[Year]

# Advanced Statistics on Hair Products

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# 1.Project Objective

The objective of this project is to study the dataset Factor-hair. This dataset contains the quantitative aspects of a hair product selling firm . there are various independent factors on which the customer's satisfaction depends. We are supposed to scrutinize this dataset and see how these factors are associated with each other and how they affect the customer satisfaction aspect and to what extent.

By finding the correlation between each variable and drawing out regression analysis, we will coagulate the similar factors into some generalized factors which share commonalities.

Our concepts of advanced statistics will thus, be put to practicality.

# 2.EXPLORATORY DATA ANALYSIS

2.1 Basic Data Summary

RCODE:

```
hair= read.csv("Factor-Hair-Revised.csv")
str(hair)
```

Output:

```
'data.frame':	100 obs. of  13 variables:
 $ ID          : int  1 2 3 4 5 6 7 8 9 10 ...
 $ ProdQual    : num  8.5 8.2 9.2 6.4 9 6.5 6.9 6.2 5.8 6.4 ...
 $ Ecom        : num  3.9 2.7 3.4 3.3 3.4 2.8 3.7 3.3 3.6 4.5 ...
 $ TechSup     : num  2.5 5.1 5.6 7 5.2 3.1 5 3.9 5.1 5.1 ...
 $ CompRes     : num  5.9 7.2 5.6 3.7 4.6 4.1 2.6 4.8 6.7 6.1 ...
 $ Advertising : num  4.8 3.4 5.4 4.7 2.2 4 2.1 4.6 3.7 4.7 ...
 $ ProdLine    : num  4.9 7.9 7.4 4.7 6 4.3 2.3 3.6 5.9 5.7 ...
 $ SalesFImage : num  6 3.1 5.8 4.5 4.5 3.7 5.4 5.1 5.8 5.7 ...
 $ ComPricing  : num  6.8 5.3 4.5 8.8 6.8 8.5 8.9 6.9 9.3 8.4 ...
 $ WartyClaim  : num  4.7 5.5 6.2 7 6.1 5.1 4.8 5.4 5.9 5.4 ...
 $ OrdBilling  : num  5 3.9 5.4 4.3 4.5 3.6 2.1 4.3 4.4 4.1 ...
 $ DelSpeed    : num  3.7 4.9 4.5 3 3.5 3.3 2 3.7 4.6 4.4 ...
 $ Satisfaction: num  8.2 5.7 8.9 4.8 7.1 4.7 5.7 6.3 7 5.5 ...
```

```
attach(hair)
names(hair)
dim(hair)
stat.desc(hair)
head(hair,n=10)
tail(hair,n=10)
```

Names- will show all the column names

```
> names(hair)
 [1] "ID"           "ProdQual"     "Ecom"         "TechSup"      "CompRes"      "Advertising
"  "ProdLine"
 [8] "SalesFImage"  "ComPricing"   "WartyClaim"   "OrdBilling"   "DelSpeed"     "Satisfactio
n"
```

Dim- will tell the dimension of our dataset

```
> dim(hair)
[1] 100  13
```

Stat.desc – will show the various statistical aspects of the dataset

```
stat.desc(hair)
                       ID    ProdQual          Ecom     TechSup     CompRes Advertising     Pro
dLine SalesFImage
nbr.val       100.000000 100.0000000 100.00000000 100.0000000 100.0000000 100.0000000 100.00
00000 100.0000000
nbr.null        0.000000   0.0000000   0.00000000   0.0000000   0.0000000   0.0000000   0.00
00000   0.0000000
nbr.na          0.000000   0.0000000   0.00000000   0.0000000   0.0000000   0.0000000   0.00
00000   0.0000000
min             1.000000   5.0000000   2.20000000   1.3000000   2.6000000   1.9000000   2.30
00000   2.9000000
max           100.000000  10.0000000   5.70000000   8.5000000   7.8000000   6.5000000   8.40
00000   8.2000000
range          99.000000   5.0000000   3.50000000   7.2000000   5.2000000   4.6000000   6.10
00000   5.3000000
sum          5050.000000 781.0000000 367.20000000 536.5000000 544.2000000 401.0000000 580.50
00000 512.3000000
median         50.500000   8.0000000   3.60000000   5.4000000   5.4500000   4.0000000   5.75
00000   4.9000000
mean           50.500000   7.8100000   3.67200000   5.3650000   5.4420000   4.0100000   5.80
50000   5.1230000
SE.mean         2.901149   0.1396279   0.07005164   0.1530457   0.1208403   0.1126943   0.13
15285   0.1072320
CI.mean.0.95    5.756509   0.2770521   0.13899765   0.3036758   0.2397734   0.2236099   0.26
09811   0.2127715
var           841.666667   1.9495960   0.49072323   2.3422980   1.4602384   1.2700000   1.72
99747   1.1498697
std.dev        29.011492   1.3962793   0.70051640   1.5304568   1.2084032   1.1269428   1.31
52850   1.0723198
coef.var        0.574485   0.1787810   0.19077244   0.2852669   0.2220513   0.2810331   0.22
65780   0.2093148
```

Head- will fetch the first 10 records of the dataset

```
> head(hair,n=10)
   ID ProdQual Ecom TechSup CompRes Advertising ProdLine SalesFImage ComPricing WartyClaim O
rdBilling DelSpeed
1   1      8.5  3.9     2.5     5.9         4.8      4.9         6.0        6.8        4.7
5.0       3.7
2   2      8.2  2.7     5.1     7.2         3.4      7.9         3.1        5.3        5.5
3.9       4.9
3   3      9.2  3.4     5.6     5.6         5.4      7.4         5.8        4.5        6.2
5.4       4.5
4   4      6.4  3.3     7.0     3.7         4.7      4.7         4.5        8.8        7.0
4.3       3.0
5   5      9.0  3.4     5.2     4.6         2.2      6.0         4.5        6.8        6.1
4.5       3.5
6   6      6.5  2.8     3.1     4.1         4.0      4.3         3.7        8.5        5.1
3.6       3.3
7   7      6.9  3.7     5.0     2.6         2.1      2.3         5.4        8.9        4.8
2.1       2.0
8   8      6.2  3.3     3.9     4.8         4.6      3.6         5.1        6.9        5.4
4.3       3.7
9   9      5.8  3.6     5.1     6.7         3.7      5.9         5.8        9.3        5.9
4.4       4.6
10 10      6.4  4.5     5.1     6.1         4.7      5.7         5.7        8.4        5.4
4.1       4.4
   Satisfaction
1           8.2
```

```
2             5.7
3             8.9
4             4.8
5             7.1
6             4.7
7             5.7
8             6.3
9             7.0
10            5.5
```

