

Group Project 1

Lee Ann & Jonathan

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#####
##### Data import and wrangling - LAS#####
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#Libraries
library(readr)
library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr     1.1.4     v purrr     1.1.0
## vforcats   1.0.0     v stringr    1.5.1
## v ggplot2   3.5.2     v tibble     3.3.0
## v lubridate 1.9.4     v tidyr     1.3.1
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
library(reshape2)

##
## Attaching package: 'reshape2'
##
## The following object is masked from 'package:tidy়':
##
##     smiths

library(pastecs)

##
## Attaching package: 'pastecs'
##
## The following objects are masked from 'package:dplyr':
##
##     first, last
##
## The following object is masked from 'package:tidy়':
##
##     extract

library(ggplot2)
library(dplyr)
library(tidyr)
library(reshape2)
```

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#Now that we both have the df available, I will make sure all of our
#variables are named appropriately and are of the correct classes
names(df)

## [1] "Group"         "Baseline"       "Six_months"    "Participant"

#These names are of reasonable lengths and descriptions so we can keep them as
#is
class (df$Group)

## [1] "numeric"

class (df$Baseline)

## [1] "numeric"

class (df$Six_months)

## [1] "numeric"

class (df$Participant)

## [1] "numeric"

#Currently all of our variables are numeric. This is appropriate for Baseline,
#Six_months, and Participants variables. Group however should be a factor.
#We will do that here
df$Group <- as.factor(df$Group)
#And check that it worked here
is.factor(df$Group)

## [1] TRUE
```

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#It is TRUE confirming we successfully converted it to a factor
#Now that our data is imported and has the correct names and classes, we can
#begin to create our figures and start our analysis.

#####
#####Box Plot - JR#####
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#I'll start by reordering the columns and then shifting to a long "tidy"
#data set by "melting" the Baseline and Six_months columns. I create an object,
#pipe df into select to reorder my columns (just a little OCD), pipe into
#rename(this is so the six months variable appears without the underscore in
#the graph),
#and pipe into melt to create a tidy data frame.

df_long <- df %>% select(Participant, Group, Baseline, Six_months) %>%
  rename("Six months" = Six_months) %>%
  melt(id.vars = c("Participant", "Group"), variable.name = "Visit",
    value.name = "Text_Count")

