Stat 3480 Midterm II

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04/11/2016

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I. Introduction

For the following analysis and test about our customers' concerns, we are going to apply the non-parametric analysis. We cannot simply use normal t-test since our data will not allow us to obtain correct conclusion through applying the t-test.

There are several advantages of using nonparametric analysis instead of the normal t-tests. Firstly, the nonparametric methods do not require the assumptions that we need for the t-test or normal distribution. Nonparametric analysis has the minimal assumptions about the distribution. It only requires continuous distribution and such a population distribution that depends on location and scale parameters. Secondly, The parametric normal methods require specific distributions with finite observations. However, it is always hard to find out the specific distributions for limited data. Thirdly, for small-size, heavy-tail and non-normal population, nonparametric methods will have higher power. Beyond these general advantages, the limitation of our data obstructs the use of t-test for our clients' concern. The sample sizes for all the data that we obtained from clients are quite small. We can not approximate the sample to be normally distributed. Furthermore, although the type I error for the non-parametric methods and parametric methods could be close or same, the power of the non-parametric methods will certainly be higher than the power of the t-test.

Therefore, the non-parametric methods will be the most appropriate methods in order to deliver our clients' concerns. And we will test for each test's hypothesis and run the analysis of the data based on the nonparametric methods.

II. Summary of data for analysis

i. The 2014 Emergency Preparedness Test Scores' summary analysis.

We obtained the summary statistics, Q-Q plot and boxplot as the following:

Table 2.1.1 Summary Statistics for the 2014 Emergency Preparedness Test Scores

Location	Observations	Minimum	Maximum	Mean	Median
Onsite Counties	8	84.05	86.94	85.42	85.43
We Come to You Counties	6	79.20	81.65	80.79	81.36

Table 2.1.2 Q-Q plot for the 2014 Emergency Preparedness Test Scores

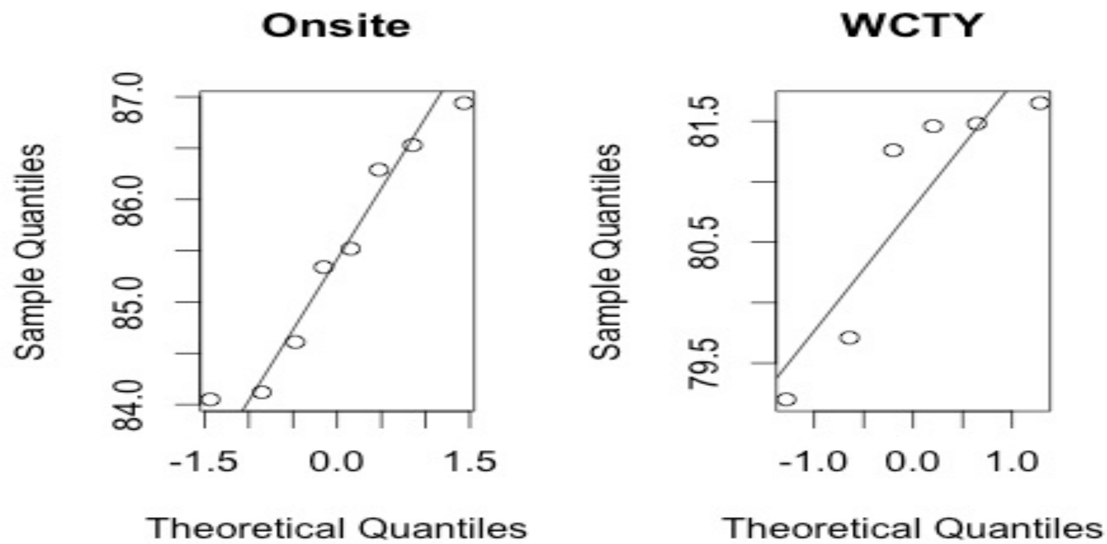
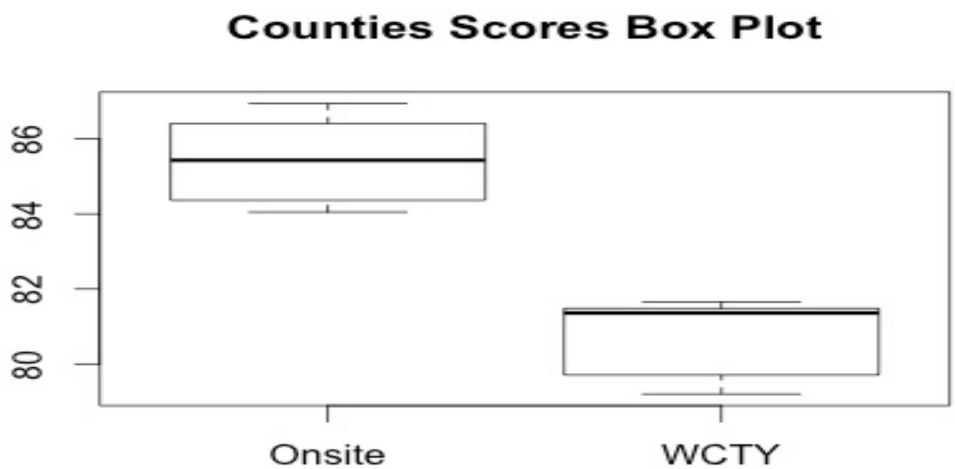


Table 2.1.3 Box plot for the 2014 Emergency Preparedness Test Scores



As what we can see from the summary statistics, the sample size is pretty small with only 14 observations overall. Although the data are not spreading out a lot, the small sample size will obstruct us to use the t-test. For the Q-Q plot, we can see that observations are deviated from the normal line and the distributions for both Onsite and WCTY data could not be the normal distributions. For the boxplot, we can see that here is a difference between two groups. Although the variances for the two groups seem to be same, the medians and means are in a large difference. Therefore, we can conclude that the data for the 2014 emergency preparedness test scores are not normally distributed. The variances for the two groups are pretty close to each other but the medians and means are different. We could not use the t-test for the 2014 Emergency Preparedness data.

ii. The State Test Data's summary analysis.

We obtained the summary statistics, Q-Q plot and Boxplot as the following:

Table 2.2.1 Summary Statistics for the State Test Data

Location	Observations	Minimum	Maximum	Mean	Median
Our state	11	83.08	86.24	84.78	84.70
State1	12	83.16	86.91	84.69	84.81
State2	9	83.37	86.72	85.09	84.88
State3	11	83.48	86.99	84.90	84.79
State4	12	74.62	78.46	75.99	76.06
State5	11	83.41	86.88	84.61	84.33

