ISSN 2229-5518

Comparision on Different Data Transformation

N.Marudachalam,M.Ramakrishnan
N.Marudachalam,
Reaseach scholar in Sathyabama University,
P.G & Research Department ,Tamilnadu,India.
kiranmarudachalam@gmail.com
M.Ramakrishnan,
Professor and Chairperson,
School of Information Technology,
Madurai Kamaraj University.Tamilnadu,India.
ramakrishod@gmail.com

Abstract— We discussing below squre root, cube root, log transformation, Tukeys lader of power transformation, ANOVA with Tukey transformation and box-Cox transformation. Applications of above said transformation's merits and demerits also pointed out in detailed manner.

Index Terms— Turkeys lader,ANOVA,Box-cox transformation,

1 Introduction

Transforming data is one step in addressing data that do not fit model assumptions, and is also used to coerce different variables to have similar distributions.

Transforming data One approach when remaining fail to meet these conditions is to transform one or more variables to better follow a normal distribution. Often, just the concern variable in a model will need to be transformed. However, in complex models and multiple regressions, it is sometimes helpful to transform both dependent and independent variables that away from this variable greatly from a normal distribution.

There is nothing invalid in transforming variables, but you must be careful about how the results from analyses with transformed variables are reported. For example, we assemble the data for our convenience and again disassembled to this for previous stage.

1.1.Example of transforming skewed data

This example uses hypothetical data of river water turbidity. Turbidity is a measure of how cloudy water is due to suspended material in the water. Water quality parameters such as this are

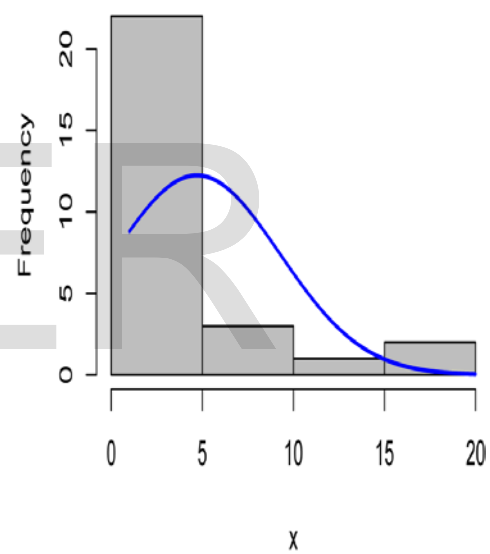
often naturally log-normally distributed: values are often low, but are occasionally high or very high.The first plot is a histogram of the Turbidity values, with a normal curve defined. Looking at the gray bars, this data is skewed strongly to the right (positive skew), and looks more or less log-normal. The gray bars deviate noticeably from the red normal curve.

The second plot is a normal quintile plot (normal Q–Q plot). If the data were normally distributed, the points would follow the red line fairly closely.

```
Turbidity = c(1.0, 1.2, 1.1, 1.1, 2.4, 2.2, 2.6, 4.1, 5.0, 10.0, 4.0, 4.1, 4.2, 4.1, 5.1, 4.5, 5.0, 15.2, 10.0, 20.0, 1.1, 1.1, 1.2, 1.6, 2.2, 3.0, 4.0, 10.5)
```

```
library(rcompanion)

plotNormalHistogram(Turbidity)
```

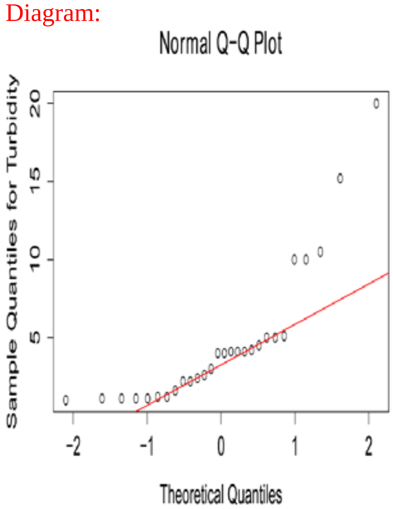
Diagram:




```
qqnorm(Turbidity,
    ylab="Sample Quantiles for Turbidity")

qqline(Turbidity,
    col="red")
```

ISSN 2229-5518

Diagram:

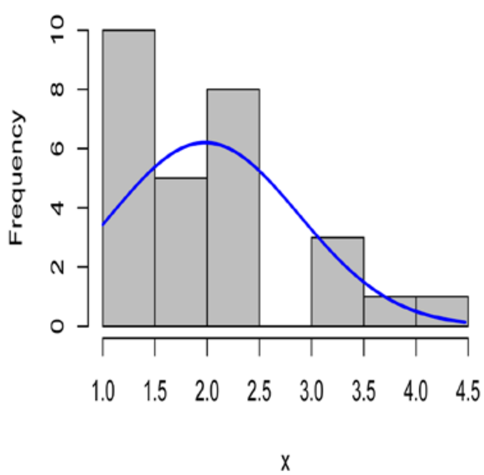


Square root transformation

Since the data is right-skewed, we will apply common transformations for right-skewed data: square root, cube root, and log. The square root transformation improves the distribution of the data somewhat.

```
T_sqrt = sqrt(Turbidity)

library(rcompanion)

plotNormalHistogram(T_sqrt)
```

Diagram:



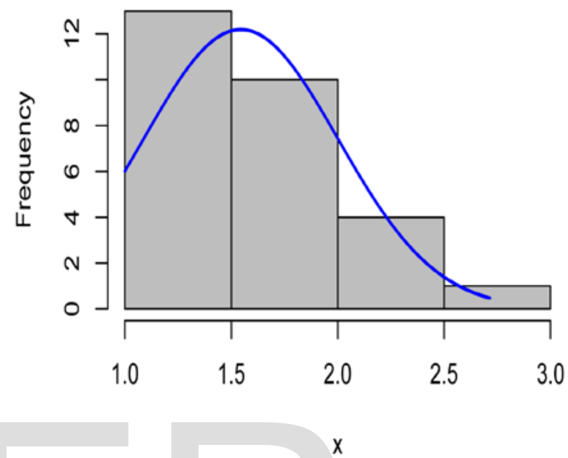
2. TYPES OF TRANSFORMATION

2.1 CUBE ROOT TRANSFORMATION

The cube root transformation is stronger than the square root transformation.

```
T_cub = sign(Turbidity) * abs(Turbidity)^(1/3)   # Avoid complex numbers
                                                  # for some cube roots

library(rcompanion)

plotNormalHistogram(T_cub)
```

Diagram:



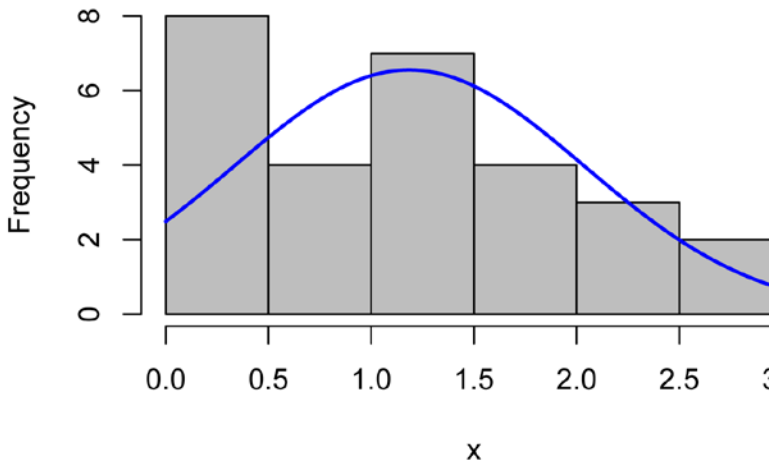
2.2 LOG TRANSFORMATION

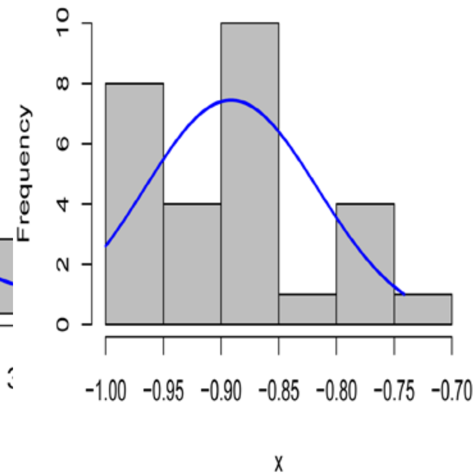
The log transformation is a relatively strong transformation. Because certain measurements in nature are naturally log-normal, it is often a successful transformation for certain data sets. While the transformed data here does not follow a normal distribution very well, it is probably about as close as we can get with these particular data.

```
T_log = log(Turbidity)

library(rcompanion)

plotNormalHistogram(T_log)
```

