

## Facebook metrics Data Set

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### Business Objective

One of the most important factor while weighing the success of a facebook cosmetic page is how many users are engaged with the page. It is not just Page Likes but over the time how many people have appreciated or not appreciated the content that is uploaded on the page. Engagement with any post is an important factor measuring how much the content uploaded is affecting and reaching people. Based on this, we have chosen "Lifetime people who have liked your page and engaged with your post" as our dependent variable and our goal is to predict this based on the other regressors. We would like to examine which are those factors affecting the success of the post by the people who have liked the page. We would like to examine what kind of post (link,video, photo, status), time. day, month and other various factors receives maximum or minimum engagement. Based on this analysis, marketers can choose what kind of content and at what particular time can get the maximum level of engagement and hence better marketing.

Dependent Variable

1. Lifetime people who have liked your page and engaged with your post

Independent Variables:

1. Post Hour
2. Post Weekday
3. Post month
4. Type
5. Category
6. Paid
7. Page total likes
8. Comments
9. Likes
10. Shares
11. Total interactions

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### Loading libraries and Initialisation

```
library(GGally)
library(ggplot2)
library(car)
library(MASS)
library(corrplot)
library(ggcorrplot)
library(perturb)
library(caTools)
library(qpcR)
options(scipen = 1000)
```

## Preliminary Data Analysis

### Inspecting the data set

```
fb.raw <- read.csv("F:/BIG DATA/ISB/Assignments/Term 2/Statistical Analysis 2/Project/data/Facebook.csv")
summary(fb.raw)
str(fb.raw)

## Page.total.likes  Type      Category  Post.Month
## Min. : 81370 Link : 22  Min. :1.00  Min. : 1.000
## 1st Qu.:112676 Photo :426 1st Qu.:1.00 1st Qu.: 4.000
## Median :129600 Status: 45 Median :2.00 Median : 7.000
## Mean :123194 Video : 7 Mean :1.88 Mean : 7.038
## 3rd Qu.:136393      3rd Qu.:3.00 3rd Qu.:10.000
## Max. :139441      Max. :3.00 Max. :12.000
##
## Post.Weekday Post.Hour      Paid      Lifetime.Post.Total.Reach
## Min. :1.00 Min. : 1.00 Min. :0.0000 Min. : 238
## 1st Qu.:2.00 1st Qu.: 3.00 1st Qu.:0.0000 1st Qu.: 3315
## Median :4.00 Median : 9.00 Median :0.0000 Median : 5281
## Mean :4.15 Mean : 7.84 Mean :0.2786 Mean :13903
## 3rd Qu.:6.00 3rd Qu.:11.00 3rd Qu.:1.0000 3rd Qu.:13168
## Max. :7.00 Max. :23.00 Max. :1.0000 Max. :180480
##
## NA's :1
## Lifetime.Post.Total.Impressions Lifetime.Engaged.Users
## Min. : 570 Min. : 9.0
## 1st Qu.: 5695 1st Qu.: 393.8
## Median : 9051 Median : 625.5
## Mean : 29586 Mean : 920.3
## 3rd Qu.: 22086 3rd Qu.: 1062.0
## Max. :1110282 Max. :11452.0
##
## Lifetime.Post.Consumers Lifetime.Post.Consumptions
## Min. : 9.0 Min. : 9.0
## 1st Qu.: 332.5 1st Qu.: 509.2
## Median : 551.5 Median : 851.0
## Mean : 798.8 Mean :1415.1
## 3rd Qu.: 955.5 3rd Qu.:1463.0
## Max. :11328.0 Max. :19779.0
##
## Lifetime.Post.Impressions.by.people.who.have.liked.your.Page
## Min. : 567
## 1st Qu.: 3970
## Median : 6256
## Mean : 16766
## 3rd Qu.: 14860
## Max. :1107833
##
## Lifetime.Post.reach.by.people.who.like.your.Page
## Min. : 236
```

```
## 1st Qu.: 2182
## Median : 3417
## Mean : 6585
## 3rd Qu.: 7989
## Max. :51456
##
## Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post
## Min. : 9.0
## 1st Qu.: 291.0
## Median : 412.0
## Mean : 610.0
## 3rd Qu.: 656.2
## Max. :4376.0
##
## comment like share Total.Interactions
## Min. : 0.000 Min. : 0.0 Min. : 0.00 Min. : 0.0
## 1st Qu.: 1.000 1st Qu.: 56.5 1st Qu.: 10.00 1st Qu.: 71.0
## Median : 3.000 Median : 101.0 Median : 19.00 Median : 123.5
## Mean : 7.482 Mean : 177.9 Mean : 27.27 Mean : 212.1
## 3rd Qu.: 7.000 3rd Qu.: 187.5 3rd Qu.: 32.25 3rd Qu.: 228.5
## Max. :372.000 Max. :5172.0 Max. :790.00 Max. :6334.0
## NA's :1 NA's :4
## 'data.frame': 500 obs. of 19 variables:
## $ Page.total.likes : int 139441 139441 139441 139441 139441 139441 139441 139441 139
441 139441 ...
## $ Type : Factor w/ 4 levels "Link","Photo",...: 2 3 2 2 2 3 2 2 3 2 ...
## $ Category : int 2 2 3 2 2 2 3 3 2 3 ...
## $ Post.Month : int 12 12 12 12 12 12 12 12 12 12 ...
## $ Post.Weekday : int 4 3 3 2 2 1 1 7 7 6 ...
## $ Post.Hour : int 3 10 3 10 3 9 3 9 3 10 ...
## $ Paid : int 0 0 0 1 0 0 1 1 0 0 ...
## $ Lifetime.Post.Total.Reach : int 2752 10460 2413 50128 7244 10472 11692 13720 11844 4694 .
..
## $ Lifetime.Post.Total.Impressions : int 5091 19057 4373 87991 13594 20849 19479 24137 22538 8
668 ...
## $ Lifetime.Engaged.Users : int 178 1457 177 2211 671 1191 481 537 1530 280 ...
## $ Lifetime.Post.Consumers : int 109 1361 113 790 410 1073 265 232 1407 183 ...
## $ Lifetime.Post.Consumptions : int 159 1674 154 1119 580 1389 364 305 1692 250 ...
## $ Lifetime.Post.Impressions.by.people.who.have.liked.your.Page : int 3078 11710 2812 61027 6228 16034 15432 1
9728 15220 4309 ...
## $ Lifetime.Post.reach.by.people.who.like.your.Page : int 1640 6112 1503 32048 3200 7852 9328 11056 7912
2324 ...
## $ Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post: int 119 1108 132 1386 396 1016 379 422 12
50 199 ...
## $ comment : int 4 5 0 58 19 1 3 0 0 3 ...
## $ like : int 79 130 66 1572 325 152 249 325 161 113 ...
## $ share : int 17 29 14 147 49 33 27 14 31 26 ...
## $ Total.Interactions : int 100 164 80 1777 393 186 279 339 192 142 ...
```

## Handling Missing Values

Few missing values were observed in columns paid, like and share. Since these rows constitute only 1% of the entire dataset, we've removed them.

```
fb.raw <- fb.raw[-c(which(is.na(fb.raw$Paid))),]
fb.raw <- fb.raw[-c(which(is.na(fb.raw$share))),]
```

### Converting Categorical Variables to factor and inspection of factor levels

```
fb.raw$Post.Hour <- as.factor(fb.raw$Post.Hour)
fb.raw$Post.Weekday <- as.factor(fb.raw$Post.Weekday)
fb.raw$Post.Month <- as.factor(fb.raw$Post.Month)
fb.raw$Type <- as.factor(fb.raw$Type)
fb.raw$Category <- as.factor(fb.raw$Category)
fb.raw$Paid <- as.factor(fb.raw$Paid)
```

```
table(fb.raw$Type)
table(fb.raw$Post.Month)
table(fb.raw$Paid)
table(fb.raw$Category)
table(fb.raw$Post.Weekday)
table(fb.raw$Post.Hour)

##
## Link Photo Status Video
## 22 421 45 7
##
## 1 2 3 4 5 6 7 8 9 10 11 12
## 24 26 36 50 37 49 52 34 35 57 45 50
##
## 0 1
## 356 139
##
## 1 2 3
## 211 129 155
##
## 1 2 3 4 5 6 7
## 68 66 64 71 66 80 80
##
## 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
## 4 39 105 34 13 15 13 11 29 77 44 29 52 13 6 1 3 3
## 19 20 22 23
## 1 1 1 1
```

We observe that Post.Hour variable has only one record for levels 16,19,20,21,22,23. This will create problems while splitting the data. Hence, we remove these records containing single values.

```
fb.raw <- fb.raw[-which(fb.raw$Post.Hour == 16),]
fb.raw <- fb.raw[-which(fb.raw$Post.Hour == 19),]
fb.raw <- fb.raw[-which(fb.raw$Post.Hour == 20),]
fb.raw <- fb.raw[-which(fb.raw$Post.Hour == 22),]
fb.raw <- fb.raw[-which(fb.raw$Post.Hour == 23),]
```

```
fb.raw$Post.Hour <- factor(fb.raw$Post.Hour)
table(fb.raw$Post.Hour)
rownames(fb.raw) <- NULL
```

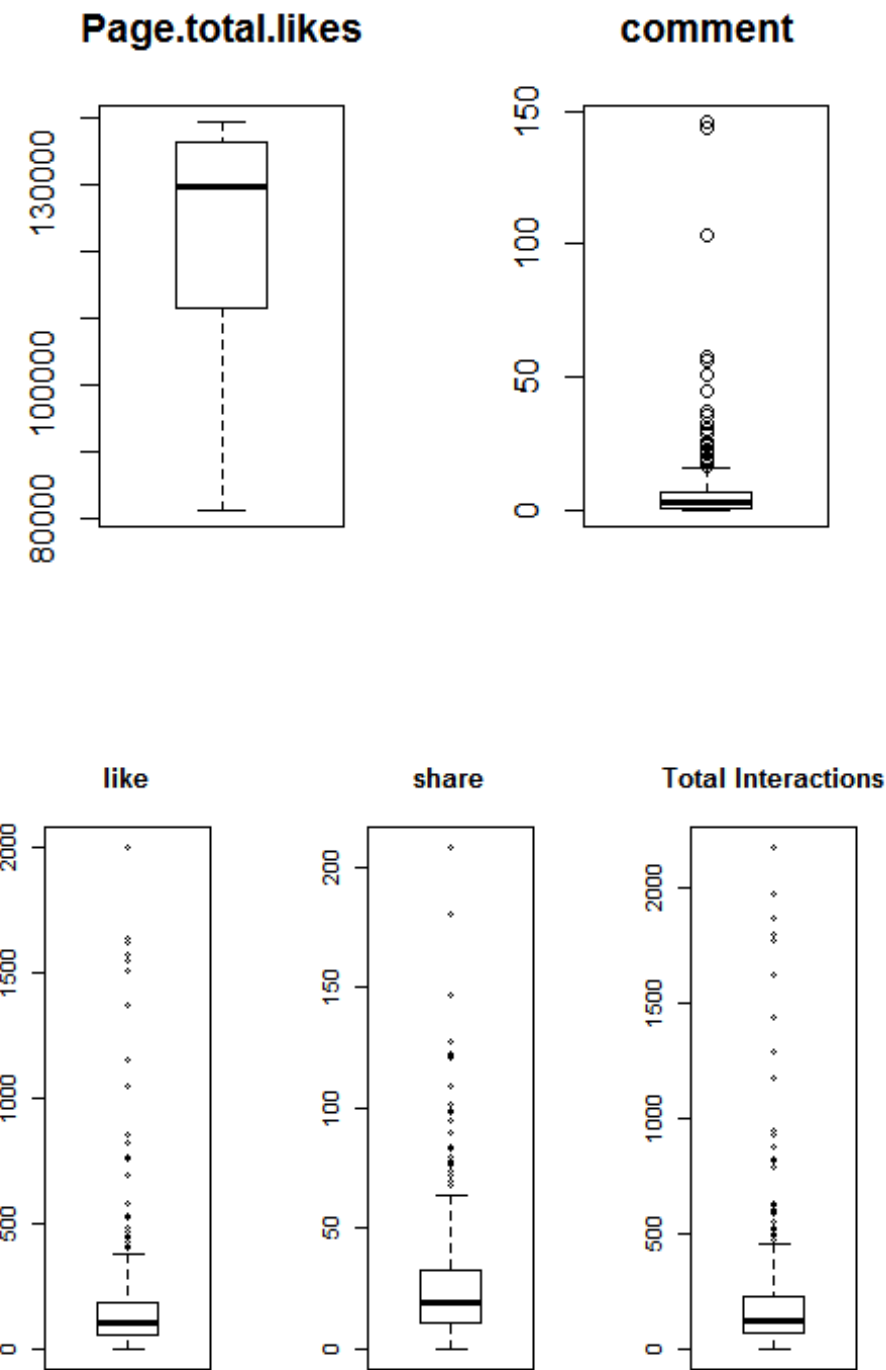
```
##  
## 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 17 18  
## 4 39 105 34 13 15 13 11 29 77 44 29 52 13 6 3 3
```

## Training and test data classification

We divide the data into training and test data sets in a ratio of 80:20

```
set.seed(55)  
spl = sample.split(fb.raw$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post, SplitRatio = 0.8)  
Train = subset(fb.raw, spl==TRUE)  
Test = subset(fb.raw, spl==FALSE)  
  
dim(Train)  
dim(Test)  
  
## [1] 392 19  
## [1] 98 19
```

---



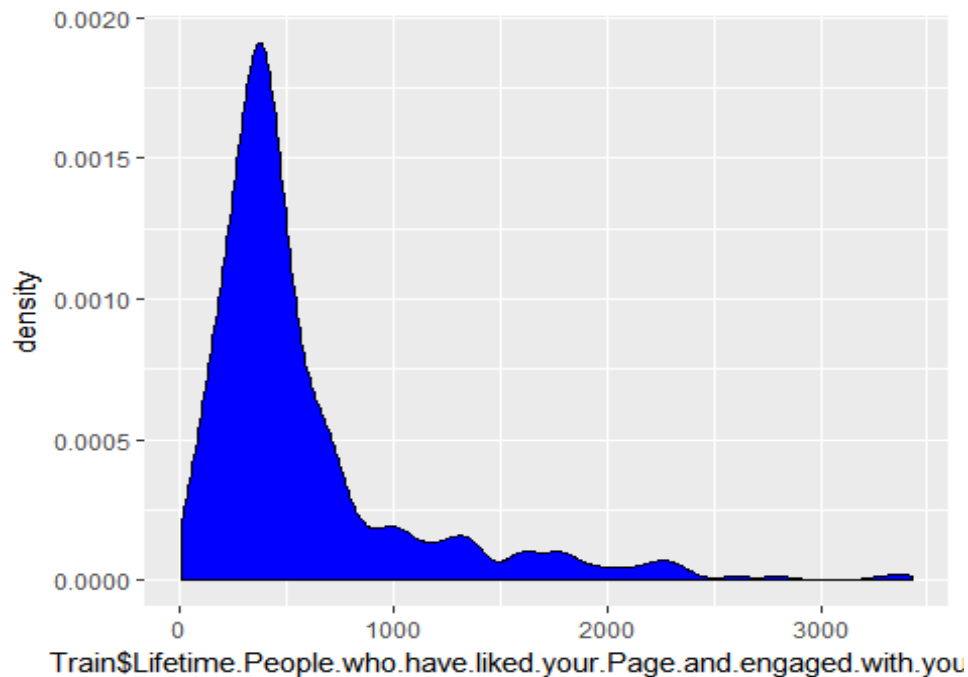
Our observations:

1. Numerous outliers in the variables such as comment, share, like, total interactions.

- The variables are heavily right skewed which could suggest a need for transformation.

