STATISTICAL METHODS IN RESEARCH

Analysis of How Stress Patterns Define Human Experience and Performance in Dexterous Tasks

May 1, 2018

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INTRODUCTION

The Microsurgery performance data represents the performance of 22 medical students in microsurgery activities. The 22 medical students or subjects in our analysis, participated in a longitudinal study regarding the relationship of sympathetic arousal and skill in learning micro-surgical tasks. The subjects had to pay five visits which we regard as sessions, lasting one hour each, in order to practice micro-surgical cutting and suturing in an inanimate simulator.A pre and post study questionnaire was also given to be completed by the subjects to know a little about their biography and anxiety.

During the main part of each session, the subjects underwent the following treatments:
1.Baseline: The subjects were relaxing for 5 min, listening to spa music. They were facially recorded by a thermal and visual camera.
2.Cutting: The subjects had to precision cutting in the inanimate simulator. They were facially recorded by a thermal and visual camera.
3.Suturing: The subjects had to perform suturing in the inanimate simulator. They were facially recorded by a thermal and visual camera.

Explicit accuracy scores per task is provided in the data. Hence, the cutting task has its own accuracy scores and so is the case with the suturing task. The perspiration values are recorded in all time frames for all subjects and sessions. The subjects were asked to fill out a NASA-TLX questionnaire after each task. he NASA-TLX instrument features five subscales measuring different aspects of the subjects' perceptions regarding task difficulty.We perform an analysis with this given data.

INITIAL ANALYSIS-QUALITY CONTROL

Biographic Data

We draw a bar plot to see how gender defines data and histogram to see whether age has any effect on the data.