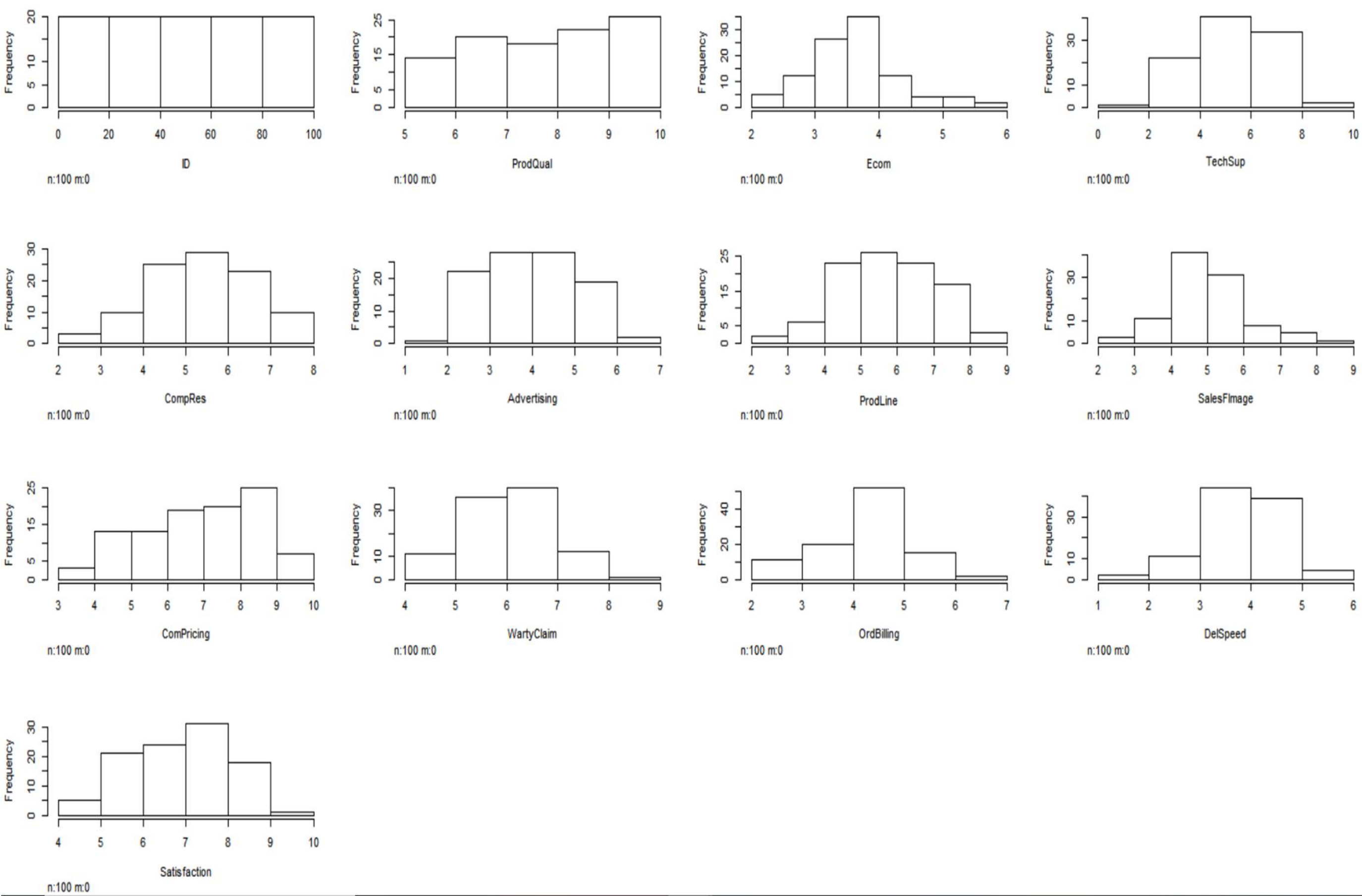
Tails- will fetch the last 10 records of the dataset

```
> tail(hair,n=10)
     ID ProdQual Ecom TechSup CompRes Advertising ProdLine SalesFImage ComPricing WartyClaim
OrdBilling DelSpeed
91   91       9.1  3.7     7.0     4.1         4.4      6.3         5.4        7.3        7.5
4.4        3.3
92   92       7.1  4.2     4.1     2.6         2.1      3.3         4.5        9.9        5.5
2.0        2.4
93   93       9.2  3.9     4.6     5.3         4.2      8.4         4.8        7.1        6.2
4.4        4.2
94   94       9.3  3.5     5.4     7.8         4.6      7.5         5.9        4.6        6.4
4.8        4.6
95   95       9.3  3.8     4.0     4.6         4.7      6.4         5.5        7.4        5.3
3.6        3.4
96   96       8.6  4.8     5.6     5.3         2.3      6.0         5.7        6.7        5.8
4.9        3.6
97   97       7.4  3.4     2.6     5.0         4.1      4.4         4.8        7.2        4.5
4.2        3.7
98   98       8.7  3.2     3.3     3.2         3.1      6.1         2.9        5.6        5.0
3.1        2.5
99   99       7.8  4.9     5.8     5.3         5.2      5.3         7.1        7.9        6.0
4.3        3.9
100 100       7.9  3.0     4.4     5.1         5.9      4.2         4.8        9.7        5.7
3.4        3.5
    Satisfaction
91           7.4
92           4.8
93           7.6
94           8.9
95           7.7
96           7.3
97           6.3
98           5.4
99           6.4
100          6.4
```

2.2UNIVARIATE DATA ANALYSIS

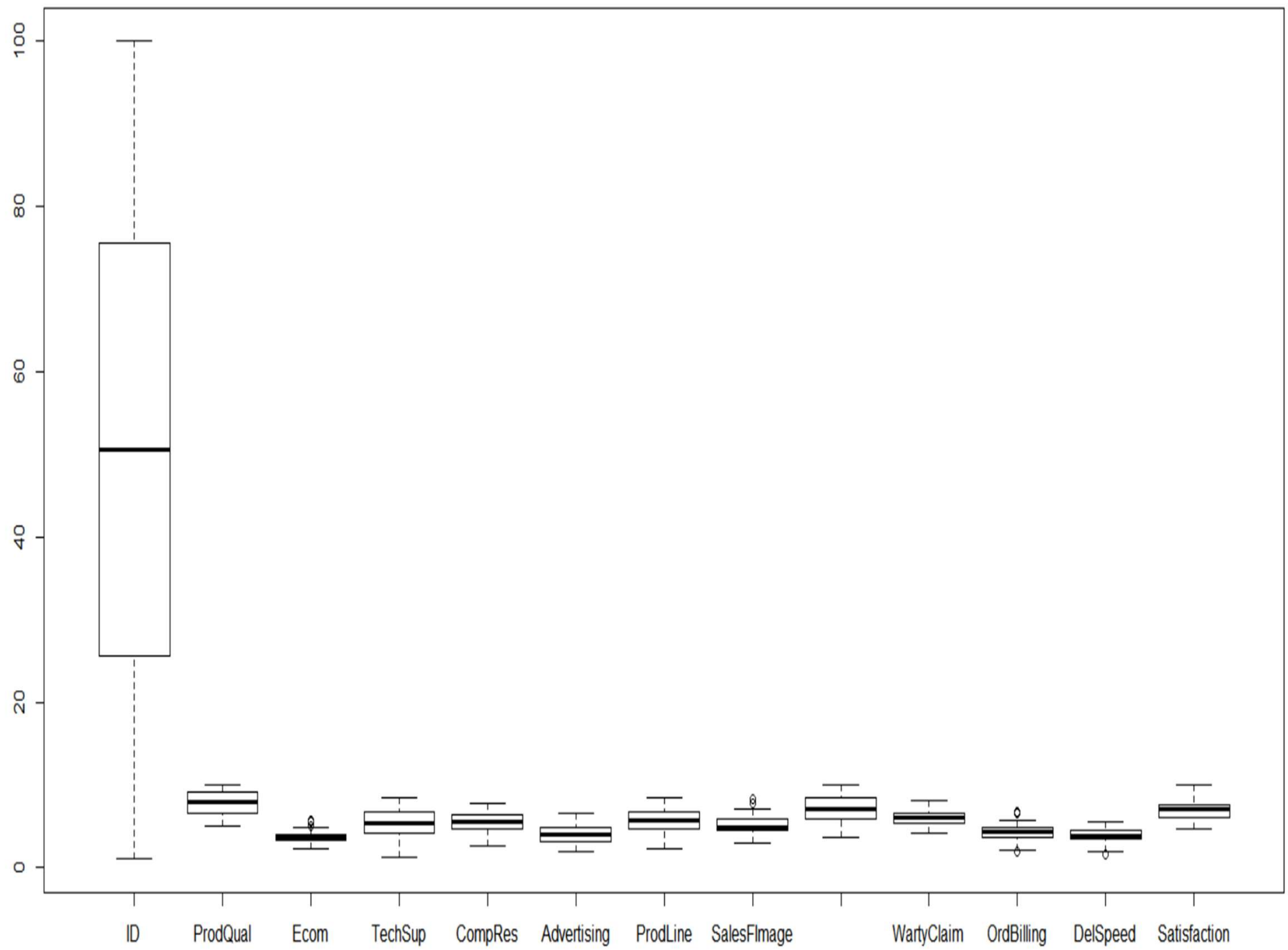
## hist(hair)

This function will give the histogram of all the variables individually.