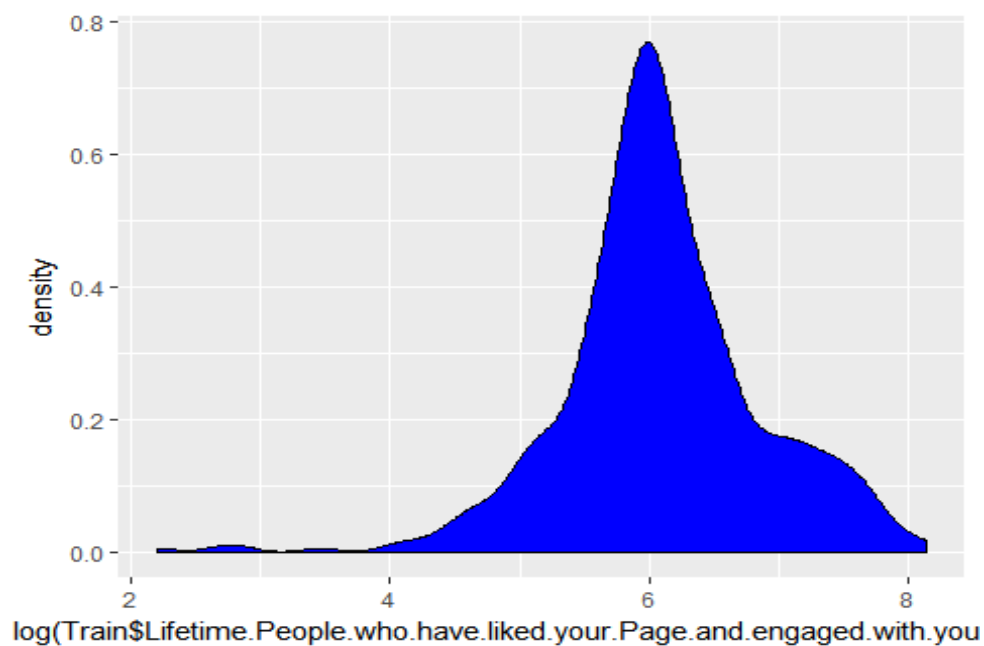
Dependent variable - Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post

```
ggplot(Train, aes(x=Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post)) +  
geom_density(fill="blue")
```



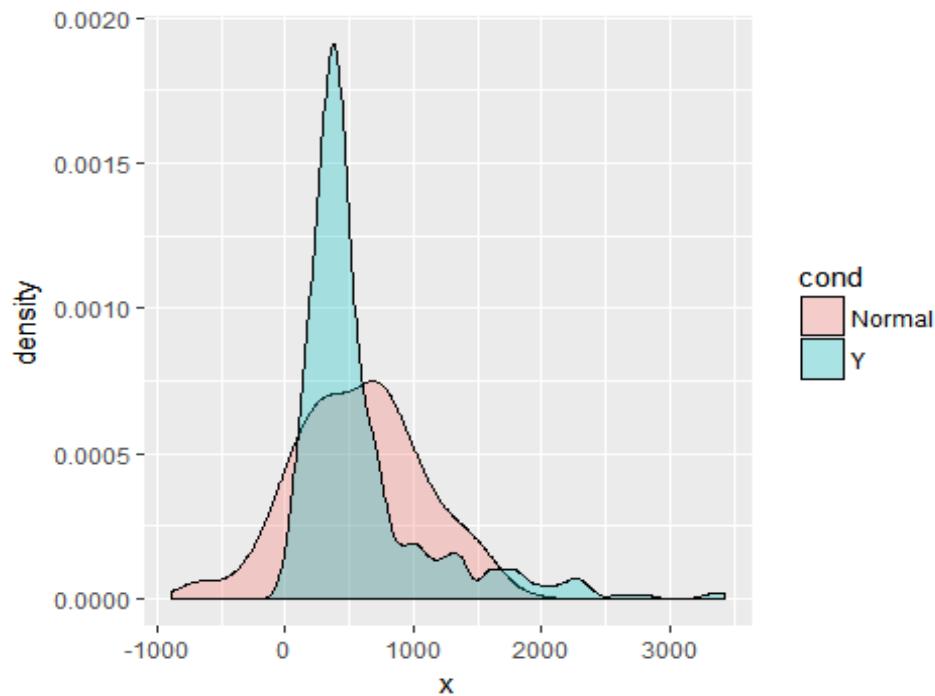
The dependent variable looks heavily right skewed. We can try a log transformation.

```
ggplot(Train, aes(x=log(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post))) +  
geom_density(fill="blue")
```



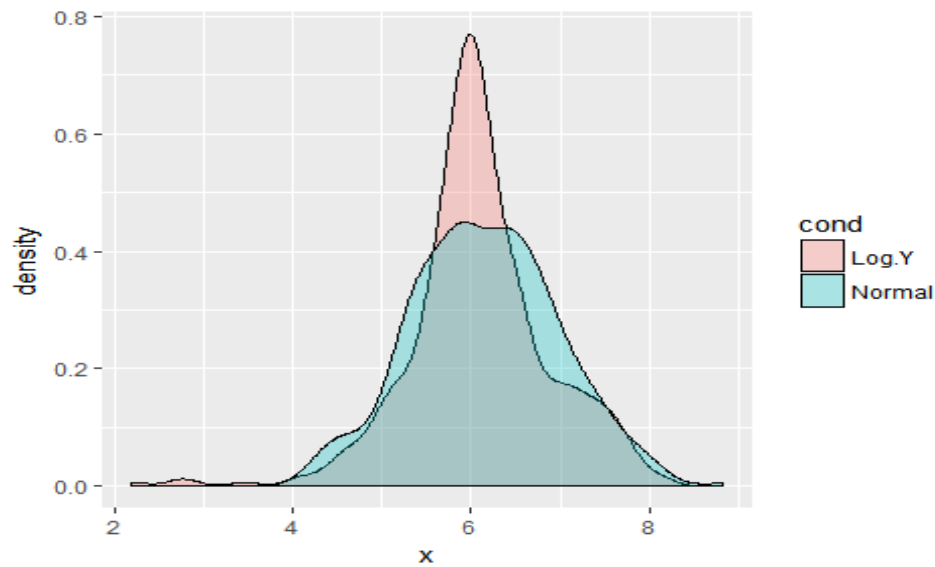
We compare the distribution of the dependent variable and its log transformation with a normal distribution of same mean and standard deviation.

```
norm<-rnorm(392, mean=mean(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post),
           sd=sd(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post))
dat <- data.frame(cond = factor(rep(c("Y", "Normal"), each=392)),
                  x = c(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post, norm))
ggplot(dat, aes(x, fill=cond)) + geom_density(alpha=.3)
```



```
lnorm<-rnorm(392, mean=mean(log(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post)),
            sd=sd(log(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post)))
dat <- data.frame(cond = factor(rep(c("Log.Y", "Normal"), each = 392)),
                  x = c(log(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post), lnorm))
ggplot(dat, aes(x, fill=cond)) + geom_density(alpha=.3)
```

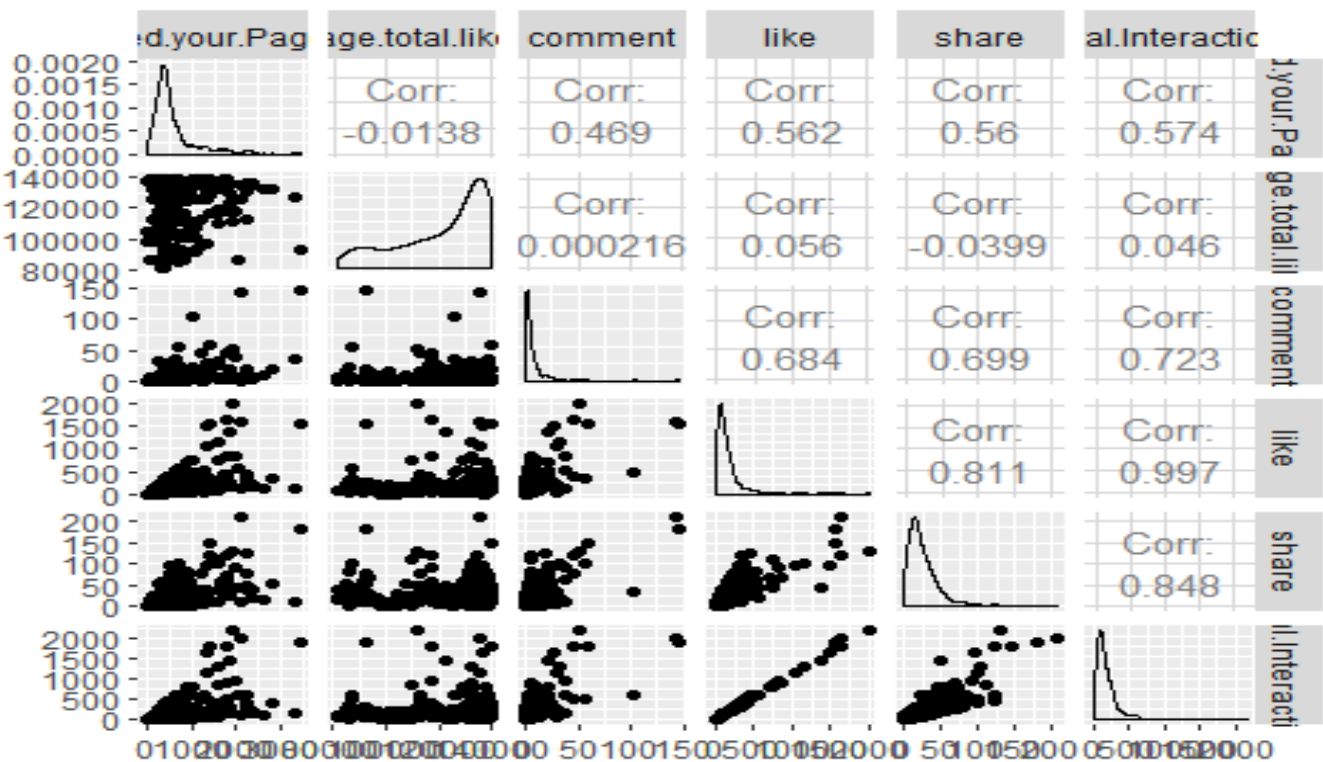




We see that the log transformed variable fits better and is close to a normal distribution.

## Correlation and Scatter Plot Matrices

```
mcor <- round(cor(Train[,c(2:15)]),2)
#corrplot(mcor, method="number")
ggpairs(Train[,c(15,1,16,17,18,19)])
```



There is positive correlation between like, comment, share and Interactions. Output variable is also positively correlated with these variables

## Initial Model Fitting and Basic Diagnostics

```
model1 <- lm(Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post ~ Page.total.likes + Type +
  Category + Post.Month + Post.Weekday + Post.Hour + Paid + comment + like + share + Total.Interactions,
  data = Train)
summary(model1)
```

```
##
## Call:
## lm(formula = Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post ~
##   Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##     Post.Hour + Paid + comment + like + share + Total.Interactions,
##   data = Train)
##
## Residuals:
##   Min     1Q   Median     3Q    Max
## -1155.67 -118.15  -27.51   96.44 1512.02
##
## Coefficients: (1 not defined because of singularities)
##              Estimate Std. Error t value    Pr(>|t|)
## (Intercept)   954.744738  895.187521  1.067    0.286923
## Page.total.likes -0.008567  0.010318 -0.830    0.406955
## TypePhoto      227.459347  76.251157  2.983    0.003056
## TypeStatus     1357.917125  93.447005 14.531 < 0.00000000000000002
## TypeVideo      616.481246 132.599953  4.649 0.0000047383955262
## Category2     -149.932447  44.297961 -3.385    0.000794
## Category3     -218.192484  38.975208 -5.598 0.0000000439766722
## Post.Month2     126.462219 108.630579  1.164    0.245161
## Post.Month3     -33.751720 170.510401 -0.198    0.843203
## Post.Month4     219.239631 264.415267  0.829    0.407589
## Post.Month5     179.397449 340.422424  0.527    0.598540
## Post.Month6     349.130412 413.895657  0.844    0.399516
## Post.Month7     349.156893 459.720903  0.759    0.448069
## Post.Month8     349.988023 493.029878  0.710    0.478259
## Post.Month9     248.108362 516.427543  0.480    0.631222
## Post.Month10    340.225118 530.084176  0.642    0.521405
## Post.Month11     2.167494 543.194575  0.004    0.996819
## Post.Month12    123.088485 557.414200  0.221    0.825362
## Post.Weekday2   -50.567424  54.858125 -0.922    0.357279
## Post.Weekday3    30.947710  57.044417  0.543    0.587808
## Post.Weekday4   -122.230736  55.815764 -2.190    0.029195
## Post.Weekday5   -99.591998  55.365700 -1.799    0.072916
## Post.Weekday6     3.361021  53.404223  0.063    0.949854
## Post.Weekday7    47.803946  52.766971  0.906    0.365592
## Post.Hour2      53.716314 150.057379  0.358    0.720581
```

```
## Post.Hour3      35.921411 142.863466 0.251      0.801623
## Post.Hour4      48.732997 150.394801 0.324      0.746107
## Post.Hour5      39.240175 163.815985 0.240      0.810829
## Post.Hour6     -133.457987 159.923453 -0.835      0.404565
## Post.Hour7     -54.898219 165.775584 -0.331      0.740723
## Post.Hour8     -101.990891 169.431532 -0.602      0.547593
## Post.Hour9      74.063873 151.048827 0.490      0.624209
## Post.Hour10     36.776937 143.496322 0.256      0.797877
## Post.Hour11      4.160009 146.535610 0.028      0.977368
## Post.Hour12     105.687337 150.962630 0.700      0.484339
## Post.Hour13      80.059622 145.723432 0.549      0.583087
## Post.Hour14     128.513781 164.977206 0.779      0.436521
## Post.Hour15     -77.534519 196.823711 -0.394      0.693875
## Post.Hour17     218.285313 222.302375 0.982      0.326817
## Post.Hour18     30.727714 249.134584 0.123      0.901911
## Paid1           45.979266 32.402695 1.419      0.156795
## comment         3.454755 1.511999 2.285      0.022920
## like            0.846200 0.107449 7.875 0.00000000000000437
## share           2.917569 1.147526 2.542      0.011439
## Total.Interactions  NA      NA      NA      NA
##
## (Intercept)
## Page.total.likes
## TypePhoto      **
## TypeStatus     ***
## TypeVideo      ***
## Category2      ***
## Category3      ***
## Post.Month2
## Post.Month3
## Post.Month4
## Post.Month5
## Post.Month6
## Post.Month7
## Post.Month8
## Post.Month9
## Post.Month10
## Post.Month11
## Post.Month12
## Post.Weekday2
## Post.Weekday3
## Post.Weekday4  *
## Post.Weekday5  .
## Post.Weekday6
## Post.Weekday7
## Post.Hour2
## Post.Hour3
## Post.Hour4
## Post.Hour5
## Post.Hour6
## Post.Hour7
## Post.Hour8
## Post.Hour9
```

```
## Post.Hour10
## Post.Hour11
## Post.Hour12
## Post.Hour13
## Post.Hour14
## Post.Hour15
## Post.Hour17
## Post.Hour18
## Paid1
## comment      *
## like         ***
## share        *
## Total.Interactions
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 270 on 348 degrees of freedom
## Multiple R-squared:  0.7592, Adjusted R-squared:  0.7295
## F-statistic: 25.52 on 43 and 348 DF, p-value: < 0.00000000000000022
```

### Interpretation from Model-1

- R-Squared for the model is 69% which indicates that the model initially fits just well.
- Few of the regressors are insignificant and these need to be analysed and removed
- Regressor Total.Interactions has coefficient values as NA. This is possibly because Total.Interactions is linearly related to the other variables (from correlation matrix we observe that correlation between like and Total Interactions is 1).