Diagram:

ISSN 2229-5518





2.3 TUKEY'S LADDER OF POWERS TRANSFORMATION

The approach of Tukey's Ladder of Powers uses a power transformation on a data set. For example, raising data to a 0.5 power is equivalent to applying a square root transformation; raising data to a 0.33 power is equivalent to applying a cube root transformation.

Here, we use the transformTukey function, which performs iterative Shapiro–Wilk tests, and finds the lambdavalue that maximizes the W statistic from those tests. In essence, this finds the power transformation that makes the data fit the normal distribution as closely as possible with this type of transformation.

Left skewed values should be adjusted with (constant – value), to convert the skew to right skewed, and perhaps making all values positive. In some cases of right skewed data, it may be beneficial to add a constant to make all data values positive before transformation. For large values, it may be helpful to scale values to a more reasonable range.

In this example, the resultant lambda of –0.1 is slightly stronger than a log transformation, since a log transformation corresponds to a lambda of 0.

```
library(rcompanion)

T_tuk =
    transformTukey(Turbidity,
    plotit=FALSE)

    lambda      W Shapiro.p.value
397   -0.1 0.935         0.08248

if (lambda >  0){TRANS = x ^ lambda}
if (lambda == 0){TRANS = log(x)}
if (lambda <  0){TRANS = -1 * x ^ lambda}


library(rcompanion)

plotNormalHistogram(T_tuk)
```

Example of Tukey-transformed data in ANOVA

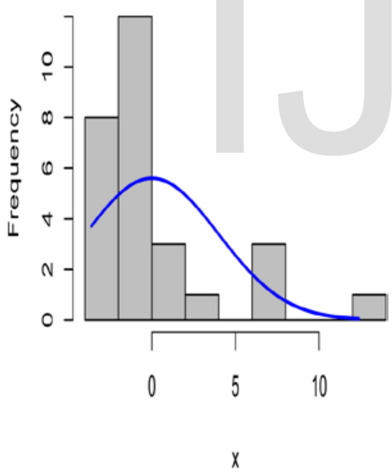
For an example of how transforming data can improve the distribution of the residuals of a parametric analysis, we will use the same turbidity values, but assign them to three different locations. Transforming the turbidity values to be more normally distributed, both improves the distribution of the residuals of the analysis and makes a more powerful test, lowering the p-value.

```
TABLE:
Input =("
Location Turbidity
a 1.0
a 1.2
a 1.1
a 1.1
a 2.4
a 2.2
a 2.6
a 4.1
a 5.0
a 10.0
b 4.0
b 4.1
b 4.2
b 4.1
b 5.1
b 4.5
b 5.0
b 15.2
b 10.0
b 20.0
c 1.1
c 1.1
c 1.2
c 1.6
c 2.2
c 3.0
c 4.0
c 10.5
")

Data = read.table(textConnection(Input),header=TRUE)
```

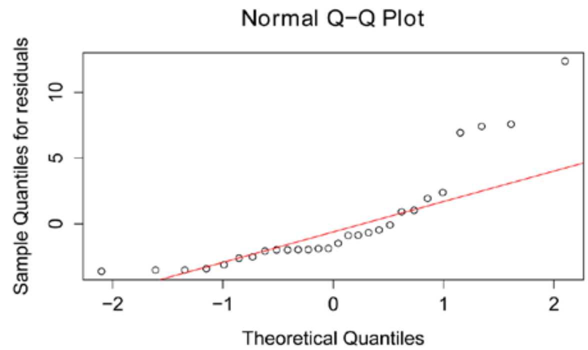
Attempt ANOVA on un-transformed data

Here, even though the analysis of variance results in a significant p-value (p = 0.03), the residuals deviate from the normal distribution enough to make the analysis invalid.