## boxplot(hair)

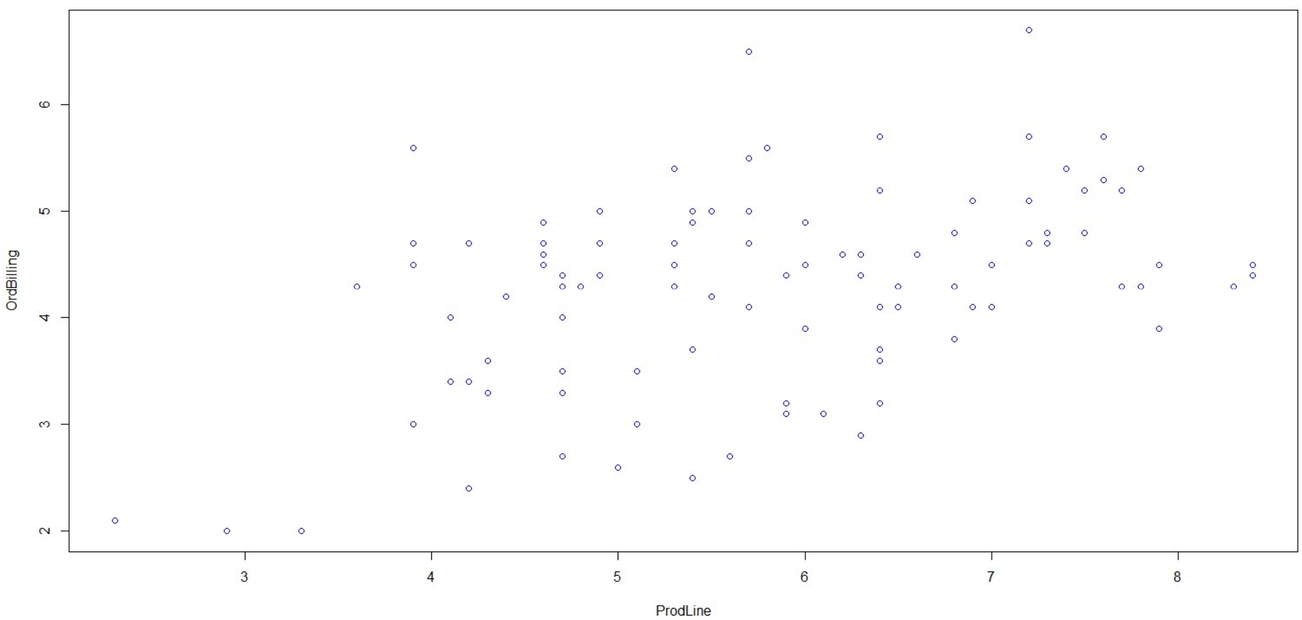
This function will make the boxplots of all the variables individually on a single chart.



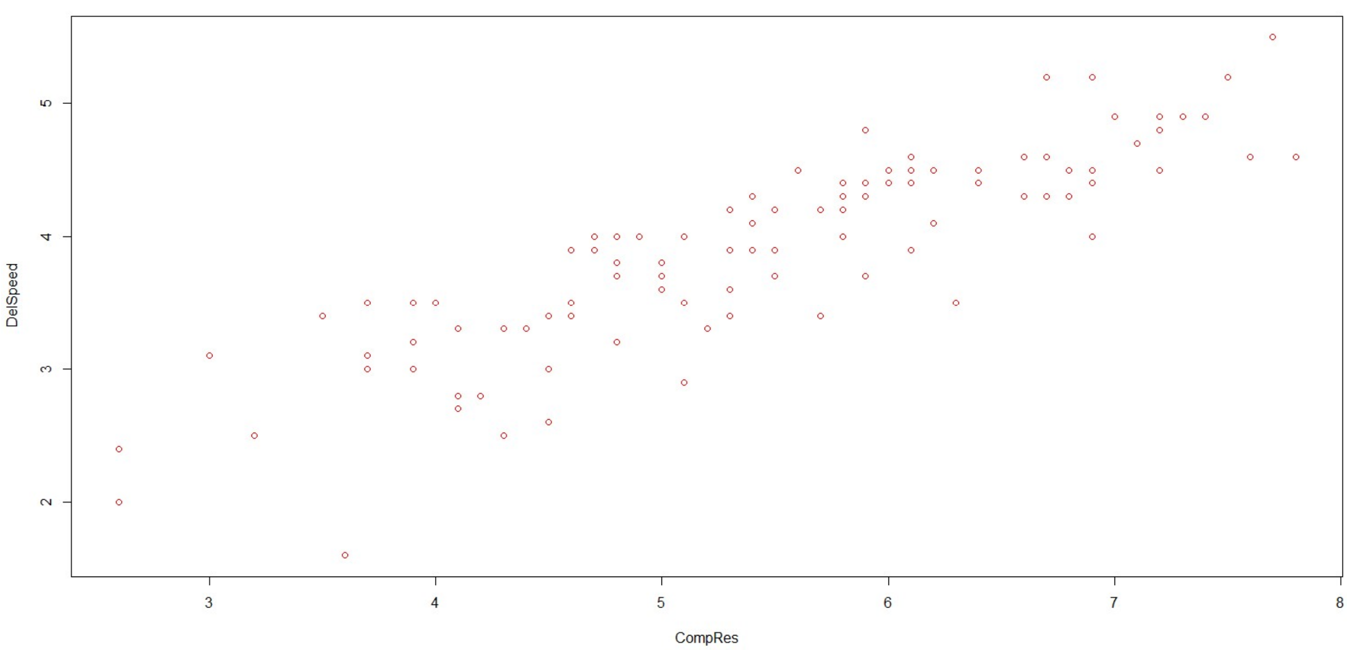

2.3BIVARIATE ANALYSIS

By default these plots will be scatterplots(for bivariate numerical variables).

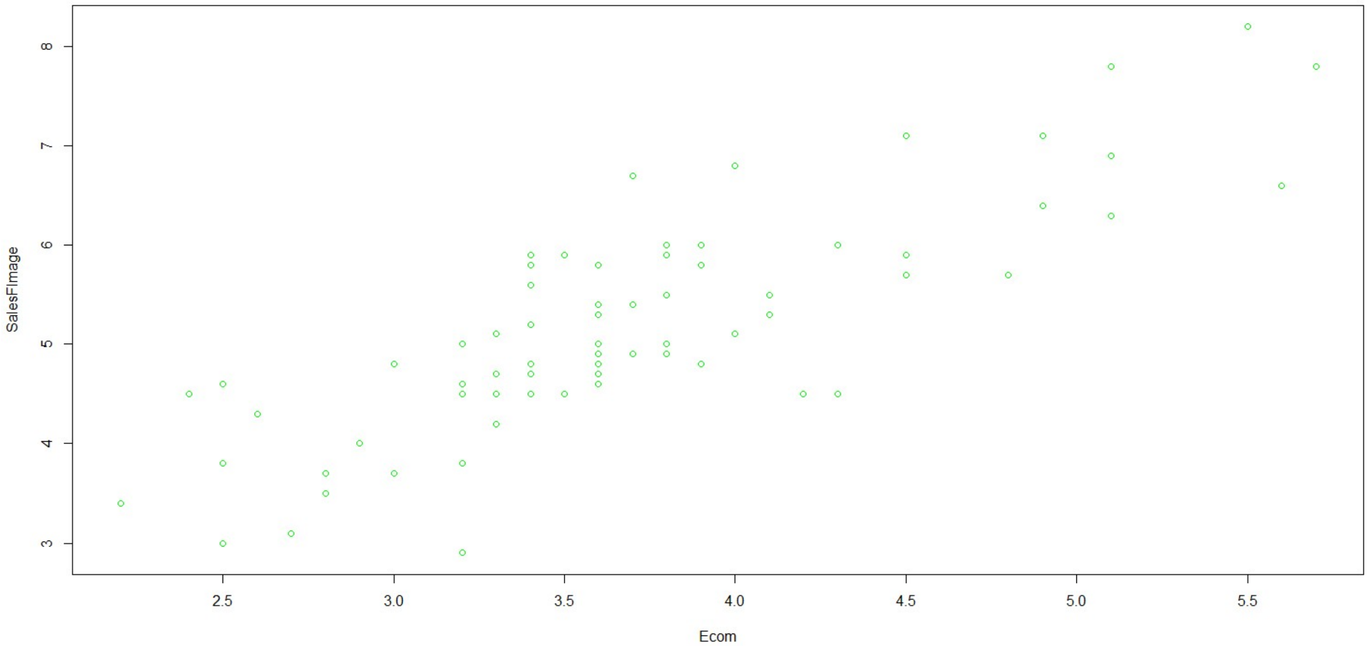
plot(ProdLine,OrdBilling)