Table 2.2.2 Q-Q Plot for the State Test Data

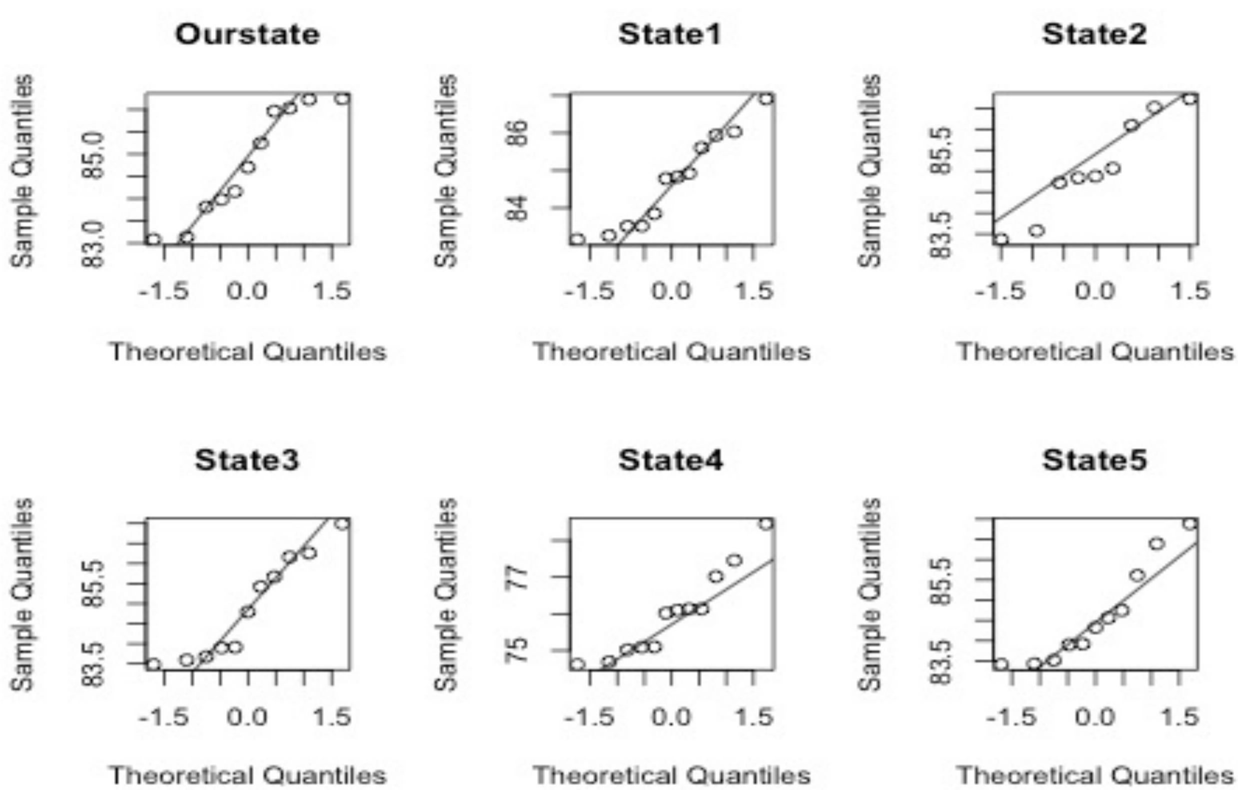
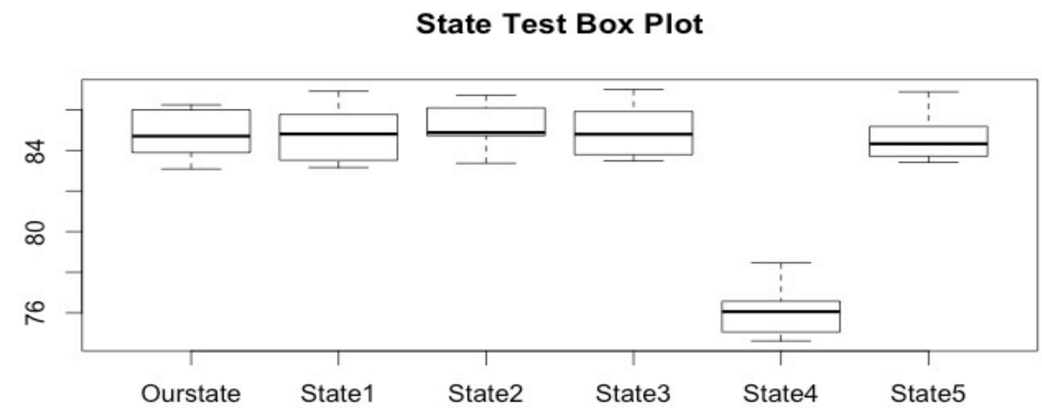


Table 2.2.3 Boxplot for the State Test Data



As what we can obtain from the summary statistics, the observations for each state is pretty small that is around 10 and not all states have the same size. Furthermore, the Box Plot tells us that the state 4 has a huge difference among all the states. Its median and mean are smaller than others, which can be seen form the Table 2.2.1 as well. Also the variances for states are not the same as we can obtain from the length of the box. It is because the sample sizes are different from each other and they are quite small. From the Q-Q plot, the test data for all states are deviated from each one's normal line. In conclusion, the state test data are not normally distributed. The variances among states are not the same and here is a difference of means and medians between state 4 and other states. We could not use the t-test for the State Test data.

iii. The Internal Research WCTY Time Data's summary analysis.

We obtained the summary statistics, Q-Q plot and Boxplot as the following:

Table 2.3.1 Summary Statistics for the Internal Research WCTY Time Data

Time Length	Observations	Minimum	Maximum	Mean	Median
Less than 30 minutes	10	81.00	83.98	82.82	82.93
Approx 60 minutes	10	80.05	83.84	81.76	81.45
Approx 90 minutes	10	80.24	83.89	82.16	82.19
Approx 120 minutes	10	80.15	83.29	81.50	81.00
Approx 180 minutes	10	80.37	83.71	82.32	82.51

Table 2.3.2 Q-Q Plot for the Internal Research WCTY Time Data

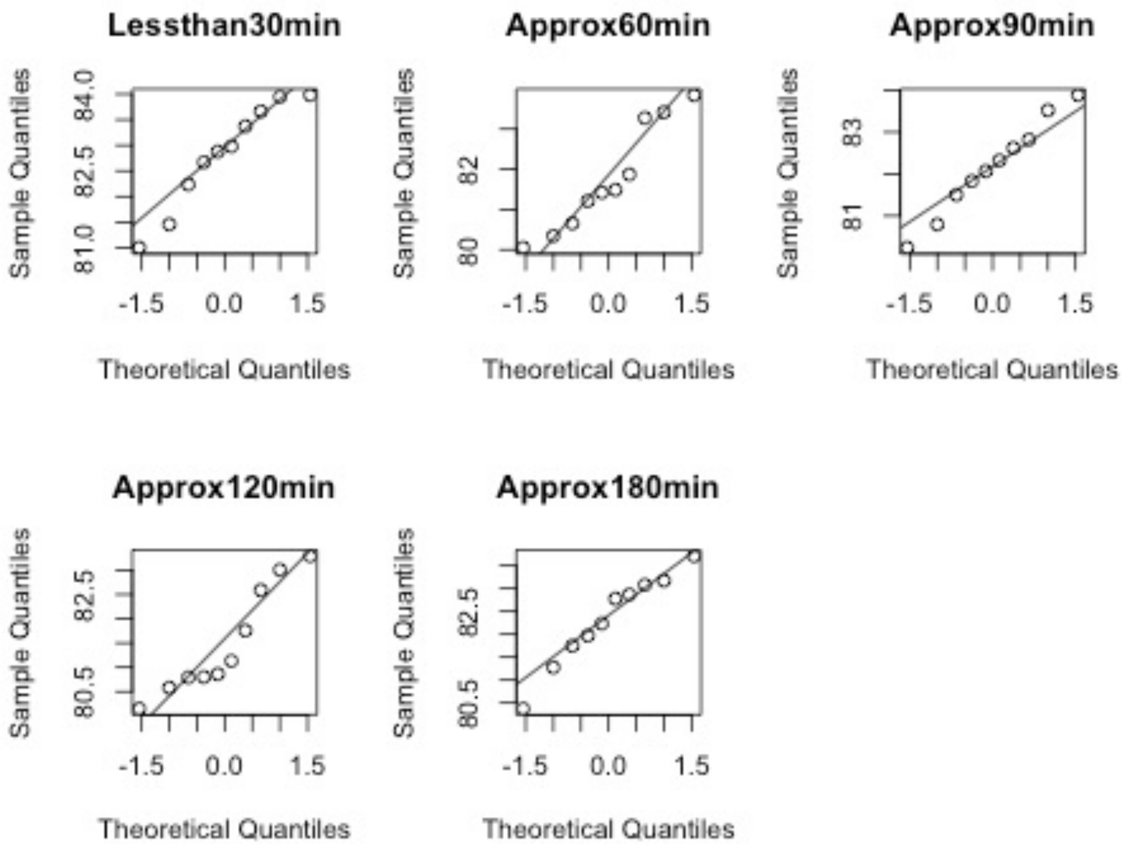
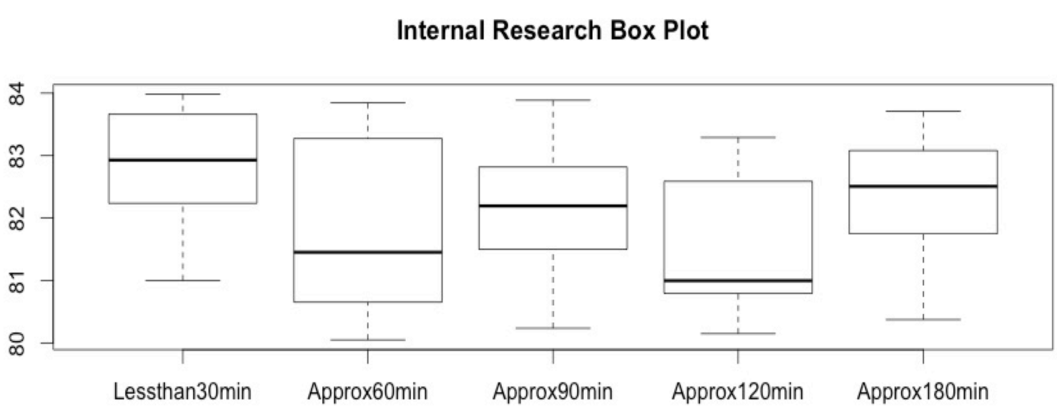