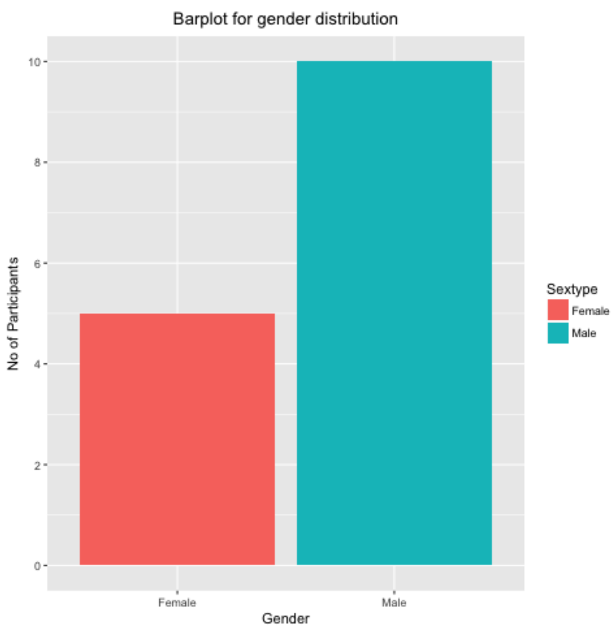

Figure 1: Barplot of Gender Distribution

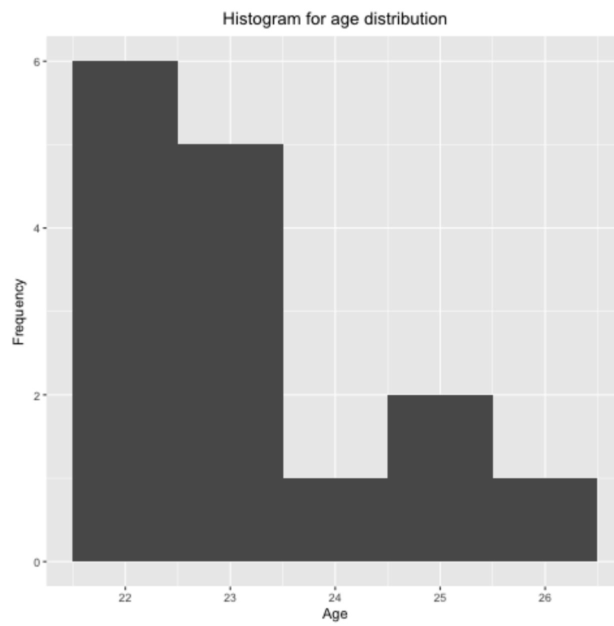

Figure 2: Histogram of age distribution

Trait Psychometric Data

We draw the histogram for Trait Anxiety Inventory(TAI) scores

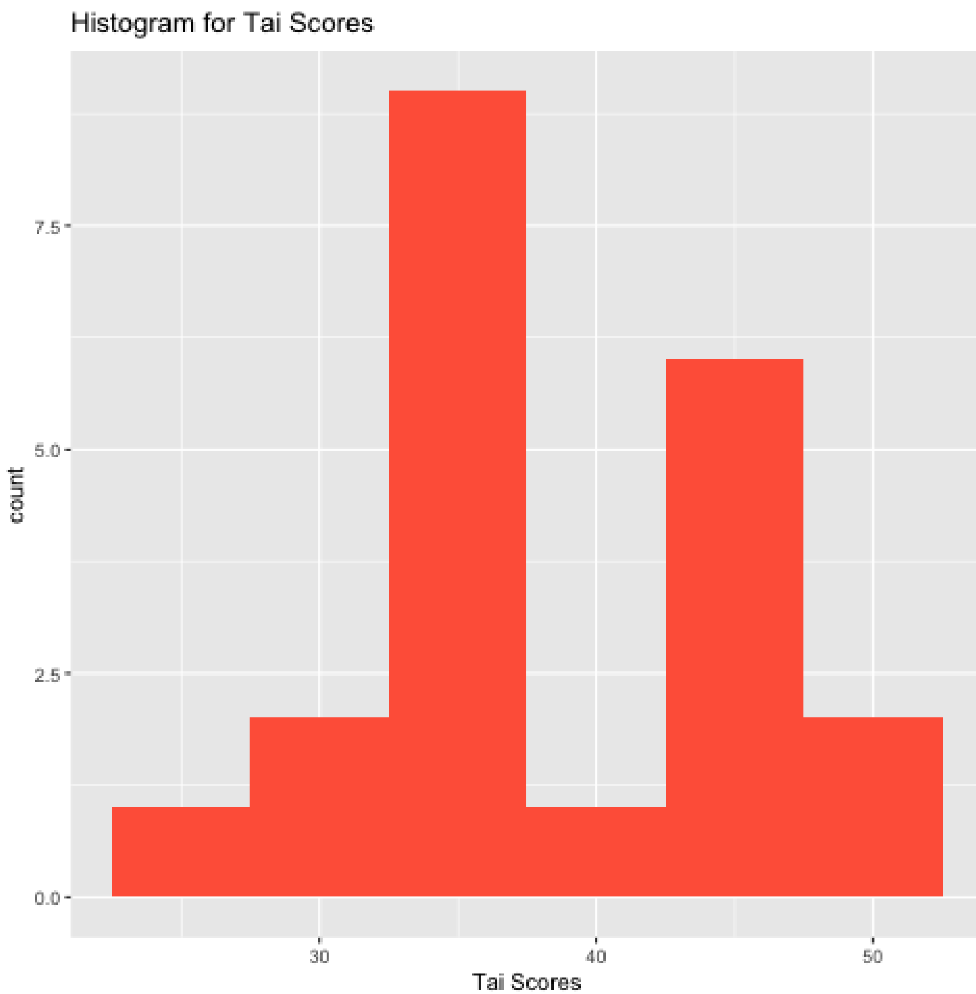

Figure 3: Histogram of Tai Scores

State Psychometric Data

For each subject draw the bar plots for all the NASA-TLX subscales per task. This will give two figures per subject per subscale, one for suturing and one for cutting, where the evolution of the scores from the initial to the final session will be evident.