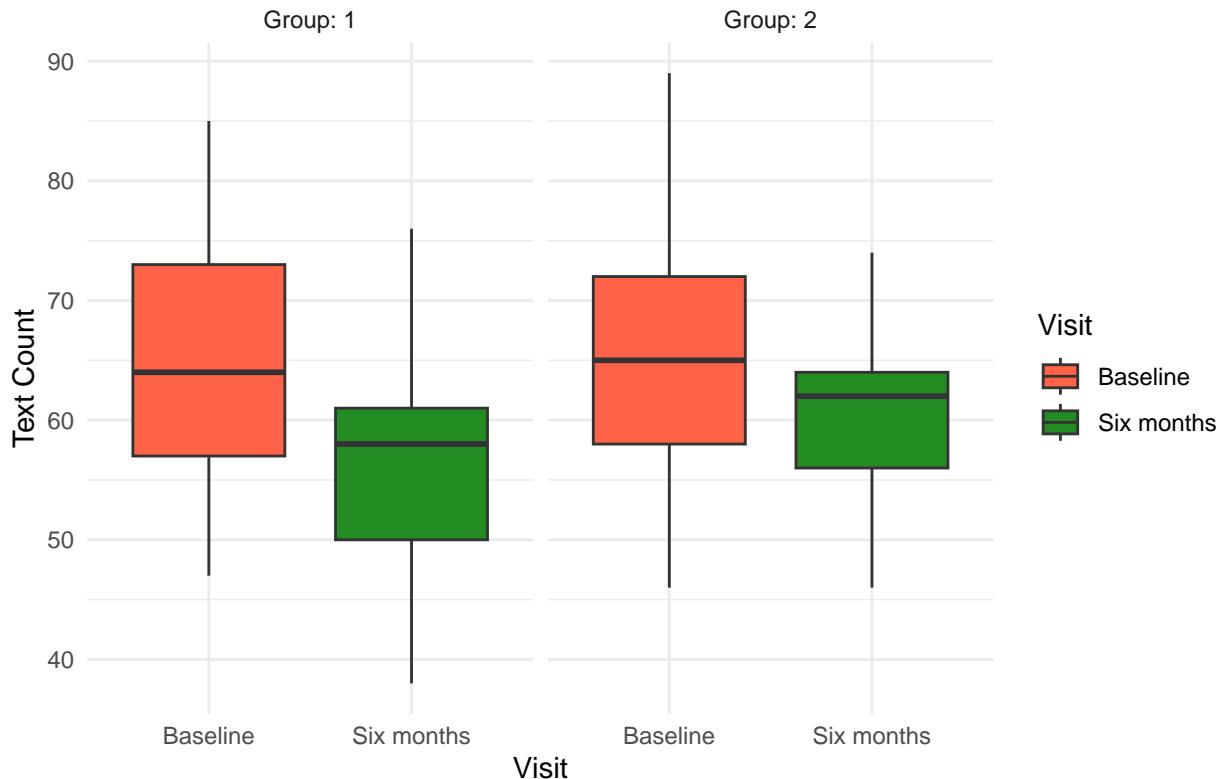
#Next, I'll create the stratified boxplot by group. I assign an object, pipe the
#new data frame into ggplot, assign aesthetics, add a boxplot layer,
#removed the outliers, used "free_y" in facet_grid; this
#allows R to handle how to assign the y-axis.facet by group with a labeller
#argument for the two groups, add a color scheme by visit, and in the themes
#layer, I remove the legend, and (just for fun) change the background color.

text_count_boxplot2 <- df_long %>%
  ggplot(aes(x = Visit, y = Text_Count, fill = Visit)) +
  geom_boxplot(outliers = FALSE) +
  facet_grid(~Group, labeller = label_both, scales = "free_y") +
  scale_fill_manual(values = c("tomato", "forestgreen")) +
  theme(legend.position = "none")
  ) + theme_minimal() +
  labs(title = "Text messages by Group", y = "Text Count")