Table 2.3.3 Boxplot for the Internal Research WCTY Time Data



As what we can obtain from the summary statistics, all groups have the same sample size but they are small with a size of only 10. For the Q-Q plot, the observations for each group are deviated from the normal line. For the boxplot, the groups have different means and medians. The different lengths of boxes for each group indicate the different variances for groups. The location parameters are also different among groups. In conclusion, the observations for the internal research data are not normally distributed. They also have different variances, means and medians from each other. We could not use the t-test for the Internal Research data.

III. Discussion of statistical tests or methodology to be used and why, including discussion of assumptions if they are required to perform any mentioned test.

i. Concern 1. The six outlying counties are not as adequately prepared for an emergency as the eight counties that attended the onsite group session.

We plan to use one-sided Wilcoxon Rank-Sum (WRS) Test for this case. WRS is a two-sample permutation test based on W, the sum of the ranks of the observations from one of the treatments. It simply ranks each observation after combing the groups together, find all possible permutations of the ranks and calculates the p-value based on the permutation results of the probability of how many number of rank sums are greater than the observed rank sum. As for the hypothesis, the null hypothesis is that $H_0 : F_1(x) = F_2(x)$; It stands for that the outlying counties and the onsite counties have the same distribution. The alternative hypothesis is that $H_a : F_1(x) \neq F_2(x)$. It means that the outlying counties have different distributions than the onsite counties.

WRS requires some assumptions. Firstly, the population distribution needs to depend on location and scale parameters. Secondly, the distribution is continuous. Thirdly, it has identical population distributions. Fourthly, it requires equal variances among groups. The first three assumptions are met here. In order to apply the WRS, we need to test the equal variances.

Here we need to use the RMD to test for the deviances. We do not know the normality of the sample variances and we do not know the location parameters. We will use the sample medians instead of means to obtain the deviances for each group. Once we obtain the equal variance testimony from the RMD test, we could use WRS to find out if the six outlying counties are different from the eight-onsite counties. The null hypothesis for RMD Test will be: $H_0 : \sigma_1 = \sigma_2$. It means that the outlying counties and onsite counties have the equal variances. The alternative hypothesis for RMD Test will be:
$H_a : \max(\sigma_{1,} \sigma_2) / \min(\sigma_{1,} \sigma_2) > 1$. This is a two sided RMD Test and we will use it to test if the variances for two treatments are different.

ii. Concern 2: the teams from these six counties were all trained differently from each other, whereas the onsite trained teams are all trained similarly.

We plan to use the Binomial Test for this concern. The binomial test can be used to test that if the mean is different from the median and further conclude that whether the observations in one treatment are different from each others or not. We need to run the Binomial Test twice for both treatments. The Binomial test requires only one assumption that the population is continuous, which is fulfilled in this case. The null hypothesis for the test is: $H_0 : \theta_{.5} = \theta_H$. It means that the median and the mean will be the same; the alternative hypothesis is that $H_a : \theta_{.5} \neq \theta_H$, It means that the median and mean of one treatment will not be the same.

iii. Concern 3: if our state's preparedness materials have in general resulted in a different level of preparedness than the surrounding states.

We plan to use the RMD Test to test for the equal variances first. Since we want to compare the test scores from our state with the test scores with the surrounding states, we will divide the observations into two groups. One group contains 11 observations and the other one contains 55 observations. RMD Test is used to test for deviances. We will use the sample medians to obtain the deviances for each group.
For this case, the RMD reject the null hypothesis and we have unequal variances. We could not use the WRS Test to determine if our state has different level of preparedness than the surrounding states. We should therefore apply Kolmogorov-Smirnov (K-S) test. This K-S test is the nonparametric analog to the two-sample t-test with unequal variances. Its assumptions are independent samples with identical distributions. Our data fulfill these requirements and we can apply the K-S Test. As for the hypothesis, the null hypothesis is that $H_0 : F_1(x) = F_2(x)$. It stands for that our state has the same distribution as other states in general. The alternative hypothesis is that $H_a : F_1(x) \neq F_2(x)$. It means that our state has different distributions than the other states.

iv. Concern 4: if there are differences in general among the states, and where and how those differences occur between states.

We plan to use the Kruskal-Wallis test and the Wilcoxon Rank-Sum (WRS) for the pairwise comparisons. For the Kruskal-Wallis test, it is used to test for multiple treatments that if they have equal distributions. We firstly obtain the KW statistic for the original data and then apply the permutation tests to obtain the p-value. Once we find here is the general difference between groups, we can further utilize the WRS to find where the differences occur. Since the Type I error rate increases quickly with the number treatments, we need to further use the Bonferroni-adjusted-p-value. The Bonferroni-adjusted—p-value is pretty conservative. If we can still reject the null hypothesis with this conservative p-value, then we will be more certainly to conclude the difference for the pairwise comparison. The null hypothesis for the Kruskal-Wallis test is that $H_0 : F_1(x) = F_2(x) = \ldots = F_k(x)$. It stands for that the distributions among all states are the same. The alternative hypothesis is that $H_a : F_1(x) \leq F_j(x)$ or $F_1(x) \geq F_j(x)$. It means that for at least one pair of (i,j), with strict inequality holding for at least one state.

The assumptions for the Kruskal-Wallis test are the following. Firstly, it requires equal variances. Secondly, it requires independent distributions. Therefore, we need to use the Fligner-Killeen Test to test for deviances for the whole groups. Fligner-Killeen Test is used to test for homogeneity of variances. It has the null hypothesis that the variances in each of the groups are the same. Its alternative hypothesis is that at least one pair of the variances is not the same.

v. Concern 5: Test the claim that the customer dissatisfaction and the low performance on the test is due to the insufficient time of training.

We plan to use the Jonckheere-Terpstra (JT) Test. JT test is used to test for ordered multiple treatments alternatives. Given the knowledge that the customer dissatisfaction is associated with the insufficient time of training, we know here is the order for the alternative hypothesis and therefore we can test for orders. We calculate the JT from the original data and use the permutation methods to find the p-value. The null hypothesis for the JT test is that $H_0 : F_1(x) = F_2(x) = \ldots = F_k(x)$. It means that the distributions for the performances scores are the same. The alternative hypothesis is that $H_a : F_1(x) \leq F_2(x) \leq \ldots \leq F_k(x)$. It stands for that the observations from the treatment 1 tend to be smaller than the treatment 2, and so on. The customers' low performance scores are associated with the insufficient time of training.

