Lab 6: Change (Pre-Post Test)

Wednesday Bushong

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Today's lab will be short and sweet :)

Overview of Pre-Post Test Analyses

In a repeated measures design, instead of having only one observation per subject, you have 2 or more. This is indeed the norm in cognitive psychology! Today we'll just be tackling the case where we have a pre-test and post-test value. We have 2 options for how we want to analyze change between a pre- and post-test:

- **Analyze straight change**: Here, we compute the change in the dependent variable between time A and time B.
- **Analyze residual change**: Here, we predict the value at time B from the value at time A. If this is positive, it means there was positive change over time; if negative, negative over time. If there's an effect of the independent variable, then

We also have a choice for whether we want to use regression or ANOVA – if we're using an ANOVA, we'll want to include an error term for participant.

The Data

Females and males had 'handicap' scores taken at two times. We're interested in whether gender affects the timecourse of these values.

```
# Load libraries & data
library(foreign)
library(tidyr)
library(ggplot2)

# data
d <- read.spss("data.sav", to.data.frame = TRUE)
```

```
## re-encoding from CP1252
```

```
# what does the data look like?
summary(d)
```

```
##    bgender      bhndicap         fhndicap          change
##  Female:51   Min.   :0.7143   Min.   :0.7143   Min.   :-1.07143
##  Male  :49   1st Qu.:1.9286   1st Qu.:1.9286   1st Qu.:-0.21429
##              Median :2.2857   Median :2.2857   Median : 0.00000
##              Mean   :2.3086   Mean   :2.3651   Mean   : 0.05651
##              3rd Qu.:2.6786   3rd Qu.:2.8036   3rd Qu.: 0.35714
##              Max.   :4.2143   Max.   :5.2000   Max.   : 3.05714
```

```r
head(d)
```

```
##   bgender bhndicap fhndicap      change
## 1  Female 2.214286 2.285714  0.07142857
## 2  Female 1.357143 1.357143  0.00000000
## 3  Female 1.714286 2.400000  0.68571429
## 4  Female 1.428571 1.785714  0.35714286
## 5  Female 3.000000 2.642857 -0.35714286
## 6  Female 3.071429 3.000000 -0.07142857
```

```r
# label participants
d$participant <- as.factor(1:nrow(d))
```

There's already a change score that has been computed for us in the data. Let's make sure that these are the right values:

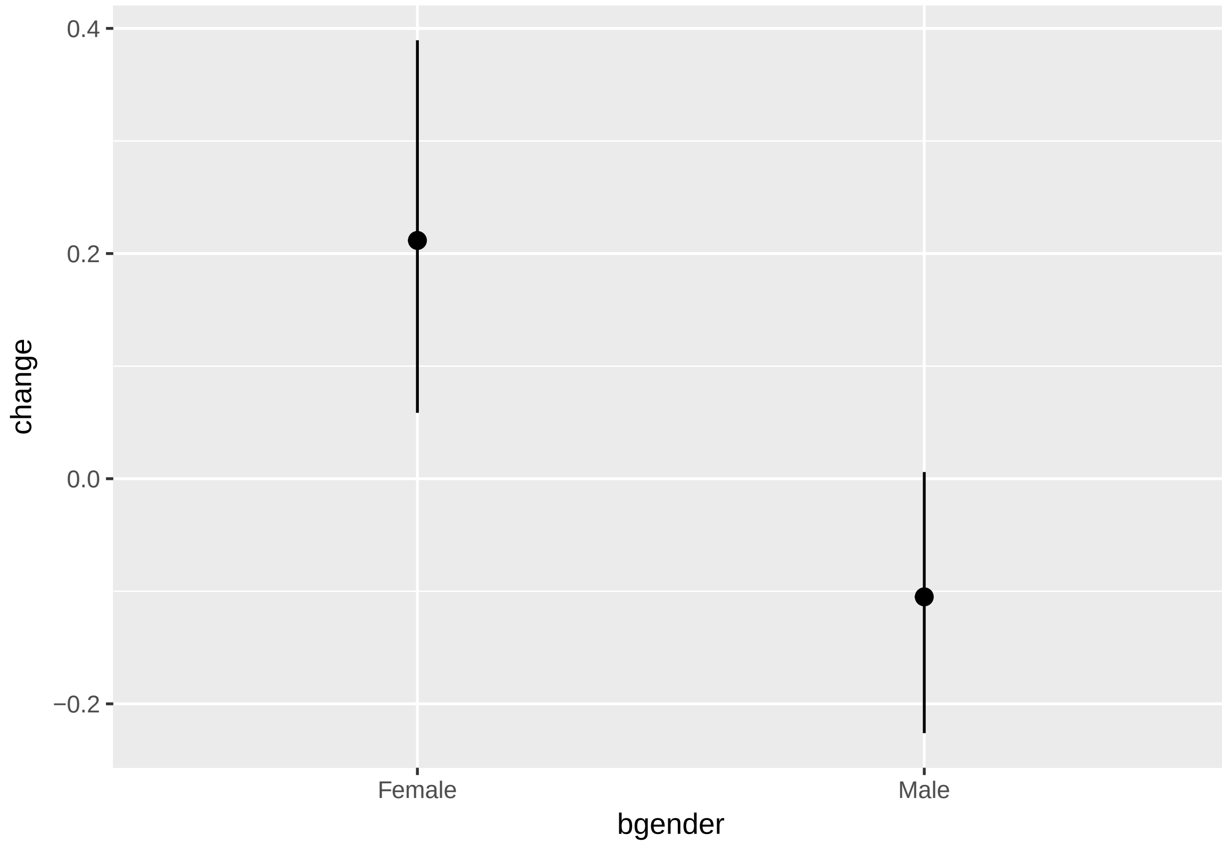
```r
all(d$change == d$fhndicap - d$bhndicap) # all function tells you if this statement returns all TRUEs
```

```
## [1] TRUE
```

