant	5	11	blue	1
## 87	Useful	Relevant	8	11	blue	1
## 88	Compelling	Empowering	1	10	blue	1
## 89	Compelling	Useful	1	8	blue	1
## 90	Empowering	Overwhelming	10	13	blue	1
## 91	Useful	Empowering	8	10	blue	1

```
plot(g)
```



```
coords <- layout_(g, as_star())
plot(g, layout = coords)
```



Plot graph clustered via cluster walktrap

```
wc <- cluster_walktrap(g)
modularity(wc)
```

```
## [1] 0.00774914
```

```
membership(wc)
```

```
##   Compelling   Creative  Easy to use   Engaging  High quality  Meaningful
##         1             1             1             1             1             1
##   Innovative    Useful  Cutting edge   Empowering    Relevant      Annoying
##         1             1             1             1             1             2
## Overwhelming    Confusing  Hard to Use
##         2             1             2
```

```
new_cols <- c("white", "lightgray")[membership(wc)]
plot(wc, g, edge.width=E(g)$weight, vertex.shape="rectangle", vertex.size=45, col=new_cols, mark.col=c(
```