The assumptions for the JT Test are equal variances and independent distribution. We still need to apply the Fligner-Killeen test to test for deviance for the whole treatments.

IV. Results of applications of statistical tests to respective data

i. Concern 1: The six outlying counties are not as adequately prepared for an emergency as the eight counties that attended the onsite group session.

Test	Test Statistic	Test Statistic Value	P-value
RMD Test	RMD_{obs}	1.214932	0.6959707
WRS Test	Wobs	48	0.000333

ii. Concern 2: the teams from these six counties were all trained differently from each other, whereas the onsite trained teams are all trained similarly.

Test	P-value
Binomial Test for Onsite	1
Binomial Test for WCTY	0.6875

iii. Concern 3: if our state's preparedness materials have in general resulted in a different level of preparedness than the surrounding states.

Test	Test Statistic	Test Statistic Value	P-value
RMD Test	RMD_{obs}	2.506031	0.0331
Kolmogorov-Smirnov Test	D_{obs}	0.25455	0.5925

iv. Concern 4: if there are differences in general among the states, and where and how those differences occur between states.

Test	Test Statistic	Test Statistic Value	P-value
Fligner Killeen Test	FK	0.30355	0.9976
Kruskal-Wallis Test	KW_{obs}	29.858	1.573e-05
WRS Pairwise Comparisons			Bonferroni adjusted p-values
Ourstate vs. State1	KW_{obs}	69	13.20168
Ourstate vs. State2	KW_{obs}	40	7.191176
Ourstate vs. State3	KW_{obs}	58	13.46494
Ourstate vs. State4	KW_{obs}	132	2.218807e-05
Ourstate vs. State5	KW_{obs}	64	12.70498
State1 vs. State2	KW_{obs}	42	6.33161
State1 vs. State3	KW_{obs}	55	7.88098
State1 vs. State4	KW_{obs}	144	1.109403e-05
State1 vs. State5	KW_{obs}	68	13.91862
State2 vs. State3	KW_{obs}	52	13.22976
State2 vs. State4	KW_{obs}	108	0.0001020651
State2 vs. State5	KW_{obs}	45	4.967433
State3 vs. State4	KW_{obs}	132	2.218807e-05
State3 vs. State5	KW_{obs}	69	9.094767
State4 vs. State5	KW_{obs}	0	2.218807e-05

v. Concern 5: Test the claim that the customer dissatisfaction and the low performance on the test is due to the insufficient time of training.

Test	Test Statistic	Test Statistic Value	P-value
Fligner Killeen Test	FK	0.89113	0.9258
Jonckheere-Terpstra Test	JT	440	0.8488

V. Discussion of results

i. Concern 1: The six outlying counties are not as adequately prepared for an emergency as the eight counties that attended the onsite group session.

The RMD Test gave us the *p-value* of 0.696. We fail to reject the null hypothesis that there are equal variances even at a significance level 0.1. We came to the conclusion that the two treatments have the equal variances and we can move forward to apply the WRS Test.

The WRS Test gave us the *p-value* of 0.000333. We can reject the null hypothesis that the preparedness for outlying counties and onsite counties are the same at a significance level of 0.01. We came to the conclusion that the six outlying counties are not as adequately prepared for an emergency as the eight counties that attended the onsite group session.

ii. Concern 2: the teams from these six counties were all trained differently from each other, whereas the onsite trained teams are all trained similarly.

The Binomial Test for the onsite eight counties gave the *p-value* of 1. We fail to reject the null hypothesis that the means and medians of the onsite treatment are the same at a significance level of 0.1. We came to the conclusion that the teams from eight onsite counties were trained the same.

The Binomial Test for the outlying six counties gave the *p-value* of 0.6875. We fail to reject the null hypothesis that the means and medians of the outlying treatment are the same at a significance level of 0.1. We came to the conclusion that the teams from six outlying counties were trained the same.

iii. Concern 3: if our state's preparedness materials have in general resulted in a different level of preparedness than the surrounding states.

The RMD Test gave us the *p-value* of 0.0331. We reject the null hypothesis that there are equal variances between our state and the surrounding states at a significance level of 0.05. We came to the conclusion that the two groups have unequal variances and we can not use the WRS Test.

Therefore, we apply the Kolmogorov-Smirnov Test. The KS Test gave us the *p-value* of 0.5925. We fail to reject the null hypothesis that our state's preparedness materials have in general resulted in a different level of preparedness than the surrounding states at a significance level of 0.1. We came to the conclusion that our state's preparedness materials have in general resulted in a same level of preparedness than the surrounding states.

iv. Concern 4: if there are differences in general among the states, and where and how those differences occur between states.

The Fligner-Killeen Test gave us the *p-value* of 0.9976. We fail to reject the null hypothesis that the variances among the states are the same at a significance level of 0.1. We came to the conclusion that the variances among the states are the same. We can move forward to conduct the Kruskal Wallis Test.

The KW Test gave us the *p-value* of 1.573e-05. We reject the null hypothesis that there are no differences in general among the states at a significance level of 0.01. We came to the conclusion that there are differences in general among the states.

I then run the WRS Test for the pairwise between two states and the results are the following:

Pairwise Groups	Bonferroni adjusted p-values	Reject or fail to reject at a significance level of 5%
Ourstate vs. State1	13.20168	Fail to reject
Ourstate vs. State2	7.191176	Fail to reject
Ourstate vs. State3	13.46494	Fail to reject
Ourstate vs. State4	2.218807e-05	**Reject**
Ourstate vs. State5	12.70498	Fail to reject
State1 vs. State2	6.33161	Fail to reject
State1 vs. State3	7.88098	Fail to reject
State1 vs. State4	1.109403e-05	**Reject**
State1 vs. State5	13.91862	Fail to reject
State2 vs. State3	13.22976	Fail to reject
State2 vs. State4	0.0001020651	**Reject**
State2 vs. State5	4.967433	Fail to reject
State3 vs. State4	2.218807e-05	**Reject**
State3 vs. State5	9.094767	Fail to reject
State4 vs. State5	2.218807e-05	**Reject**

We can make the conclusion that there are differences between the State 4 and all other states.

v. Concern 5: Test the claim that the customer dissatisfaction and the low performance on the test is due to the insufficient time of training.

The Fligner Killeen Test gave us the *p-value* of 0.9258. We fail to reject the null hypothesis that the variances among the performance scores are the same. We came to the conclusion that there are equal variances for the performance scores. We can further apply the Jonckheere-Terpstra Test.

The JT Test gave us the *p-value* of 0.8488. We fail to reject the null hypothesis that the distributions for performance scores are the same. We came to the conclusion that there are not an increasing performance scores across the increasing time of train. The distributions of performance scores are the same.

VI. Conclusion and summarizing remarks

The We Come To You service is not that effective as the onsite services. The Respond2Emergencies did not live up to the claims of their promotional materials for the six counties, which received training via the We Come to You service. The six outlying counties are not as adequately prepared for an emergency as the eight counties that attended the onsite group session. However, those six outlying counties were all trained the same from each other and those eight onsite counties were all trained the same from each other as well. Their performances scores are in general the same within the group.

Our state government has managed our state's preparedness process for years. Our state's preparedness materials have in general resulted in a same level of preparedness with the surrounding states. Although the Emergency Preparedness Test has been issued over a decade and a half, the effectiveness of our state's preparedness test is the same as our surrounding states. However, there are differences in general among all the states. According to our analysis, the State 4 is different from all other states. Its performance scores are statistically significantly lower than other states. There might be a problem for the State 4 materials or preparedness.