## Model-2

Observing our model1, we build model2 by removing Total.Interactions.

```
model2 <- lm(Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post ~ Page.total.likes + Type +
  Category + Post.Month + Post.Weekday + Post.Hour + Paid + comment + like + share,
  data = Train)
summary(model2)

##
## Call:
## lm(formula = Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post ~
##   Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + Paid + comment + like + share, data = Train)
##
## Residuals:
##   Min     1Q  Median     3Q    Max
## -1155.67 -118.15 -27.51  96.44 1512.02
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   954.744738  895.187521  1.067      0.286923
## Page.total.likes -0.008567  0.010318 -0.830      0.406955
## TypePhoto      227.459347  76.251157  2.983      0.003056 **
## TypeStatus     1357.917125  93.447005 14.531 < 0.0000000000000002 ***
## TypeVideo      616.481246 132.599953  4.649 0.0000047383955262 ***
```

```
## Category2 -149.932447 44.297961 -3.385 0.000794 ***
## Category3 -218.192484 38.975208 -5.598 0.0000000439766722 ***
## Post.Month2 126.462219 108.630579 1.164 0.245161
## Post.Month3 -33.751720 170.510401 -0.198 0.843203
## Post.Month4 219.239631 264.415267 0.829 0.407589
## Post.Month5 179.397449 340.422424 0.527 0.598540
## Post.Month6 349.130412 413.895657 0.844 0.399516
## Post.Month7 349.156893 459.720903 0.759 0.448069
## Post.Month8 349.988023 493.029878 0.710 0.478259
## Post.Month9 248.108362 516.427543 0.480 0.631222
## Post.Month10 340.225118 530.084176 0.642 0.521405
## Post.Month11 2.167494 543.194575 0.004 0.996819
## Post.Month12 123.088485 557.414200 0.221 0.825362
## Post.Weekday2 -50.567424 54.858125 -0.922 0.357279
## Post.Weekday3 30.947710 57.044417 0.543 0.587808
## Post.Weekday4 -122.230736 55.815764 -2.190 0.029195 *
## Post.Weekday5 -99.591998 55.365700 -1.799 0.072916 .
## Post.Weekday6 3.361021 53.404223 0.063 0.949854
## Post.Weekday7 47.803946 52.766971 0.906 0.365592
## Post.Hour2 53.716314 150.057379 0.358 0.720581
## Post.Hour3 35.921411 142.863466 0.251 0.801623
## Post.Hour4 48.732997 150.394801 0.324 0.746107
## Post.Hour5 39.240175 163.815985 0.240 0.810829
## Post.Hour6 -133.457987 159.923453 -0.835 0.404565
## Post.Hour7 -54.898219 165.775584 -0.331 0.740723
## Post.Hour8 -101.990891 169.431532 -0.602 0.547593
## Post.Hour9 74.063873 151.048827 0.490 0.624209
## Post.Hour10 36.776937 143.496322 0.256 0.797877
## Post.Hour11 4.160009 146.535610 0.028 0.977368
## Post.Hour12 105.687337 150.962630 0.700 0.484339
## Post.Hour13 80.059622 145.723432 0.549 0.583087
## Post.Hour14 128.513781 164.977206 0.779 0.436521
## Post.Hour15 -77.534519 196.823711 -0.394 0.693875
## Post.Hour17 218.285313 222.302375 0.982 0.326817
## Post.Hour18 30.727714 249.134584 0.123 0.901911
## Paid1 45.979266 32.402695 1.419 0.156795
## comment 3.454755 1.511999 2.285 0.022920 *
## like 0.846200 0.107449 7.875 0.0000000000000437 ***
## share 2.917569 1.147526 2.542 0.011439 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 270 on 348 degrees of freedom
## Multiple R-squared: 0.7592, Adjusted R-squared: 0.7295
## F-statistic: 25.52 on 43 and 348 DF, p-value: < 0.00000000000000022
```

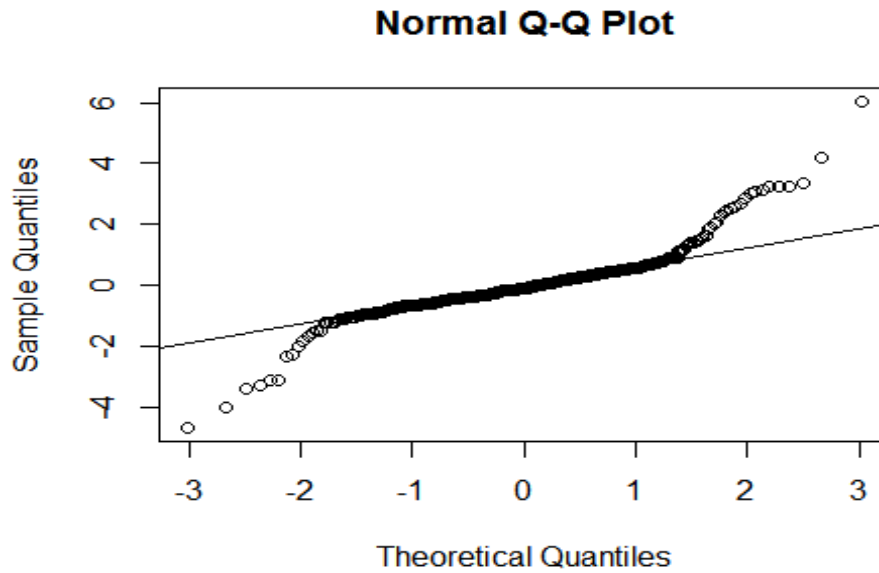
We obtain a model with R-Squared value of 0.7592

### Observing the residual plots and checking for Normality

```
residuals <- rstandard(model2)
```

```
qqnorm(residuals)
```

```
qqline(residuals)
```



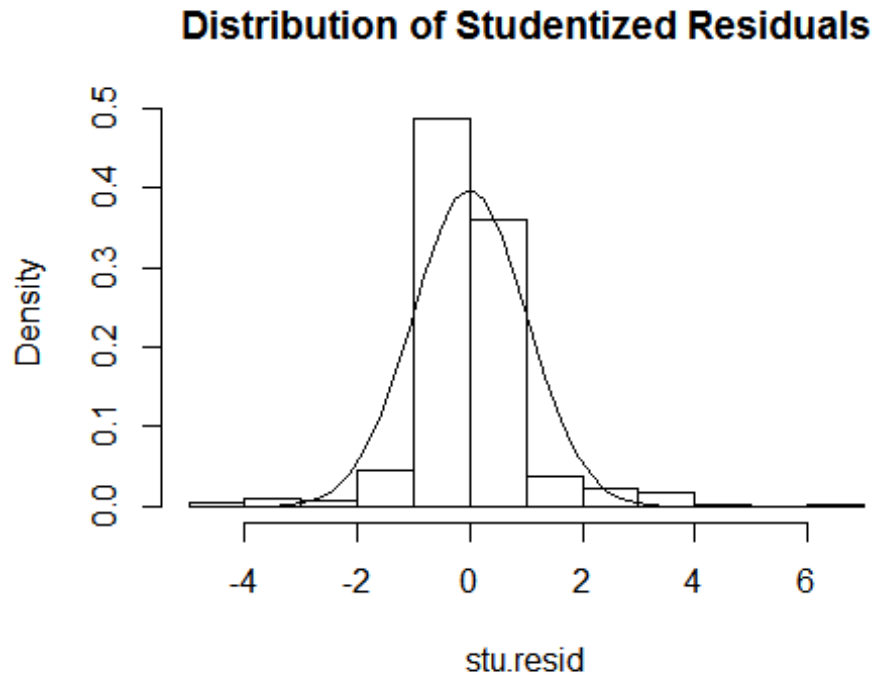
```
stu.resid <- studres(model2)
```

```
hist(stu.resid, freq=FALSE, main="Distribution of Studentized Residuals")
```

```
xfit<-seq(-3.5, 7,length=40)
```

```
yfit<-dnorm(xfit)
```

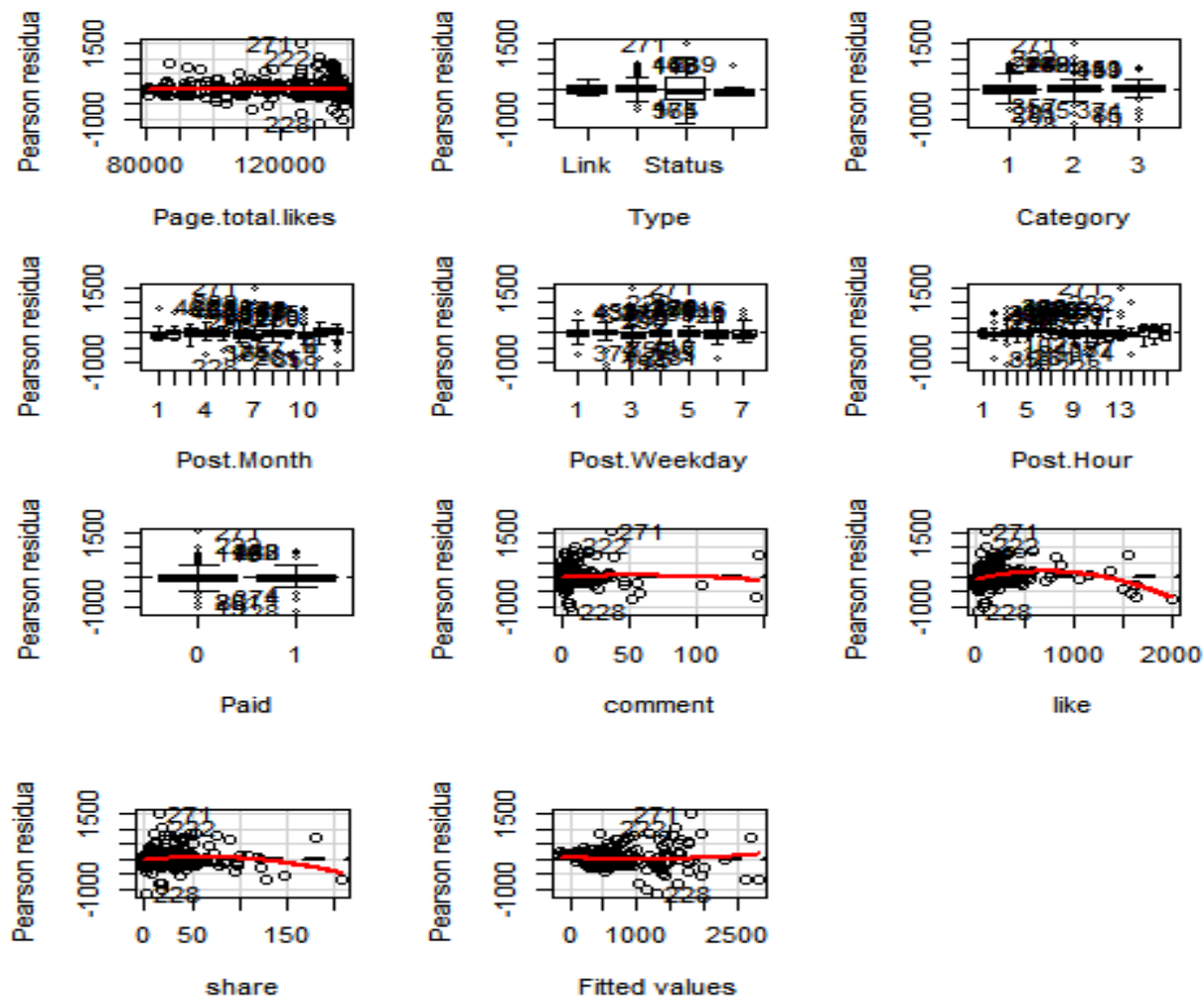
```
lines(xfit, yfit)
```



Observing the above plots shows that the model fits just well with the data, however the histogram is distorted

Residuals plot with Fitted values and other Regressors

```
residualPlots(model2,id.n=3)
```



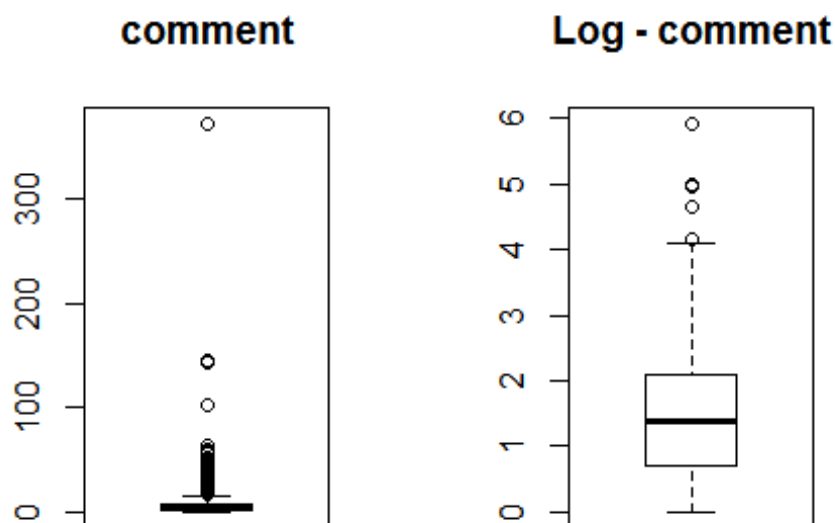
```
##      Test stat Pr(>|t|)
## Page.total.likes -1.738 0.083
## Type           NA    NA
## Category       NA    NA
## Post.Month     NA    NA
## Post.Weekday   NA    NA
## Post.Hour      NA    NA
## Paid          NA    NA
## comment       -1.107 0.269
## like         -6.418 0.000
## share        -3.911 0.000
## Tukey test     1.730 0.084
```

