Carle Rehab Consolidated Report

Analysis of Cognition Domains on the FIM

Ash Raj Bala

January 19, 2016

Assessing Cognitive and Behavioral Impairments Following Body/Brain Injury

Stroke and traumatic brain injury are forms of acquired brain injury (ABI), that have the highest prevalence rates amongst neurological disorders affecting the central nervous system (Eng et al., 2002). The long-term manifestations of these disorders include impaired cognitive and motor functioning, problems in emotional expression and communication, and a greatly reduced quality of life (Wade and Hewer, 1987). In light of these factors, it may not be surprising that they are also the two most common conditions for which patients receive inpatient neurological rehabilitation.

The extant rehabilitation literature has primarily focused on addressing and differentiating cognitive deficits in these populations. For example, Cicerone et al. (2000) showed strong evidence for the effectiveness of treatments for language and visuospatial perception after stroke and of attention and executive functioning after TBI. However, in adopting a cognitive framework, these studies failed to provide a coherent picture of inter-and intra-individual variability of dysfunction in these populations. We posit that in order to assess the "true" functioning of these individuals (at an intra- and inter- level), it is necessary to employ a multivariate framework which accounts for multiple factors including demographics (e.g. age, gender, race) and unique patient characteristics (e.g. severity of injury, length of stay, comorbid symptoms). Thus, we aim to (i) identify the distribution of cognitive and motor impairments in each group, (ii) associate these impairments to demographic and patient variables, and (iii) differentiate the two groups based on these impairments and related factors. We will use the Functional Independence Measure (FIM) instrument to evaluate functional impairments for both groups. We will determine improvements in functioning based on differences in FIM scores (or specific subdomains of FIM) on admission and discharge.

DATASET: A Brief Overview

Assessment Type (1=admission)	Participant ID	Actual Length of Stay	6 - Birth Date	Age	8 - Gender (1=M; 2=F)	9A - Hispanic	9B- Indian	9C - Asian	9D - Black	9E - Islander	9F - White	Race (1=9A,2= 9B,3=9C, 4=9D,5= 9E,6=9F, 0=Other)	10 - Marital Status (1=Never married; 2=married; 3=widowed; 4=separated;5= Divorced)
1	1626	24	8/19/39	75	1	0	0	0	0	0	1	6	2
1	296	17	10/30/21	93	1	0	0	0	0	0	1	6	2
1	411	16	3/30/31	83	2	0	0	0	0	0	1	6	2
1	491	7	8/1/45	69	2	0	0	0	0	0	1	6	5
1	1069	7	7/25/56	58	2	0	0	0	0	0	1	6	2
1	1216	12	9/22/34	80	1	0	0	0	0	0	1	6	2
1	1218	15	7/4/39	75	2	0	0	0	1	0	0	4	2
1	1841	5	3/28/33	81	2	0	0	0	0	0	1	6	2
1	1877	8	7/9/34	80	1	0	0	0	0	0	1	6	3
1	1902	9	8/18/37	77	2	0	0	0	0	0	1	6	3
1	1987	14	1/6/36	79	2	0	0	0	0	0	1	6	2
1	2055	8	8/28/61	53	2	0	0	0	0	0	1	6	5
1	2113	14	9/25/65	49	1	0	0	0	0	0	1	6	4

Typical Patient (UDS Criteria): A "**typical patient**" has a **length of stay (LOS) of more than 3 days**, received a **full course of inpatient rehabilitation care**, and is **discharged to the community**.

ANALYSES:

PART1 - MULTIPLE REGRESSION

Comprehension change and its relation to demographics, other aspects of cognitive functioning, and overall motor functioning

DATASET: A BRIEF OVERVIEW:

Name of file: StrokeTBI_Diff.csv.

```
Data <-read.csv(file="StrokeTBI_Diff.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
```

VARIABLES CONSIDERED:

- SubID : Subject ID
- Class : B=TBI; S=Stroke
- Code : Impairment Code (1.1, 1.2, 1.3, 1.4, 1.9 = Stroke; 2.21, 2.22 = TBI)
- LOS : Length of Stay
- Age : Age in years
- Gender : 1=Male, 2=Female
- Race : 1=Caucasian, 0=All other
- With_1 : Pre-Hospital Living With: 1=With someone; 0=Alone

- Comp_1 : Admission Comprehension Scores
- Comp_3 : Discharge Comprehension Scores

- Comp_Change : Change in Comprehension Scores (Discharge - Admission)

- Expr_1 : Admission Expression Scores
- Expr_3 : Discharge Expression Scores
- Expr_Change : Change in Expression Scores (Discharge - Admission)

- Soc_1 : Admission Social Interaction Scores
- Soc_3 : Discharge Social Interaction Scores
- Soc_Change : Change in Social Interaction Scores (Discharge - Admission)

- ProbSolv_1 : Admission Problem Solving Scores
- ProbSolv_3 : Discharge Problem Solving Scores
- ProbSolv_Change : Change in Problem solving Scores (Discharge - Admission)

- Memo_1 : Admission Memory Scores
- Memo_3 : Discharge Memory Scores
- Memo_Change : Change in Memory Scores (Discharge - Admission)

- Total_Cog_1 : Admission Total Cognition Scores
- Total_Cog_3 : Discharge Total Cognition Scores
- Total_Cog_Change: Change in Total Cognition Scores (Discharge - Admission)

- Total_Mot_1 : Admission Total Motor Scores
- Total_Mot_3 : Discharge Total Motor Scores
- Total_Mot_Change: Change in Total Motor Scores (Discharge - Admission)

- Zscore_CMG_Relwt: CMG Relative Weight, Z-Scored (index of severity)

For the purposes of our analyses, we treat motor and cognition measures (including subdomains) as continuous variables

RESULTS:

	Estimate	Estimate Std. Error	t-value	Pr(>|t|)
Intercept	0.32	0.18	1.82	0.07
ClassS	-0.03	0.07	-0.45	0.66
LOS	0.00	0.00	0.72	0.47
Age	**-0.00**	**0.00**	**-2.30**	**0.02***
Gender	0.01	0.07	0.20	0.85
Race	-0.03	0.09	-0.40	0.69
Expr_Change	**0.42**	**0.03**	**12.56**	**0.00*****
Soc_Change	**-0.10**	**0.03**	**3.59**	**0.00*****
ProbSolv_Change	**0.14**	**0.04**	**3.81**	**0.00*****
Memo_Change	**0.15**	**0.03**	**4.55**	**0.00 *****
Total_Mot_Change	0.01	0.00	1.34	0.18

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05**
Residual standard error: 0.7763 on 634 degrees of freedom
Multiple R-squared: 0.6247; Adjusted R-squared: 0.6188
F-statistic: 105.5 on 10 and 634 DF, p-value: < 2.2e-16

While 62% of the variance is explained by this model, it is considered inaccurate, on account of the review published by Paul D. Allison (1980; Change Scores as Dependent Variables in Regression Analysis). Specifically, in this paper, the author notes, *"I claim that the change score method is superior to the regressor variable method whenever X is temporally subsequent to Y1 and* ***uncorrelated*** *with the* ***transient*** *component of Y1"*. Clearly, in the multiple regression model above, Comp_Change is ***significantly associated*** with ***changes*** in expression (Expr_Change), social interaction (Soc_Change), problem solving skills (ProbSolv_Change), and memory (Memo_Change) - all of which are components of cognition per the FIM instrument. That is to say, cognition-related x variables **are** correlated with the transient component of Y, on account of shared variance (since y is also a cognition-related variable).

A mixed ANOVA allows for the analysis of change both across subjects (between-subjects factor, e.g. Class) as well as within subjects (within-subject factor, e.g., Time). This method is discussed below:

PART 2: MIXED ANOVA : Comprehension

Note: For the purposes of our analyses, we treat comprehension as a continuous variable.

Dataset name: StrokeTBI_MixedANOVA_Comp.csv

Design (2x2):

Time/Class	Stroke(S)	TBI(B)
Pre	Comp	Comp
Post	Comp	Comp

Where "Comp" implies Comprehension Scores; "Pre" = Assessment type 1; and "Post" = Assessment type 3

- **BETWEEN-SUBJECTS FACTOR**: Class (S=Stroke, B=TBI)
- **WITHIN-SUBJECTS FACTOR**: Time (each subject is measured at Pre (coded as 1) and Post(coded as 3))
- **DEPENDENT VARIABLE**: Comprehension Score (Comp)

Other interpretations of design: - **RANDOM FACTOR/BLOCKING FACTOR** = Subject ID (SubID) *Note*: factor on which we can no control over (pre-existing) - **FIXED FACTOR** = Class(S=Stroke, B=TBI) - **REPEATED MEASURES FACTOR** = Time (Pre =1 or Post =3)

ASSUMPTIONS TO BE MET:

ASSUMPTION1: NORMALITY:

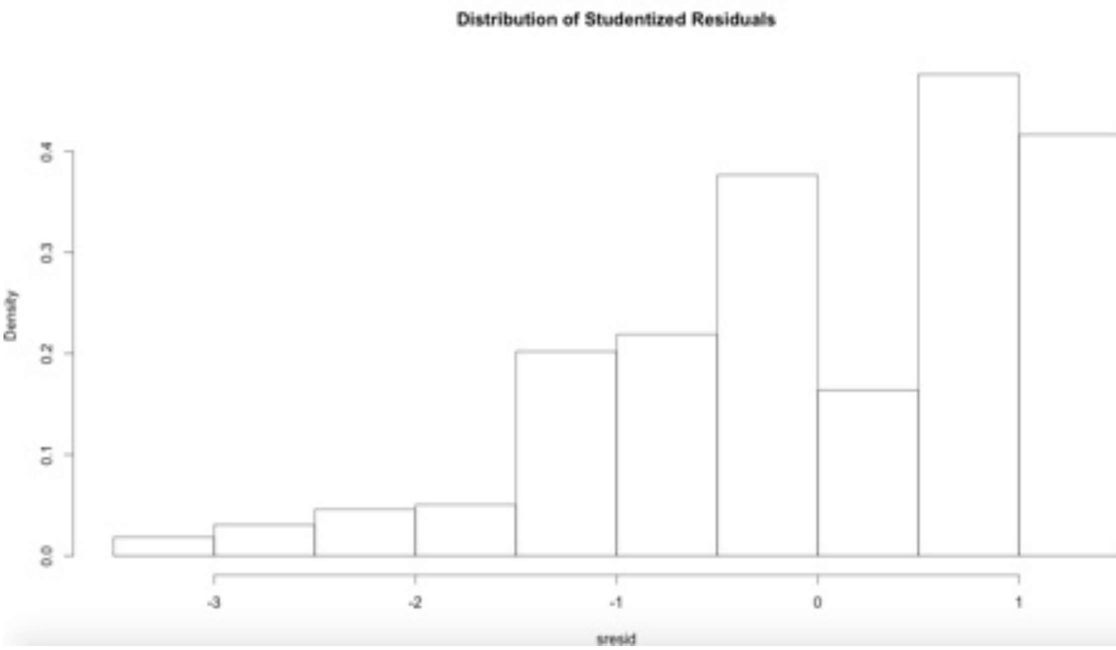
DV (Comp) is normally distributed in each cell.