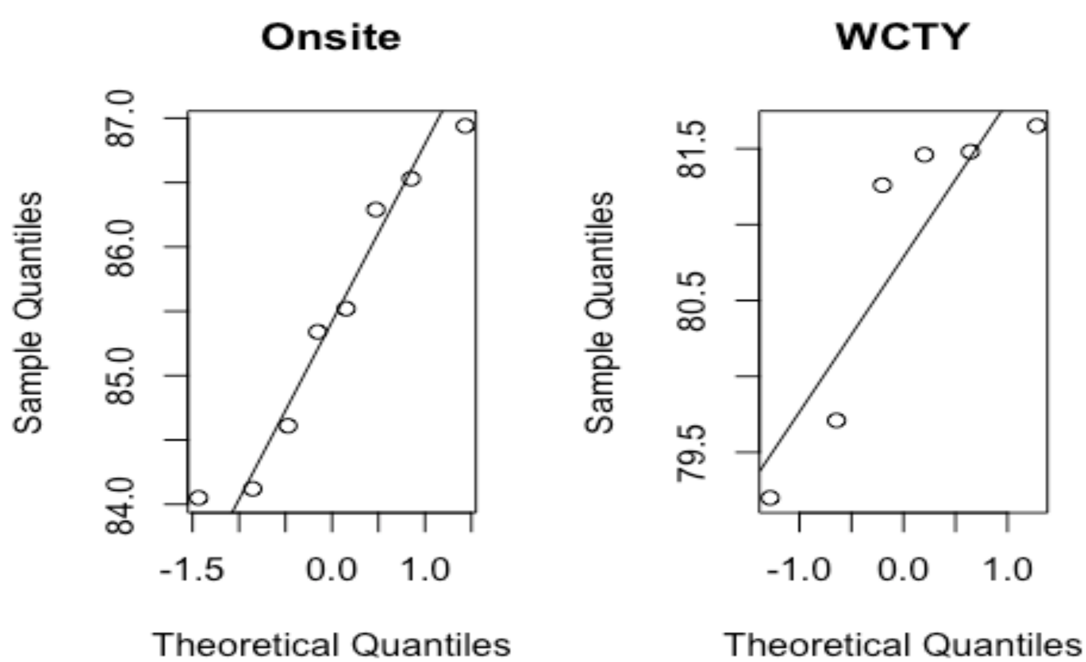
The specific claim made by Respond2Emergencies regarding the We Come To You service is not true according to the internal research data. No matter how long the training instructors spent with the client offsite, the clients will prepare the same for the test. It is not true that the more time their offsite instructors spend with a client, the better prepared the client becomes. The instructors spent a great deal of the workshop chatting with each other, goofing off, or otherwise wasting time.

VII. Software/ Code Appendix

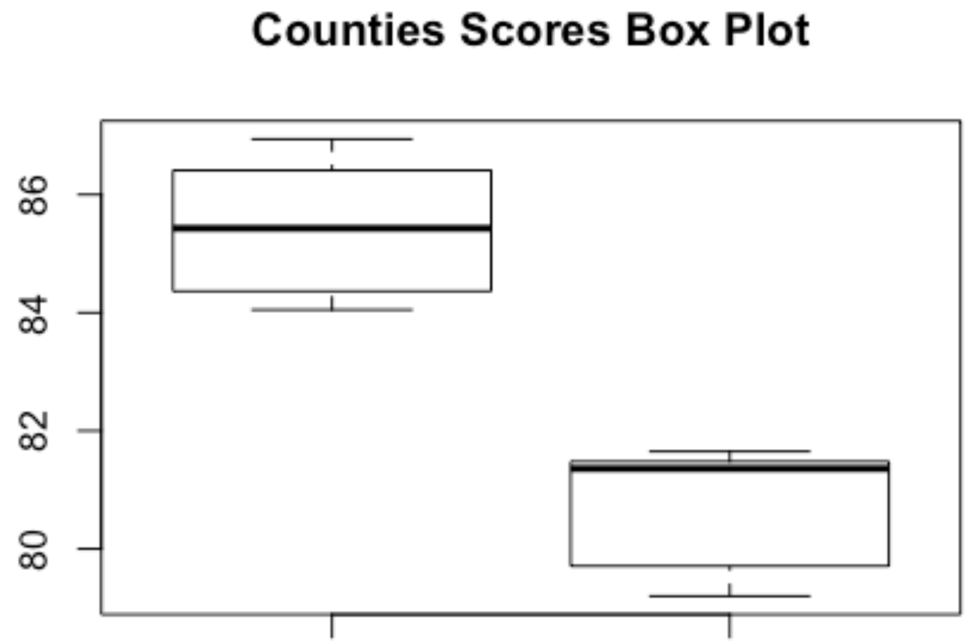
Summary Stats

```
##WCTY Analysis
Onsite<-c(85.34,84.12,86.53,85.52,84.61,86.94,84.05,86.29)
```

```
WCTY<-c(81.48,81.26,79.71,81.46,79.20,81.65)
#summary statistics
summary(Onsite)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   84.05   84.49   85.43   85.42   86.35   86.94

summary(WCTY)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   79.20   80.10   81.36   80.79   81.47   81.65

#qqplot
par(mfrow=c(1,2))
qqnorm(Onsite,main="Onsite")
qqline(Onsite)
qqnorm(WCTY,main="WCTY")
qqline(WCTY)
```

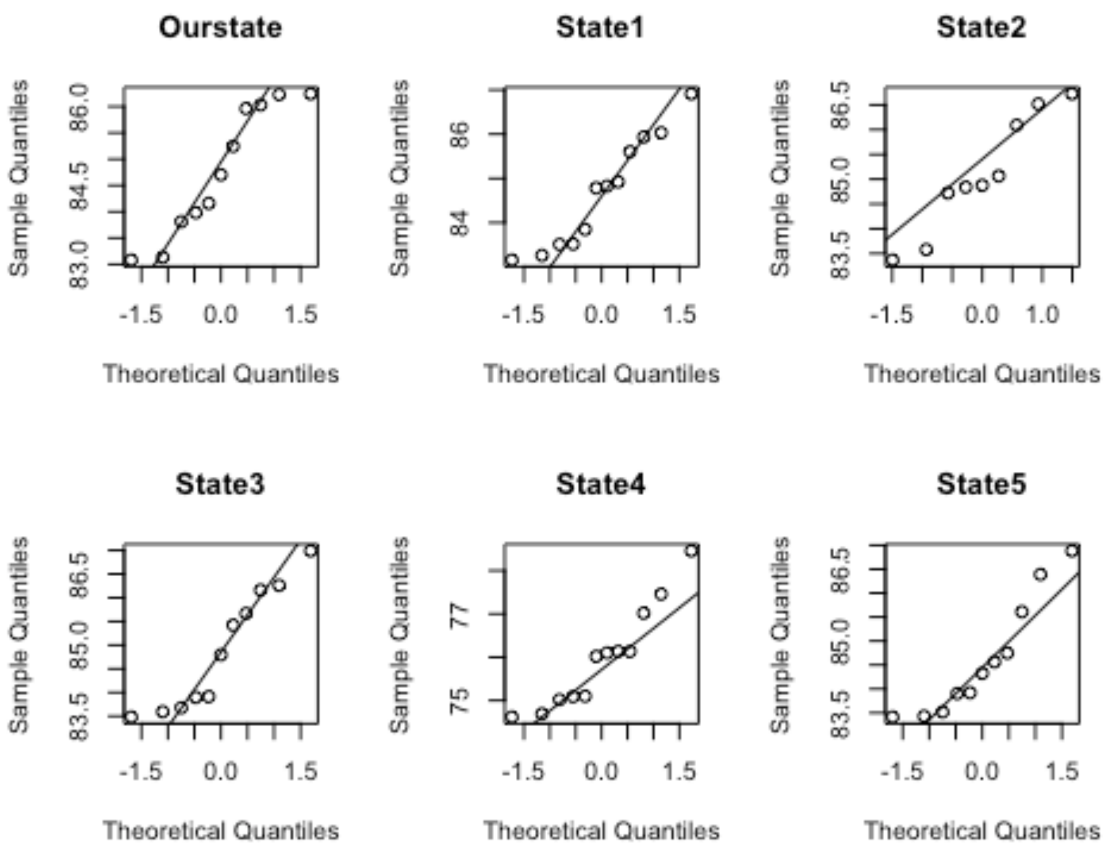



```
#boxplot
par(mfrow=c(1,1))
boxplot(Onsite,WCTY,main="Counties Scores Box Plot")
```