Observing the residual plots, we perform the following Transformation

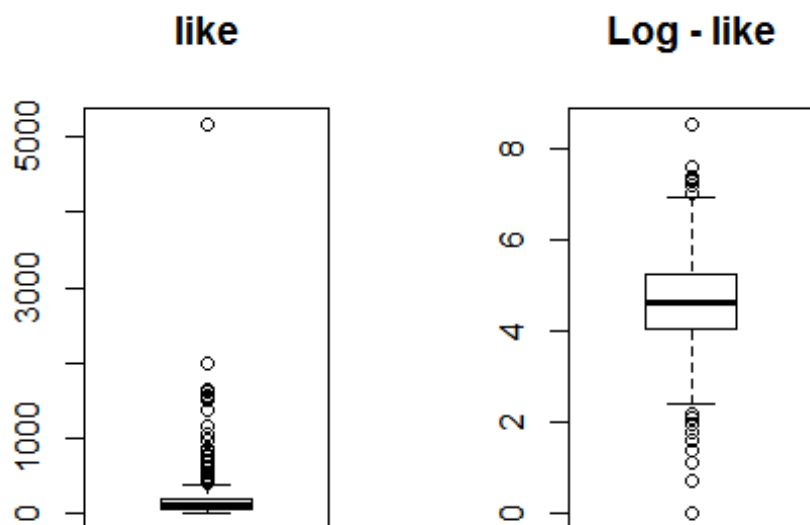
- Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post - Logarithmic transformation (Since skewed to right)
- comment - Logarithmic transformation (Since skewed to right)
- like - Logarithmic transformation (Since skewed to right)
- share - Logarithmic transformation (Since skewed to right)



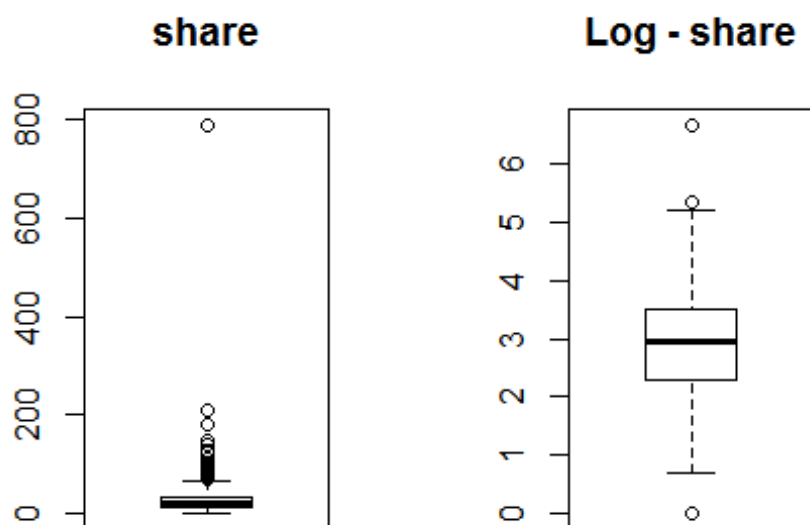
```
log.comment <- log(fb.raw$comment+1)
par(mfrow=c(1, 2))
boxplot(fb.raw$comment, main = "comment")
boxplot(log.comment, main = "Log - comment")
```



```
log.like <- log(fb.raw$like)
par(mfrow=c(1, 2))
boxplot(fb.raw$like, main = "like")
boxplot(log.like, main = "Log - like")
```



```
log.share <- log(fb.raw$share)
par(mfrow=c(1, 2))
boxplot(fb.raw$share, main = "share")
boxplot(log.share, main = "Log - share")
```

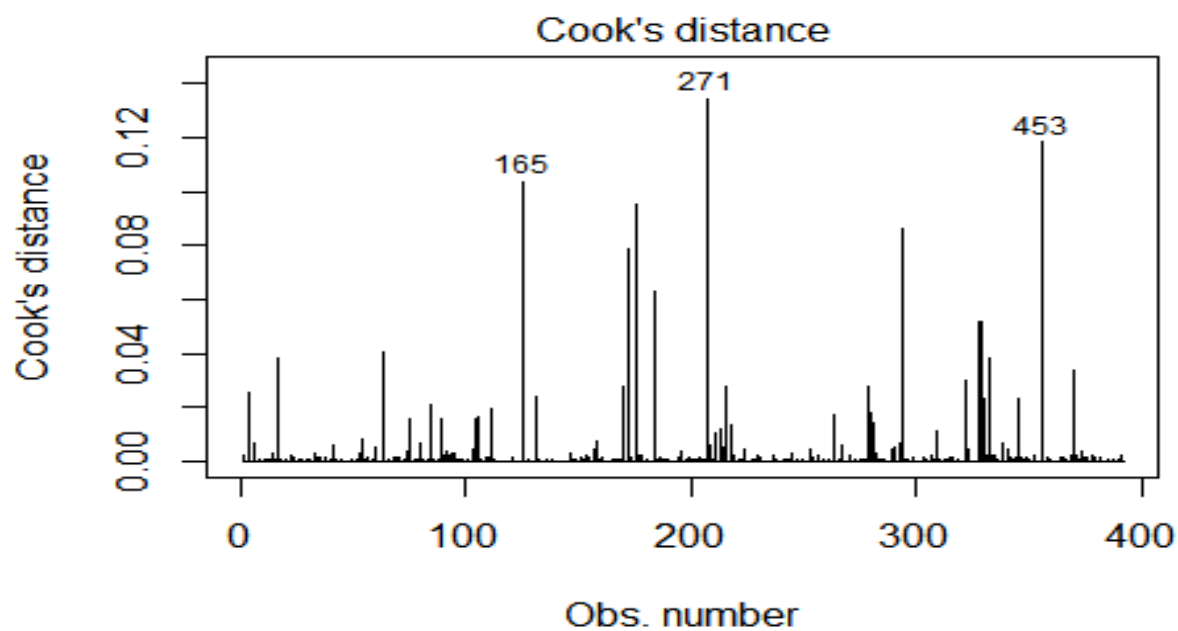


The data fits better after performing the Transformations

### Checking for Influential Observations/ Deletion Diagnostics

Analysing the influential variables using Cook's Distance

```
cutoff <- 4/((nrow(Train)-length(model2$coefficients)-2))
plot(model2, which=4, cook.levels=cutoff)
```



Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.pos

We observe that observation 165, 271, 453 have very large Cook's distance. Next we check whether their deletion affects our model or not

### Model 3 - Running the model by removing the influential observation

```
## Post.Hour4      54.549914 148.352784 0.368      0.713318
## Post.Hour5      36.203896 161.582793 0.224      0.822844
## Post.Hour6     -125.373910 157.760085 -0.795      0.427324
## Post.Hour7     -64.261417 163.538039 -0.393      0.694602
## Post.Hour8    -103.563375 167.119721 -0.620      0.535865
## Post.Hour9      75.169980 148.987606 0.505      0.614203
## Post.Hour10     46.799197 141.570965 0.331      0.741168
## Post.Hour11      4.996563 144.535831 0.035      0.972443
## Post.Hour12    123.841242 149.005615 0.831      0.406479
## Post.Hour13     75.075797 143.742588 0.522      0.601799
## Post.Hour14    146.056212 162.813866 0.897      0.370301
## Post.Hour15    -68.626094 194.156449 -0.353      0.723960
## Post.Hour17    231.095535 219.303238 1.054      0.292721
## Post.Hour18     44.291468 245.769238 0.180      0.857088
## Paid1           47.757982 31.965070 1.494      0.136067
## comment         1.000286 1.669528 0.599      0.549468
## like           0.865210 0.106142 8.151 0.00000000000000662 ***
## share          3.125749 1.133653 2.757      0.006138 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 266.3 on 347 degrees of freedom
## Multiple R-squared:  0.747, Adjusted R-squared:  0.7156
## F-statistic: 23.83 on 43 and 347 DF, p-value: < 0.00000000000000022
```

Removing influential observation did not affect the model.

We will now perform transformation on the dependent variable and few of the independent variable by observing the residual plots from model2

## Model 4

```
Train$log.comment <- log(Train$comment+1)
Train$log.like <- log(Train$like+1)
Train$log.share <- log(Train$share+1)
Train$log.Y <- log(Train$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post)

model4 <- lm(log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday + Post.Hour + Paid +
             log.comment + log.like + log.share,
             data = Train)
summary(model4)

##
## Call:
## lm(formula = log.Y ~ Page.total.likes + Type + Category + Post.Month +
##   Post.Weekday + Post.Hour + Paid + log.comment + log.like +
##   log.share, data = Train)
```

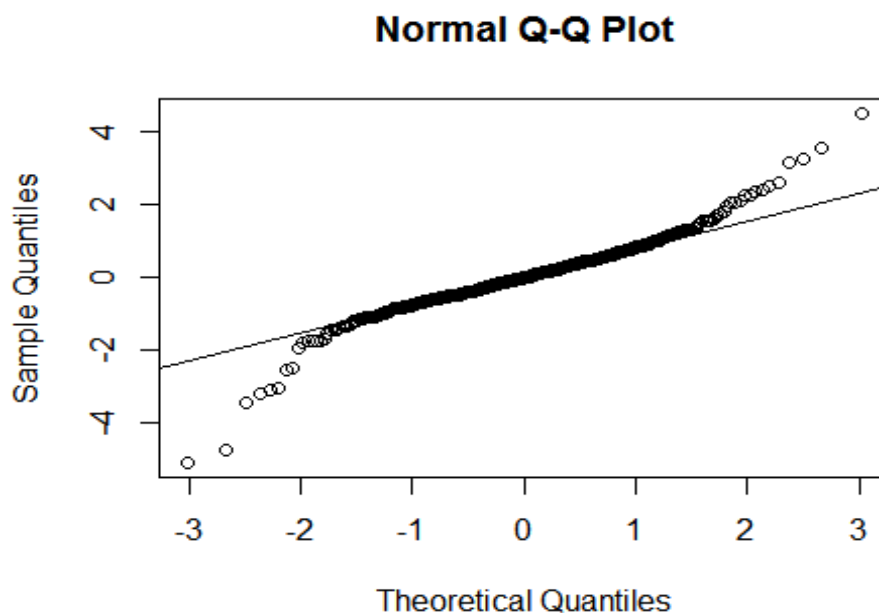
```
##
## Residuals:
##   Min     1Q   Median     3Q      Max
## -1.66463 -0.17884 -0.00784  0.16947  1.52990
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)   5.63617267  1.17924468  4.779  0.00000259710058 ***
## Page.total.likes -0.00002615  0.00001361  -1.922      0.0555 .
## TypePhoto      0.72273554  0.10117026  7.144  0.000000000000535 ***
## TypeStatus      1.88254673  0.12357322 15.234 < 0.0000000000000002 ***
## TypeVideo      1.16823945  0.17350435  6.733  0.000000000006868 ***
## Category2      -0.37343372  0.06013821  -6.210  0.00000000151377 ***
## Category3      -0.46347493  0.05349838  -8.663 < 0.0000000000000002 ***
## Post.Month2     0.24003961  0.14356663  1.672      0.0954 .
## Post.Month3     0.08495988  0.22529287  0.377      0.7063
## Post.Month4     0.66017136  0.34845928  1.895      0.0590 .
## Post.Month5     0.68025287  0.44834042  1.517      0.1301
## Post.Month6     1.10816601  0.54493317  2.034      0.0428 *
## Post.Month7     0.99057102  0.60574692  1.635      0.1029
## Post.Month8     1.06189838  0.64983387  1.634      0.1031
## Post.Month9     0.97436139  0.68147967  1.430      0.1537
## Post.Month10    1.25257545  0.69919500  1.791      0.0741 .
## Post.Month11    0.48087932  0.71593271  0.672      0.5022
## Post.Month12    0.80144306  0.73429080  1.091      0.2758
## Post.Weekday2   -0.03735547  0.07215373  -0.518      0.6050
## Post.Weekday3    0.03801590  0.07574590  0.502      0.6161
## Post.Weekday4   -0.17431760  0.07387508  -2.360      0.0188 *
## Post.Weekday5   -0.13138854  0.07325130  -1.794      0.0737 .
## Post.Weekday6    0.01290201  0.07019559  0.184      0.8543
## Post.Weekday7    0.12866271  0.06954814  1.850      0.0652 .
## Post.Hour2      0.05399090  0.19869242  0.272      0.7860
## Post.Hour3     -0.04366312  0.18901613  -0.231      0.8174
## Post.Hour4      0.06906503  0.19909683  0.347      0.7289
## Post.Hour5      0.08245327  0.21682085  0.380      0.7040
## Post.Hour6     -0.21916498  0.21151035  -1.036      0.3008
## Post.Hour7      0.06553770  0.21959985  0.298      0.7655
## Post.Hour8     -0.17697778  0.22443548  -0.789      0.4309
## Post.Hour9      0.01653453  0.19999619  0.083      0.9342
## Post.Hour10    -0.00389007  0.18984246  -0.020      0.9837
## Post.Hour11    -0.07121409  0.19400241  -0.367      0.7138
## Post.Hour12     0.21477356  0.19968052  1.076      0.2829
## Post.Hour13     0.06254419  0.19289912  0.324      0.7460
## Post.Hour14     0.14692064  0.21777779  0.675      0.5004
## Post.Hour15     0.51324958  0.26210354  1.958      0.0510 .
## Post.Hour17     0.24352324  0.29456466  0.827      0.4090
## Post.Hour18     0.29109130  0.33009682  0.882      0.3785
## Paid1          0.04851222  0.04301862  1.128      0.2602
## log.comment     0.02296330  0.02436795  0.942      0.3467
## log.like        0.46281027  0.03727588 12.416 < 0.0000000000000002 ***
## log.share       0.06175024  0.04602506  1.342      0.1806
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.3572 on 348 degrees of freedom
## Multiple R-squared:  0.8175, Adjusted R-squared:  0.7949
## F-statistic: 36.25 on 43 and 348 DF, p-value: < 0.00000000000000022
```

By using Transformation, we obtain R-Squared value of 0.8175. The model fits well with the data. Comparing Adjusted R-squared with the previous model value, this value is also very high