First, Some Plotting

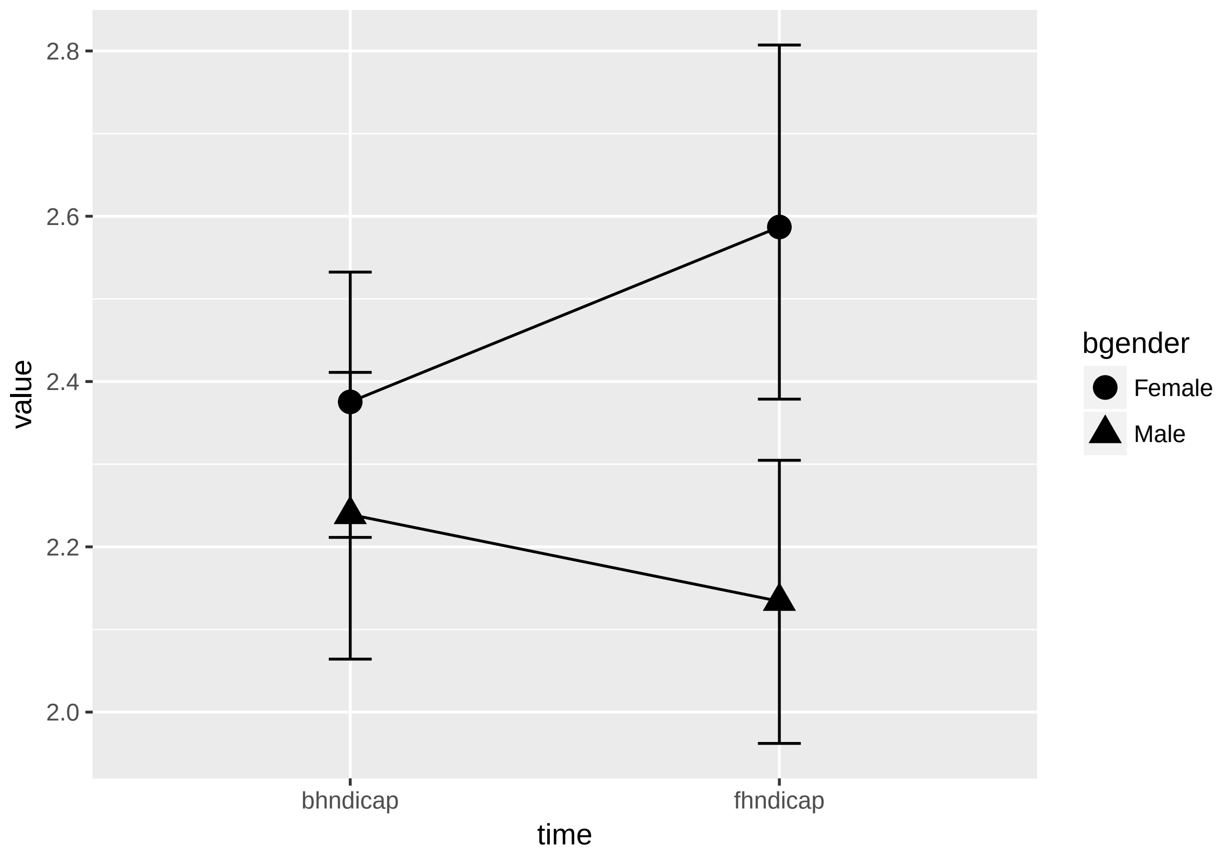
We can visualize the straight change scores or the scores over time.

```r
p.change <- ggplot(d, aes(x = bgender, y = change)) +
  stat_summary(fun.data = mean_cl_boot, geom = "pointrange")
p.change
```




```
d.gathered <- gather(d, time, value, bhndicap:fhndicap)
# we 'gather' the data so that bhndicap and fhndicap are compressed into one column
# that columns essentially represents time, so I call it 'time' (argument 2 of gather)
# the other column, which I assign the name 'value', will contain the actual values that were the origi

# plot data over time
p.over.time <- ggplot(d.gathered, aes(x = time, y = value,
    group = bgender, shape = bgender)) +
    stat_summary(fun.y = mean, geom = "point", size = 4) +
    stat_summary(fun.data = mean_cl_boot, geom = "errorbar", width = 0.1) +
    stat_summary(fun.y = mean, geom = "line")
p.over.time
```