Important:...the assumption to be met in ANOVA is the normality of the residuals of the model and **not** the normality of the dependent variables in combinations of all factors levels."

ASSUMPTION2: HOMOGENEITY OF VARIANCE:

Each cell has similar variance

Brief overview of assumptions and related results: Whilst testing for residual distribution (are the residuals for Comp normally distributed w.r.t which class they come from?; i.e. for model <- lm(Comp) ~ Class, data=Data, resid(m) should be normally distributed). However, we did not get a normalized distribution by doing any of the following recommended steps: 1. applying log/sqrt. transform 2. box-cox tranformation 3. removing outliers (for more on this, see here: http://stats.stackexchange.com/questions/117873/how-to-detect-outliers-from-residual-plot, and here http://stackoverflow.com/questions/26247255/writing-command-in-r-to-remove-outliers-in-residual-plot). This is the least preferred method and should be used only when few subjects are removed.



As evident from the figure above, the residuals for this model were heavily skewed to the right. Therefore, we had to use a non-normal mixed effects model to evaluate comprehension change.

Non-Normal Mixed Effects Model Analysis

We used the WRS2 package in R (follow through example here: https://cran.r-project.org/web/packages/WRS2/vignettes/WRS2.pdf; p.14).

Given our skewed residual distrubtion above, a robust alternative to the mean is the trimmed mean, which discards a certain percentage (usually 20%) at both ends of the distribution.

The main function in WRS2 for computing a between-within subjects ANOVA on the trimmed means is bwtrim.

First, we prepare our dataset for use in this analysis:

```
library(WRS2)
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//Active//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA_Comp.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Time <- factor(Data$Time)
str(Data)
```

```
Loading required package: boot
```

```
'data.frame':  1276 obs. of  4 variables:
```

```
 $ Comp : int  4 6 3 6 2 3 2 4 6 3 ...
 $ Class: Factor w/ 2 levels "B","S": 2 2 2 2 2 2 2 2 2 1 ...
 $ Time : Factor w/ 2 levels "1","3": 1 1 1 1 1 1 1 1 1 1 ...
 $ SubID: int  1 3 7 10 11 12 19 20 26 33 ...
```

Second, we fit our model using the bwtrim function described above.

```
bwtrim(Comp ~ Class*Time, id = SubID, data = Data)

Call:
bwtrim(formula = Comp ~ Class * Time, id = SubID, data = Data)

              value p.value
Class       21.9630  0.0000
Time       161.3835  0.0000
Class:Time   6.5097  0.0115
```

We find a significant difference (at alpha = 0.01) for Class (not distinguishing comp scores at Pre and Post), for Time (not distinguishing comp scores for Group), as well as for the interaction between Class and Time.

Third, we attempt to obtain CI estimates for each of the effects (between-subjects, within-subjects, and interaction effects). Of particular interest to us are the between-subject effects and interaction effects.

These are evaluated using built-in M-estimators. This package offers the bootstrap based functions sppba, sppbb, and sppbi for the between-subjects effect, the within-subjects effect, and the interaction effect, respectively.

Unfortunately, to use these functions, the data must be evenly balanced in both groups. In our case, the number of stroke individuals is much higher than TBI patients. (Error message received suggests that data must be balanced in each class; *see here for explanation of error message:* http://stackoverflow.com/questions/18816622/error-in-boot-related-to-replacement-length-and-data-or-data-types-r).

Noting the current "best practice" in the research field towards reporting effect sizes and corresponding confident intervals (CIs) (Kirby & Gerlanc, 2013), we used the BootES package in R to separately analyze our between-subject and interaction effects. Effect size emphasizes the size of the difference rather than confounding this with sample size (providing further impetus to use this statistic given the difference in group size in our dataset). Additionally, the package is suited for non-normal distributions and uses bias-correct-and-accelerated bootstrapping (BCa) to accurately determine effect size and CI.

```
library(bootES)
```

Between-Subject Effects

Ref: http://www.ncbi.nlm.nih.gov/pubmed/23519455 (p.912)

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA_BW_WN_bootES.csv",
```

```
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=FALSE)
Data <- data.frame(Data)
str(Data)

bootES(Data, data.col="Comp", group.col="Class",contrast=c(B=1,S=-1))
# bootES(Data, data.col="Comp", group.col="Class",contrast=c(B=1,S=-1),plot=T
RUE)
# Use plot=TRUE to generate histogram and qq plot for t

'data.frame':   1276 obs. of  4 variables:
 $ Comp : int  4 6 3 6 2 3 2 4 6 3 ...
 $ Class: chr  "S" "S" "S" "S" ...
 $ Time : chr  "Pre" "Pre" "Pre" "Pre" ...
 $ SubID: int  1 3 7 10 11 12 19 20 26 33 ...



User-specified lambdas: (1, -1)
Scaled lambdas: (1, -1)
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
-0.479      -0.658      -0.294      -0.001      0.094
```

Note that although the general mean difference between the two groups suggests the comprehension scores for Stroke were greater (see below), the bootstrapped effect sizes provide a more accurate picture of the data.

```
# General mean Difference Between Groups:
by(Data$Comp, Data$Class, mean)

Data$Class: B
[1] 4.740476
------------------------------------------------------------
Data$Class: S
[1] 5.219626
```

Interpretation (*see p.912*):

Stroke comprehension scores were 0.48 units less than those for TBI, on average, with a 95% BCa boostrap CI from -0.669 to -0.296

Within-Subject Effects

Ref: http://www.ncbi.nlm.nih.gov/pubmed/23519455 (p.919)

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA_Comp_Bootstrap.csv",
                head=TRUE,sep=',',
                na.strings = "",
```

```
                stringsAsFactors=FALSE)
Data <- data.frame(Data)
str(Data)
bootES(Data$Comp_Change)
```

```
'data.frame':   653 obs. of  3 variables:
 $ SubID      : int  1567 1424 1013 221 521 925 699 1586 3470 1014 ...
 $ Class      : chr  "B" "B" "S" "S" ...
 $ Comp_Change: int  -2 -1 -2 0 -1 0 0 -1 0 1 ...
```

```
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
1.064       0.965       1.168       -0.001      0.050
```

```
# General mean Difference Between Groups:
by(Data$Comp, Data$Time, mean)
```

```
Data$Time: Post
[1] 5.590909
------------------------------------------------------------
Data$Time: Pre
[1] 4.532915
```

Interpretation:

Post comprehension scores were 1.06 units higher, on average, with a 95% BCa boostrap CI from 0.965 to 1.168

Group by Time Interaction Effects

** Method 1:**

Ref: http://www.ncbi.nlm.nih.gov/pubmed/23519455 (p.921)

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//Active//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA_Comp_Bootstrap.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=FALSE)
Data <- data.frame(Data)
str(Data)
```

bootES(Data, data.col = "Comp_Change", group.col="Class",contrast = c(B=1,S=-1), block.col="SubID")

```
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
0.523       0.508       0.539       0.000       0.008
```

Interpretation (*see p.921*):

TBI change scores were 0.5 units greater than those for Stroke, on average, with a 95% BCa boostrap CI from 0.508 to 0.539.

PART 2: MIXED ANOVA : Memory

Note: For the purposes of our analyses, we treat memory as a continuous variable.

```
wants <- c("AICcmodavg", "lme4", "multcomp", "nlme", "pbkrtest", "nortest", "
lawstat", "car")
has   <- wants %in% rownames(installed.packages())
if(any(!has)) install.packages(wants[!has])
library(nortest)
library(lawstat)
library(car)
library(nlme)
library(MASS) # For boxcox
```

Dataset Name: StrokeTBI_MixedANOVA.csv

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                  head=TRUE,sep=',',
                  na.strings = "",
                  stringsAsFactors=TRUE)
Data$Time <- as.factor(Data$Time)
str(Data)
```

```
'data.frame':   1306 obs. of  17 variables:
 $ SubID           : int  1 1 3 3 7 7 10 10 11 11 ...
 $ Time            : Factor w/ 2 levels "1","3": 1 2 1 2 1 2 1 2 1 2 ...
 $ Class           : Factor w/ 2 levels "B","S": 2 2 2 2 2 2 2 2 2 2 ...
 $ LOS             : int  6 6 26 26 19 19 12 12 14 14 ...
 $ Age             : int  76 76 95 95 103 103 89 89 99 99 ...
 $ Gender          : int  1 1 1 1 2 2 2 2 1 1 ...
 $ Race            : int  1 1 1 1 1 1 1 1 1 1 ...
 $ With_1          : int  1 1 1 1 0 0 1 1 1 1 ...
 $ Comp            : int  4 5 6 7 3 5 6 7 2 3 ...
 $ Expr            : int  4 5 6 7 1 5 6 7 2 4 ...
 $ Soc             : int  5 5 7 7 5 7 7 7 3 3 ...
 $ ProbSolv        : int  4 4 4 7 3 4 6 6 2 3 ...
 $ Memo            : int  4 5 5 7 5 6 6 6 2 3 ...
 $ Total_Cog       : int  21 24 28 35 17 27 31 33 11 16 ...
 $ Total_Mot       : int  43 59 26 60 32 59 50 64 31 59 ...
 $ Total_FIM       : int  69 88 55 100 52 91 82 101 46 80 ...
 $ Zscore_CMG_RelWt: num  -0.0536 -0.0536 1.3605 1.3605 0.942 ...
```

Design (2x2):

Time/Class	Stroke(S)	TBI(B)
Pre	Memo	Memo
Post	Memo	Memo

Where "Memo" implies Memory Scores; "Pre" = Assessment type 1; and "Post" = Assessment type 3

- **BETWEEN-SUBJECTS FACTOR**: Class (S=Stroke, B=TBI)
- **WITHIN-SUBJECTS FACTOR**: Time (each subject is measured at Pre (coded as 1) and Post(coded as 3))
- **DEPENDENT VARIABLE**: Memory Score (Memo)

Other interpretations of design:

- **RANDOM FACTOR/BLOCKING FACTOR** = Subject ID (SubID) *Note*: factor on which we can no control over (pre-existing)
- **FIXED FACTOR** = Class(S=Stroke, B=TBI)
- **REPEATED MEASURES FACTOR** = Time (Pre =1 or Post =3)