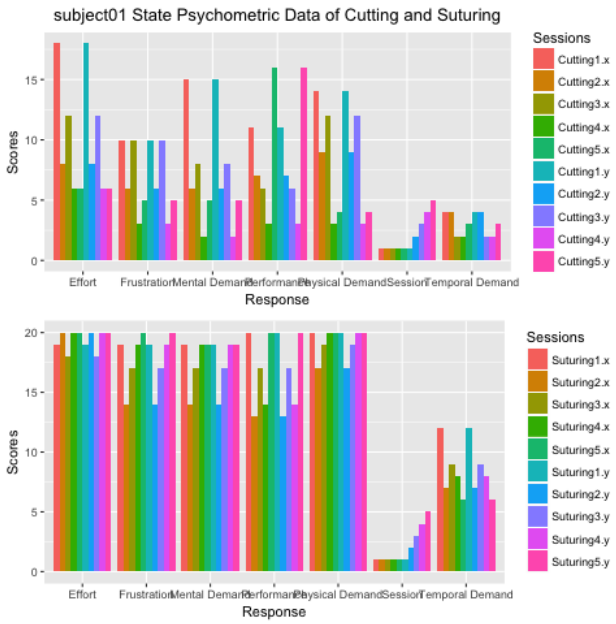

Figure 4: Subject 1

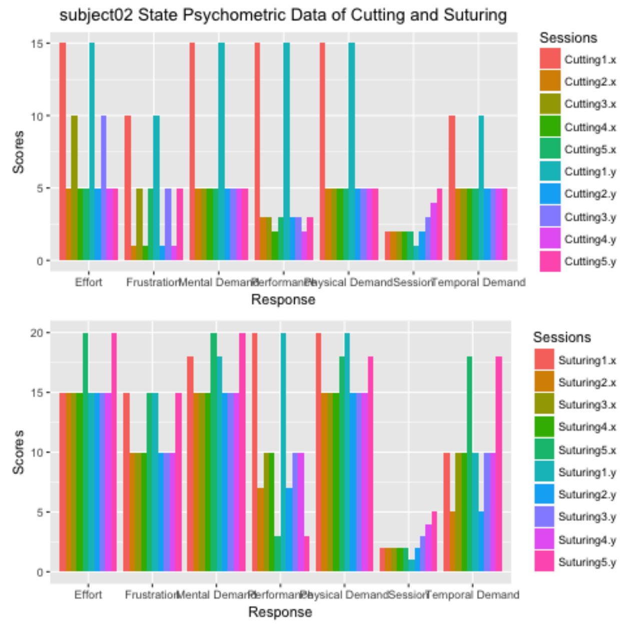

Figure 5: Subject 2

Perinasal Perspiration (Stress) Signal Data

For each session of each subject we draw the perspiration values using black for baseline, green for cutting, and red for suturing.

Performance Data

We draw the accuracy and time bar plots of each subject for each session and each task.