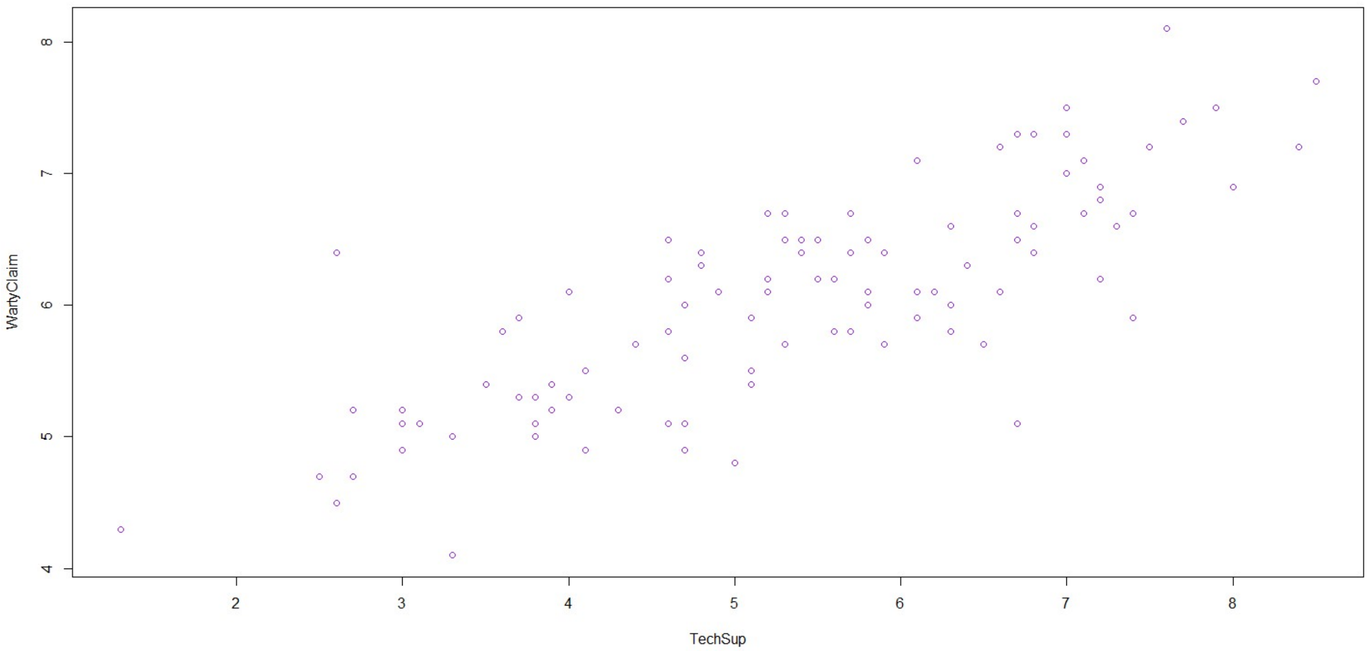

plot(CompRes,DelSpeed)



plot(Ecom,SalesFImage)




plot(TechSup,WartyClaim)



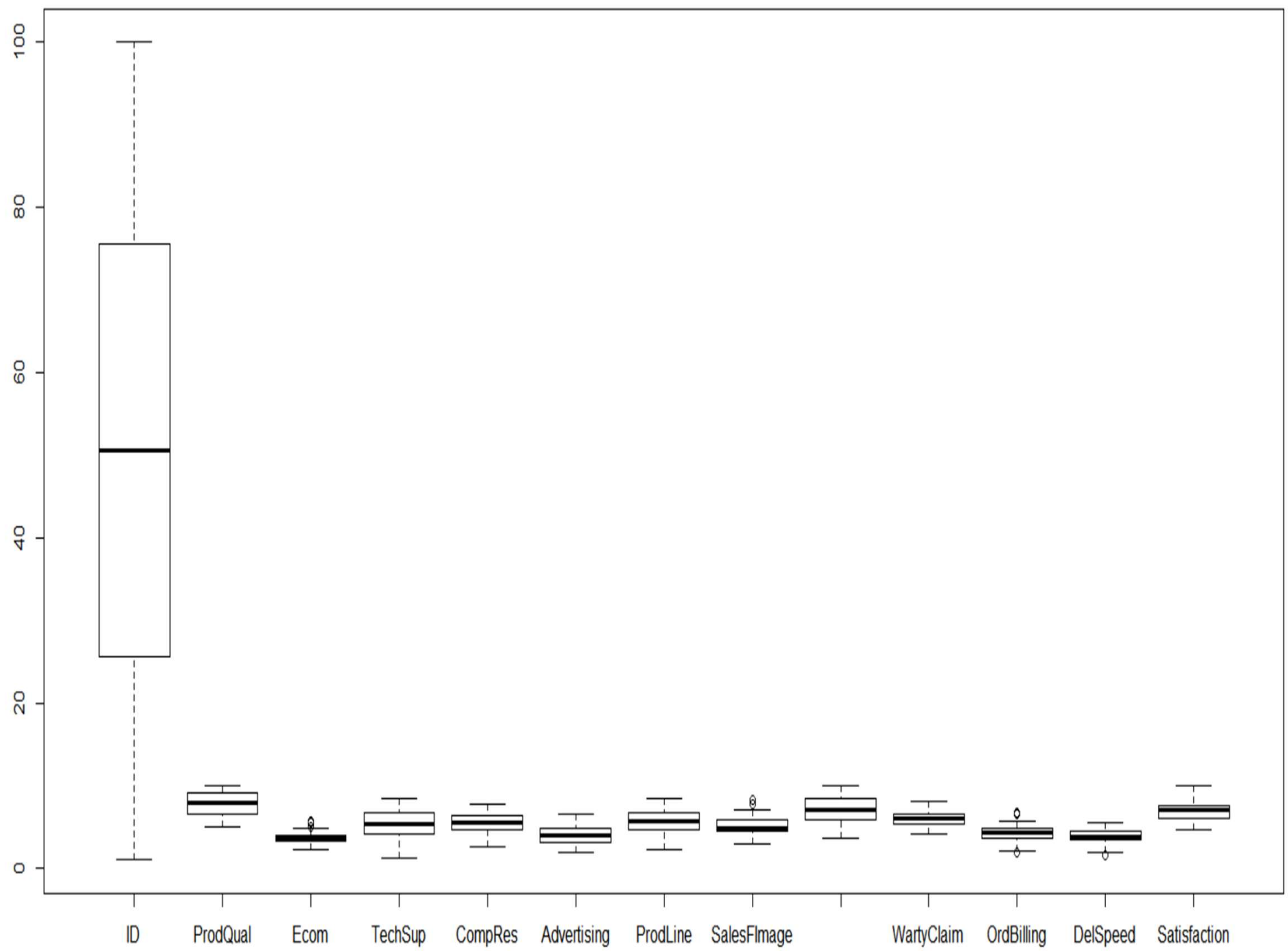
WartyClaim
TechSup

# <u>3.CHECKING FOR THE INTEGRITY OF THE DATA</u>

3.1 Outlier Detection using Boxplot

Boxplot depicts that there are outliers in our data.

These plots are being made after seeing the correlation matrix and thus, figuring out which variables are to an extent related to each other and then we can visualize their relationship.