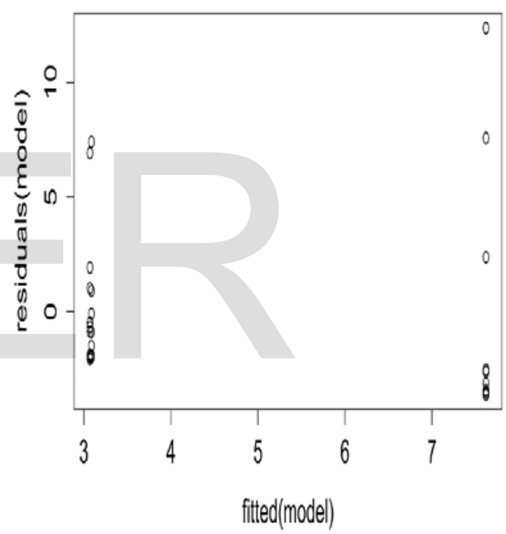
```
boxplot(Turbidity ~ Location,
        data = Data,
        ylab="Turbidity",
        xlab="Location")

model = lm(Turbidity ~ Location,
           data=Data)

library(car)

Anova(model, type="II")

Anova Table (Type II tests)

          Sum Sq Df F value  Pr(>F)
Location  132.63  2 3.8651 0.03447 *
Residuals 428.95 25

x = (residuals(model))

library(rcompanion)

plotNormalHistogram(x)
```




```
qqnorm(residuals(model),
       ylab="Sample Quantiles for residuals")
qqline(residuals(model),
     col="red")
```




```
plot(fitted(model),
     residuals(model))
```



3.TRANSFORM DATA

```
library(rcompanion)

Data$Turbidity_tuk =
               transformTukey(Data$Turbidity,
       plotit=FALSE)

    lambda      W Shapiro.p.value
397   -0.1  0.935         0.08248

if (lambda >  0){TRANS = x ^ lambda}
if (lambda == 0){TRANS = log(x)}
if (lambda <  0){TRANS = -1 * x ^ lambda}
```

3.1. ANOVA with Tukey-transformed data

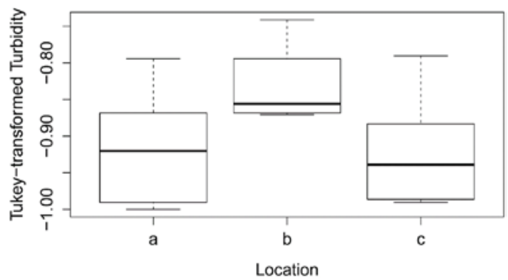
After transformation, the residuals from the ANOVA are closer to a normal distribution—although not perfectly—, making the F-test more appropriate. In addition, the test is more powerful as indicated by the lower p-value (p = 0.005) than with the untransformed data. The plot of the residuals vs. the fitted values shows that the residuals

ISSN 2229-5518

are about as multiple as they were with the untransformed data.

syntax:

```
boxplot(Turbidity_tuk ~ Location,
        data = Data,
        ylab="Tukey-transformed Turbidity",
        xlab="Location")
```

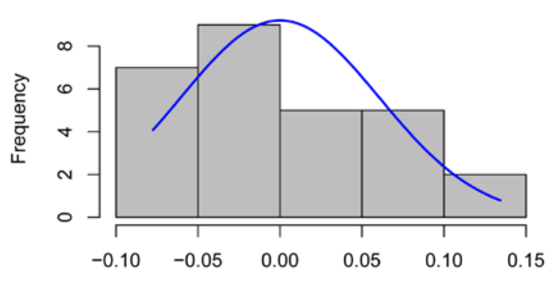



```
model = lm(Turbidity_tuk ~ Location,
           data=Data)

library(car)

Anova(model, type="II")
```

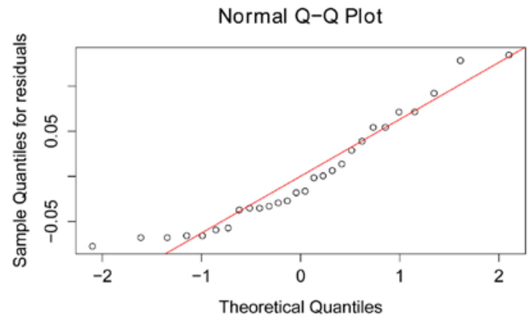
Anova Table (Type II tests)