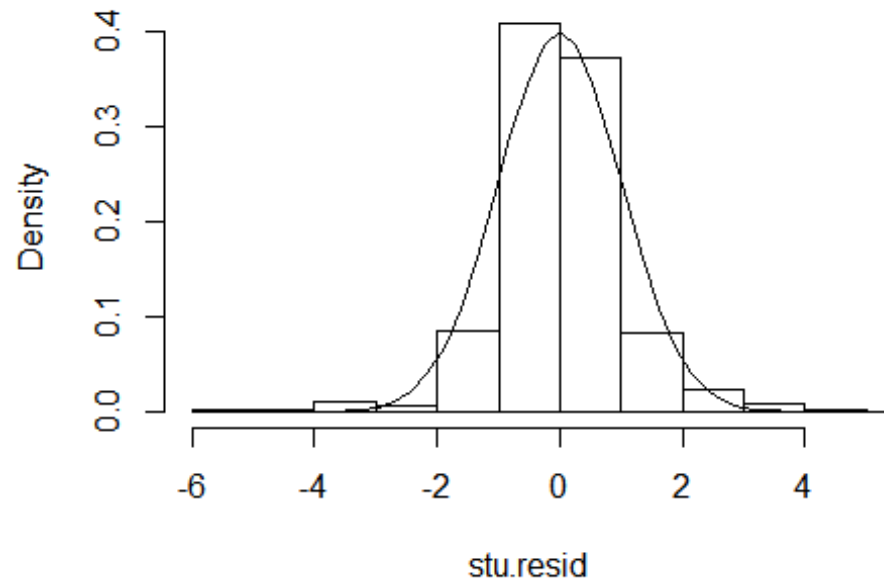
Observing the residual plots and checking for Normality

```
residuals <- rstandard(model4)
qqnorm(residuals)
qqline(residuals)
```



```
stu.resid <- studres(model4)
hist(stu.resid, freq=FALSE, main="Distribution of Studentized Residuals")
xfit<-seq(-3.5, 7,length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)
```

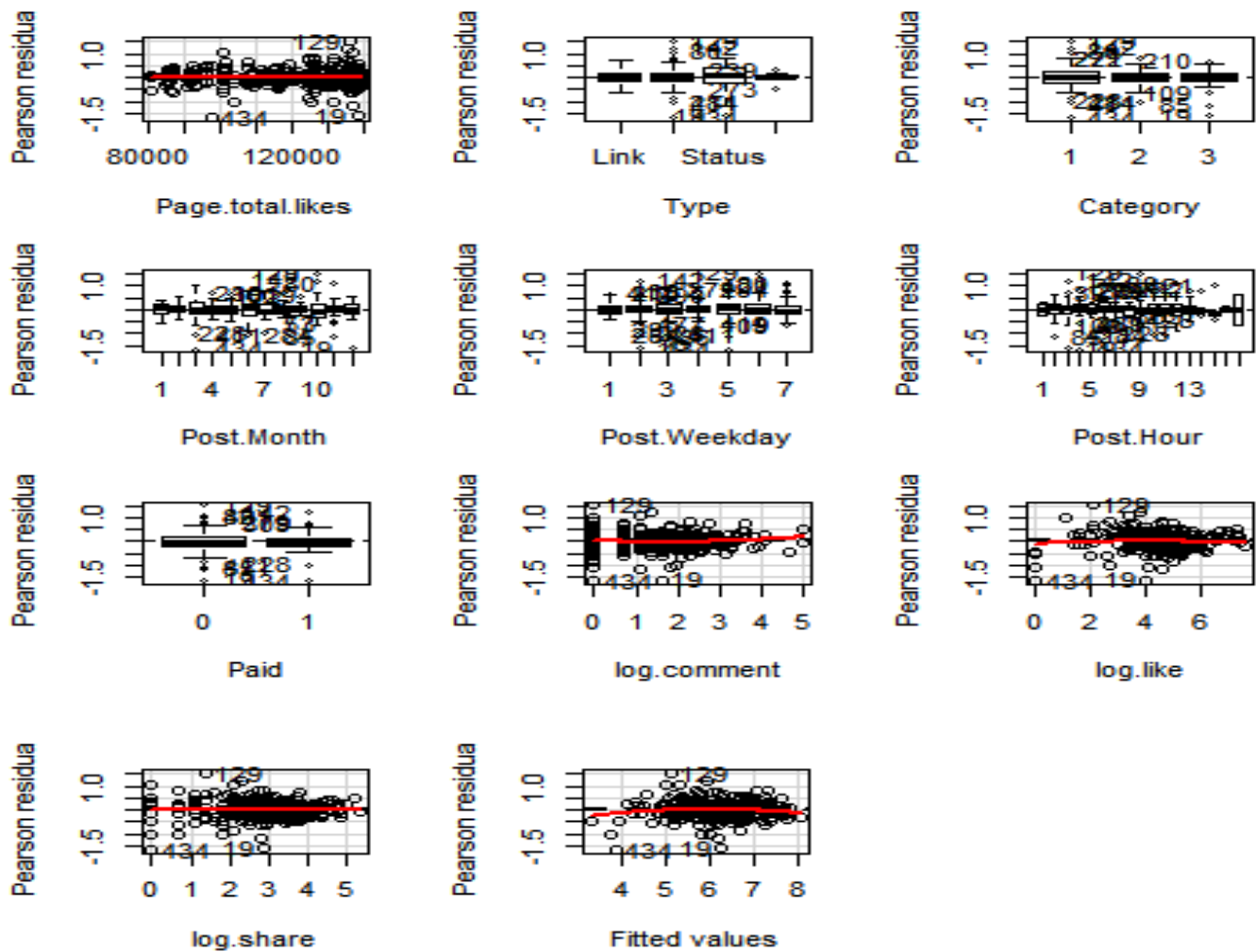
## Distribution of Studentized Residuals



The residual plots, QQplot and Histogram, both are almost normally distributed. This means the model fits well

Residuals plot with Fitted values and other Regressors

```
residualPlots(model4,id.n=3)
```



```
##      Test stat Pr(>|t|)
## Page.total.likes -1.841 0.066
## Type            NA    NA
## Category        NA    NA
## Post.Month       NA    NA
## Post.Weekday     NA    NA
## Post.Hour        NA    NA
## Paid            NA    NA
## log.comment      1.595 0.112
## log.like        -1.026 0.305
## log.share        0.021 0.983
## Tukey test      -2.187 0.029
```

Observing the residual vs fitted plots and residuals vs regressors plot, the errors are almost randomly distributed. We see that our model fits well



## Variance Inflation Factors

```
vif(model4)

##          GVIF Df GVIF^(1/(2*Df))
## Page.total.likes 157.695262 1 12.557677
## Type            1.829232 3 1.105889
## Category        2.440324 2 1.249862
## Post.Month      790.590084 11 1.354332
## Post.Weekday    1.788789 6 1.049655
## Post.Hour       6.135301 16 1.058327
## Paid           1.147515 1 1.071221
## log.comment     2.043645 1 1.429561
## log.like        5.558619 1 2.357672
## log.share       5.992470 1 2.447952
```

Observing the Variance Inflation Factors, the values are almost less than or close to 10 (cut-off factor)

## Variance Decomposition Proportion

```
colldiag(Train[,c(2:15, 20:23)], center = TRUE)

## Condition
## Index  Variance Decomposition Proportions
##          Page.total.likes comment like share
## 1      1.000 0.000      0.000 0.000 0.000
## 2      1.835 0.959      0.000 0.000 0.000
## 3      2.958 0.006      0.000 0.000 0.000
## 4      3.986 0.035      0.000 0.000 0.000
## 5 16309146577994740.000 0.000      1.000 1.000 1.000
## Total.Interactions
## 1 0.000
## 2 0.000
## 3 0.000
## 4 0.000
## 5 1.000
```

- Observing Variance Decomposition Proportion, it hints that comment, like and share are linearly correlated.
- Observing the correlation matrix also suggest high correlation between the three

We now build a model by dropping one of them, mostly the one which is least correlated with the output - Comment

---

## Model 5

```
model5 <- lm(log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday + Post.Hour + Paid + log.like + log.sh
are,
```

```
data = Train)
```

```
summary(model5)
```

```
##
```

```
## Call:
```

```
## lm(formula = log.Y ~ Page.total.likes + Type + Category + Post.Month +
```

```
## Post.Weekday + Post.Hour + Paid + log.like + log.share, data = Train)
```

```
##
```

```
## Residuals:
```

```
## Min 1Q Median 3Q Max
```

```
## -1.63264 -0.18679 -0.00712 0.16854 1.52826
```

```
##
```

```
## Coefficients:
```

```
## Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 5.62412732 1.17898624 4.770 0.00000270765100 ***
```

```
## Page.total.likes -0.00002639 0.00001361 -1.940 0.0532 .
```

```
## TypePhoto 0.71927546 0.10108739 7.115 0.000000000000638 ***
```

```
## TypeStatus 1.87741012 0.12343314 15.210 < 0.0000000000000002 ***
```

```
## TypeVideo 1.17032032 0.17346247 6.747 0.000000000006298 ***
```

```
## Category2 -0.37487409 0.06010914 -6.237 0.00000000129311 ***
```

```
## Category3 -0.46801505 0.05327246 -8.785 < 0.0000000000000002 ***
```

```
## Post.Month2 0.24284217 0.14351280 1.692 0.0915 .
```

```
## Post.Month3 0.08766509 0.22523844 0.389 0.6974
```

```
## Post.Month4 0.66012382 0.34840338 1.895 0.0590 .
```

```
## Post.Month5 0.68970732 0.44815625 1.539 0.1247
```

```
## Post.Month6 1.12294327 0.54462012 2.062 0.0400 *
```

```
## Post.Month7 1.00877858 0.60534158 1.666 0.0965 .
```

```
## Post.Month8 1.07207340 0.64963993 1.650 0.0998 .
```

```
## Post.Month9 0.98501424 0.68127660 1.446 0.1491
```

```
## Post.Month10 1.26838773 0.69888150 1.815 0.0704 .
```

```
## Post.Month11 0.49699644 0.71561358 0.695 0.4878
```

```
## Post.Month12 0.81318037 0.73406738 1.108 0.2687
```

```
## Post.Weekday2 -0.03454393 0.07208045 -0.479 0.6321
```

```
## Post.Weekday3 0.04235939 0.07559341 0.560 0.5756
```

```
## Post.Weekday4 -0.16666498 0.07341560 -2.270 0.0238 *
```

```
## Post.Weekday5 -0.12956936 0.07321411 -1.770 0.0776 .
```

```
## Post.Weekday6 0.01591256 0.07011160 0.227 0.8206
```

```
## Post.Weekday7 0.12935323 0.06953312 1.860 0.0637 .
```

```
## Post.Hour2 0.06142372 0.19850395 0.309 0.7572
```

```
## Post.Hour3 -0.04580579 0.18897213 -0.242 0.8086
```

```
## Post.Hour4 0.06950675 0.19906434 0.349 0.7272
```

```
## Post.Hour5 0.07562980 0.21666515 0.349 0.7273
```

```
## Post.Hour6 -0.21733362 0.21146749 -1.028 0.3048
```

```
## Post.Hour7 0.05395116 0.21922021 0.246 0.8057
```

```
## Post.Hour8 -0.17533458 0.22439271 -0.781 0.4351
```

```
## Post.Hour9 0.01727549 0.19996256 0.086 0.9312
```

```
## Post.Hour10 -0.00154621 0.18979571 -0.008 0.9935
```

```
## Post.Hour11 -0.07747443 0.19385753 -0.400 0.6897
```

```
## Post.Hour12 0.20873570 0.19954568 1.046 0.2963
```

```
## Post.Hour13 0.06607627 0.19283176 0.343 0.7321
```

```
## Post.Hour14 0.15479544 0.21758250 0.711 0.4773
```

```
## Post.Hour15  0.52905116 0.26152466 2.023      0.0438 *
## Post.Hour17  0.25485358 0.29427196 0.866      0.3871
## Post.Hour18  0.29119491 0.33004384 0.882      0.3782
## Paid1        0.05030013 0.04296987 1.171      0.2426
## log.like     0.47349941 0.03550244 13.337 < 0.0000000000000002 ***
## log.share    0.06725331 0.04564576 1.473      0.1416
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3572 on 349 degrees of freedom
## Multiple R-squared:  0.817, Adjusted R-squared:  0.795
## F-statistic: 37.1 on 42 and 349 DF, p-value: < 0.00000000000000022
```

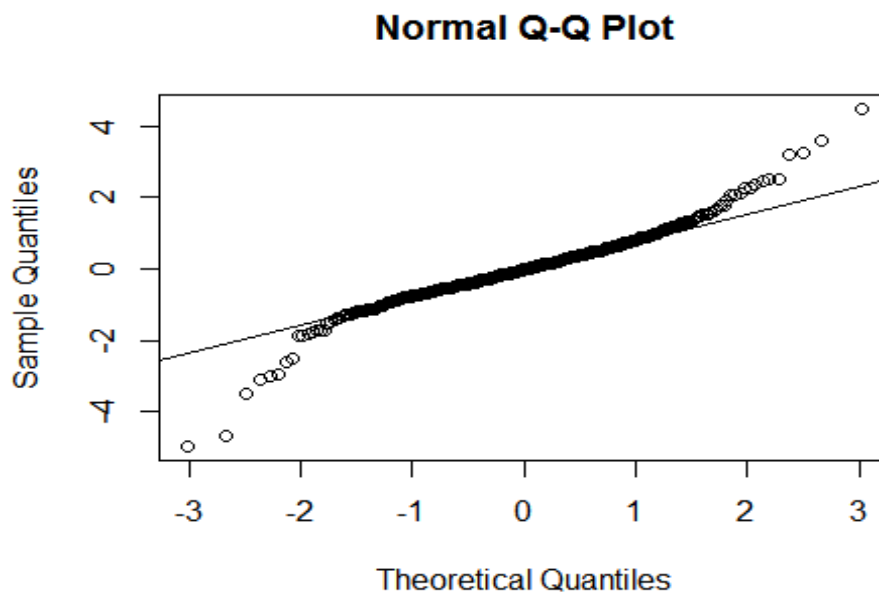
The R-Squared value increases to 0.817

### Observing the residual plots and checking for Normality

```
residuals <- rstandard(model5)
```

```
qqnorm(residuals)
```

```
qqline(residuals)
```



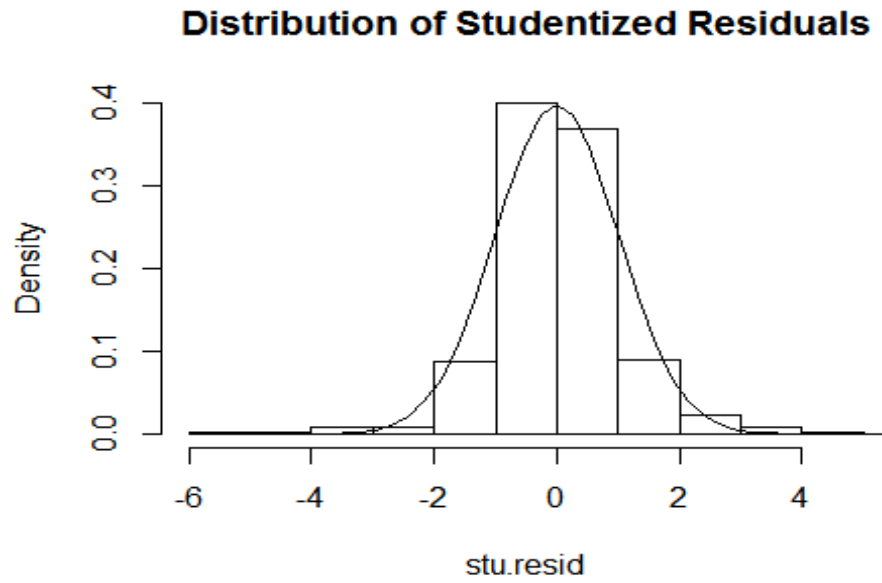
```
stu.resid <- studres(model5)
```

```
hist(stu.resid, freq=FALSE, main="Distribution of Studentized Residuals")
```

```
xfit<-seq(-3.5, 7,length=40)
```