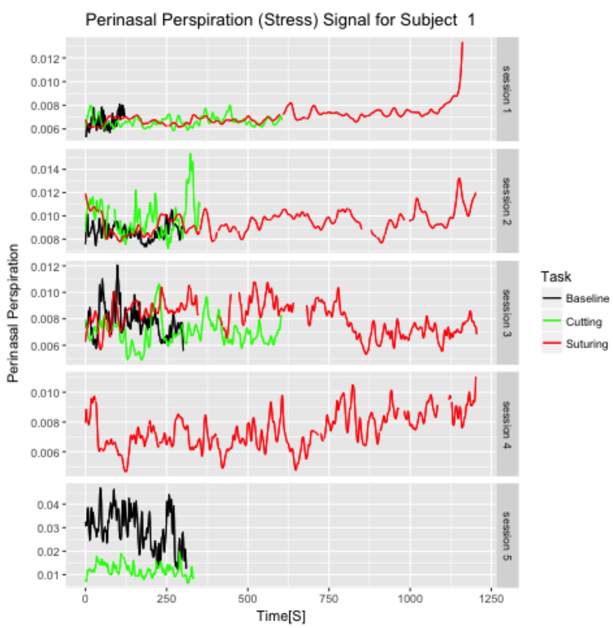

Figure 6: Subject 1

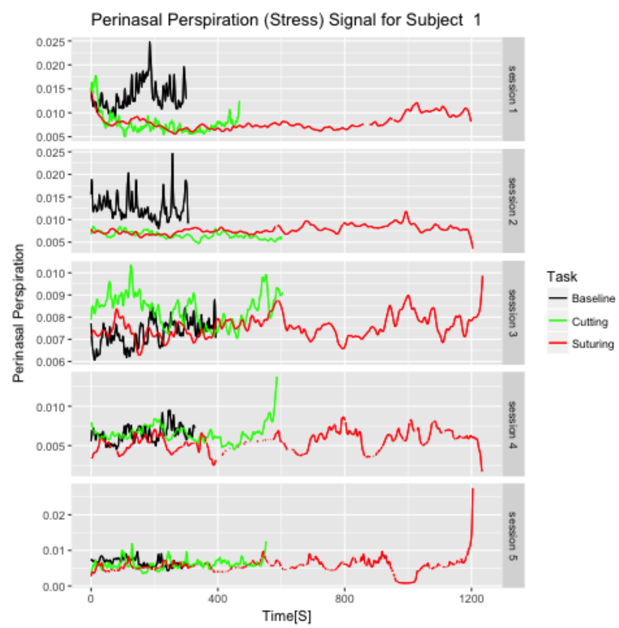

Figure 7: Subject 2

HYPOTHESIS TESTING

1. Analysis of effect of each attribute on Score

Hypothesis:
$NullHypothesis: H_0$ = The score obtained does not depend on the demographics of the subject , session , age , year , sex and perspiration.
$AlternateHypothesis: H_1$ = The score obtained depends on the demographics of the subject , session , age , year , sex and perspiration.

Approach:Linear Modelling:
Linear modeling gives the relationship between the dependent and independent variables. In our data set we are finding the hypothesis between each attribute such as Age, sex, year and mean perspiration with the scores of scorer.