3.2 Missing Value Detection

null=is.na(hair)

summary(null)

There are no missing values

```
> summary(null)# Shows there are no null values
      ID           ProdQual          Ecom           TechSup         CompRes        Advertising  
ProdLine      
 Mode :logical   Mode :logical   Mode :logical   Mode :logical   Mode :logical   Mode :logic
al   Mode :logical  
 FALSE:100       FALSE:100       FALSE:100       FALSE:100       FALSE:100       FALSE:100      
FALSE:100      
 SalesFImage     ComPricing      WartyClaim      OrdBilling       DelSpeed       Satisfactio
n  
 Mode :logical   Mode :logical   Mode :logical   Mode :logical   Mode :logical   Mode :logic
al  
 FALSE:100       FALSE:100       FALSE:100       FALSE:100       FALSE:100       FALSE:100      
```

3.3 Summary of the dataset

All the variables are numeric except for the ID which is a number.

```
summary(hair)
       ID            ProdQual          Ecom           TechSup         CompRes        Advertis
ing       ProdLine    
 Min.   :  1.00   Min.   : 5.000   Min.   :2.200   Min.   :1.300   Min.   :2.600   Min.   :1
.900   Min.   :2.300  
 1st Qu.: 25.75   1st Qu.: 6.575   1st Qu.:3.275   1st Qu.:4.250   1st Qu.:4.600   1st Qu.:3
.175   1st Qu.:4.700  
 Median : 50.50   Median : 8.000   Median :3.600   Median :5.400   Median :5.450   Median :4
.000   Median :5.750  
 Mean   : 50.50   Mean   : 7.810   Mean   :3.672   Mean   :5.365   Mean   :5.442   Mean   :4
.010   Mean   :5.805  
 3rd Qu.: 75.25   3rd Qu.: 9.100   3rd Qu.:3.925   3rd Qu.:6.625   3rd Qu.:6.325   3rd Qu.:4
.800   3rd Qu.:6.800  
 Max.   :100.00   Max.   :10.000   Max.   :5.700   Max.   :8.500   Max.   :7.800   Max.   :6
.500   Max.   :8.400  
  SalesFImage      ComPricing      WartyClaim      OrdBilling       DelSpeed      Satisfacti
on    
 Min.   :2.900   Min.   :3.700   Min.   :4.100   Min.   :2.000   Min.   :1.600   Min.   :4.7
00  
 1st Qu.:4.500   1st Qu.:5.875   1st Qu.:5.400   1st Qu.:3.700   1st Qu.:3.400   1st Qu.:6.0
00  
 Median :4.900   Median :7.100   Median :6.100   Median :4.400   Median :3.900   Median :7.0
50  
 Mean   :5.123   Mean   :6.974   Mean   :6.043   Mean   :4.278   Mean   :3.886   Mean   :6.9
18  
 3rd Qu.:5.800   3rd Qu.:8.400   3rd Qu.:6.600   3rd Qu.:4.800   3rd Qu.:4.425   3rd Qu.:7.6
25  
 Max.   :8.200   Max.   :9.900   Max.   :8.100   Max.   :6.700   Max.   :5.500   Max.   :9.9
00  
```

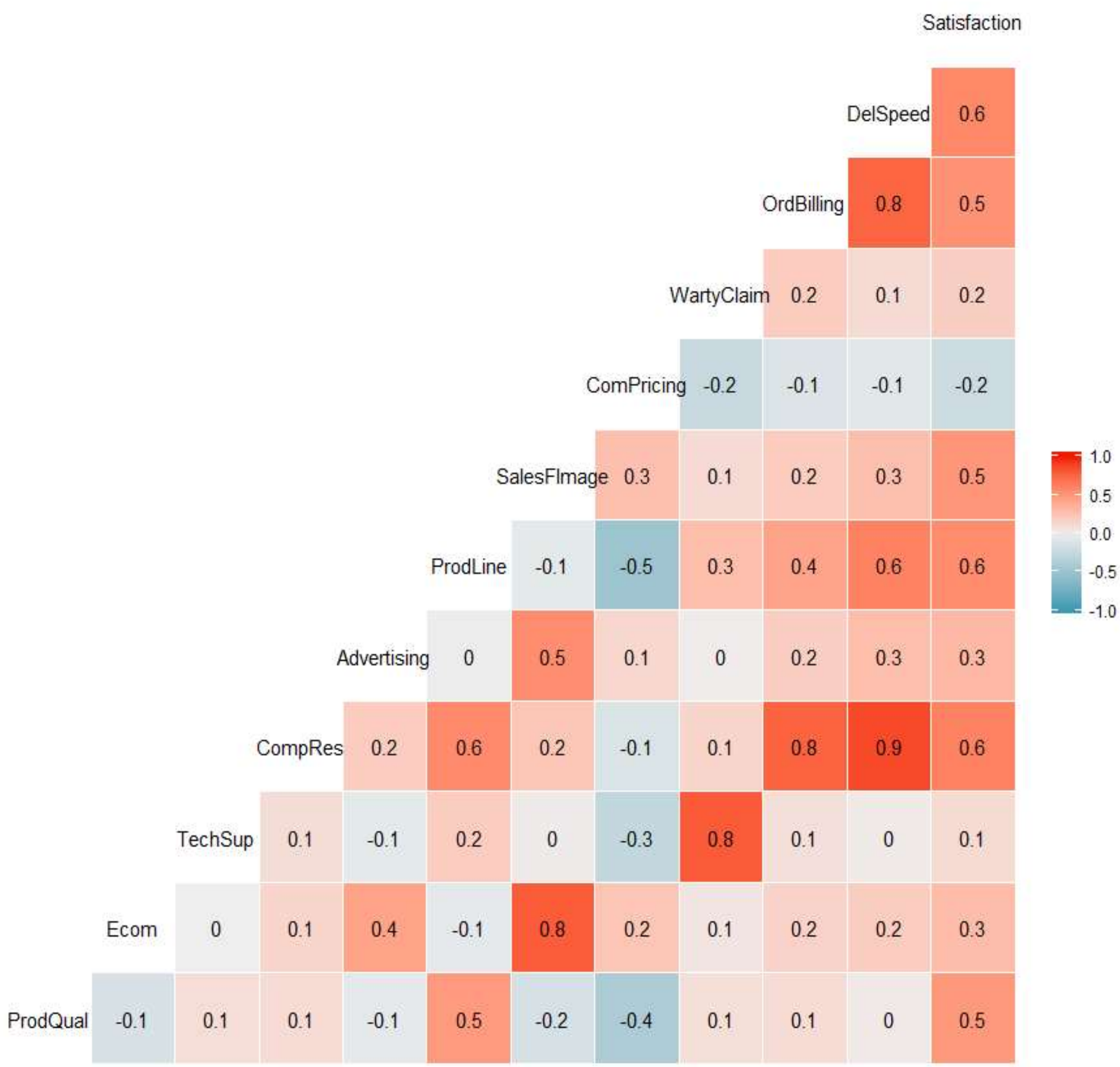
## 4. MULTICOLLINEARITY DETECTION

4.1 First method- Using Correlation Matrix

ggcorr(hair[,2:13],label= TRUE)

We see that there are so many factor-pairs which exhibit a high correlation with each other. Thus, the presence of multiple corelated variables proves the presence of Multicollinearity.

We see that the dependent variable 'Satisfcation' is variably dependent on the various other independent variables. There is high co-relation amongst various pairs of variables showing multicollinearity.



4.2 Second Method- Multiple Regression

We'll test for multicollinearity using multiple-regression too.

RCODE:

```
model=
lm(Satisfaction~ProdQual+Ecom+TechSup+CompRes+Advertising+ProdLine+SalesFImage+ComPricing+WartyClaim+OrdBilling+DelSpeed)

summary(model)
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.66961    0.81233  -0.824  0.41199    
ProdQual     0.37137    0.05177   7.173 2.18e-10 ***
Ecom        -0.44056    0.13396  -3.289  0.00145 ** 
TechSup      0.03299    0.06372   0.518  0.60591    
CompRes      0.16703    0.10173   1.642  0.10416    
Advertising -0.02602    0.06161  -0.422  0.67382    
ProdLine     0.14034    0.08025   1.749  0.08384 .  
SalesFImage  0.80611    0.09775   8.247 1.45e-12 ***
ComPricing  -0.03853    0.04677  -0.824  0.41235    
WartyClaim  -0.10298    0.12330  -0.835  0.40587    
OrdBilling   0.14635    0.10367   1.412  0.16160    
DelSpeed     0.16570    0.19644   0.844  0.40124    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5623 on 88 degrees of freedom
Multiple R-squared:  0.8021,	Adjusted R-squared:  0.7774 
F-statistic: 32.43 on 11 and 88 DF,  p-value: < 2.2e-16
```

We see that the amalgamated  effect of each one upon the other makes the explanatory power extremely difficult. There are 3 variables which are significantly affecting the satisfaction - Product Quality , Ecommerce, Salesforce Image and we cannot say if Product Quality is more significant than Ecommerce or Salesforce Image.