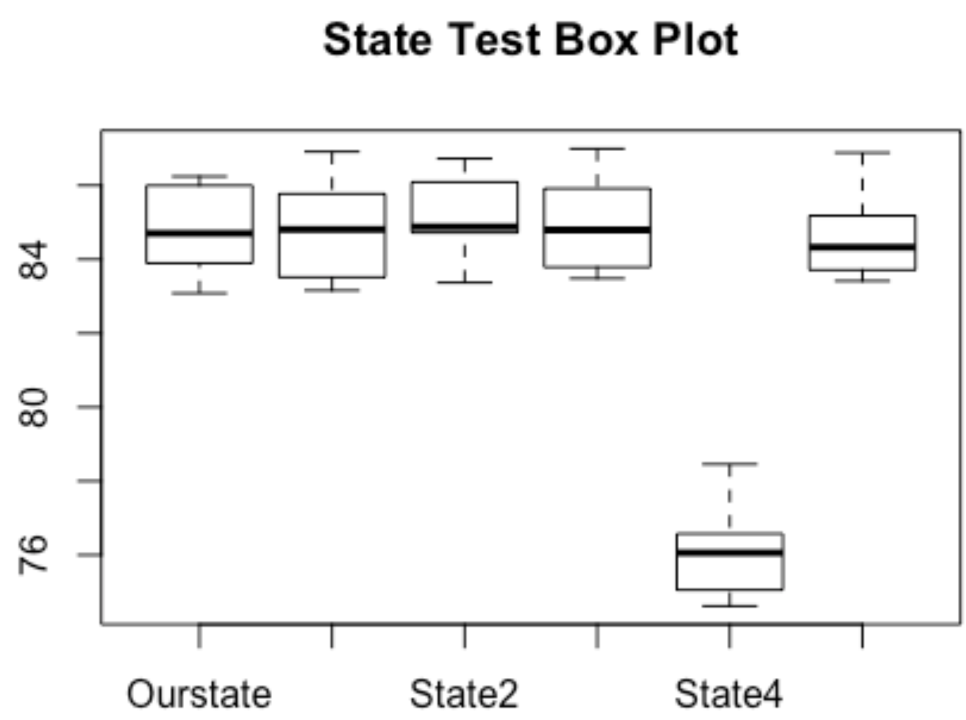



```
##State Analysis
`State+Test+Data` <- read.delim("~/Desktop/Fourth-Year Second Semester/
STAT 3480/Midterm2/State+Test+Data.txt")
attach(`State+Test+Data`)
summary(`State+Test+Data`)

##     Ourstate          State1          State2          State3     
##  Min.   :83.08   Min.   :83.16   Min.   :83.37   Min.   :83.48  
##  1st Qu.:83.90   1st Qu.:83.52   1st Qu.:84.72   1st Qu.:83.79  
##  Median :84.70   Median :84.81   Median :84.88   Median :84.79  
##  Mean   :84.78   Mean   :84.69   Mean   :85.09   Mean   :84.90  
##  3rd Qu.:86.00   3rd Qu.:85.69   3rd Qu.:86.09   3rd Qu.:85.91  
##  Max.   :86.24   Max.   :86.91   Max.   :86.72   Max.   :86.99  
##  NA's   :1                       NA's   :3       NA's   :1      
##      State4          State5     
##  Min.   :74.62   Min.   :83.41  
##  1st Qu.:75.07   1st Qu.:83.71  
##  Median :76.06   Median :84.33  
##  Mean   :75.99   Mean   :84.61  
##  3rd Qu.:76.35   3rd Qu.:85.18  
##  Max.   :78.46   Max.   :86.88  
##                  NA's   :1      
```

```r
#qqplot
par(mfrow=c(2,3))
qqnorm(Ourstate,main="Ourstate")
qqline(Ourstate)
qqnorm(State1,main="State1")
qqline(State1)
qqnorm(State2,main="State2")
qqline(State2)
qqnorm(State3,main="State3")
qqline(State3)
qqnorm(State4,main="State4")
qqline(State4)
qqnorm(State5,main="State5")
qqline(State5)
```



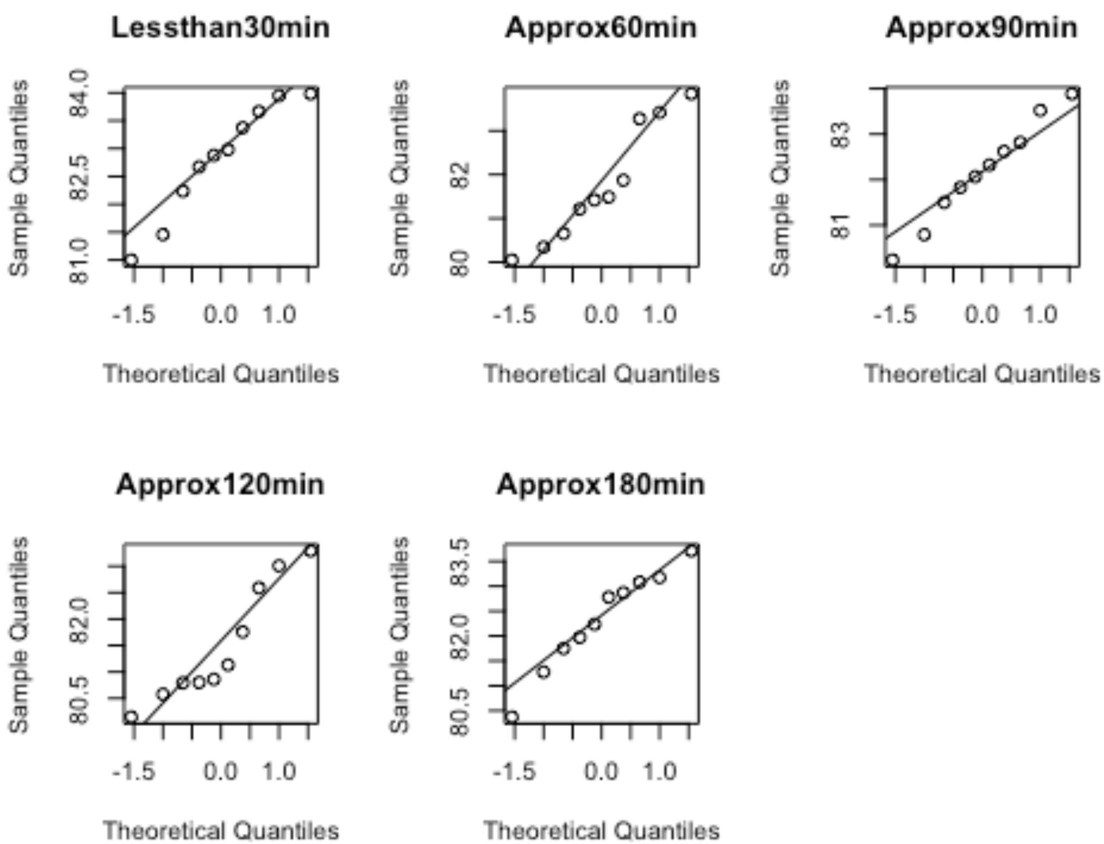

```r
#boxplot
par(mfrow=c(1,1))
boxplot(`State+Test+Data`,main="State Test Box Plot")
```