text_count_boxplot2

```

Text messages by Group



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#####
#####bar charts - LAS#####
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#To make our bar plot we will first convert our data from wide to long format.
#Jonathan has already done this above
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#Next, since our bar plot will compare the means between groups, we will
#calculate the mean text messages and 95% CI for each group and timepoint.
# Compute summary statistics for mean and 95% CI per group/time. We will
#put these results in their own data frame called df_summary
```

```
df_summary <- df_long %>%
  group_by(Group, Visit) %>%
  summarize(
    mean_count = mean(Text_Count, na.rm = TRUE),
    sd = sd(Text_Count, na.rm = TRUE),
    n = n(),
    se = sd / sqrt(n),
    ci_lower = mean_count - 1.96 * se,
    ci_upper = mean_count + 1.96 * se,
    .groups = "drop"
  )
```

```
#Now that we have our values, I will rename them so that they look more
#aesthetically pleasing in our plot.
```

```

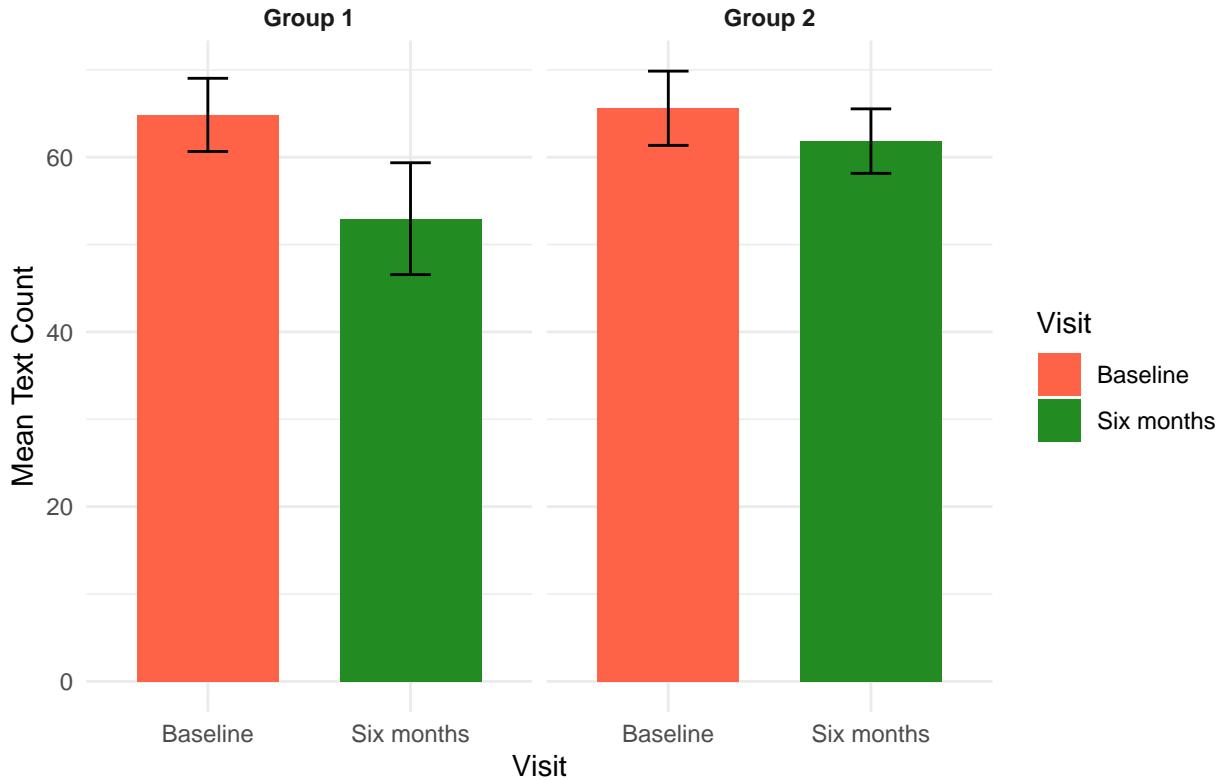
df_summary <- df_summary %>%
  mutate(
    Visit = recode(Visit,
      "Baseline" = "Baseline",
      "Six_months" = "Six months"),
    Group = recode_factor(as.factor(Group),
      "1" = "Group 1",
      "2" = "Group 2")
  )

#we can now plot our bar plot. We will use ggplot to
#make a bar plot that compares the mean text messages at each time point and
#we will facet by groups so that we can visualize the differences in time
#points between groups as well

ggplot(df_summary, aes(x = Visit, y = mean_count, fill = Visit)) +
  geom_col(position = position_dodge(), width = 0.7) +
  geom_errorbar(aes(ymin = ci_lower, ymax = ci_upper),
    width = 0.2, position = position_dodge(0.7)) +
  facet_wrap(~ Group) +
  labs(
    title = "Average Number of Text Messages by Group",
    x = "Visit",
    y = "Mean Text Count",
    fill = "Visit"
  ) +
  theme_minimal() +
  scale_fill_manual(values = c("tomato", "forestgreen")) +
  theme(
    legend.position = "right",
    strip.text = element_text(face = "bold")
  )

```

Average Number of Text Messages by Group



```
#Here we can see the mean and 95% CI plotted at each time point for each group
#Baseline values are pink and six month follow up values are blue. The color
#designations are described in the legend on the right. The panel
#on the left shows the results of group 1 while the one on the right shows the
#results of group 2. The error bars on the top of each bar represent the 95%
#CI. We can clearly see that both group one and group 2 experience a decrease
#In the mean number of messages at follow up compared to baseline. The 95% CI
#do not appear to overlap in group one, but they do appear to overlap in group
#2 suggesting that the decrease in messages was statistically significant for
#group 1 but not for group 2.
```