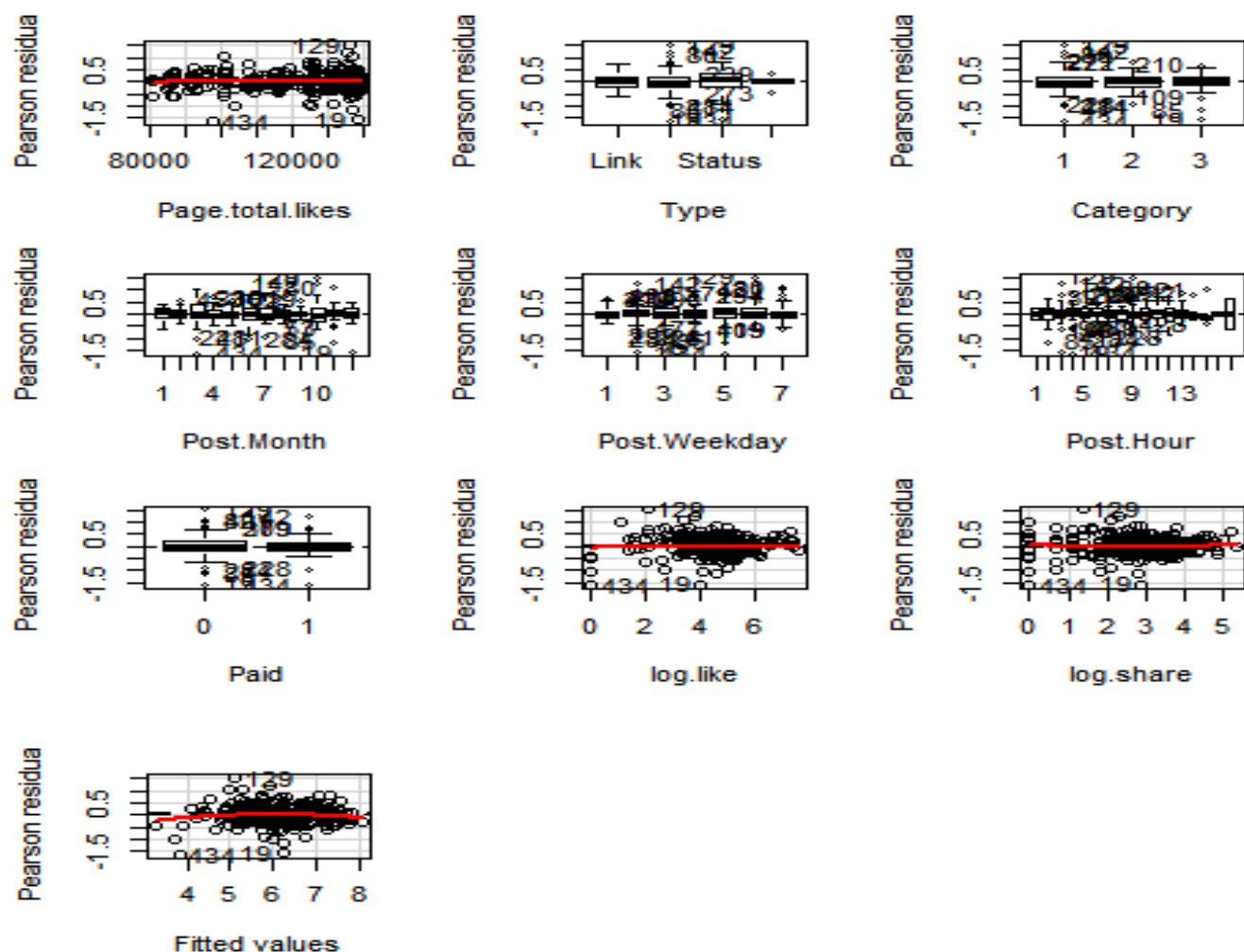
```
yfit<-dnorm(xfit)
```

```
lines(xfit, yfit)
```



Residuals plot with Fitted values and other Regressors

```
residualPlots(model5,id.n=3)
```



```
##      Test stat Pr(>|t|)
## Page.total.likes -1.857 0.064
## Type           NA    NA
## Category        NA    NA
## Post.Month       NA    NA
## Post.Weekday     NA    NA
## Post.Hour        NA    NA
## Paid            NA    NA
## log.like        -0.691 0.490
## log.share        0.366 0.715
## Tukey test      -1.980 0.048
```

We have built a model with R-Squared equal close to 0.82. The model fits the data well which can be even confirmed from the residual plots

Next we try to see if interactions can improve the performance of the model.

We try to see how interactions between categorical variables can improve the performance of the model. Interactions will help to identify how a particular post of particular kind when uploaded at a particular hour/month and if paid or not is able to attract maximum engagement from the user

On checking different permutations and combinations, we observed that interactions between Type, Post.Weekday and Post.Hour improves the performance of the model significantly. This interaction will help us determine which type of post when uploaded at what particular weekday and hour attracts maximum engagement from the user

```
model6 = lm(log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday + Post.Hour + Paid + log.like + log.share +
            Type*Post.Weekday*Post.Hour , data = Train)
summary(model6)
```

(Complete Output not shown)

```
##
## Call:
## lm(formula = log.Y ~ Page.total.likes + Type + Category + Post.Month +
##   Post.Weekday + Post.Hour + Paid + log.like + log.share +
##   Type * Post.Weekday * Post.Hour, data = Train)
##
## Residuals:
##   Min     1Q   Median     3Q      Max
## -0.9463 -0.1237  0.0000  0.1059  1.3538
##
## Coefficients: (339 not defined because of singularities)
##              Estimate Std. Error t value
## (Intercept)      6.94382533  1.85391396   3.745
## Page.total.likes    -0.00002743  0.00001547  -1.773
## TypePhoto          1.39667315  0.95007800   1.470
## TypeStatus         3.45614804  1.06117365   3.257
## TypeVideo          1.14536920  0.89456069   1.280
## Category2         -0.41929123  0.06405323  -6.546
## Category3         -0.40538588  0.05570633  -7.277
## Post.Month2         0.12936171  0.14939841   0.866
## Post.Month3        -0.02802130  0.24936702  -0.112
## Post.Month4         0.48147535  0.38043885   1.266
## Post.Month5         0.52069277  0.50402292   1.033
## Post.Month6         0.95504180  0.60866303   1.569
## Post.Month7         0.89160163  0.67749465   1.316
## Post.Month8         0.99677340  0.72804153   1.369
## Post.Month9         0.91882522  0.76402528   1.203
## Post.Month10        1.13908002  0.78847890   1.445
## Post.Month11        0.44710979  0.80328434   0.557
## Post.Month12        0.73959693  0.82640201   0.895
## Post.Weekday2       -2.41209511  0.88351524  -2.730
## Post.Weekday3       -2.16065670  0.91236374  -2.368
## Post.Weekday4       -2.57533648  1.42397950  -1.809
## Post.Weekday5       -1.90686467  1.18995522  -1.602
## Post.Weekday6       -1.66315573  1.06425744  -1.563
## Post.Weekday7       -0.80500325  1.13751048  -0.708
## Post.Hour2         -0.54449018  1.30254588  -0.418
```

```
## Post.Hour3      -0.29340856  1.48150862 -0.198
## Post.Hour4      -0.83500582  1.54677795 -0.540
## Post.Hour5      -1.92327977  0.76433066 -2.516
```

```
.....
```

```
.....
```

```
## TypePhoto:Post.Weekday5:Post.Hour18      NA
## TypeStatus:Post.Weekday5:Post.Hour18      NA
## TypeVideo:Post.Weekday5:Post.Hour18      NA
## TypePhoto:Post.Weekday6:Post.Hour18      NA
## TypeStatus:Post.Weekday6:Post.Hour18      NA
## TypeVideo:Post.Weekday6:Post.Hour18      NA
## TypePhoto:Post.Weekday7:Post.Hour18      NA
## TypeStatus:Post.Weekday7:Post.Hour18      NA
## TypeVideo:Post.Weekday7:Post.Hour18      NA
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 0.316 on 238 degrees of freedom
```

```
## Multiple R-squared:  0.9024, Adjusted R-squared:  0.8396
```

```
## F-statistic: 14.38 on 153 and 238 DF,  p-value: < 0.000000000000000022
```

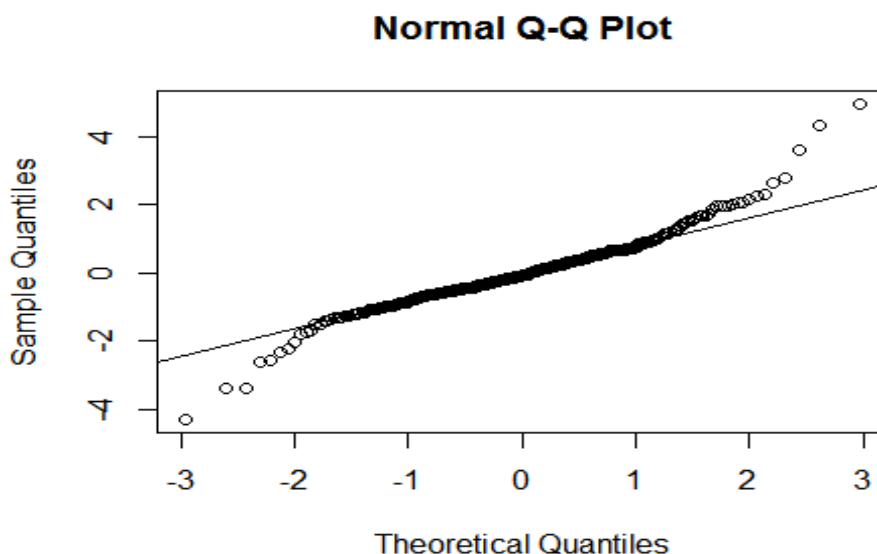
The R-Squared of the model has increased to 0.9024. The Adjusted R-Squared has also improved

Observing the residual plots and checking for Normality

```
residuals <- rstandard(model6)
```

```
qqnorm(residuals)
```

```
qqline(residuals)
```

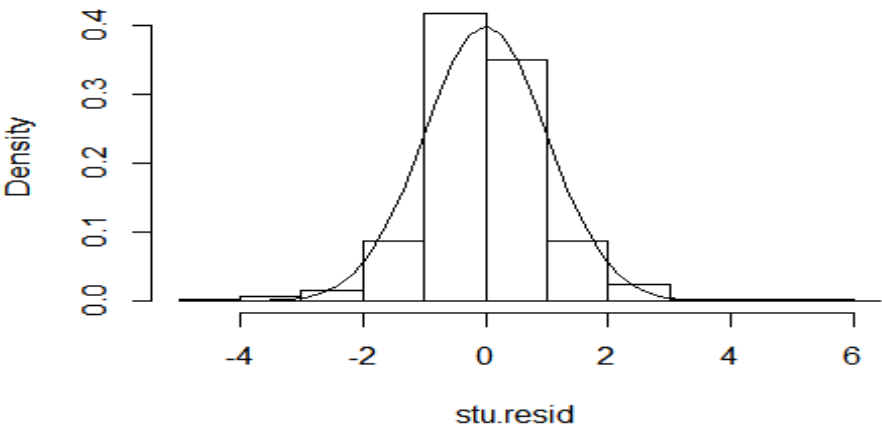


```
stu.resid <- studres(model6)
```

```
hist(stu.resid, freq=FALSE, main="Distribution of Studentized Residuals")
```

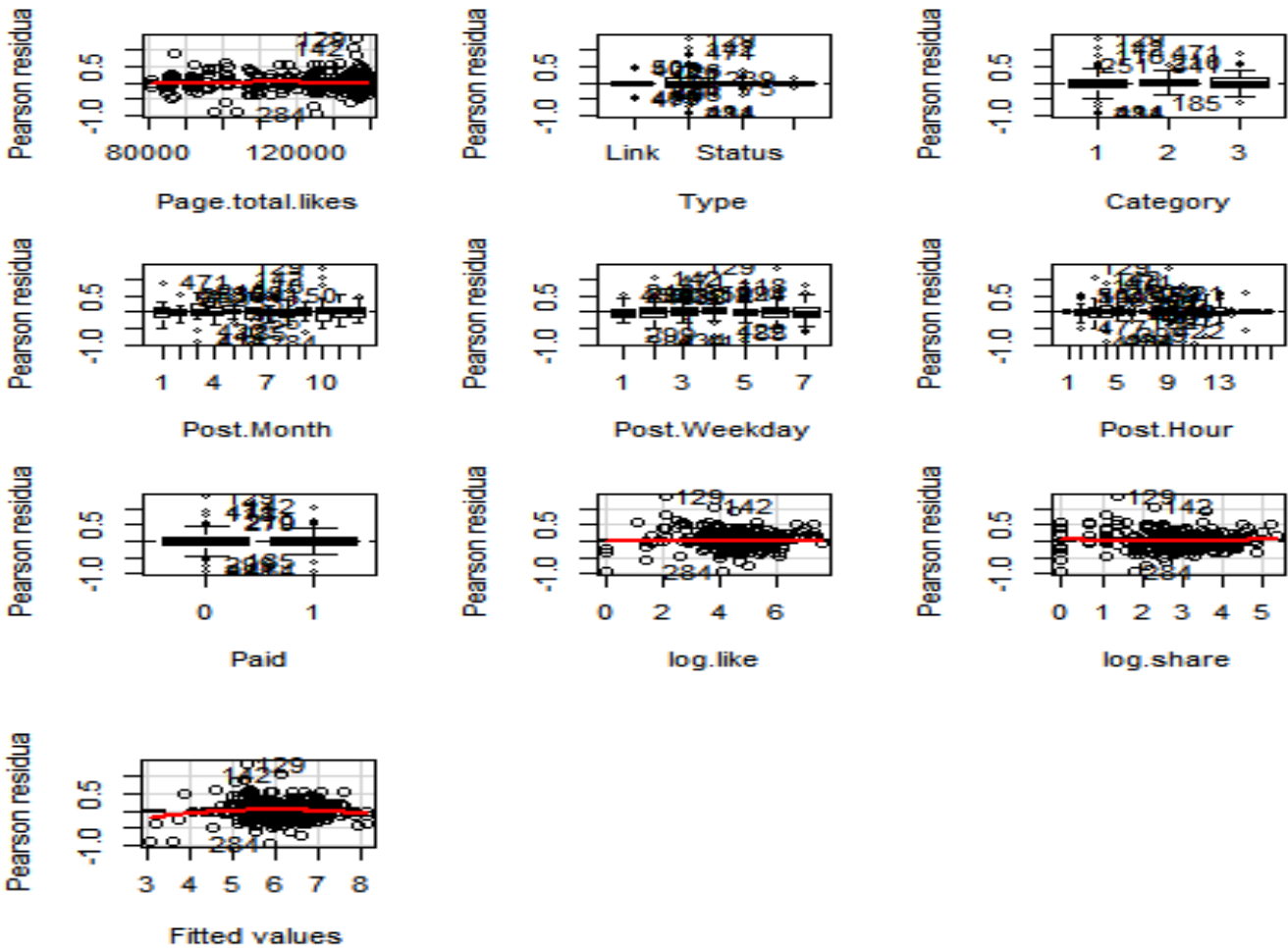
```
xfit<-seq(-3.5, 7,length=40)
```

# Distribution of Studentized Residuals



Residuals plot with Fitted values and other Regressors

```
residualPlots(model6,id.n=3)
```





```
##          Test stat Pr(>|t|)
## Page.total.likes -0.756 0.450
## Type           NA    NA
## Category        NA    NA
## Post.Month       NA    NA
## Post.Weekday     NA    NA
## Post.Hour        NA    NA
## Paid            NA    NA
## log.like        -0.234 0.815
## log.share        0.797 0.426
## Tukey test      -2.651 0.008
```

Observing the residuals plots, the model fits well.