ASSUMPTIONS TO BE MET:

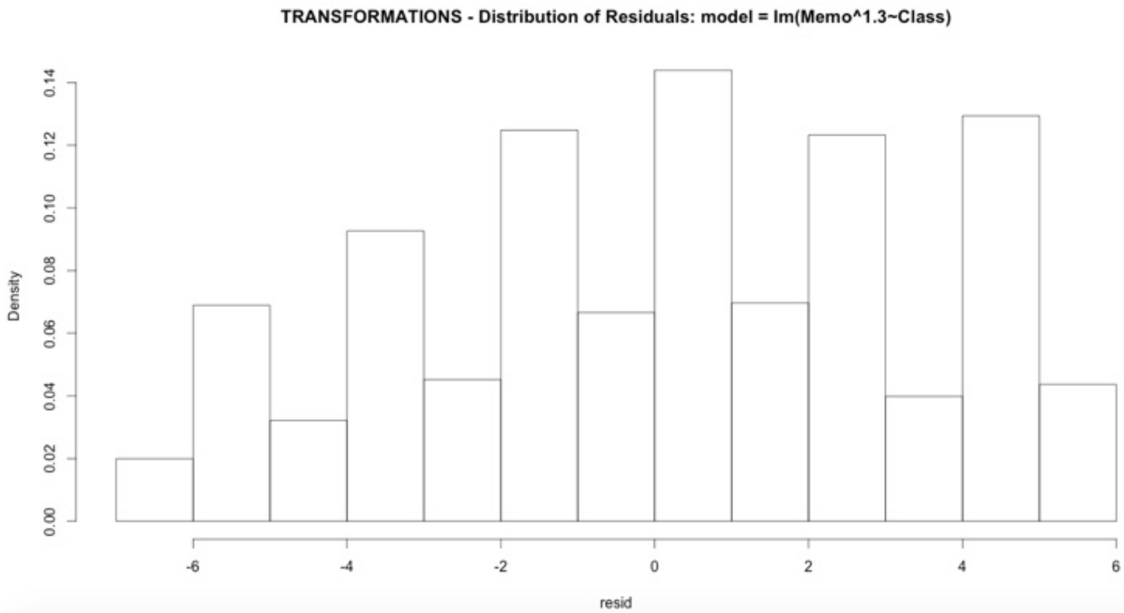
ASSUMPTION1: NORMALITY:

DV (Memo) is normally distributed in each cell.

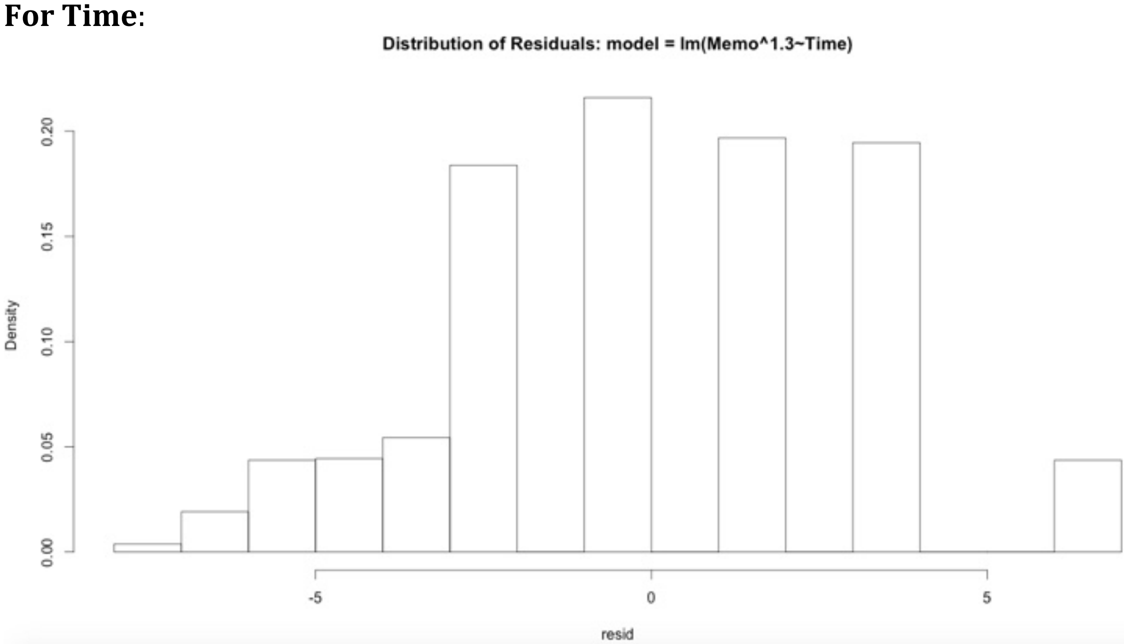
Important:...the assumption to be met in ANOVA is the normality of the residuals of the model and **not** the normality of the dependent variables in combinations of all factors levels."

Brief overview of assumptions and related results: Whilst testing for residual distribution (are the residuals for Comp normally distributed w.r.t which class they come from?; i.e. for model <- lm(Comp) ~ Class, data=Data, resid(m) should be normally distributed). However, we did not get a normalized distribution by doing the following recommended steps: 1. applying log/sqrt. transform 2. removing outliers (while a normal distribution was obtainable using this approach,it required the removal of a little over 50 participants, and therefore was considered unsuitable for our purposes. 3. A box-cox transformation suggested that the model residuals werely fairly normally distributed for Memo^1.3. Therefore, our model for all further analyses included the model as: m < lm(Memo^1.3 ~Class + Time + class:Time, Data)

For Class:



For Time:



In conclusion, assumption 1 has been met.

ASSUMPTION2: HOMOGENEITY OF VARIANCE:

Each cell has similar variance

```r
# General idea:
# ------------
tapply(Data$Memo^1.3, list(Data$Class,Data$Time),sd)
```

```
         1        3
B 3.366152 2.941730
S 3.190286 3.118748
```

```r
#Variances don't seem to be significantly different from each other.

# Levene's test
# -------------
#-----------------------------------------------------------------------------
---------------------------------------------------------------
# SEE ALSO/REF: http://stats.stackexchange.com/questions/43929/variances-not-
homogeneous-problem-in-anova-mixed-between-within-subjects-too-ba
#-----------------------------------------------------------------------------
---------------------------------------------------------------
Data$Memo <- Data$Memo^1.3
Memo_SandB_Pre <- data.frame(subset(Data, Time == 1, select = c(Class,Memo)))
with(Memo_SandB_Pre, leveneTest(Memo, as.factor(Class), center="mean"))
#RESULT: p-value =0.62 #Okay!
```

Levene's Test of Homogeneity of Variances (center="mean")

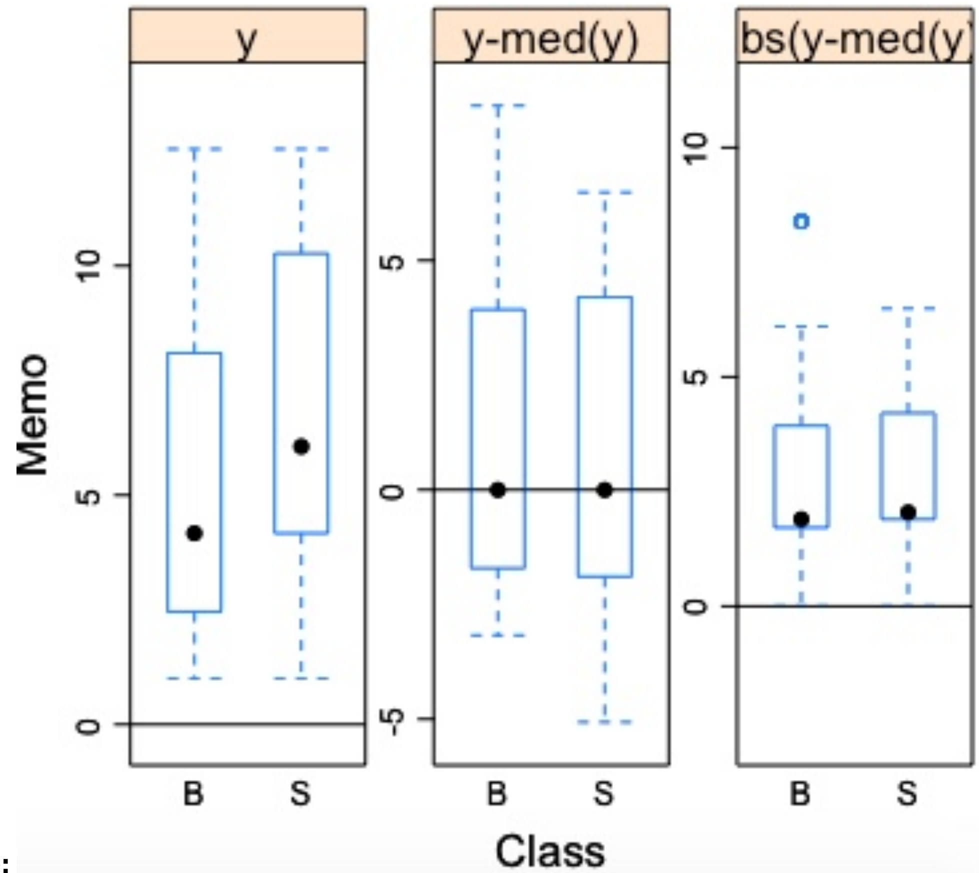
	Df	F	Pr (>F)
Group	1	0.2504	0.617
	651	-	-

```r
Memo_SandB_Post <- data.frame(subset(Data, Time == 3, select = c(Class,Memo))
)
with(Memo_SandB_Post, leveneTest(Memo, as.factor(Class), center="mean"))
#RESULT: p-value = 0.01* Significant!!!
```