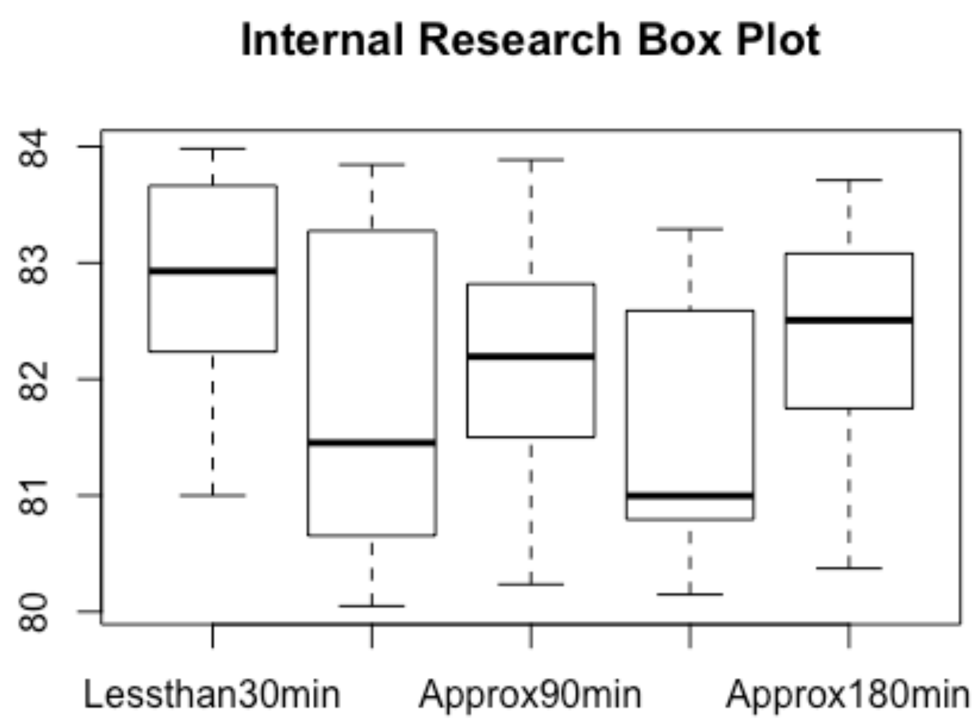

```
##Internal Research Analysis
`Internal+Research+.+WCtY+Time+Data` <- read.delim("~/Desktop/Fourth-Ye
ar Second Semester/STAT 3480/Midterm2/Internal+Research+-+WCtY+Time+Dat
a.txt")
attach(`Internal+Research+.+WCtY+Time+Data`)
#summary statistics
summary(`Internal+Research+.+WCtY+Time+Data`)
```

```
##  Lessthan30min    Approx60min     Approx90min     Approx120min
##  Min.   :81.00   Min.   :80.05   Min.   :80.24   Min.   :80.15
##  1st Qu.:82.34   1st Qu.:80.79   1st Qu.:81.58   1st Qu.:80.80
##  Median :82.93   Median :81.45   Median :82.19   Median :81.00
##  Mean   :82.82   Mean   :81.76   Mean   :82.16   Mean   :81.50
##  3rd Qu.:83.59   3rd Qu.:82.92   3rd Qu.:82.77   3rd Qu.:82.38
##  Max.   :83.98   Max.   :83.84   Max.   :83.89   Max.   :83.29
##   Approx180min
##  Min.   :80.37
##  1st Qu.:81.80
##  Median :82.51
##  Mean   :82.32
##  3rd Qu.:83.03
##  Max.   :83.71
```

```
#qqplot
par(mfrow=c(2,3))
qqnorm(Lessthan30min,main="Lessthan30min")
qqline(Lessthan30min)
qqnorm(Approx60min,main="Approx60min")
qqline(Approx60min)
qqnorm(Approx90min,main="Approx90min")
qqline(Approx90min)
qqnorm(Approx120min,main="Approx120min")
qqline(Approx120min)
qqnorm(Approx180min,main="Approx180min")
qqline(Approx180min)
#boxplot
par(mfrow=c(1,1))
```




```
boxplot(`Internal+Research+.+WCtY+Time+Data`,main="Internal Research Bo
x Plot")
```



Concerns

Concern1

```
#RMD Test
library('jmuOutlier')

## Warning: package 'jmuOutlier' was built under R version 3.2.4

rmd.test(Onsite,WCTY,alternative=c("two.sided"),all.perms=TRUE,num.sim=
20000)

## [[1]]
## [1] "Exact p-value was calculated."
##
## $alternative
## [1] "two.sided"
##
## $rmd.hat
## [1] 1.214932
##
## $p.value
## [1] 0.6959707
```

```
#WRS Test
library("exactRankTests")

##  Package 'exactRankTests' is no longer under development.
##  Please consider using package 'coin' instead.
##
##
## Attaching package: 'exactRankTests'
##
## The following object is masked from 'package:jmuOutlier':
##
##     perm.test

wilcox.exact(Onsite,WCTY, alternative="greater")

##
##  Exact Wilcoxon rank sum test
##
## data:  Onsite and WCTY
## W = 48, p-value = 0.000333
## alternative hypothesis: true mu is greater than 0

pvalue<-wilcox.exact(Onsite,WCTY,alternative="greater")$p.value
pvalue

## [1] 0.0003330003
```

Concern2

```
#Binomial Test
library(BSDA)

## Loading required package: e1071
## Loading required package: lattice
##
## Attaching package: 'BSDA'
##
## The following object is masked from 'package:datasets':
##
##     Orange

SIGN.test(Onsite,md=85.42,alternative="two.sided",conf.level=.95)

##
##  One-sample Sign-Test
##
## data:  Onsite
## s = 4, p-value = 1
## alternative hypothesis: true median is not equal to 85.42
## 95 percent confidence interval:
##  84.09725 86.66325
## sample estimates:
```

```
## median of x
##       85.43
```

```
##                     Conf.Level  L.E.pt  U.E.pt
## Lower Achieved CI     0.9297 84.1200 86.5300
## Interpolated CI       0.9500 84.0973 86.6633
## Upper Achieved CI     0.9922 84.0500 86.9400
```

```
SIGN.test(WCTY,md=80.79,alternative="two.sided",conf.level=.95)
```

```
##
##  One-sample Sign-Test
##
## data:  WCTY
## s = 4, p-value = 0.6875
## alternative hypothesis: true median is not equal to 80.79
## 95 percent confidence interval:
##  79.251 81.633
## sample estimates:
## median of x
##       81.36
```

```
##                     Conf.Level L.E.pt U.E.pt
## Lower Achieved CI     0.7812 79.710 81.480
## Interpolated CI       0.9500 79.251 81.633
## Upper Achieved CI     0.9688 79.200 81.650
```

Concern3

```
State1<-State1[!is.na(State1)]
State2<-State2[!is.na(State2)]
State3<-State3[!is.na(State3)]
State4<-State4[!is.na(State4)]
State5<-State5[!is.na(State5)]
Ourstate<-Ourstate[!is.na(Ourstate)]
Other_States<-c(State1,State2,State3,State4,State5)
#RMD Test
rmd.test(Ourstate,Other_States,alternative=c("two.sided"),all.perms=TRU
E,num.sim=20000)
```

```
## [[1]]
## [1] "p-value was estimated based on 20000 simulations."
##
## $alternative
## [1] "two.sided"
##
## $rmd.hat
## [1] 2.506031
##
## $p.value
## [1] 0.03725
```

```
#WRS
ks.test(Ourstate,Other_States)

## Warning in ks.test(Ourstate, Other_States): cannot compute exact p-v
alue
## with ties

##
##  Two-sample Kolmogorov-Smirnov test
##
## data:  Ourstate and Other_States
## D = 0.25455, p-value = 0.5925
## alternative hypothesis: two-sided

pvalue<-wilcox.exact(Ourstate,Other_States)$p.value
pvalue

## [1] 0.2978926
```