Straight Change

Super easy: just predict change scores from gender! We can either predict straight change, or predict value from the time * gender interaction.

```
m <- aov(change ~ bgender + Error(participant), d) # Error(participant) adds in the within-subject erro
summary(m)
```

```
##
## Error: participant
##           Df Sum Sq Mean Sq F value  Pr(>F)
## bgender    1  2.505  2.5048   8.602 0.00418 **
## Residuals 98 28.536  0.2912
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# equivalent to:
m.int <- aov(value ~ bgender * time + Error(participant), d.gathered)
summary(m.int)
```

```
##
## Error: participant
##           Df Sum Sq Mean Sq F value Pr(>F)
## bgender    1   4.34   4.337   5.859 0.0173 *
```

```
## Residuals 98  72.54   0.740
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Error: Within
##              Df Sum Sq Mean Sq F value  Pr(>F)
## time          1  0.160  0.1596   1.096 0.29761
## bgender:time  1  1.252  1.2524   8.602 0.00418 **
## Residuals    98 14.268  0.1456
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
m2 <- lm(change ~ bgender, d)
summary(m2)
```

```
##
## Call:
## lm(formula = change ~ bgender, data = d)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.2831 -0.2831 -0.0379  0.2884  2.8455
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.21164    0.07556   2.801  0.00614 **
## bgenderMale -0.31659    0.10795  -2.933  0.00418 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5396 on 98 degrees of freedom
## Multiple R-squared:  0.08069,    Adjusted R-squared:  0.07131
## F-statistic: 8.602 on 1 and 98 DF,  p-value: 0.004181
```

Residual Change

For a residual change analysis, we predict scores at the second time point (fhndicap) from the first time point & our independent variable, gender.

```r
m3 <- aov(fhndicap ~ bhndicap + bgender, d)
summary(m3)
```

```
##             Df Sum Sq Mean Sq F value   Pr(>F)
## bhndicap     1 24.339  24.339   89.48 1.97e-15 ***
## bgender      1  3.006   3.006   11.05  0.00125 **
## Residuals   97 26.383   0.272
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
m4 <- lm(fhndicap ~ bhndicap + bgender, d)
summary(m4)
```

```
##
## Call:
## lm(formula = fhndicap ~ bhndicap + bgender, data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.25347 -0.28313 -0.05844  0.24707  2.79031
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.77557    0.21330   3.636 0.000446 ***
## bhndicap     0.76259    0.08437   9.038  1.6e-14 ***
## bgenderMale -0.34895    0.10496  -3.325 0.001250 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5215 on 97 degrees of freedom
## Multiple R-squared:  0.509,  Adjusted R-squared:  0.4988
## F-statistic: 50.27 on 2 and 97 DF,  p-value: 1.046e-15
```