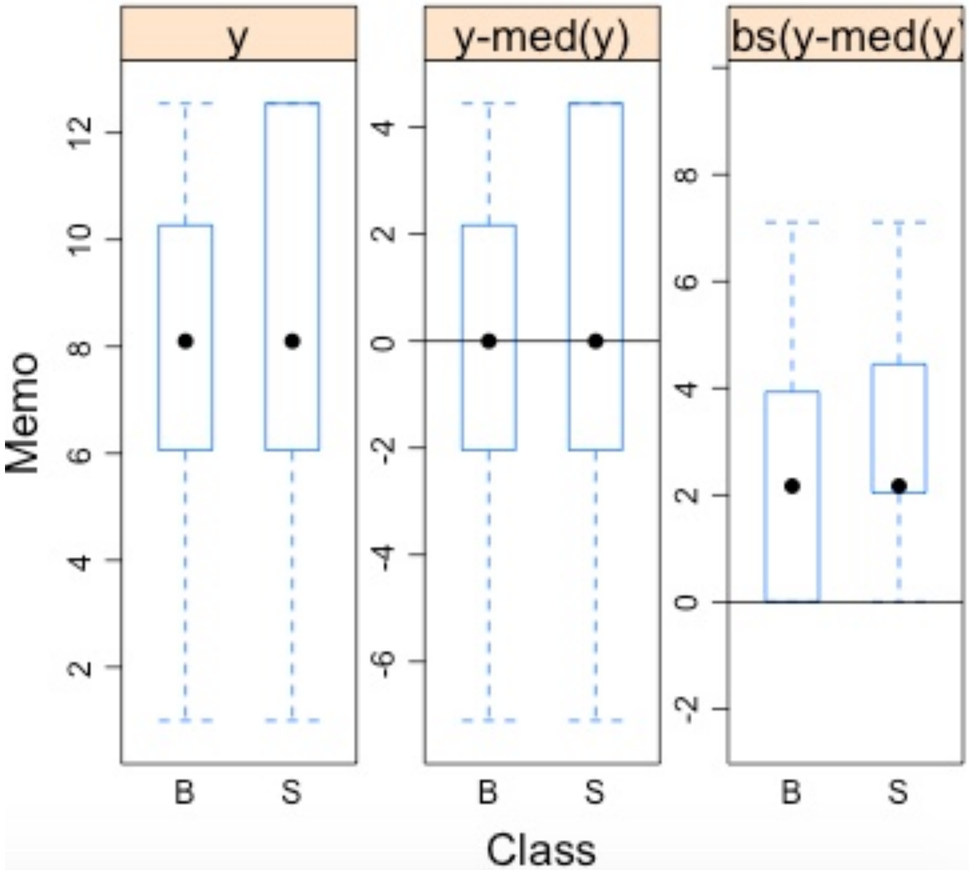
Levene's Test of Homogeneity of Variances (center="mean")

	Df	F	Pr (>F)
Group	1	6.6066	0.0104*
	651	-	-

Visualization of Variability (using Brown-Forsyth Test):



Pre:



Post:

In conclusion, assumption 2 is not met. That is, there is heteroskedasticity.

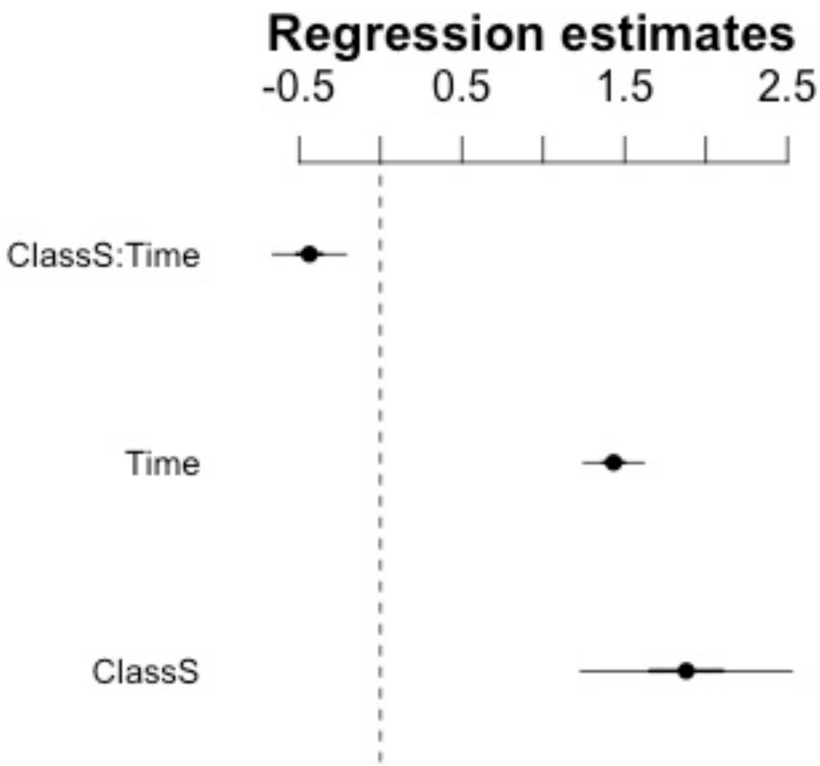
```
# Given that the model is heteroskedastic, we use the lmer package in R.
# We weight the model, to account for heteroskedasticity
# See here: http://stats.stackexchange.com/questions/118391/accounting-for-heteroskedasticity-in-lme-linear-mixed-model
# and here: https://stat.ethz.ch/pipermail/r-help/2003-April/033031.html
# and here, for syntax assistance: http://www.uni-kiel.de/psychologie/rexrepos/posts/anovaMixed.html#mixed-effects-analysis-1

lme.model <- lme(Memo ~ Class*Time, random= ~1 |SubID, method="ML", data=Data, weights=varPower(form =~fitted(.)))
(aov.lme <- anova(lme.model))
```

	numDF	denDF	F-value	p-value
(Intercept)	1	665	2667.3032	<.0001
Class	1	665	28.3560	<.0001
Time	1	665	519.8853	<.0001
Class:Time	1	665	15.2779	1e-04

These results suggest significant effects for Class, Time and Interaction of Class and Time for memory scores.

VISUALIZATION OF RESULTS:

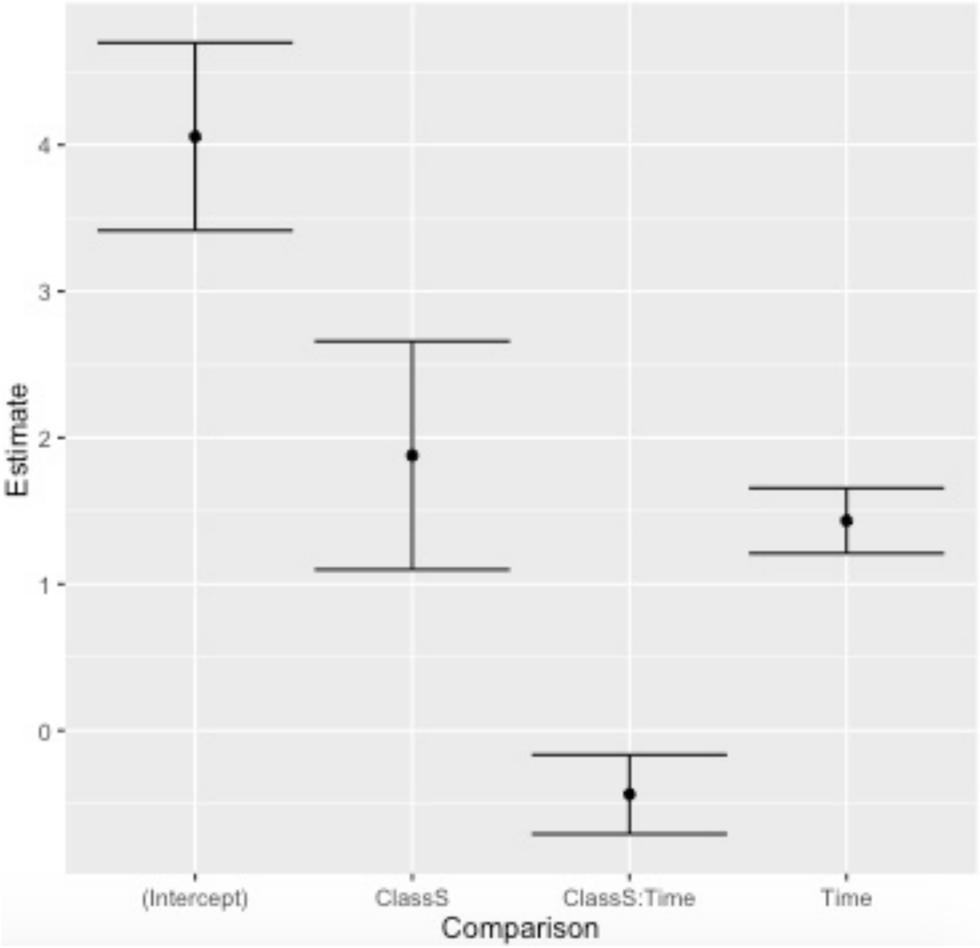
- **PARAMETER ESTIMATES**



- **CONFIDENCE INTERVALS**

```
tmp <- as.data.frame(confint(glht(lme.model))$confint)
tmp$Comparison <- rownames(tmp)
tmp
```

```
               Estimate       lwr        upr   Comparison
(Intercept)    9.204058  8.077734 10.3303819  (Intercept)
ClassS         3.166349  1.775927  4.5567713       ClassS
Time3          6.717797  5.749358  7.6862358        Time3
ClassS:Time3  -1.959603 -3.167232 -0.7519729 ClassS:Time3
```

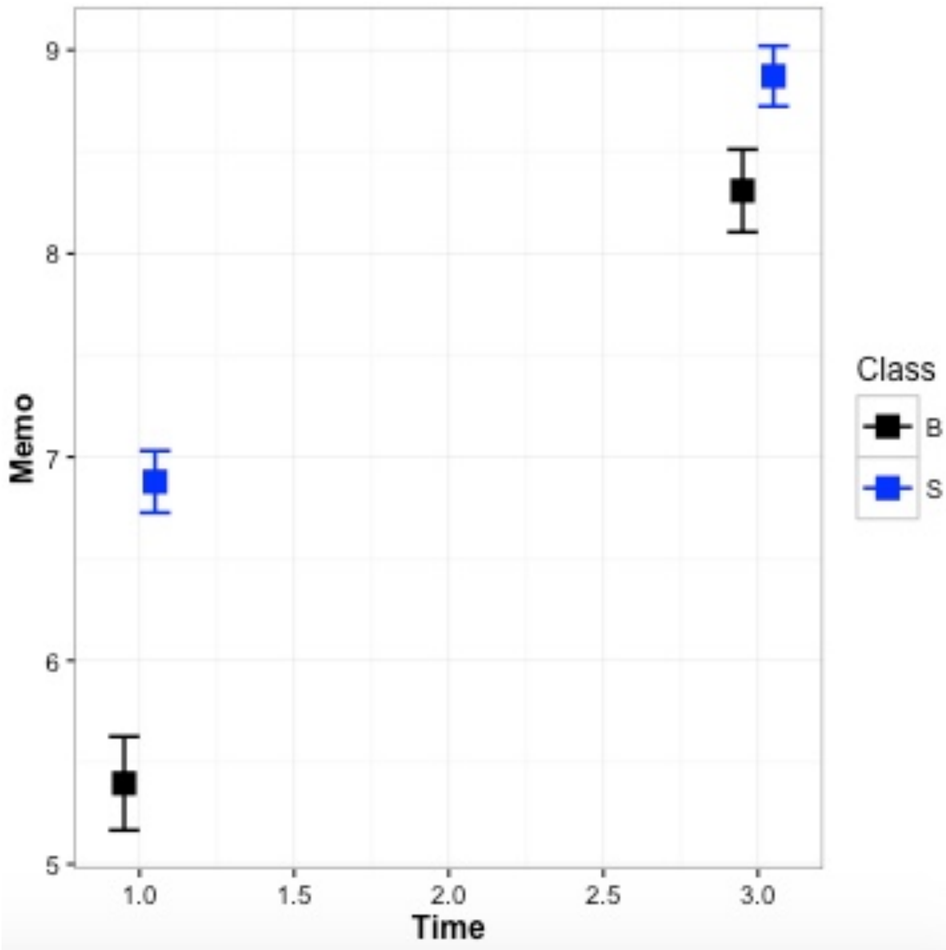


- **MEANS AND SUMMARY STATISTICS (BY CLASS)**

```
library(Rmisc)
sum = summarySE(Data,
                measurevar="Memo",
                groupvars=c("Class","Time"))
sum
```