From the above we observe that,
Intercept = 2.128

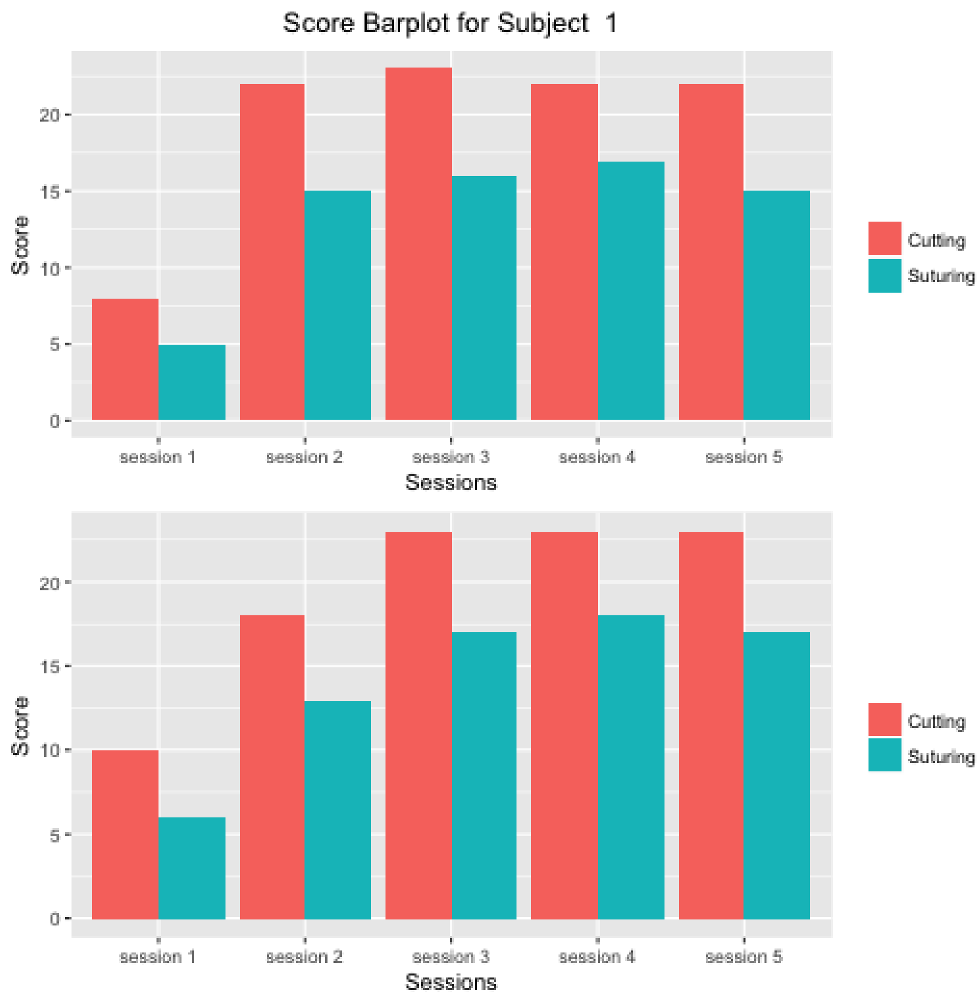

Figure 8: Subject 1 Score Barplot

coefficient for mean perspiration = -34.67

coefficient for age = 0.4606

coefficient for sex = 2.127

coefficient for session = 1.916

Based on this, the complete regression equation is

Score1=2.128+(-34.67)*meanperspiration+0.4607*Age2.127*Sex+1.916*Session+-1.015*task+0.029*scorer

Inference:

The above equation informs us that scores will increase by -34.67 for every one percent increase