This shows that there is multicollinearity because there are multiple variables which are affecting the dependent variable Satisfaction. However, Multicollinearity is not a problem.

## 5. SIMPLE REGRESSION FOR EACH VARIABLE

RCODE:

model1= lm(Satisfaction~ProdQual)

summary(model1) # 23.65% of the changes in Satisfcation are explained by Product Quality

```
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.67593    0.59765   6.151 1.68e-08 ***
ProdQual     0.41512    0.07534   5.510 2.90e-07 ***
```

model2= lm(Satisfaction~Ecom)

summary(model2) # 7.99% of the changes in Satisfcation are explained by E-Commerce

```
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   5.1516     0.6161   8.361 4.28e-13 ***
Ecom          0.4811     0.1649   2.918  0.00437 ** 
```

model3= lm(Satisfaction~TechSup)

summary(model3) # 1.26% of the changes in Satisfcation are explained by Technical Support

```
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  6.44757    0.43592  14.791   <2e-16 ***
TechSup      0.08768    0.07817   1.122    0.265    
```

model4= lm(Satisfaction~CompRes)

summary(model4) # 36.39% of the changes in Satisfcation are explained by Complaint Resolution

```
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.68005    0.44285   8.310 5.51e-13 ***
CompRes      0.59499    0.07946   7.488 3.09e-11 ***
```

model5= lm(Satisfaction~Advertising)

summary(model5) # 9.2% of the changes in Satisfcation are explained by Advertising

```
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   5.6259     0.4237  13.279  < 2e-16 ***
Advertising   0.3222     0.1018   3.167  0.00206 ** 
```

model6= lm(Satisfaction~ProdLine)

summary(model6) # 30.31% of the changes in Satisfcation are explained by Product Line

```
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.02203    0.45471   8.845 3.87e-14 ***
ProdLine     0.49887    0.07641   6.529 2.95e-09 ***
```

model7= lm(Satisfaction~SalesFImage)

summary(model7) # 25.02% of the changes in Satisfcation are explained by Salesforce Image

```
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  4.06983    0.50874   8.000 2.54e-12 ***
SalesFImage  0.55596    0.09722   5.719 1.16e-07 ***
```

model8= lm(Satisfaction~ComPricing)

summary(model8) # 4.33% of the changes in Satisfcation are explained by Competitive Pricing

```
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  8.03856    0.54427  14.769   <2e-16 ***
ComPricing  -0.16068    0.07621  -2.108   0.0376 *  
```

model9= lm(Satisfaction~WartyClaim)

summary(model9) # 3.15% of the changes in Satisfcation are explained by Warranty and Claims

```
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   5.3581     0.8813   6.079 2.32e-08 ***
WartyClaim    0.2581     0.1445   1.786   0.0772 .  
```

model10= lm(Satisfaction~OrdBilling)

summary(model10) # 27.22% of the changes in Satisfcation are explained by Order and billing

```
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   4.0541     0.4840   8.377 3.96e-13 ***
OrdBilling    0.6695     0.1106   6.054 2.60e-08 ***
```

model11= lm(Satisfaction~DelSpeed)

summary(model11) # 33.3% of the changes in Satisfaction are explained by Delivery Speed

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.2791     0.5294   6.194 1.38e-08 ***
DelSpeed      0.9364     0.1339   6.994 3.30e-10 ***
```

Thus, we have performed Simple linear Regression for each variable.

## 6. TO PERFORM FACTOR ANALYSIS

6.1 To find Eigen Values

RCODE:

```
Hair_factor= hair[,2:12]
str(Hair_factor)

ev= eigen(cor(Hair_factor))
print(ev,digits= 5)

eigenvalue= ev$values
eigenvalue
factor= c(1,2,3,4,5,6,7,8,9,10,11)
```

# These eigen values are in descending order

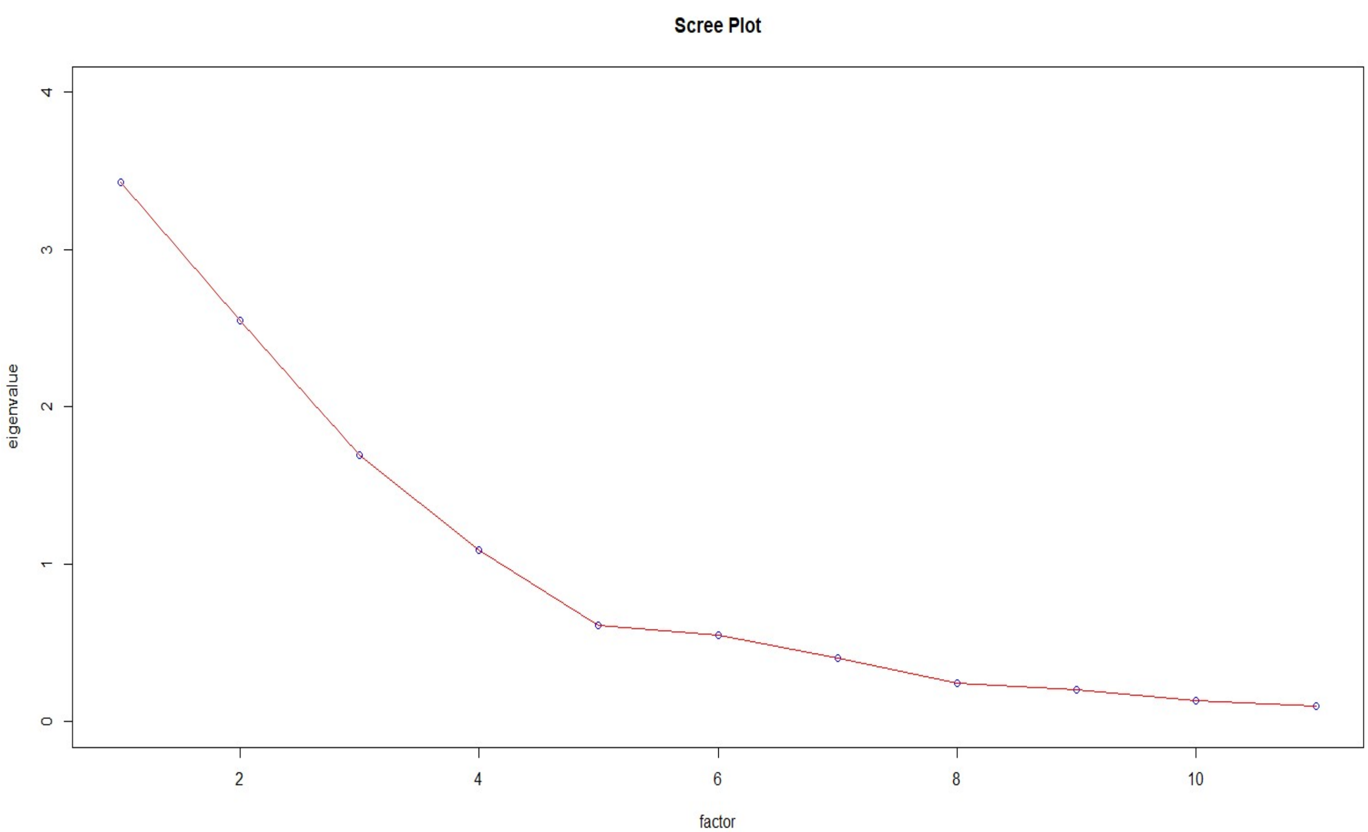
```
eigen() decomposition
$values
 [1] 3.426971 2.550897 1.690976 1.086556 0.609424 0.551884 0.401518 0.246952 0.203553 0.1328
42 0.098427
```

6.2 Make a Scree Plot

RCODE:

```
scree= data.frame(factor,eigenvalue)


plot(scree, main= "Scree Plot", col= "Blue",
    ylim= c(0,4))
lines(scree, col="Red")
```

# We observe that there are 4 significant factors according to Kaiser Rule, rest factor will be discarded



First, we will create an UNROTATED MATRIX and scrutinize the factor loadings and the communality.

RCODE:

```
unrotate= principal(Hair_factor, nfactors = 4, rotate="none")

print(unrotate)
```

```
              PC1   PC2   PC3   PC4   h2    u2 com
ProdQual     0.25 -0.50 -0.08  0.67 0.77 0.232 2.2
Ecom         0.31  0.71  0.31  0.28 0.78 0.223 2.1
TechSup      0.29 -0.37  0.79 -0.20 0.89 0.107 1.9
CompRes      0.87  0.03 -0.27 -0.22 0.88 0.119 1.3
Advertising  0.34  0.58  0.11  0.33 0.58 0.424 2.4
ProdLine     0.72 -0.45 -0.15  0.21 0.79 0.213 2.0
SalesFImage  0.38  0.75  0.31  0.23 0.86 0.141 2.1
ComPricing  -0.28  0.66 -0.07 -0.35 0.64 0.359 1.9
WartyClaim   0.39 -0.31  0.78 -0.19 0.89 0.108 2.0
OrdBilling   0.81  0.04 -0.22 -0.25 0.77 0.234 1.3
DelSpeed     0.88  0.12 -0.30 -0.21 0.91 0.086 1.4

                       PC1  PC2  PC3  PC4
SS loadings           3.43 2.55 1.69 1.09
Proportion Var        0.31 0.23 0.15 0.10
Cumulative Var        0.31 0.54 0.70 0.80
Proportion Explained  0.39 0.29 0.19 0.12
Cumulative Proportion 0.39 0.68 0.88 1.00
```

# The picture isn't very clear, we will make a ROTATED MATRIX now.

```
rotate= principal(Hair_factor,nfactors = 4, rotate = "verimax")

print(rotate)
```

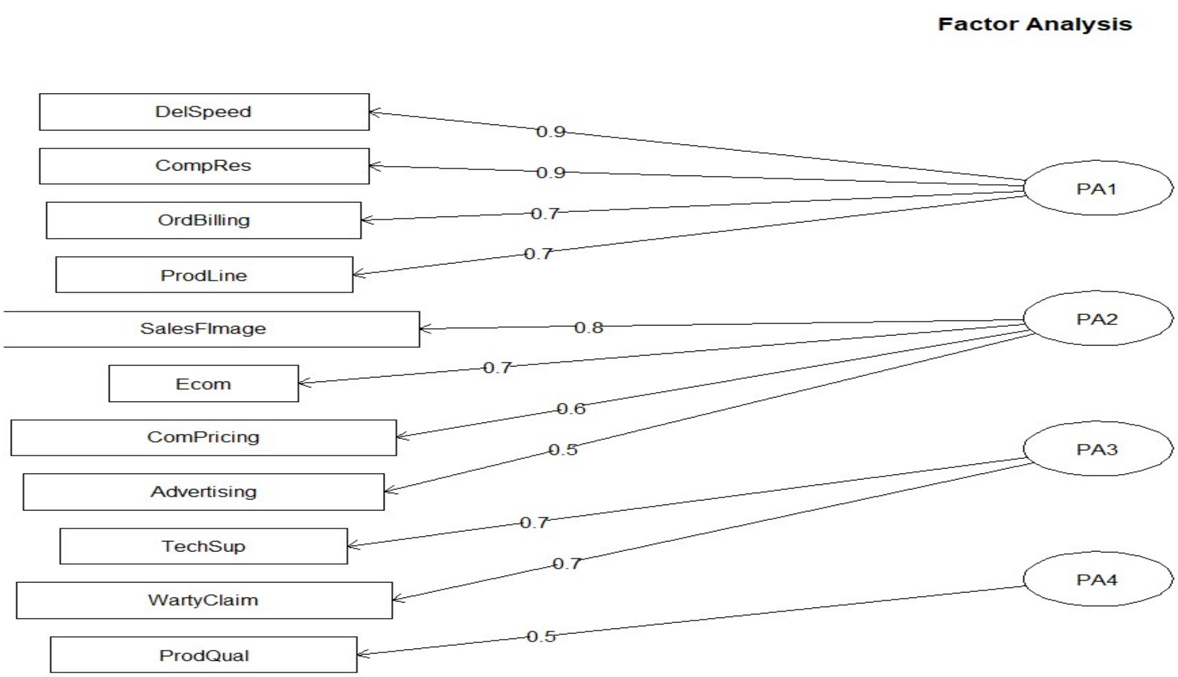
```
              PC1   PC2   PC3   PC4   h2    u2 com
ProdQual     0.25 -0.50 -0.08  0.67 0.77 0.232 2.2
Ecom         0.31  0.71  0.31  0.28 0.78 0.223 2.1
TechSup      0.29 -0.37  0.79 -0.20 0.89 0.107 1.9
CompRes      0.87  0.03 -0.27 -0.22 0.88 0.119 1.3
Advertising  0.34  0.58  0.11  0.33 0.58 0.424 2.4
ProdLine     0.72 -0.45 -0.15  0.21 0.79 0.213 2.0
SalesFImage  0.38  0.75  0.31  0.23 0.86 0.141 2.1
ComPricing  -0.28  0.66 -0.07 -0.35 0.64 0.359 1.9
WartyClaim   0.39 -0.31  0.78 -0.19 0.89 0.108 2.0
OrdBilling   0.81  0.04 -0.22 -0.25 0.77 0.234 1.3
DelSpeed     0.88  0.12 -0.30 -0.21 0.91 0.086 1.4

                       PC1  PC2  PC3  PC4
SS loadings           3.43 2.55 1.69 1.09
Proportion Var        0.31 0.23 0.15 0.10
Cumulative Var        0.31 0.54 0.70 0.80
Proportion Explained  0.39 0.29 0.19 0.12
Cumulative Proportion 0.39 0.68 0.88 1.00
```

# Communality H2 tells the ability of all the 4 factors to capture as much of the variance of the variables as possible

## 7.INTERPRETATION OF THE FACTORS CHOSEN BY KAISER RULE

RCODE:

```
fa= fa(Hair_factor, nfactors = 4, rotate = "none",fm= "pa")
print(fa)
fa.diagram(fa)
```




Thus, we know know the variables which belong to a generalized component factor.

# DelSpeed + CompRes + OrdBilling + ProdLine belong to PA1 and by pondering about the characteristics of these variables, we understand that we can rename that component as = Orders_and_Service

# Salesforce Image + E-Commerce + Advertising + Competitive Pricing belong to PA2 and by contemplating about the characteristics of these variables, we understand that we can rename that component as= Marketising_Quality

# TechSup + WartyClaim belong to PA3 and we understand that we can rename that component as= Support_Assistance

# ProdQual is an indepdent factor and will remian as it is and doesn't belong to any of the generalized groups

## 8. CREATION OF A 5 COLUMN DATASET AFTER PERFORMING PCA/FA

# Now , we will combine the columns of the original dataset and this PCA_hair dataset and create

# a new dataset by the name= new_hair containing 5 columns.

RCODE:

```
new_hair= cbind(PCA_hair, hair[,13])

new_hair= as.data.frame(new_hair)

str(new_hair)

colnames(new_hair)[1]<- 'Orders_and_Service'

colnames(new_hair)[2]<- 'Marketising_Quality'

colnames(new_hair)[3]<- 'Support_Assistance'

colnames(new_hair)[4]<- 'Product_Quality'

colnames(new_hair)[5]<- 'Customer Satisfaction'


str(new_hair)

attach(new_hair)  # This is the new dataset with 5 columns and 100 rows
```

```
> str(new_hair)
'data.frame':	100 obs. of  5 variables:
 $ Orders_and_Service    : num  -0.237 0.77 1.012 -1.093 -0.416 ...
 $ Marketising_Quality   : num  1.24 -1.7015 -0.0967 -0.4988 -0.5765 ...
 $ Support_Assistance    : num  -1.1289 -1.8403 0.0637 1.3867 -0.0133 ...
 $ Product_Quality       : num  0.978 -0.778 1.299 -0.629 0.372 ...
 $ Customer Satisfaction: num  8.2 5.7 8.9 4.8 7.1 4.7 5.7 6.3 7 5.5 ...
```

# 9.MULTIPLE LINEAR REGRESSION USING NEW REDUCED FACTORS

Perform Multiple linear regression with customer satisfaction as dependent variables and the four factors as independent variables.

RCODE:

multimodel=lm(Satisfaction~Orders_and_Service+Marketising_Quality+Support_Assistance+Product_Quality,data = new_hair)