	Class	Time	N	Memo	sd	se	ci
1	B	1	214	9.629322	7.441127	0.5086649	1.0026620
2	B	3	210	16.084377	7.077362	0.4883844	0.9627910
3	S	1	439	12.807823	7.309820	0.3488787	0.6856844
4	S	3	443	17.514378	7.573897	0.3598467	0.7072231

Interaction plot using summary statistics:



BOOTSTRAPPED EFFECT SIZE ESTIMATES AND ASSOCIATED CONFIDENCE INTERVALS:

For Class by Time Interaction:

```
library(bootES)
#Mixed design
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//Active//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA_Memo_Bootstrap.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data <- data.frame(Data)
bootES(Data, data.col = "Memo_Change", group.col="Class",contrast = c(B=1,S=-1), block.col="SubID")

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
0.780       0.750       0.811       -0.000      0.017
```

INTERPRETATION:

This means that that there is a 0.78 (~1 unit) increase in memory scores for the TBI group over time, relative to the Stroke group.

For Time:

```
bootES(Data$Memo_Change)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
2.422       2.212       2.622       -0.001      0.103
```

INTERPRETATION:

This means that that there is a 2.4 (~2) unit increase in memory scores over time, across both groups.

The difference in means and related confidence interval for memory scores is described by the **Games-Howell** statistic. This is *preferred over Tukey's* when the groups are of unequal sizes and there is heteroskedasticity in the data.

```
library(userfriendlyscience)

Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//Active//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Memo <- Data$Memo^1.3
Data$Time <- as.factor(Data$Time)
str(Data)

'data.frame':   1306 obs. of  17 variables:
 $ SubID          : int  1 1 3 3 7 7 10 10 11 11 ...
 $ Time           : Factor w/ 2 levels "1","3": 1 2 1 2 1 2 1 2 1 2 ...
 $ Class          : Factor w/ 2 levels "B","S": 2 2 2 2 2 2 2 2 2 2 ...
 $ LOS            : int  6 6 26 26 19 19 12 12 14 14 ...
 $ Age            : int  76 76 95 95 103 103 89 89 99 99 ...
 $ Gender         : int  1 1 1 1 2 2 2 2 1 1 ...
 $ Race           : int  1 1 1 1 1 1 1 1 1 1 ...
 $ With_1         : int  1 1 1 1 0 0 1 1 1 1 ...
 $ Comp           : int  4 5 6 7 3 5 6 7 2 3 ...
 $ Expr           : int  4 5 6 7 1 5 6 7 2 4 ...
 $ Soc            : int  5 5 7 7 5 7 7 7 3 3 ...
 $ ProbSolv       : int  4 4 4 7 3 4 6 6 2 3 ...
 $ Memo           : num  6.06 8.1 8.1 12.55 8.1 ...
 $ Total_Cog      : int  21 24 28 35 17 27 31 33 11 16 ...
 $ Total_Mot      : int  43 59 26 60 32 59 50 64 31 59 ...
 $ Total_FIM      : int  69 88 55 100 52 91 82 101 46 80 ...
 $ Zscore_CMG_RelWt: num  -0.0536 -0.0536 1.3605 1.3605 0.942 ...
```

```
posthocTGH(Data$Memo,Data$Time, method="games-howell", digits=2)

    n means variances
1 653   6.4      11.0
3 653   8.7       9.4

     t   df p
1:3 13 1296 0
```

For Class:

```
bootES(Data, data.col="Memo", group.col="Class",contrast=c(B=1,S=-1))

User-specified lambdas: (1, -1)
Scaled lambdas: (1, -1)
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
-1.040      -1.399      -0.612      -0.001      0.198
```

INTERPRETATION:

Not accounting for specific time points, on average, the Stroke group had more than 1 point in their memory scores compared to the TBI group.

```
posthocTGH(Data$Memo,Data$Class, method="games-howell", digits=2)

    n means variances
B 424   6.8        12
S 882   7.9        11

      t  df       p
B:S 5.1 798 3.4e-07
```

PART 2: MIXED ANOVA : Social Interaction

Note: For the purposes of our analyses (i.e. to be able to derive some meaning), we treat social interaction as a continuous variable.

Our model (m <- lm(Soc ~ Class, Data)) did not hold up to the normality assumption. Therefore, similar to the comprehension subdomain (see above), we used the WRS2 package to perform a robust ANOVA analysis, with 20% trimmed means on both sides of the distribution. Additionally, we used the bootES function in the bootES package to determine effect sizes estimates and related confidence intervals.

```
library(WRS2)
library(bootES)
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
```

```
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Time <- as.factor(Data$Time)
str(Data)
```

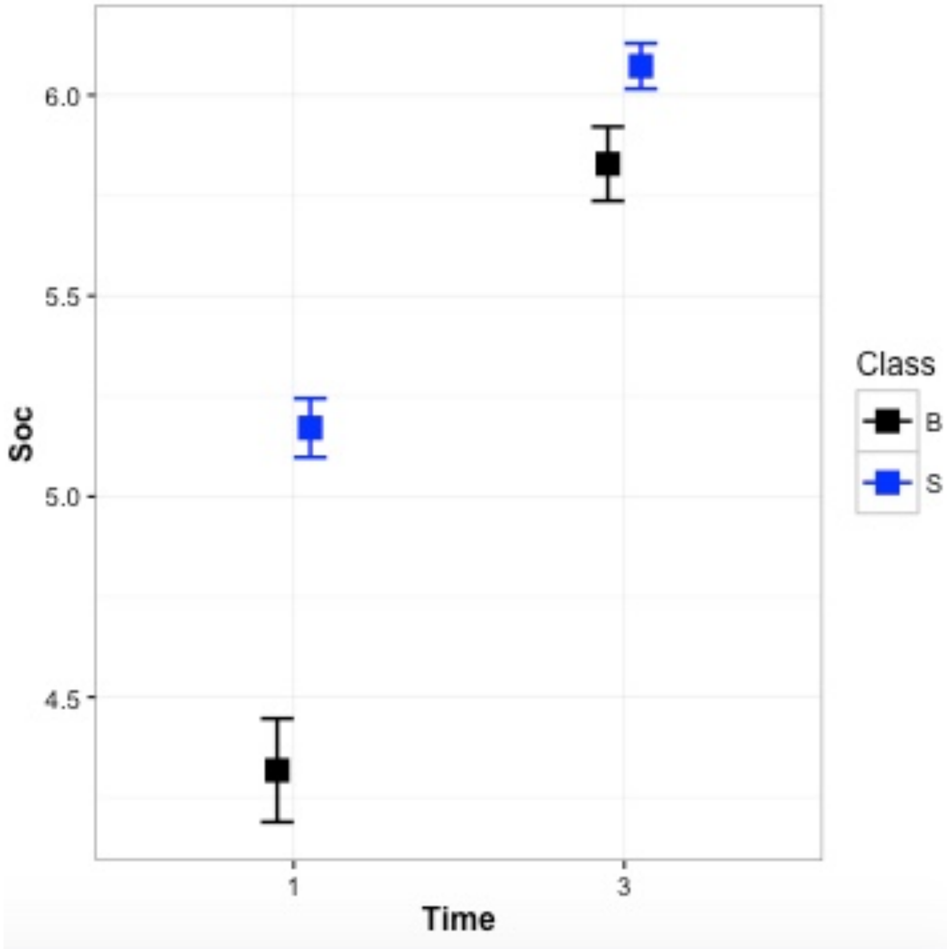
```
'data.frame':  1306 obs. of  17 variables:
 $ SubID          : int  1 1 3 3 7 7 10 10 11 11 ...
 $ Time           : Factor w/ 2 levels "1","3": 1 2 1 2 1 2 1 2 1 2 ...
 $ Class          : Factor w/ 2 levels "B","S": 2 2 2 2 2 2 2 2 2 2 ...
 $ LOS            : int  6 6 26 26 19 19 12 12 14 14 ...
 $ Age            : int  76 76 95 95 103 103 89 89 99 99 ...
 $ Gender         : int  1 1 1 1 2 2 2 2 1 1 ...
 $ Race           : int  1 1 1 1 1 1 1 1 1 1 ...
 $ With_1         : int  1 1 1 1 0 0 1 1 1 1 ...
 $ Comp           : int  4 5 6 7 3 5 6 7 2 3 ...
 $ Expr           : int  4 5 6 7 1 5 6 7 2 4 ...
 $ Soc            : int  5 5 7 7 5 7 7 7 3 3 ...
 $ ProbSolv       : int  4 4 4 7 3 4 6 6 2 3 ...
 $ Memo           : int  4 5 5 7 5 6 6 6 2 3 ...
 $ Total_Cog      : int  21 24 28 35 17 27 31 33 11 16 ...
 $ Total_Mot      : int  43 59 26 60 32 59 50 64 31 59 ...
 $ Total_FIM      : int  69 88 55 100 52 91 82 101 46 80 ...
 $ Zscore_CMG_RelWt: num  -0.0536 -0.0536 1.3605 1.3605 0.942 ...
```

INTERACTION PLOTS:

```
# Means and summary statistics by group (REF:http://rcompanion.org/rcompanion
/d_08.html)
# -----------------------------------------

library(Rmisc)
sum = summarySE(Data,
                measurevar="Soc",
                groupvars=c("Class","Time"))
sum

# Interaction Plot Using Summary Statistics (REF: http://rcompanion.org/rcomp
anion/d_08.html)
# -----------------------------------------

library(ggplot2)
time <-Data$Time
Soc <-Data$Soc
Class <- Data$Class
pd = position_dodge(.2)
ggplot(sum, aes(x=Time,
                y=Soc,
```

```
                color=Class)) +
  geom_errorbar(aes(ymin=Soc-se,
                    ymax=Soc+se),
                width=.2, size=0.7, position=pd) +
  geom_point(shape=15, size=4, position=pd) +
  theme_bw() +
  theme(
    axis.title.y = element_text(vjust= 1.8),
    axis.title.x = element_text(vjust= -0.5),
    axis.title = element_text(face = "bold")) +
  scale_color_manual(values = c("black", "blue"))
```