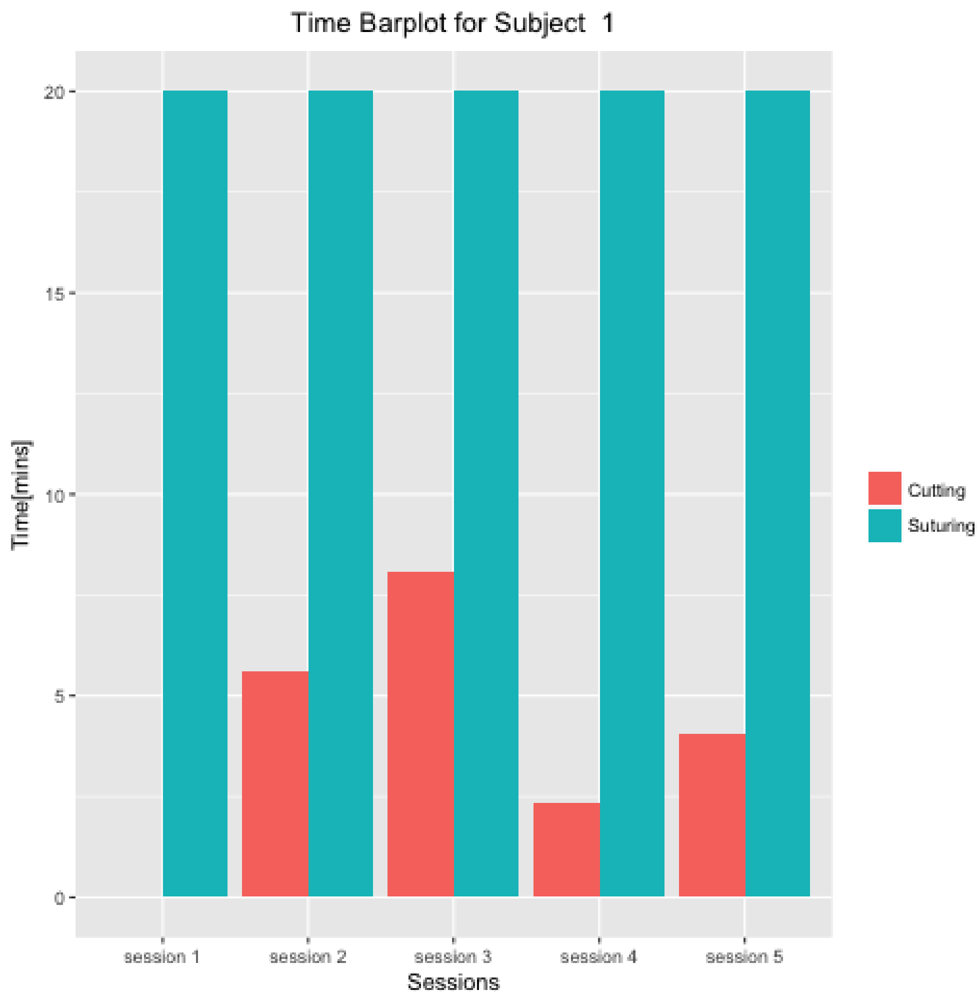

Figure 9: Subject 1 Time Barplot

```
> scorer1lm= lm(formula = df$Scores~df$Mean_Perspiration+df$Age+df$Sex+df$Session+df$Task+df$Scorer)
> print(scorer1lm)

Call:
lm(formula = df$Scores ~ df$Mean_Perspiration + df$Age + df$Sex +
    df$Session + df$Task + df$Scorer)

Coefficients:
         (Intercept)  df$Mean_Perspiration                df$Age                df$Sex            df$Session
             2.12823             -34.67233               0.46067               2.12787               1.91609
      df$TaskSuturing      df$ScorerScorer2
            -1.01505               0.02941
```

Figure 10: Linear model of score vs all other attributes

in mean Perspiration value , and score is directly proportional to age which states that the if older age people are hired the score would have increased

2. Analysis of Age on Score

Hypothesis:

$NullHypothesis: H_0$ = The score obtained does not depend on the age of the subject .

$AlternateHypothesis: H_1$ = The score obtained depends on the age of the subject .

Approach:Linear Modelling:

```
> score1_age=lm(formula = df$Scores~df$Age )
> print(score1_age)

Call:
lm(formula = df$Scores ~ df$Age)

Coefficients:
(Intercept)       df$Age
      5.865        0.641
```

Figure 11: Linear model of score vs age

From the above we observe that,

Intercept = 5.865

coefficient for age = 0.641

Based on this, the complete regression equation is

Score= 5.865 + 0.641xAge

Inference:

The above equation informs us that scores increase with Age.

3. Analysis of Year on Score

Hypothesis:

$NullHypothesis : H_0$ = The score obtained does not depend on the year of the subject .

$AlternateHypothesis : H_1$ = The score obtained depends on the year of the subject .

Approach:Linear Modelling:

```
> score1_year=lm(formula = df$Scores~df$Year)
> print(score1_year)

Call:
lm(formula = df$Scores ~ df$Year)

Coefficients:
(Intercept)      df$Year
     18.816        1.341
```

Figure 12: Linear model of score vs year

From the above we observe that,

Intercept = 18.816

coefficient for year = 1.341

Based on this, the complete regression equation is

Score= 18.816 + 1.341xYear

Inference:

The above equation informs us that scores increase with Year . With every 1 year increase, the Score increases with a value of 20.157.

4. Analysis of Sex on Score

Hypothesis:

$NullHypothesis : H_0$ = The score obtained does not depend on the sex of the subject .

$AlternateHypothesis : H_1$ = The score obtained depends on the sex of the subject .

Approach:Linear Modelling:

```
> score1_sex=lm(formula = df$Scores~df$Sex)
> print(score1_sex)

Call:
lm(formula = df$Scores ~ df$Sex)

Coefficients:
(Intercept)       df$Sex
      17.24         2.59
```

Figure 13: Linear model of score vs sex

From the above we observe that,

Intercept = 17.24

coefficient for sex = 2.59

Based on this, the complete regression equation is

Score= 17.24 + 2.59xSex

Inference:

The above equation informs us that scores depend on sex .

5. Analysis of Perspiration on Score

Hypothesis:

$NullHypothesis : H_0$ = The score obtained does not depend on the perspiration value of the subject .