	Sum Sq	Df	F value	Pr(>F)	
Location	0.052506	2	6.6018	0.004988	**
Residuals	0.099416	25			

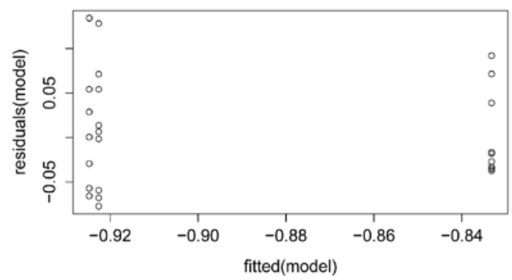
```
x = residuals(model)

library(rcompanion)

plotNormalHistogram(x)
```




```
qqnorm(residuals(model),
       ylab="Sample Quantiles for residuals")
qqline(residuals(model),
       col="red")
```



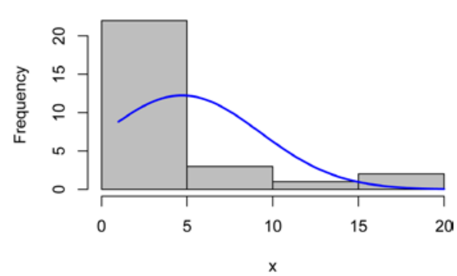

```
plot(fitted(model),
     residuals(model))
```



3.2 BOX–COX TRANSFORMATION

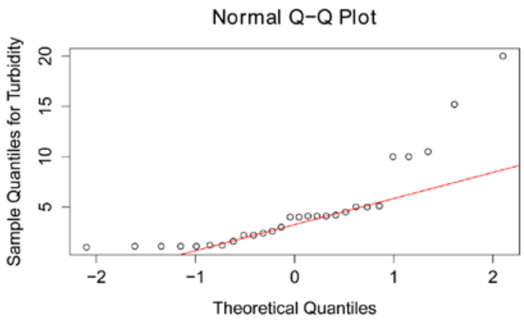
The Box–Cox procedure is similar in concept to the Tukey Ladder of Power procedure described above. However, instead of transforming a single variable, it maximizes a log-chance statistic for a linear model (such as ANOVA or linear regression). It will also work on a single variable using a formula of x ~ 1.The Box–Cox procedure is available with the boxcox function in the MASS package. However, a few steps are needed to extract the lambda value and transform the data set.
This example uses the same turbidity data.

```
Turbidity = c(1.0, 1.2, 1.1, 1.1, 2.4, 2.2, 2.6, 4.1, 5.0, 10.0, 4.0,
4.1, 4.2, 4.1, 5.1, 4.5, 5.0, 15.2, 10.0, 20.0, 1.1, 1.1, 1.2, 1.6,
2.2, 3.0, 4.0, 10.5)

library(rcompanion)

plotNormalHistogram(Turbidity)
```



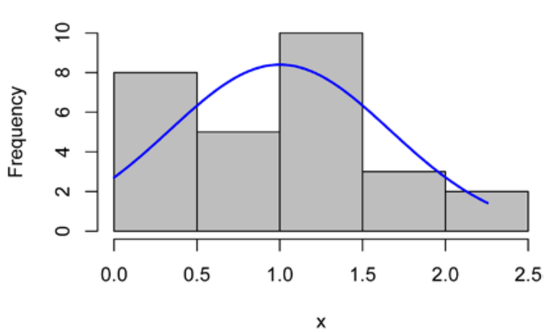

```
qqnorm(Turbidity,
       ylab="Sample Quantiles for Turbidity")
```

```
qqline(Turbidity,
    col="red")
```



3.3 BOX–COX TRANSFORMATION FOR A SINGLE VAR IABLE

```
library(MASS)

Box = boxcox(Turbidity ~ 1,          # Transform Turbidity as a single vector
      lambda = seq(-6,6,0.1)    # Try values -6 to 6 by 0.1
)

Cox = data.frame(Box$x, Box$y)        # Create a data frame with the results

Cox2 = Cox[with(Cox, order(-Cox$Box.y)),] # Order the new data frame by decreasing y

Cox2[1,]                      # Display the lambda with the greatest
                              # log likelihood

        Box.x        Box.y
59      -0.2         -41.35829

lambda = Cox2[1, "Box.x"]          # Extract that lambda

T_box = (Turbidity ^ lambda - 1)/lambda   # Transform the original data

library(rcompanion)

plotNormalHistogram(T_box)
```