	Class	Time	N	Soc	sd	se	ci
1	B	1	214	4.317757	1.884446	0.1288181	0.2539216
2	B	3	210	5.828571	1.337405	0.09228975	0.1819381
3	S	1	439	5.170843	1.538091	0.07340907	0.1442778
4	S	3	443	6.072235	1.191684	0.05661859	0.1112751



WRS2 Robust Mixed ANOVA: bwtrim function:

```
bwtrim(Soc ~ Class*Time, id = SubID, data = Data)

Call:
bwtrim(formula = Soc ~ Class * Time, id = SubID, data = Data)

              value p.value
Time       120.2004  0.0000
Class       19.1573  0.0000
Time:Class   5.2741  0.0225
```

SOC scores are significantly affected by Time, Class, and their interaction.

bootES Effect Size estimation: bootES function:

```
#Mixed design
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//Active//Rehab_Carle//bin//Input//StrokeTBI_Diff.csv",
                head=TRUE,sep=',',
```

```
                na.strings = "",
                stringsAsFactors=FALSE)

bootES(Data, data.col = "Soc_Change", group.col="Class",contrast = c(B=1,S=-1
), block.col="SubID")

User-specified lambdas: (1, -1)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
0.618       0.601       0.635       0.000       0.009
```

INTERPRETATION:

There is a 0.6 increase in SOC scores for the TBI group, compared to the Stroke group, on average, over time.

```
bootES(Data$Soc_Change)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
1.139       1.032       1.260       -0.001      0.058
```

INTERPRETATION:

There is a 1 point increase in SOC scores from Pre to Post, across both groups.

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)

Data$Time <- as.factor(Data$Time)

bootES(Data, data.col="Soc", group.col="Class",contrast=c(B=1,S=-1))

User-specified lambdas: (1, -1)
Scaled lambdas: (1, -1)
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
-0.558      -0.752      -0.368      -0.000      0.098
```

INTERPRETATION:

On average, the stroke group performs better on SOC scores than the TBI group, by 0.5 units.

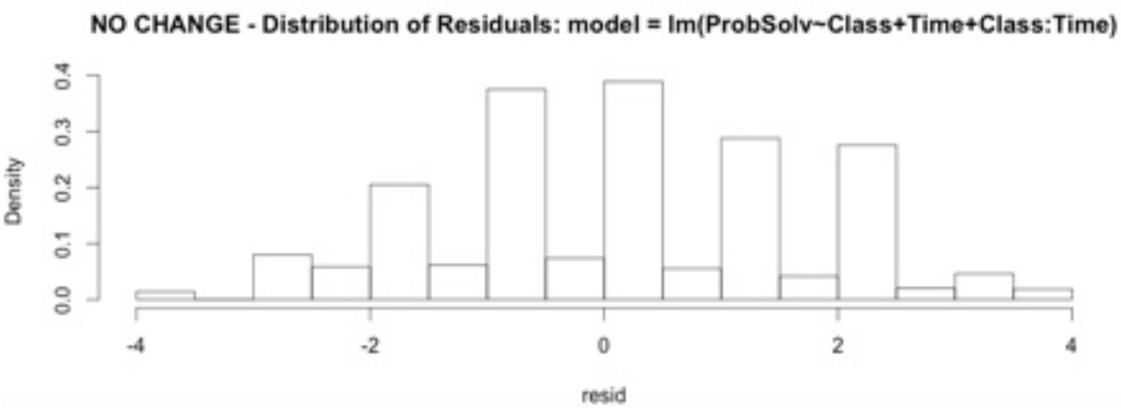
PART 2: MIXED ANOVA : Problem Solving

Note: For the purposes of our analyses (i.e. to be able to derive some meaning), we treat problem solving as a continuous variable.

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//Active//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Time <- as.factor(Data$Time)
```

ASSUMPTION 1: NORMALITY OF RESIDUALS:

The residuals for our model were normally distributed and required no transformation.



ASSUMPTION2: HOMOGENEITY OF VARIANCE:

Our model passed the levene's test for homogeneity of variance (p-value > 0.05).

ProbSolv_SandB_Pre <- data.frame(subset(Data, Time == 1, select = c(Class,ProbSolv)))
with(ProbSolv_SandB_Pre, leveneTest(ProbSolv, as.factor(Class), center="mean"))

Levene's Test of Homogeneity of Variances (center="mean")

	Df	F	Pr (>F)
Group	1	2.5382	0.1116
	651	-	-

ProbSolv_SandB_Post <- data.frame(subset(Data, Time == 3, select = c(Class,ProbSolv)))
with(ProbSolv_SandB_Post, leveneTest(ProbSolv, as.factor(Class), center="mean"))

Levene's Test of Homogeneity of Variances (center="mean")

	Df	F	Pr (>F)
Group	1	0.096	0.7568

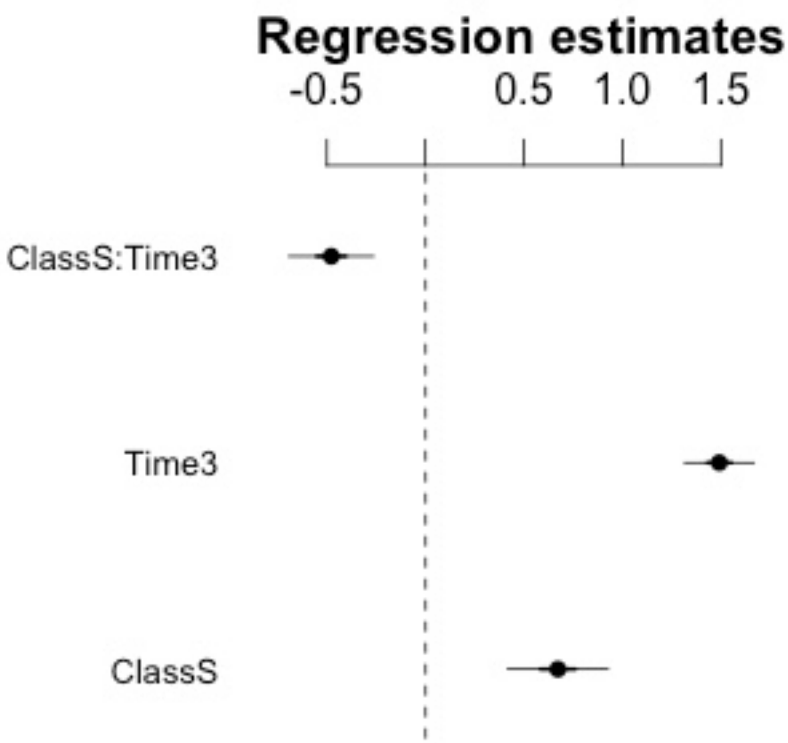
651 - -

```
lme.model <- lme(ProbSolv ~ Class*Time, random= ~1 |SubID, method="ML", data=Data)
(aov.lme <- anova(lme.model))
```

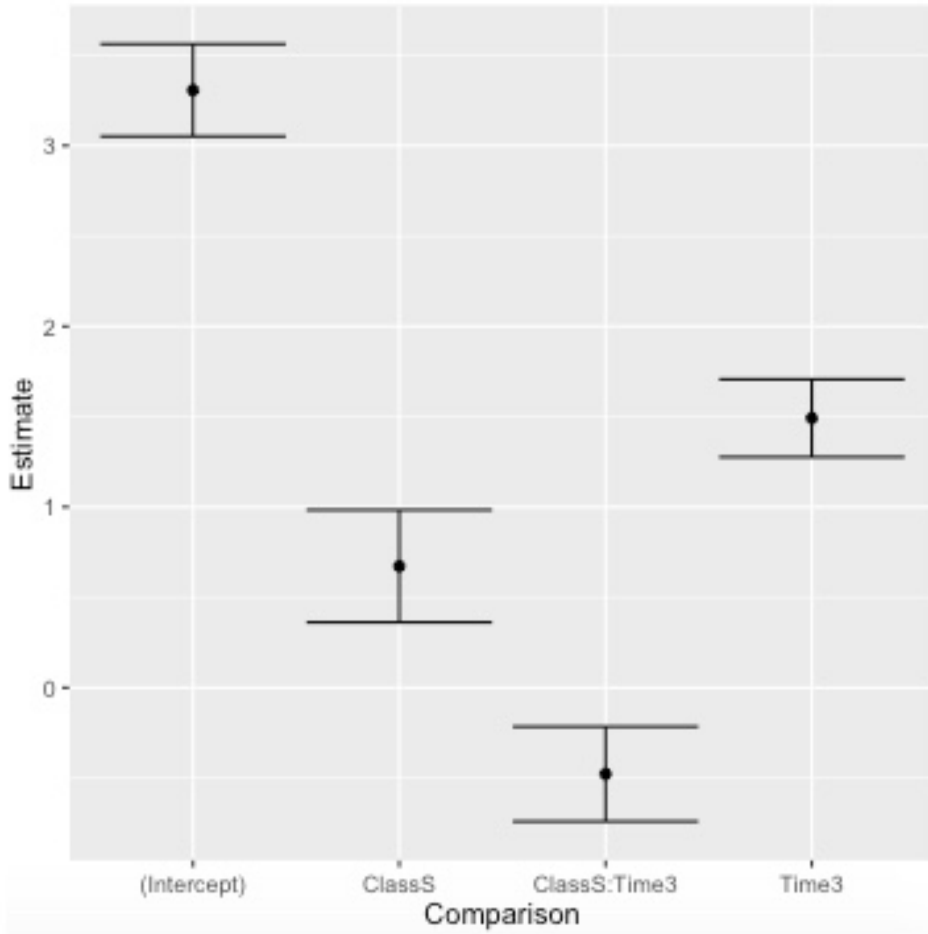
	numDF	denDF	F-value	p-value
(Intercept)	1	665	5952.812	0
Class	1	665	16.15314	6.510307e-05
Time	1	665	522.3896	0
Class:Time	1	665	19.04329	1.481164e-05

VISUALIZATIONS:

- PARAMETER ESTIMATES:

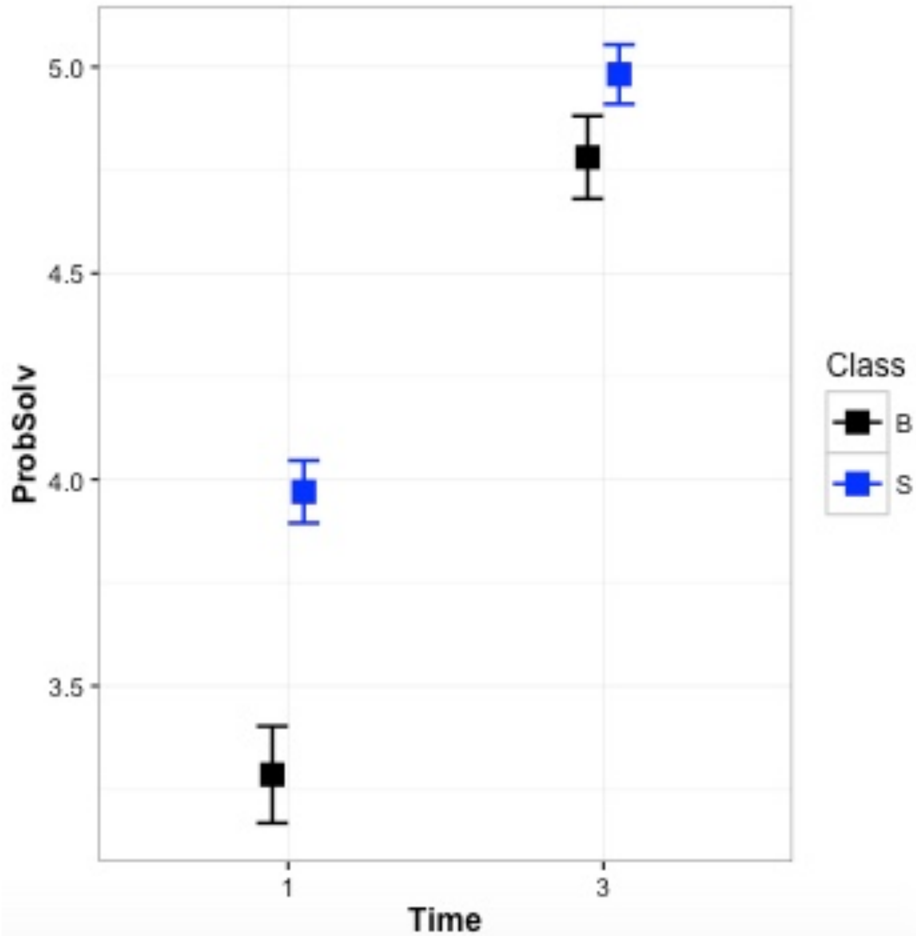


- CONFIDENCE INTERVAL COMPARISON ESTIMATES:



	Estimate	lwr	upr	Comparison
(Intercept)	3.3071229	3.0516560	3.5625899	(Intercept)
ClassS	0.6724202	0.3613106	0.9835298	ClassS
Time3	1.4917019	1.2762965	1.7071073	Time3
ClassS:Time3	-0.4780384	-0.7404001	-0.2156767	ClassS:Time3

- INTERPRETATION PLOTS BASED ON SUMMARY STATISTICS:



Summary Stats:

	Class	Time	N	ProbSolv	sd	se	ci
1	B	1	214	3.285047	1.716548	0.11734078	0.2312979
2	B	3	210	4.780952	1.454121	0.10034388	0.1978159
3	S	1	439	3.970387	1.588066	0.07579423	0.1489656
4	S	3	443	4.981941	1.514527	0.07195733	0.1414210

CONFIDENCE INTERVAL ESTIMATES:

Class By Time Interactions

```
#Mixed design
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_Diff.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
bootES(Data, data.col = "ProbSolv_Change", group.col="Class",contrast = c(B=1
,S=-1), block.col="SubID")
```

```
User-specified lambdas: (1, -1)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
0.442       0.428       0.457       -0.000      0.008
```

INTERPRETATION:

Average 0.44 unit increase in Probsolv scores for TBI in comparison to Stroke group.

Time: *Effect Size Estimates*

```
bootES(Data$ProbSolv_Change)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
1.224       1.121       1.315       -0.001      0.049
```

INTERPRETATION:

Average 1 unit increase in Probsolv scores from Pre to Post across both groups.

Time: *Mean difference Estimates* (Calculated using Games-Howell (ideal for unequal group sizes))

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Time <- as.factor(Data$Time)

posthocTGH(Data$ProbSolv,Data$Time, method="games-howell", digits=2)

    n means variances
1 653   3.7       2.8
3 653   4.9       2.2

     t   df p
1:3 13 1290 0
```

Class: *Effect Size Estimates*

```
bootES(Data, data.col="ProbSolv", group.col="Class",contrast=c(B=1,S=-1))

User-specified lambdas: (1, -1)
Scaled lambdas: (1, -1)
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
-0.453      -0.648      -0.268      -0.001      0.098
```

INTERPRETATION:

Not accounting for group size differences, on average, the Stroke group had >0.45 points in their problem solving scores compared to the TBI group.

Class: ***Mean difference Estimates*** (Calculated using Games-Howell (ideal for unequal group sizes))

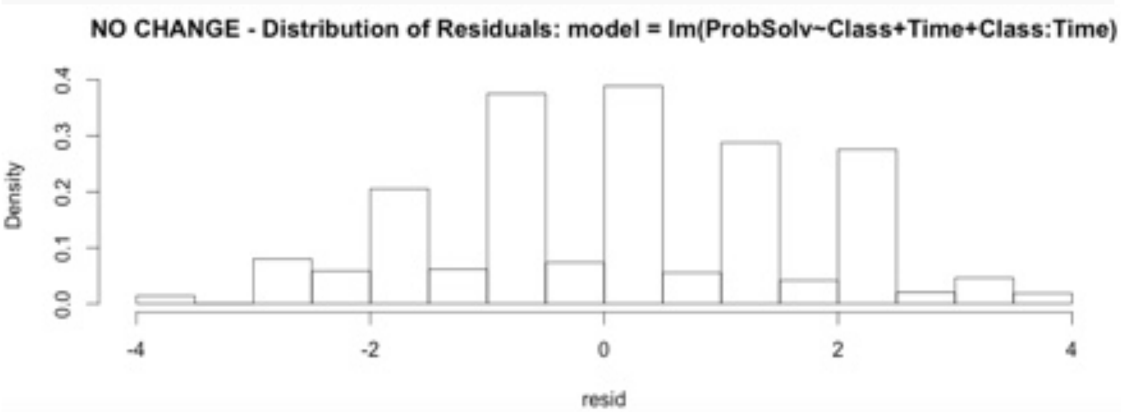
```
posthocTGH(Data$ProbSolv,Data$Class, method="games-howell", digits=2)

    n means variances
B 424   4.0       3.1
S 882   4.5       2.7

      t  df       p
B:S 4.5 781 9.5e-06
```

PART 2: MIXED ANOVA : Expressiveness

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Time <- as.factor(Data$Time)
```

ASSUMPTION 1: NORMALITY OF RESIDUALS

A box-cox transformation of 1.68 helped normalize the model.



ASSUMPTION 1: HOMOGENEITY OF VARIANCE

Our model did **not** pass the test of homogeneity of variance:

Expr_SandB_Pre <- data.frame(subset(Data, Time == 1, select = c(Class,Expr)))
with(Expr_SandB_Pre, leveneTest(Expr, as.factor(Class), center="mean"))

Levene's Test of Homogeneity of Variances (center="mean")

	Df	F	Pr (>F)
Group	1	0.3019	0.5829
	651		

Expr_SandB_Post <- data.frame(subset(Data, Time == 3, select = c(Class,Expr)))
with(Expr_SandB_Post, leveneTest(Expr, as.factor(Class), center="mean"))

Levene's Test of Homogeneity of Variances (center="mean")

	Df	F	Pr (>F)
Group	1	8.7574	0.0031**
	651		

```
# MAKE SURE THAT Data$Expr <- Data$Expr^1.68

# Given that the model is heteroskedastic, we use the lmer package in R.
# We weight the model, to account for heteroskedasticity
# See here: http://stats.stackexchange.com/questions/118391/accounting-for-he
teroskedasticity-in-lme-linear-mixed-model
# and here: https://stat.ethz.ch/pipermail/r-help/2003-April/033031.html
# and here, for syntax assistance: http://www.uni-kiel.de/psychologie/rexrepo
s/posts/anovaMixed.html#mixed-effects-analysis-1

Data$Expr <- Data$Expr^1.68
str(Data)
lme.model <- lme(Expr ~ Class*Time, random= ~1 |SubID, method="ML", data=Data
, weights=varPower(form =~fitted(.)))
aov.lme <- anova(lme.model)

'data.frame':  1306 obs. of  17 variables:
 $ SubID          : int  1 1 3 3 7 7 10 10 11 11 ...
 $ Time           : Factor w/ 2 levels "1","3": 1 2 1 2 1 2 1 2 1 2 ...
 $ Class          : Factor w/ 2 levels "B","S": 2 2 2 2 2 2 2 2 2 2 ...
 $ LOS            : int  6 6 26 26 19 19 12 12 14 14 ...
 $ Age            : int  76 76 95 95 103 103 89 89 99 99 ...
 $ Gender         : int  1 1 1 1 2 2 2 2 1 1 ...
 $ Race           : int  1 1 1 1 1 1 1 1 1 1 ...
 $ With_1         : int  1 1 1 1 0 0 1 1 1 1 ...
 $ Comp           : int  4 5 6 7 3 5 6 7 2 3 ...
 $ Expr           : num  50 93.9 157.1 242.8 1 ...
 $ Soc            : int  5 5 7 7 5 7 7 7 3 3 ...
 $ ProbSolv       : int  4 4 4 7 3 4 6 6 2 3 ...
 $ Memo           : int  4 5 5 7 5 6 6 6 2 3 ...
 $ Total_Cog      : int  21 24 28 35 17 27 31 33 11 16 ...
```