```
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         6.918000   0.066959 103.317  < 2e-16 ***
Orders_and_Service  0.902499   0.068701  13.137  < 2e-16 ***
Marketising_Quality 0.129861   0.069265   1.875   0.0639 .  
Support_Assistance  0.002653   0.070735   0.038   0.9702    
Product_Quality     0.515861   0.076533   6.740 1.22e-09 ***
```

summary(multimodel)

anova(multimodel)

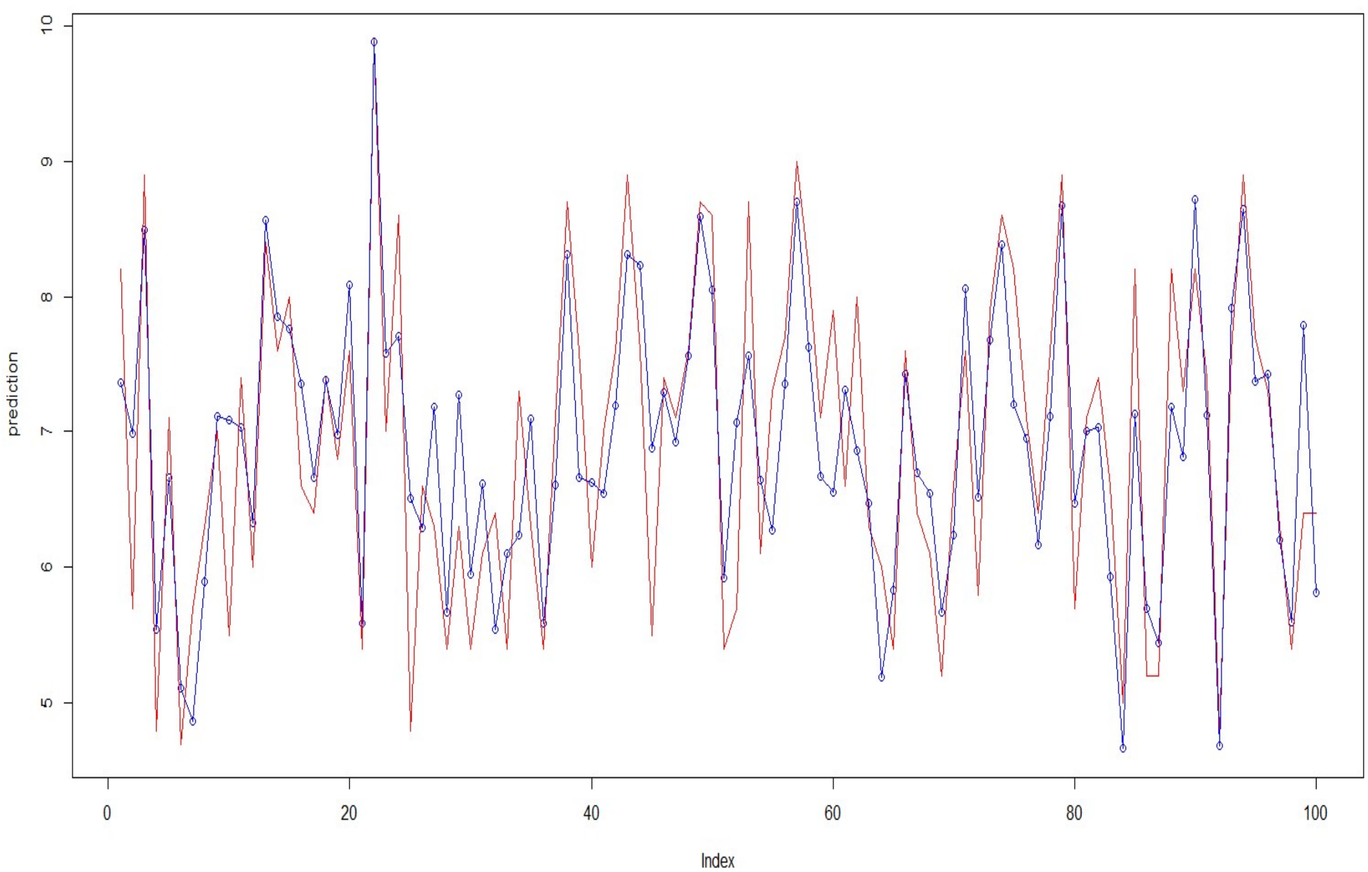
# Yhat= 6.918 + .902x1 + .129x2 + .0026x3 + .5158x4

# multipled R Squared : .6971 implies 69.71% of the variations in Customer Satisfaction is explained the independent variables namely : Orders_and_Service , Marketising_Quality , Support_Assistance , and Product_Quality

The Significant independant factors are : Orders_and_Service , Marketising_Quality and Product_Quality and the non-significant factor is Support_Assistance because it only explains 2.65% of the changes and it can also be neglected leaving us with 3 independant factors derived from factor analysis

prediction= predict(multimodel)

```
actual= Satisfaction

backtrack= data.frame(actual,prediction)

plot(actual, col= 'red')

lines(actual, col='red')

plot(prediction, col='blue')

lines(prediction, col='blue')
```



We can clearly infer that the prediction falls mostly in line with the actual data.

# Now we'll check for the confidence level

?confint()

confint(multimodel, level = 0.95)

```
                          2.5 %    97.5 %
(Intercept)          6.785069371 7.0509306
Orders_and_Service   0.766110020 1.0388882
Marketising_Quality -0.007647819 0.2673707
Support_Assistance  -0.137773264 0.1430792
Product_Quality      0.363923251 0.6677992
```

Therefore we will not take the slopes which are extracted by Multiple Regression because we are conservative and will take only the slopes corresponding to the 2.5% of the predicted levels.

## 10.INTERPRETATION OF THE SUMMARY OF MLR

```
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          6.918000   0.066959 103.317  < 2e-16 ***
Orders_and_Service   0.902499   0.068701  13.137  < 2e-16 ***
Marketising_Quality  0.129861   0.069265   1.875   0.0639 .
Support_Assistance   0.002653   0.070735   0.038   0.9702
Product_Quality      0.515861   0.076533   6.740 1.22e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6696 on 95 degrees of freedom
Multiple R-squared:  0.6971,   Adjusted R-squared:  0.6844
F-statistic: 54.66 on 4 and 95 DF,  p-value: < 2.2e-16
```

**Significance of Rsquared**= By MLR , the value is coming to be .6971. This means that 69.71 % of the changes in Satisfaction are a explained by the four factors we have.

**Degrees of freedom=** There are total 100 records and the number of factors are 4, therefore, it's explainable that the Dof is = 100-4-1= 95

**F-statistic=** This value of F-statistic is fairly high and thus, the result is significant.

**P-Values**= The P-Values of every factor is fairly low and thus, being very less than alpha of .5, we consider that the null hypothesis is rejected and the factors are considerable and significantly contributing.

**As we concluded that the Support_Assistance didn't contribute much to the predictions we can neglect it and still the model will be valid.multimodel2= lm(Satisfaction~Orders_and_Service+Marketising_Quality+Product_Quality, data = new_hair)

summary(multimodel2)

```
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           6.91800    0.06661 103.858  < 2e-16 ***
Orders_and_Service    0.90249    0.06834  13.205  < 2e-16 ***
Marketising_Quality   0.12991    0.06889   1.886   0.0624 .
Product_Quality       0.51600    0.07604   6.786  9.5e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6661 on 96 degrees of freedom
Multiple R-squared:  0.6971,   Adjusted R-squared:  0.6876
F-statistic: 73.65 on 3 and 96 DF,  p-value: < 2.2e-16
```

# We see that in absence of the factor Support_Assistance doesn't affect the variance explaining feature

# of model and thus , we can also suffice with the three factors.

# These 3 factors will explain the variance in the satisfaction 69.71 % .