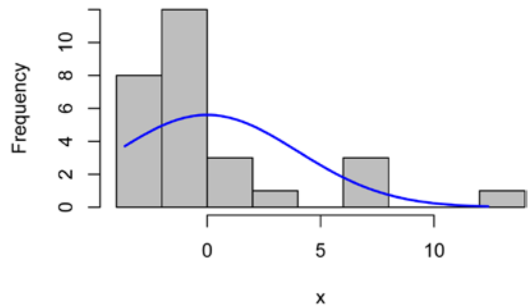


Example of Box–Cox transformation for ANOVA model

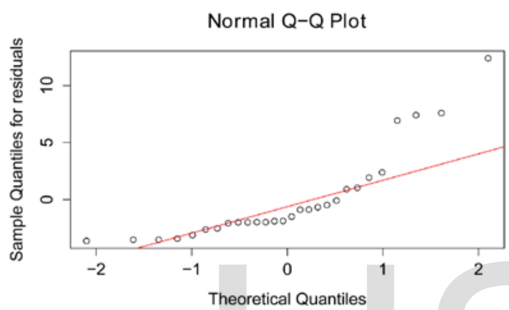
```
Input =("
Location     Turbidity
 a    1.0
 a    1.2
 a    1.1
 a    1.1
 a    2.4
 a    2.2
 a    2.6
 a    4.1
 a    5.0
 a    10.0
 b    4.0
 b    4.1
 b    4.2
 b    4.1
 b    5.1
 b    4.5
 b    5.0
 b    15.2
 b    10.0
 b    20.0
 c    1.1
 c    1.1
 c    1.2
 c    1.6
 c    2.2
 c    3.0
 c    4.0
 c    10.5
")

Data = read.table(textConnection(Input),header=TRUE)
```

3.4 ATTEMPT ANOVA ON UN-TRANSFORMED DATA

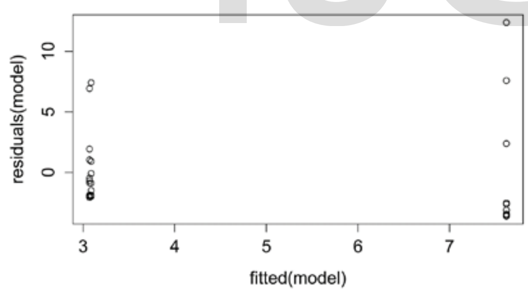
```
model = lm(Turbidity ~ Location,
           data=Data)

library(car)

Anova(model, type="II")

Anova Table (Type II tests)

           Sum Sq  Df   F value   Pr(>F)
Location   132.63   2   3.8651   0.03447  *
Residuals  428.95  25

x = residuals(model)

library(rcompanion)

plotNormalHistogram(x)
```



qqnorm(residuals(model),
ylab="Sample Quantiles for residuals")
qqline(residuals(model),
col="red")



plot(fitted(model),
residuals(model))



Transform data

library(MASS)

Box = boxcox(Turbidity ~ Location,
data = Data,
lambda = seq(-6,6,0.1)
)

Cox = data.frame(Boxx, Boxy)

Cox2 = Cox[with(Cox, order(-Cox$Box.y)),]

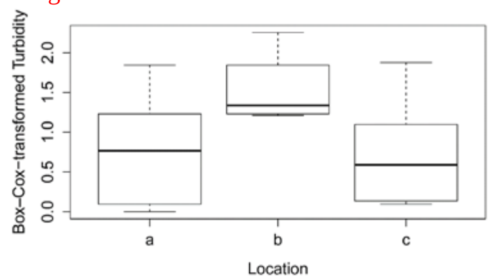
Cox2[1,]

lambda = Cox2[1, "Box.x"]

Data$Turbidity_box = (Data$Turbidity ^ lambda - 1)/lambda

boxplot(Turbidity_box ~ Location,
data = Data,
ylab="Box–Cox-transformed Turbidity",
xlab="Location")

Diagram:



Perform ANOVA and check residuals

model = lm(Turbidity_box ~ Location, data=Data)

library(car)

Anova(model, type="II")

Anova Table (Type II tests)

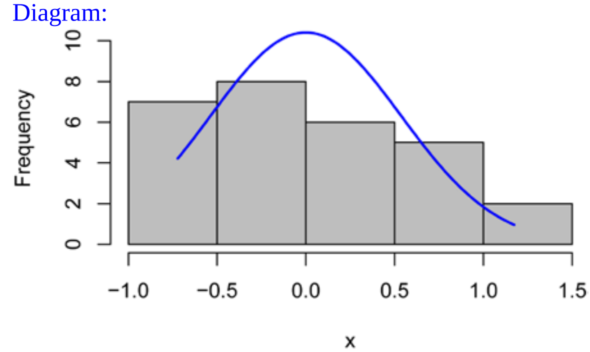
	Sum Sq	Df	F value	Pr(>F)	
Location	0.16657	2	6.6929	0.0047	**
Residuals	0.31110	25			

xresiduals(model)

library(rcompanion)

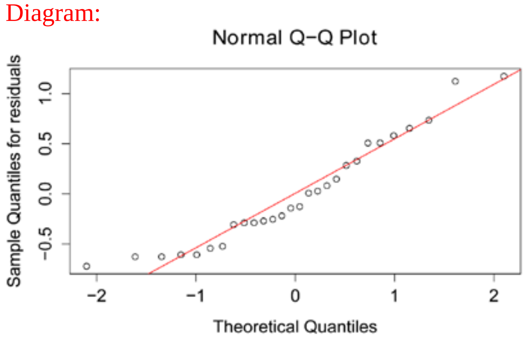
plotNormalHistogram(x)

Diagram:



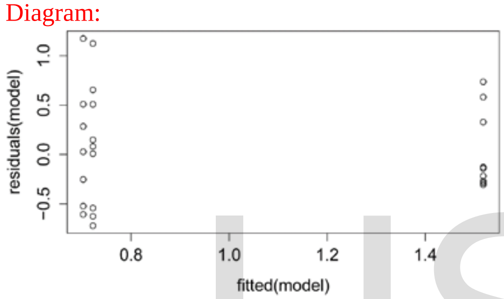
```
qqnorm(residuals(model),
ylab="Sample Quantiles for residuals")
qqline(residuals(model),
col="red")
```

Diagram:




```
plot(fitted(model),
   residuals(model))
```

Diagram:



4. CONCLUSIONS

Both the Tukey's Ladder of Powers principle as implemented by the transformTukey function and the Box–Cox procedure were successful at transforming a single variable to follow a more normal distribution. They were also both successful at improving the distribution of residuals from a simple ANOVA.

The Box–Cox procedure has the advantage of dealing with the dependent variable of a linear model, while the transformTukey function works only for a single variable without considering other variables. Because of this, the Box–Cox procedure may be advantageous when a relatively simple model is considered. In cases where there are complex models or multiple regression, it may be helpful to transform both dependent and independent variables independently.

5.REFERENCES

[1] Arindam Paul, Varuni Ganesan, Jagat Sesh Challa, Yashvardhan Sharma" A Novel Approach for Data Cleaning by Selecting the Optimal Data to Fill the Missing Values for Maintaining Reliable Data Warehouse" https://www.researchgate.net/publication/301543768 Mar-2012

[2] Sanjay Krishnan, Jiannan Wang, Eugene Wu y, Michael J. Franklin, Ken Goldberg" ActiveClean: Interactive Data Cleaning While Learning
Convex Loss Models" Columbia University,Jan-2016

[3] Dollars for docs. http://projects.propublica.org/open-payments/.

[4] For big-data scientists, 'janitor work' is key hurdle to insights. http://www.nytimes.com/2014/08/18/technology/for-big-datascientists- hurdle-to-insights-is-janitor-work.html.

[5] A pharma payment a day keeps docs' finances okay.https://www.propublica.org/article/ a-pharma-payment-a-day-keeps-docs-finances ok.

[6] A. Alexandrov, R. Bergmann, S. Ewen, J. Freytag, F. Hueske, A. Heise, O. Kao, M. Leich, U. Leser, V. Markl, F. Naumann,