Next we select the best subset model using stepwise regression

## Best Subset selection

We will use the AIC criterion for obtaining the best subset.

```
step <- stepAIC(model6, direction="both")
step$anova # display results

## Start: AIC=-790.88
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + Paid + log.like + log.share + Type * Post.Weekday *
##   Post.Hour
##
##           Df Sum of Sq  RSS   AIC
## - Type:Post.Weekday:Post.Hour 6  0.1815 23.941 -799.90
## - log.share                   1  0.0901 23.850 -791.40
## <none>                        23.760 -790.88
## - Paid                       1  0.1411 23.901 -790.56
## - Page.total.likes           1  0.3138 24.074 -787.74
## - Category                   2  6.2428 30.003 -703.43
## - Post.Month                 11 10.6932 34.453 -667.21
## - log.like                   1 15.5567 39.317 -595.45
##
## Step: AIC=-799.9
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + Paid + log.like + log.share + Type:Post.Weekday +
##   Type:Post.Hour + Post.Weekday:Post.Hour
##
##           Df Sum of Sq  RSS   AIC
## - Post.Weekday:Post.Hour    71 10.0982 34.040 -803.95
## - log.share                 1  0.0652 24.007 -800.83
## - Paid                     1  0.0986 24.040 -800.29
## <none>                     23.941 -799.90
## - Page.total.likes         1  0.3345 24.276 -796.46
## + Type:Post.Weekday:Post.Hour 6  0.1815 23.760 -790.88
```

```
## - Type:Post.Hour      16  2.7328 26.674 -789.53
## - Type:Post.Weekday   12  4.1031 28.044 -761.89
## - Category            2  6.3790 30.320 -711.30
## - Post.Month          11 10.7900 34.731 -676.06
## - log.like            1 16.5228 40.464 -596.17
##
## Step: AIC=-803.95
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + Paid + log.like + log.share + Type:Post.Weekday +
##   Type:Post.Hour
##
##              Df Sum of Sq  RSS   AIC
## - log.share      1  0.0773 34.117 -805.06
## <none>              34.040 -803.95
## - Paid            1  0.1758 34.215 -803.93
## - Page.total.likes  1  0.2635 34.303 -802.92
## + Post.Weekday:Post.Hour 71 10.0982 23.941 -799.90
## - Type:Post.Hour   18  4.7812 38.821 -788.42
## - Type:Post.Weekday 12  3.8198 37.859 -786.25
## - Category          2  9.1732 43.213 -714.41
## - Post.Month        11 16.6826 50.722 -669.60
## - log.like          1 21.3224 55.362 -615.29
##
## Step: AIC=-805.06
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + Paid + log.like + Type:Post.Weekday + Type:Post.Hour
##
##              Df Sum of Sq  RSS   AIC
## - Paid            1  0.155 34.272 -805.28
## <none>              34.117 -805.06
## - Page.total.likes  1  0.241 34.358 -804.30
## + log.share         1  0.077 34.040 -803.95
## + Post.Weekday:Post.Hour 71 10.110 24.007 -800.83
## - Type:Post.Hour   18  4.804 38.921 -789.42
## - Type:Post.Weekday 12  3.877 37.994 -786.86
## - Category          2  9.647 43.764 -711.44
## - Post.Month        11 16.607 50.723 -671.59
## - log.like          1 86.827 120.943 -310.97
##
## Step: AIC=-805.28
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + log.like + Type:Post.Weekday + Type:Post.Hour
##
##              Df Sum of Sq  RSS   AIC
## <none>              34.272 -805.28
## + Paid            1  0.155 34.117 -805.06
## - Page.total.likes  1  0.223 34.494 -804.74
## + log.share         1  0.056 34.215 -803.93
## + Post.Weekday:Post.Hour 71 10.182 24.089 -801.48
## - Type:Post.Hour   18  4.833 39.105 -789.57
## - Type:Post.Weekday 12  3.918 38.189 -786.85
## - Category          2  9.726 43.997 -711.36
## - Post.Month        11 16.645 50.916 -672.10
```

```
## - log.like      1  87.357 121.628 -310.75
## Stepwise Model Path
## Analysis of Deviance Table
##
## Initial Model:
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + Paid + log.like + log.share + Type * Post.Weekday *
##   Post.Hour
##
## Final Model:
## log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
##   Post.Hour + log.like + Type:Post.Weekday + Type:Post.Hour
##
##
##              Step Df   Deviance Resid. Df Resid. Dev
## 1                      238  23.75987
## 2 - Type:Post.Weekday:Post.Hour 6  0.18145316    244  23.94132
## 3   - Post.Weekday:Post.Hour 71 10.09819607    315  34.03952
## 4     - log.share 1  0.07725916    316  34.11678
## 5      - Paid 1  0.15475534    317  34.27153
##   AIC
## 1 -790.8795
## 2 -799.8971
## 3 -803.9460
## 4 -805.0573
## 5 -805.2832
```

It is observed that many regressors have dropped. The best model is

**lm(log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday + Post.Hour + log.like + Type:Post.Weekday + Type:Post.Hour, data = Train)**

```
BestModel <- lm(log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
  Post.Hour + log.like + Type:Post.Weekday + Type:Post.Hour, data = Train)
summary(BestModel)
```

```
##
## Call:
## lm(formula = log.Y ~ Page.total.likes + Type + Category + Post.Month +
##   Post.Weekday + Post.Hour + log.like + Type:Post.Weekday +
##   Type:Post.Hour, data = Train)
##
## Residuals:
##   Min     1Q   Median     3Q    Max
## -1.71563 -0.14492 -0.02016  0.13705  1.54899
##
## Coefficients: (32 not defined because of singularities)
##              Estimate Std. Error t value
## (Intercept)    4.28971731  1.41044749  3.041
## Page.total.likes -0.00001861  0.00001297 -1.435
## TypePhoto      1.48363424  0.77329938  1.919
## TypeStatus     3.39249746  0.80399652  4.220
## TypeVideo      0.83143779  0.80490701  1.033
```

```
## Category2      -0.39966068 0.05688039 -7.026
## Category3      -0.43802327 0.04856116 -9.020
## Post.Month2      0.12649177 0.13805673 0.916
## Post.Month3     -0.10738353 0.21637312 -0.496
## Post.Month4      0.42831639 0.33177593 1.291
## Post.Month5      0.38399626 0.42738775 0.898
## Post.Month6      0.72600669 0.51745093 1.403
## Post.Month7      0.58286255 0.57814267 1.008
## Post.Month8      0.62914500 0.61771340 1.019
## Post.Month9      0.54763016 0.64930574 0.843
## Post.Month10     0.80164131 0.66674052 1.202
## Post.Month11     0.05235743 0.68272223 0.077
## Post.Month12     0.30656392 0.69879593 0.439
## Post.Weekday2    -0.68599074 0.41121287 -1.668
.....

.....

## TypePhoto:Post.Hour13      0.01747 *
## TypeStatus:Post.Hour13      NA
## TypeVideo:Post.Hour13      NA
## TypePhoto:Post.Hour14      0.03665 *
## TypeStatus:Post.Hour14      NA
## TypeVideo:Post.Hour14      NA
## TypePhoto:Post.Hour15      NA
## TypeStatus:Post.Hour15      NA
## TypeVideo:Post.Hour15      NA
## TypePhoto:Post.Hour17      NA
## TypeStatus:Post.Hour17      NA
## TypeVideo:Post.Hour17      NA
## TypePhoto:Post.Hour18      NA
## TypeStatus:Post.Hour18      NA
## TypeVideo:Post.Hour18      NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3288 on 317 degrees of freedom
## Multiple R-squared:  0.8592, Adjusted R-squared:  0.8263
## F-statistic: 26.13 on 74 and 317 DF, p-value: < 0.00000000000000022
```

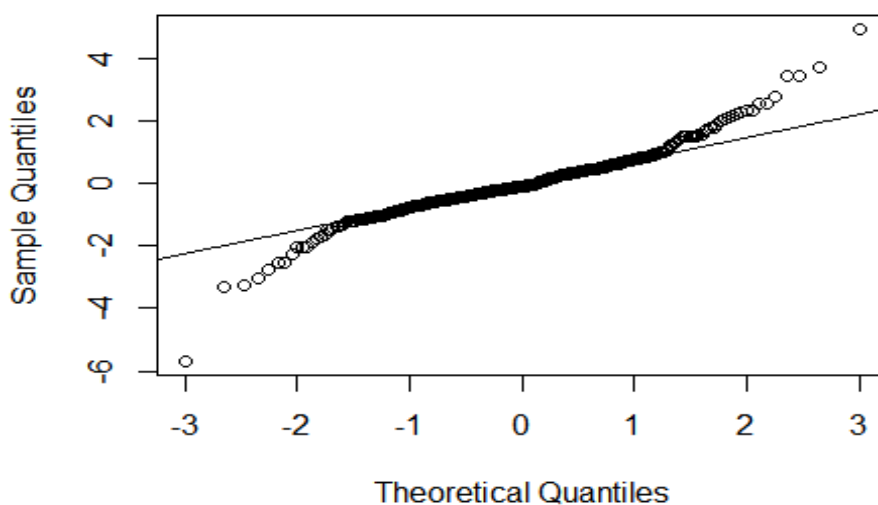
### Observing the residual plots and checking for Normality

```
residuals <- rstandard(BestModel)
```

```
qqnorm(residuals)
```

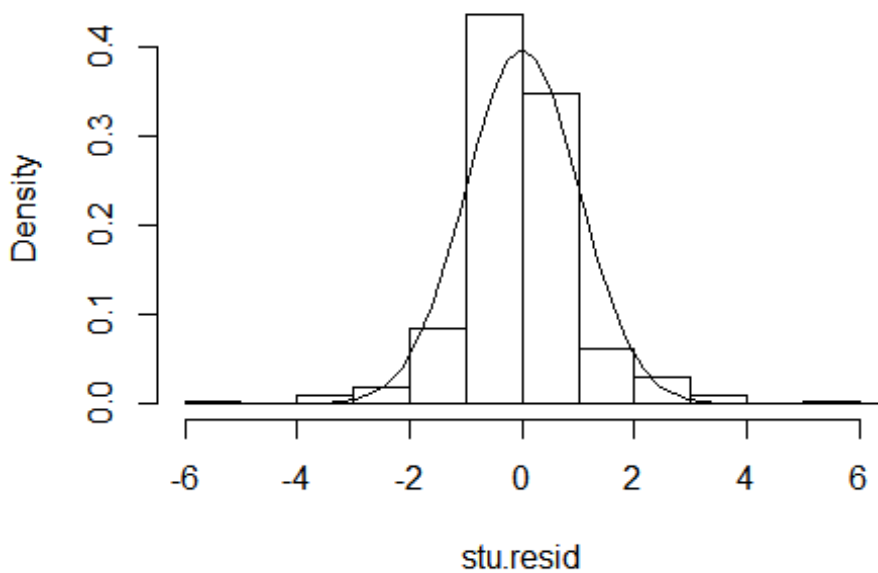
```
qqline(residuals)
```

### Normal Q-Q Plot



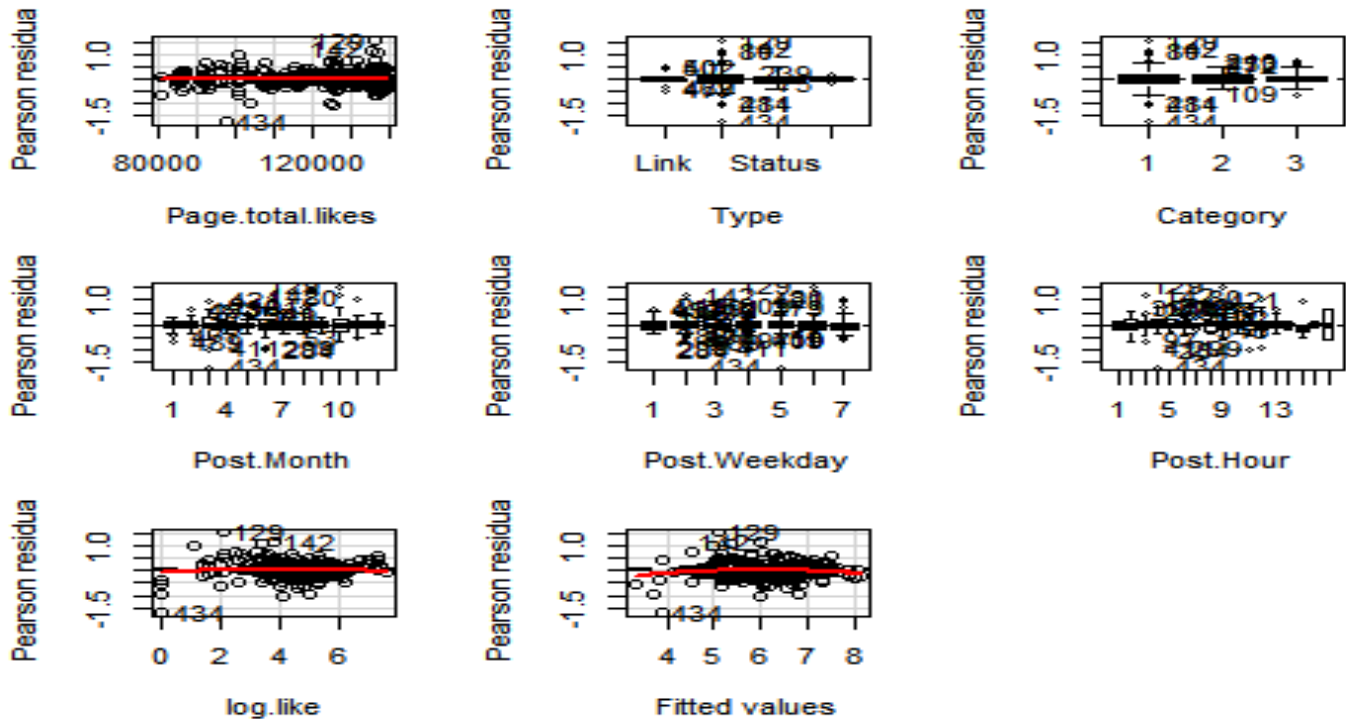
```
stu.resid <- studres(BestModel)
hist(stu.resid, freq=FALSE, main="Distribution of Studentized Residuals")
xfit<-seq(-3.5, 7,length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)
```