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#####
#####Summary statistics - JR#####
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```
#Summary statistics by group and time:
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```
by(df$Baseline, df$Group, function(x) round(stat.desc(x, norm = TRUE), 3))
```

```
## df$Group: 1
##      nbr.val    nbr.null     nbr.na      min       max     range
##      25.000      0.000      0.000    47.000    85.000    38.000
##      sum        median      mean    SE.mean  CI.mean.0.95      var
##  1621.000     64.000    64.840     2.136     4.408   114.057
##      std.dev    coef.var  skewness  skew.2SE    kurtosis  kurt.2SE
##      10.680      0.165     0.035     0.037    -1.273    -0.706
```

```

## normtest.W normtest.p
## 0.962 0.448
## -----
## df$Group: 2
##   nbr.val    nbr.null     nbr.na      min      max    range
##   25.000      0.000      0.000    46.000    89.000   43.000
##   sum        median       mean    SE.mean CI.mean.0.95      var
## 1640.000     65.000     65.600    2.167     4.473   117.417
##   std.dev    coef.var   skewness  skew.2SE  kurtosis kurt.2SE
## 10.836      0.165      0.418     0.451     -0.587   -0.325
## normtest.W normtest.p
## 0.971      0.669

by(df$Baseline, df$Group, summary)

## df$Group: 1
##   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
## 47.00 57.00 64.00 64.84 73.00 85.00
## -----
## df$Group: 2
##   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
## 46.0 58.0 65.0 65.6 72.0 89.0

#At Baseline, the two groups are quite similar with similar means, medians and interquartile ranges. The variances are also quite close, thus so is the coefficients of variation and 95% CIs. For both groups, a Shapiro-Wilks normality test shows both groups with a high likelihood of being normally distributed.

by(df$Six_months, df$Group, function(x) round(stat.desc(x, norm = TRUE), 3))

## df$Group: 1
##   nbr.val    nbr.null     nbr.na      min      max    range
##   25.000      0.000      0.000    9.000    78.000   69.000
##   sum        median       mean    SE.mean CI.mean.0.95      var
## 1324.000     58.000     52.960    3.266     6.741   266.707
##   std.dev    coef.var   skewness  skew.2SE  kurtosis kurt.2SE
## 16.331      0.308     -1.100    -1.186     0.808   0.448
## normtest.W normtest.p
## 0.877      0.006
## -----
## df$Group: 2
##   nbr.val    nbr.null     nbr.na      min      max    range
##   25.000      0.000      0.000    46.000    79.000   33.000
##   sum        median       mean    SE.mean CI.mean.0.95      var
## 1546.000     62.000     61.840    1.882     3.884   88.557
##   std.dev    coef.var   skewness  skew.2SE  kurtosis kurt.2SE
## 9.410       0.152      0.164     0.177     -0.741   -0.411
## normtest.W normtest.p
## 0.942      0.161

by(df$Six_months, df$Group, summary)

## df$Group: 1
##   Min. 1st Qu. Median   Mean 3rd Qu.   Max.
## 9.00 50.00 58.00 52.96 61.00 78.00
## -----

```

```
## df$Group: 2
##      Min. 1st Qu. Median   Mean 3rd Qu.   Max.
##     46.00  56.00  62.00  61.84  64.00  79.00
#At six months, Group 1 is lower in almost every category: mean, median,
#interquartile range. However, group 1 shows significantly more deviation, with
#a coefficient of variation more than twice that of group 2. Group 1 also may
#not be normally distributed, as the output for the Shapiro-Wilks test would
#reject the null at an alpha level = .05 with a p-value of .006, suggesting that
#the data is likely not normally distributed. Group two, on the other hand,
#tests as likely normal.
```