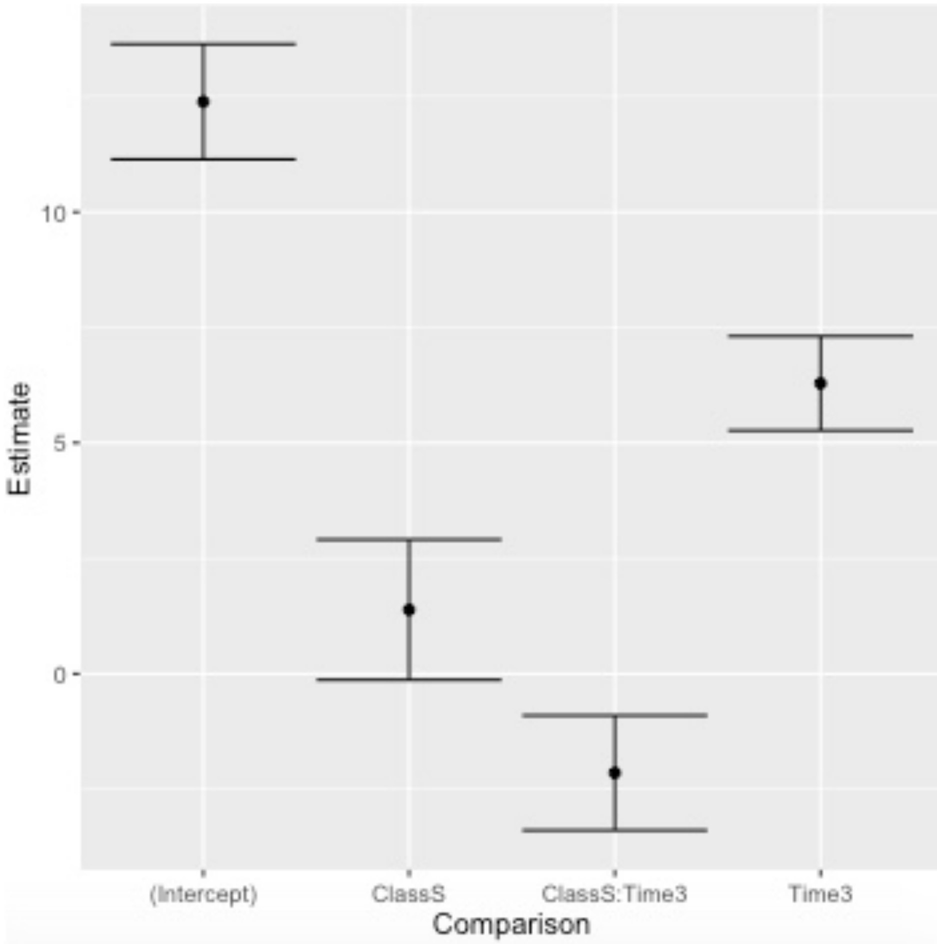
```
$ Total_Mot       : int  43 59 26 60 32 59 50 64 31 59 ...
$ Total_FIM       : int  69 88 55 100 52 91 82 101 46 80 ...
$ Zscore_CMG_RelWt: num  -0.0536 -0.0536 1.3605 1.3605 0.942 ...
```

	numDF	denDF	F-value	p-value
(Intercept)	1	665	3166.081	0
Class	1	665	0.9513703	0.3297254
Time	1	665	400.8145	0
Class:Time	1	665	17.1977	3.804832e-05

VISUALIZATIONS

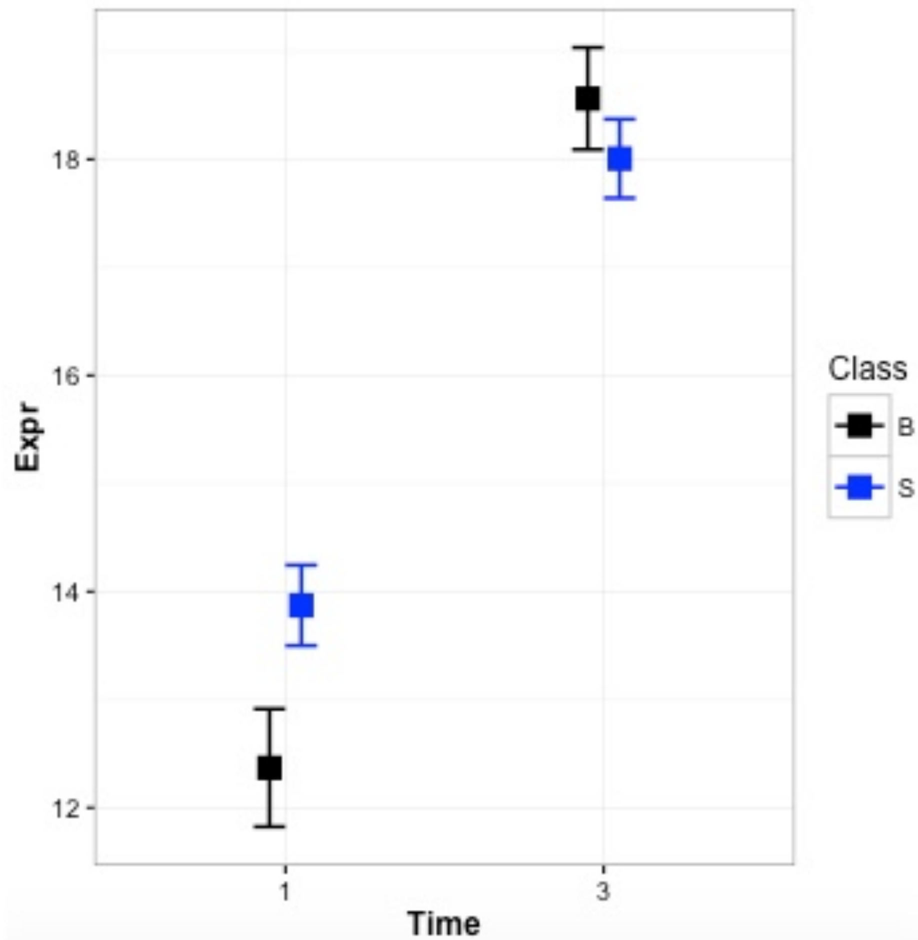
- PARAMETER ESTIMATES

- CONFIDENCE INTERVAL COMPARISON ESTIMATES



	Estimate	lwr	upr	Comparison
(Intercept)	12.388954	11.141251	13.636656	(Intercept)
ClassS	1.386192	-0.134097	2.906482	ClassS
Time3	6.288824	5.268593	7.309055	Time3
ClassS:Time3	-2.146539	-3.389853	-0.903225	ClassS:Time3

- INTERACTION PLOTS BASED ON SUMMARY STATISTICS



Summary Stats:

	Class	Time	N	Expr	sd	se	ci
1	B	1	214	12.36842	7.977224	0.5453118	1.0748989
2	B	3	210	18.56051	6.840541	0.4720422	0.9305743
3	S	1	439	13.87129	7.808815	0.3726944	0.7324917
4	S	3	443	18.00479	7.690075	0.3653665	0.7180714

CONFIDENCE INTERVAL ESTIMATIONS:

Class by Time

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA_Expr_Bootstrap.csv",
                head=TRUE,sep=',',
                na.strings = "",
```

```
                stringsAsFactors=TRUE)
bootES(Data, data.col = "Expr_Change", group.col="Class",contrast = c(B=1,S=-
1), block.col="SubID")

User-specified lambdas: (1, -1)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
2.012       1.940       2.087       0.001       0.038
```

INTERPRETATION:

There is a 2 point increase in expression scores over time for TBI, in comparison to the Stroke group.

Time: *Effect Size Estimates*

```
bootES(Data$Expr_Change)

95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
5.051       4.624       5.512       0.007       0.231
```

INTERPRETATION:

There is a 5 point increase in expression scores from pre to post.

Time: *Mean Difference Estimates* (Calculated using Games-Howell (ideal for unequal group sizes and heteroskedastic data)

```
Data <-read.csv(file="~//Dropbox//InteractiveResearchHub//ResearchProjects//A
ctive//Rehab_Carle//bin//Input//StrokeTBI_MixedANOVA.csv",
                head=TRUE,sep=',',
                na.strings = "",
                stringsAsFactors=TRUE)
Data$Expr <- Data$Expr^1.68
Data$Time <- as.factor(Data$Time)
str(Data)

'data.frame':   1306 obs. of  17 variables:
 $ SubID            : int  1 1 3 3 7 7 10 10 11 11 ...
 $ Time             : Factor w/ 2 levels "1","3": 1 2 1 2 1 2 1 2 1 2 ...
 $ Class            : Factor w/ 2 levels "B","S": 2 2 2 2 2 2 2 2 2 2 ...
 $ LOS              : int  6 6 26 26 19 19 12 12 14 14 ...
 $ Age              : int  76 76 95 95 103 103 89 89 99 99 ...
 $ Gender           : int  1 1 1 1 2 2 2 2 1 1 ...
 $ Race             : int  1 1 1 1 1 1 1 1 1 1 ...
 $ With_1           : int  1 1 1 1 0 0 1 1 1 1 ...
 $ Comp             : int  4 5 6 7 3 5 6 7 2 3 ...
 $ Expr             : num  10.3 14.9 20.3 26.3 1 ...
 $ Soc              : int  5 5 7 7 5 7 7 7 3 3 ...
```

```
 $ ProbSolv        : int  4 4 4 7 3 4 6 6 2 3 ...
 $ Memo            : int  4 5 5 7 5 6 6 6 2 3 ...
 $ Total_Cog       : int  21 24 28 35 17 27 31 33 11 16 ...
 $ Total_Mot       : int  43 59 26 60 32 59 50 64 31 59 ...
 $ Total_FIM       : int  69 88 55 100 52 91 82 101 46 80 ...
 $ Zscore_CMG_RelWt: num  -0.0536 -0.0536 1.3605 1.3605 0.942 ...
```

```
posthocTGH(Data$Expr,Data$Time, method="games-howell", digits=2)

    n means variances
1 653    13        62
3 653    18        55

     t   df p
1:3 11 1299 0
```

Class: ***Effect Size Estimates***

```
bootES(Data, data.col="Expr", group.col="Class",contrast=c(B=1,S=-1))

User-specified lambdas: (1, -1)
Scaled lambdas: (1, -1)
95.00% bca Confidence Interval, 2000 replicates
Stat        CI (Low)    CI (High)   bias        SE
-0.512      -1.482      0.410       -0.015      0.475
```

INTERPRETATION:

There is a 0.5 point difference in expression scores in favor of the Stroke group. Note however, that the effect size estimate is **NOT** significant.

Class: ***Mean Difference Estimates***

```
posthocTGH(Data$Expr,Data$Class, method="games-howell", digits=2)

    n means variances
B 424    15        65
S 882    16        64

      t  df    p
B:S 1.1 832 0.28
```

CONCLUSION:

- On average, the Stroke group generally has better scores across all FIM-cognitive domains across time, with the exception of the Expressiveness domain, where both groups have similar scores obtained across time.

- On average, the change is scores in greater for the TBI group than for the Stroke group across **all** FIM-cognitive domains. The most meaningful change (that is, at least a 1 unit change in scores) was produced in the expressiveness domain (2 unit change), followed by the problem solving (1 unit change) and social interaction (1 unit) domains respectively.
- On average, the strongest parameter estimates were generated for change in scores (for each domain) across time for both groups, suggesting the effectiveness and strong clinical utility of rehabilitation programs in general.