Concern4

```
#Fligner Killeen Test
fligner.test(`State+Test+Data`)

##
##  Fligner-Killeen test of homogeneity of variances
##
## data:  State+Test+Data
## Fligner-Killeen:med chi-squared = 0.30355, df = 5, p-value =
## 0.9976

#Kruskal-Wallis Test
kruskal.test(`State+Test+Data`)

##
##  Kruskal-Wallis rank sum test
##
## data:  State+Test+Data
## Kruskal-Wallis chi-squared = 29.858, df = 5, p-value = 1.573e-05

#Ourstate and State1
a<-choose(6,2)
wilcox.exact(Ourstate,State1)

##
##  Exact Wilcoxon rank sum test
##
## data:  Ourstate and State1
## W = 69, p-value = 0.8801
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(Ourstate,State1)$p.value
pvalue
```

```
## [1] 0.8801119

adjustedpval=a*pvalue
adjustedpval

## [1] 13.20168

#Ourstate and State2
wilcox.exact(Ourstate,State2)

##
##  Exact Wilcoxon rank sum test
##
## data:  Ourstate and State2
## W = 40, p-value = 0.4794
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(Ourstate,State2)$p.value
pvalue

## [1] 0.4794118

adjustedpval=a*pvalue
adjustedpval

## [1] 7.191176

#Ourstate and State3
wilcox.exact(Ourstate,State3)

##
##  Exact Wilcoxon rank sum test
##
## data:  Ourstate and State3
## W = 58, p-value = 0.8977
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(Ourstate,State3)$p.value
pvalue

## [1] 0.8976627

adjustedpval=a*pvalue
adjustedpval

## [1] 13.46494

#Ourstate and State4
wilcox.exact(Ourstate,State4)

##
##  Exact Wilcoxon rank sum test
##
## data:  Ourstate and State4
```

```
## W = 132, p-value = 1.479e-06
## alternative hypothesis: true mu is not equal to 0
```

```
pvalue<-wilcox.exact(Ourstate,State4)$p.value
pvalue
```

```
## [1] 1.479205e-06
```

```
adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 2.218807e-05
```

```
#Ourstate and State5
wilcox.exact(Ourstate,State5)
```

```
##
##  Exact Wilcoxon rank sum test
##
## data:  Ourstate and State5
## W = 64, p-value = 0.847
## alternative hypothesis: true mu is not equal to 0
```

```
pvalue<-wilcox.exact(Ourstate,State5)$p.value
pvalue
```

```
## [1] 0.8469987
```

```
adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 12.70498
```

```
#State1 and State2
wilcox.exact(State1,State2)
```

```
##
##  Exact Wilcoxon rank sum test
##
## data:  State1 and State2
## W = 42, p-value = 0.4221
## alternative hypothesis: true mu is not equal to 0
```

```
pvalue<-wilcox.exact(State1,State2)$p.value
pvalue
```

```
## [1] 0.4221073
```

```
adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 6.33161
```

```
#State1 and State3
wilcox.exact(State1,State3)
```

```
##
##  Exact Wilcoxon rank sum test
##
## data:  State1 and State3
## W = 55, p-value = 0.5254
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(State1,State3)$p.value
pvalue

## [1] 0.5253987

adjustedpval=a*pvalue
adjustedpval

## [1] 7.88098

#State1 and State4
wilcox.exact(State1,State4)

##
##  Exact Wilcoxon rank sum test
##
## data:  State1 and State4
## W = 144, p-value = 7.396e-07
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(State1,State4)$p.value
pvalue

## [1] 7.396023e-07

adjustedpval=a*pvalue
adjustedpval

## [1] 1.109403e-05

#State1 and State5
wilcox.exact(State1,State5)

##
##  Exact Wilcoxon rank sum test
##
## data:  State1 and State5
## W = 68, p-value = 0.9279
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(State1,State5)$p.value
pvalue

## [1] 0.927908

adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 13.91862
```

```r
#State2 and State3
wilcox.exact(State2,State3)
```

```
##
##  Exact Wilcoxon rank sum test
##
## data:  State2 and State3
## W = 52, p-value = 0.882
## alternative hypothesis: true mu is not equal to 0
```

```r
pvalue<-wilcox.exact(State2,State3)$p.value
pvalue
```

```
## [1] 0.8819838
```

```r
adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 13.22976
```

```r
#State2 and State4
wilcox.exact(State2,State4)
```

```
##
##  Exact Wilcoxon rank sum test
##
## data:  State2 and State4
## W = 108, p-value = 6.804e-06
## alternative hypothesis: true mu is not equal to 0
```

```r
pvalue<-wilcox.exact(State2,State4)$p.value
pvalue
```

```
## [1] 6.804341e-06
```

```r
adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 0.0001020651
```

```r
#State2 and State5
wilcox.exact(State2,State=5)
```

```
##
##  Exact Wilcoxon signed rank test
##
## data:  State2
## V = 45, p-value = 0.003906
## alternative hypothesis: true mu is not equal to 0
```

```r
pvalue<-wilcox.exact(State2,State5)$p.value
pvalue
```

```
## [1] 0.3311622

adjustedpval=a*pvalue
adjustedpval

## [1] 4.967433

#State3 and State4
wilcox.exact(State3,State4)

##
##  Exact Wilcoxon rank sum test
##
## data:  State3 and State4
## W = 132, p-value = 1.479e-06
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(State3,State4)$p.value
pvalue

## [1] 1.479205e-06

adjustedpval=a*pvalue
adjustedpval

## [1] 2.218807e-05

#State3 and State5
wilcox.exact(State3,State5)

##
##  Exact Wilcoxon rank sum test
##
## data:  State3 and State5
## W = 69, p-value = 0.6063
## alternative hypothesis: true mu is not equal to 0

pvalue<-wilcox.exact(State3,State5)$p.value
pvalue

## [1] 0.6063178

adjustedpval=a*pvalue
adjustedpval

## [1] 9.094767

#State4 and State5
wilcox.exact(State4,State5)

##
##  Exact Wilcoxon rank sum test
##
## data:  State4 and State5
```

```
## W = 0, p-value = 1.479e-06
## alternative hypothesis: true mu is not equal to 0
```

```
pvalue<-wilcox.exact(State4,State5)$p.value
pvalue
```

```
## [1] 1.479205e-06
```

```
adjustedpval=a*pvalue
adjustedpval
```

```
## [1] 2.218807e-05
```

Concern5

```
#Fligner Killeen Test
fligner.test(`Internal+Research+.+WCtY+Time+Data`)
```

```
##
##  Fligner-Killeen test of homogeneity of variances
##
## data:  Internal+Research+.+WCtY+Time+Data
## Fligner-Killeen:med chi-squared = 0.89113, df = 4, p-value =
## 0.9258
```

```
#Jonckheere-Terpstra Test
library(clinfun)
pieces<-list(Lessthan30min,Approx60min,Approx90min,Approx120min,Approx1
80min)
n<-c(10,10,10,10,10)
grp<-as.ordered(factor(rep(1:length(n),n)))
jonckheere.test(unlist(pieces),grp,alternative="increasing")
```

```
##
##  Jonckheere-Terpstra test
##
## data:
## JT = 440, p-value = 0.8488
## alternative hypothesis: increasing
```