$AlternateHypothesis : H_1$ = The score obtained depends on the perspiration value of the subject .

Approach:Linear Modelling:

```
> score1_meanp=lm(formula = df$Scores~df$Mean_Perspiration)
> print(score1_meanp)

Call:
lm(formula = df$Scores ~ df$Mean_Perspiration)

Coefficients:
         (Intercept)  df$Mean_Perspiration
               20.82                368.27
```

Figure 14: Linear model of score vs Perspiration

From the above we observe that,
Intercept = 20.82
coefficient for perspiration = 368.27
Based on this, the complete regression equation is
Score= 20.82 + 368.27xPerspiration

Inference:
The above equation informs us that scores are directly proportional to the perspiration value.

6. Analysis of Scorers on Task:

Hypothesis:
$NullHypothesis : H_0$ = The mean of scores is same for both the Scorers
$AlternateHypothesis : H_1$ = The mean of scores is different for both the Scorers

Approach:Wilcox Test:

Cutting : When performed Wilcox test, p-value is greater than 0.05, which applies the means

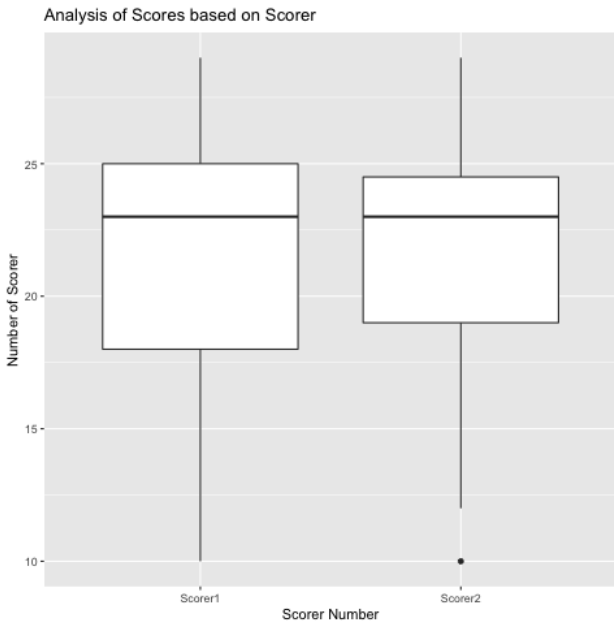

Figure 15: Cutting Scores

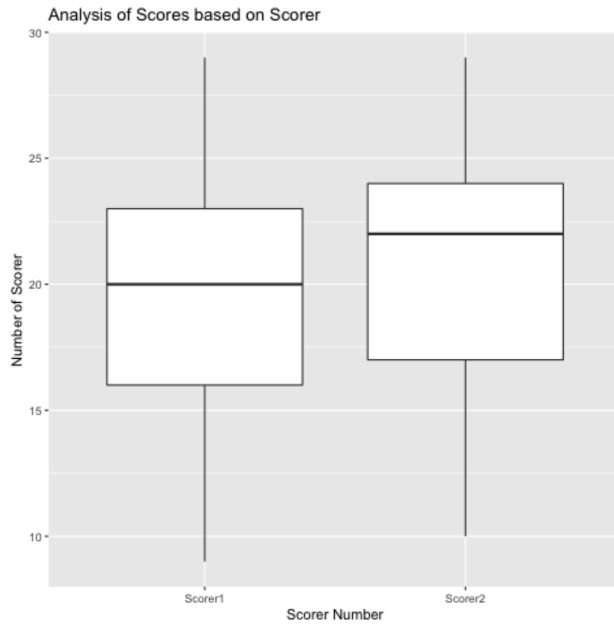

Figure 16: Suturing Scores

have not changed
Suturing: When performed Wilcox test, p-value is less than 0.05, which states that the means of the scorers is different.

Inference:
Scorer has an effect for Suturing ,not Cutting

CONCLUSION

APPENDIX

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REFERENCES