### Distribution of Studentized Residuals



Residuals plot with Fitted values and other Regressors

```
residualPlots(BestModel,id.n=3)
```



```
##      Test stat Pr(>|t|)
## Page.total.likes -2.078 0.039
## Type           NA    NA
## Category        NA    NA
## Post.Month       NA    NA
## Post.Weekday     NA    NA
## Post.Hour        NA    NA
## log.like         -0.392 0.695
## Tukey test       -2.576 0.010
```

We have successfully built a model which explains almost 86% variability in the data with most significant regressors

## Validation

We test our model using the test data set and use the model BestModel for predictions

```
Test$log.Y <- log(Test$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post)
Test$log.like <- log(Test$like+1)

y_hat <- predict.lm(BestModel, newdata = Test, se.fit=TRUE)$fit
y_hat <- as.vector(y_hat)
dev <- Test$log.Y - (y_hat)
num <- sum(dev^2)
dev1 <- Test$log.Y - mean(log(Test$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post))
den <- sum(dev1^2)
Predicted.Rsq <- 1 - (num/den)
Predicted.Rsq

## [1] 0.6230459
```

We obtain an R-Squared value of 0.623. Overall the R-Squared value is well

#### PRESS Statistics

```
press <- PRESS(BestModel)
press$P.square
```

```
sum(press$residuals^2)
sum(BestModel$residuals^2)

## .....10.....20.....30.....40.....50
## .....60.....70.....80.....90.....100
## .....110.....120.....130.....140.....150
## .....160.....170.....180.....190.....200
## .....210.....220.....230.....240.....250
## .....260.....270.....280.....290.....300
## .....310.....320.....330.....340.....350
## .....360.....370.....380.....390..
## [1] 0.6817248
## [1] 77.44487
## [1] 34.27153
```

- A low value of PRESS statistics is a good indicator that the model is good for predictions
- This can be further confirmed by comparing the sum of PRESS residuals and sum of Best Model residuals, since the two residuals are close, the model can be used for predictions

#### Running the model on our original data. [Using the entire data(n = 490)]

```
fb.raw$log.Y <- log(fb.raw$Lifetime.People.who.have.liked.your.Page.and.engaged.with.your.post)
fb.raw$log.like <- log(fb.raw$like+1)
```

```
FbModel <- lm(log.Y ~ Page.total.likes + Type + Category + Post.Month + Post.Weekday +
  Post.Hour + log.like + Type:Post.Weekday + Type:Post.Hour, data = fb.raw)
summary(FbModel)
```

```
##
## Call:
## lm(formula = log.Y ~ Page.total.likes + Type + Category + Post.Month +
##   Post.Weekday + Post.Hour + log.like + Type:Post.Weekday +
##   Type:Post.Hour, data = fb.raw)
##
## Residuals:
##   Min     1Q   Median     3Q    Max
## -1.72856 -0.18196 -0.01136  0.15224  2.44822
##
## Coefficients: (30 not defined because of singularities)
##              Estimate Std. Error t value
## (Intercept)    3.01855779  1.55880658  1.936
## Page.total.likes -0.00002122  0.00001306 -1.625
## TypePhoto      3.00473332  1.01670620  2.955
```

```
## TypeStatus      3.95929498 0.93241062 4.246
## TypeVideo       1.46853081 0.56927235 2.580
## Category2      -0.40395934 0.05479461 -7.372
## Category3      -0.44257688 0.04806866 -9.207
....
....

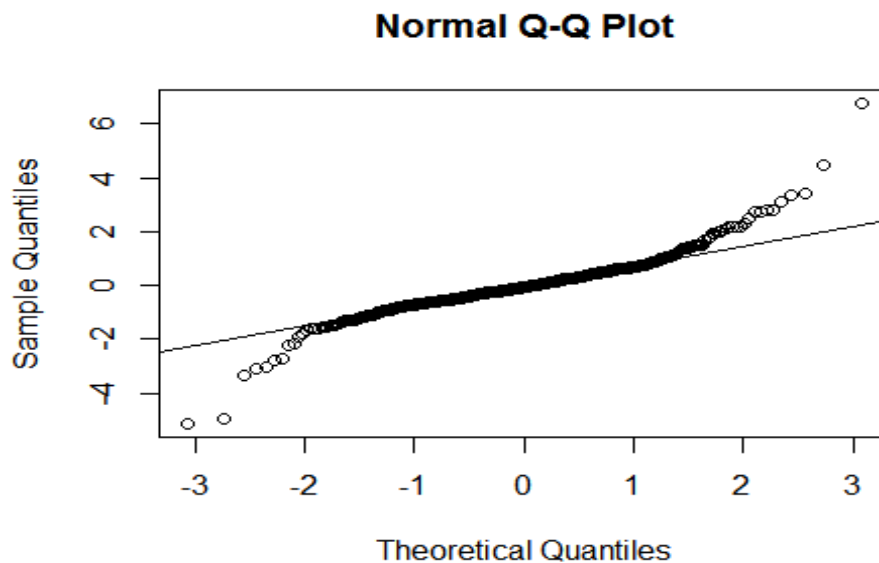
## TypePhoto:Post.Hour14      0.010637 *
## TypeStatus:Post.Hour14      NA
## TypeVideo:Post.Hour14      NA
## TypePhoto:Post.Hour15      NA
## TypeStatus:Post.Hour15      NA
## TypeVideo:Post.Hour15      NA
## TypePhoto:Post.Hour17      NA
## TypeStatus:Post.Hour17      NA
## TypeVideo:Post.Hour17      NA
## TypePhoto:Post.Hour18      NA
## TypeStatus:Post.Hour18      NA
## TypeVideo:Post.Hour18      NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3738 on 413 degrees of freedom
## Multiple R-squared:  0.8267, Adjusted R-squared:  0.7948
## F-statistic: 25.92 on 76 and 413 DF, p-value: < 0.000000000000000022
```

### Observing the residual plots and checking for Normality

```
residuals <- rstandard(FbModel)
```

```
qqnorm(residuals)
```

```
qqline(residuals)
```



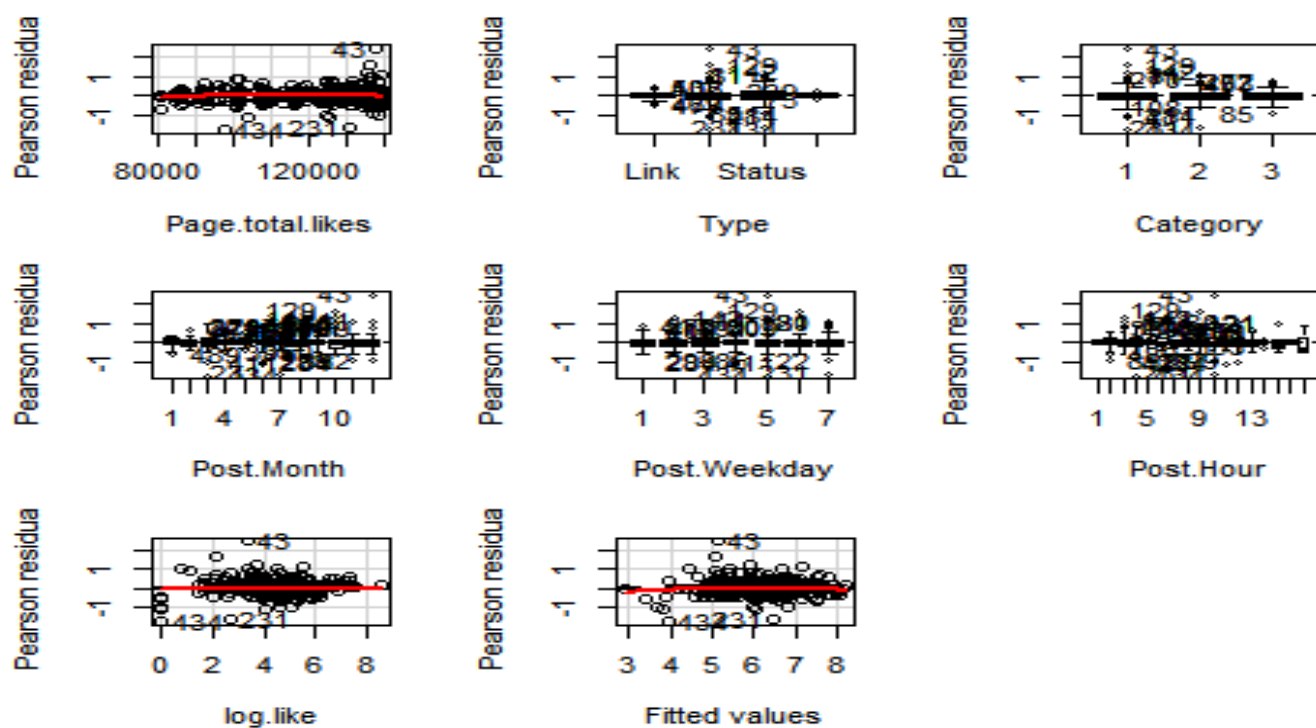
```
stu.resid <- studres(FbModel)
```

```
hist(stu.resid, freq=FALSE, main="Distribution of Studentized Residuals")
```



A histogram showing the distribution of student residuals. The x-axis is labeled 'stu.resid' and ranges from -6 to 8. The y-axis is labeled 'Density' and ranges from 0.0 to 0.4. The histogram bars are centered around 0, with a peak density of approximately 0.4. A smooth, bell-shaped curve is overlaid on the histogram, representing a normal distribution fit.

```
residualPlots(FbModel,id.n=3)
```



```
##          Test stat Pr(>|t|)
## Page.total.likes -3.090 0.002
## Type            NA      NA
## Category        NA      NA
## Post.Month       NA      NA
## Post.Weekday     NA      NA
## Post.Hour        NA      NA
## log.like         -0.303 0.762
## Tukey test       -2.004 0.045
```

We are able to build a model to predict the performance of the page in terms of Lifetime people who have liked your page and engaged with your post which explains close to 83% variability.

## INTERPRETATION

```
FbModel$coefficients1 <- FbModel$coefficients[!is.na(FbModel$coefficients)]
```

### Positive coefficients

```
sort(FbModel$coefficients1[FbModel$coefficients1 > 0], decreasing = T)
```

```
##      TypeStatus      Post.Hour10      Post.Hour3
##      3.95929498      3.18429267      3.11646277
##      (Intercept)      TypePhoto      Post.Hour6
##      3.01855779      3.00473332      2.95083450
##      Post.Hour7      Post.Hour13      Post.Hour2
##      2.91073530      2.70287984      2.64174197
##      Post.Hour4      Post.Hour11      Post.Hour14
##      2.61455364      2.53720947      1.59799659
##      TypeVideo      Post.Hour12      Post.Month10
##      1.46853081      1.07374862      0.87650400
##      Post.Hour9      Post.Month6      Post.Month8
##      0.86395972      0.83892138      0.83027192
## TypePhoto:Post.Weekday5      Post.Month9      Post.Month7
##      0.73459941      0.70456693      0.67487153
## TypePhoto:Post.Weekday7 TypePhoto:Post.Weekday6 TypePhoto:Post.Weekday2
##      0.66618948      0.65189695      0.62118930
##      Post.Month12      log.like      Post.Hour15
##      0.50680170      0.50098850      0.47601360
## TypePhoto:Post.Weekday4      Post.Month4      Post.Month5
##      0.47166813      0.46720562      0.46629500
## TypeStatus:Post.Weekday7 TypePhoto:Post.Weekday3 TypeStatus:Post.Weekday6
##      0.40130336      0.37067232      0.36966180
## TypeStatus:Post.Weekday5 TypeStatus:Post.Weekday3      Post.Month11
##      0.31108257      0.29449208      0.22309295
##      Post.Month2      Post.Hour17      Post.Hour5
##      0.17569164      0.13248821      0.08618151
## TypeVideo:Post.Weekday3      Post.Month3
##      0.04815655      0.01913903
```

`sort(FbModel$coefficients1[FbModel$coefficients1 < 0], decreasing = F)`

```
## TypePhoto:Post.Hour10 TypePhoto:Post.Hour3 TypePhoto:Post.Hour6
## -3.24070070727 -3.15783374832 -3.10368460543
## TypeStatus:Post.Hour7 TypePhoto:Post.Hour13 TypePhoto:Post.Hour7
## -2.71658644033 -2.66742679692 -2.66207828620
## TypePhoto:Post.Hour11 TypePhoto:Post.Hour2 TypePhoto:Post.Hour4
## -2.66004649892 -2.60333841326 -2.59846367974
## TypeStatus:Post.Hour3 TypeStatus:Post.Hour10 TypeStatus:Post.Hour2
## -2.48376804938 -2.40794440983 -2.34367765213
## TypeStatus:Post.Hour4 TypeStatus:Post.Hour6 TypeStatus:Post.Hour11
## -2.30808527027 -2.29009822395 -1.74019030647
## TypePhoto:Post.Hour14 TypeStatus:Post.Hour13 TypeStatus:Post.Weekday2
## -1.57321576896 -1.40122912970 -1.15742990170
## TypePhoto:Post.Hour9 TypePhoto:Post.Hour12 Post.Weekday5
## -0.90062676439 -0.87047188938 -0.78396486560
## Post.Weekday6 Post.Weekday4 Post.Weekday2
## -0.62160594811 -0.56582244666 -0.56314248263
## TypeVideo:Post.Weekday2 Post.Weekday7 Category3
## -0.53449179501 -0.52893335848 -0.44257688432
## Category2 TypeVideo:Post.Weekday5 Post.Weekday3
## -0.40395933760 -0.39212148398 -0.36303331988
## TypeVideo:Post.Weekday4 TypeVideo:Post.Hour10 Post.Hour8
## -0.18205492840 -0.11869049104 -0.08050849230
## TypeStatus:Post.Weekday4 Post.Hour18 Page.total.likes
## -0.03127278968 -0.02002780958 -0.00002121669
```

- A page can get maximum engagement from people based on what type of content is uploaded, during what time, the category of the page, how many likes the post has received and number of people who have liked the page
- The base model with just the intercept (Type: Link, Category: 1, Post.Month: 1, Post.Weekday: 1, Post.Hour: 1) suggest that on average, close to 20 people ( $\exp(3.01855778735)$ ) who have liked the page will also engage with the post
- One percent increase in the number of likes increases the engagement level by 0.5%
- Engagement level increases when the post is
  1. Type Photo is uploaded on Weekday3, Weekday5, Weekday7
  2. Type Photo is uploaded at hour 7,13,11,2,4
  3. Type Status is uploaded on Weekday3, Weekday5, Weekday6, Weekday7
  4. Type Status is uploaded at hour 2,4,11
  5. Significantly, Type Photo, Status is uploaded at hour 3,6,10
  6. Type Video is uploaded on Weekday3
- Engagement level increases very little when the post is
  1. Type Video is uploaded on Weekday4, Weekday5
  2. Type Video is uploaded on Hour10