Sales Analysis with R

Nishit Kothari (I.D. No. 205453)

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```
rm(list = ls()) #clear previous varibales
library(readxl) # to read excel
library(plyr)
library(caTools)
```

```
## Warning: package 'caTools' was built under R version 4.0.4
```

```
library(e1071)
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
library(randomForest)
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
attribset = read_excel('Attribute DataSet.xlsx')
dresssale = read_excel('Dress Sales.xlsx')

View(attribset)
View(dresssale)

#remove Dress_ID column
attribset_ = attribset[2:14]
dresssale_ = dresssale[2:24]
View(dresssale_)
```

```r
# check the unique values for each columns
#lapply(attribset[2:14], unique)

# values checking
# style
attribset_$Style[attribset_$Style == 'sexy'] = 'Sexy'

# Price
attribset_$Price[attribset_$Price == 'low'] = 'Low'
attribset_$Price[attribset_$Price == 'high'] = 'High'

# Size
attribset_$Size[attribset_$Size == 's'] = 'S'
attribset_$Size[attribset_$Size == 'small'] = 'S'

# Season
attribset_$Season[attribset_$Season == 'spring'] = 'Spring'
attribset_$Season[attribset_$Season == 'summer'] = 'Summer'
attribset_$Season[attribset_$Season == 'Automn'] = 'Autumn'
attribset_$Season[attribset_$Season == 'winter'] = 'Winter'

# NeckLine
attribset_$NeckLine[attribset_$NeckLine == 'sweetheart'] = 'Sweetheart'

# SleeveLength
attribset_$SleeveLength[attribset_$SleeveLength == 'sleevless'] = 'sleeveless'
attribset_$SleeveLength[attribset_$SleeveLength == 'sleeevless'] = 'sleeveless'
attribset_$SleeveLength[attribset_$SleeveLength == 'sleveless'] = 'sleeveless'
attribset_$SleeveLength[attribset_$SleeveLength == 'threequater'] = 'threequarter'
attribset_$SleeveLength[attribset_$SleeveLength == 'thressqatar'] = 'threequarter'
attribset_$SleeveLength[attribset_$SleeveLength == 'urndowncollor'] = 'turndowncollar'

# FabricType
attribset_$FabricType[attribset_$FabricType == 'shiffon'] = 'chiffon'
attribset_$FabricType[attribset_$FabricType == 'sattin'] = 'satin'
attribset_$FabricType[attribset_$FabricType == 'wollen'] = 'woolen'
attribset_$FabricType[attribset_$FabricType == 'flannael'] = 'flannel'
attribset_$FabricType[attribset_$FabricType == 'knitting'] = 'knitted'


# Decoration
attribset_$Decoration[attribset_$Decoration == 'embroidary'] = 'embroidery'
attribset_$Decoration[attribset_$Decoration == 'sequined'] = 'sequins'
attribset_$Decoration[attribset_$Decoration == 'ruched'] = 'ruche'
attribset_$Decoration[attribset_$Decoration == 'none'] = 'null'

# Pattern Type
attribset_$'Pattern Type'[attribset_$'Pattern Type' == 'none'] = 'null'
attribset_$'Pattern Type'[attribset_$'Pattern Type' == 'leapord'] = 'leopard'

# factoring

attribset_$Style = factor(attribset_$Style,
```

```r
                          levels = c('Sexy', 'Casual', 'vintage', 'Brief', 'cute', 'bohemian', 'Novelty
                          labels = c(0,1,2,3,4,5,6,7,8,9,10,11))

attribset_$Price = factor(attribset_$Price,
                          levels = c('Low', 'High', 'Average', 'Medium', 'very-high'),
                          labels = c(0,1,2,3,4))

attribset_$Size = factor(attribset_$Size,
                         levels = c('M', 'L', 'XL', 'free', 'S'),
                         labels = c(0,1,2,3,4))

attribset_$Season = factor(attribset_$Season,
                           levels = c('Summer', 'Autumn', 'Spring', 'Winter'),
                           labels = c(0,1,2,3))

attribset_$NeckLine = factor(attribset_$NeckLine,
                             levels = c('o-neck', 'v-neck', 'boat-neck', 'peterpan-collor', 'ruffled',
                             labels = c(0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15))

attribset_$SleeveLength = factor(attribset_$SleeveLength,
                                 levels = c('sleeveless', 'Petal', 'full', 'butterfly', 'short', 'threee
                                 labels = c(0,1,2,3,4,5,6,7,8,9,10,11,12))

attribset_$waiseline = factor(attribset_$waiseline,
                              levels = c('empire', 'natural', 'null', 'princess', 'dropped'),
                              labels = c(0,1,2,3,4))

attribset_$Material = factor(attribset_$Material,
                             levels = c('null', 'microfiber', 'polyster', 'silk', 'chiffonfabric', 'cott
                             labels = c(0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23))
attribset_$FabricType = factor(attribset_$FabricType,
                               levels = c('chiffon', 'null', 'broadcloth', 'jersey', 'other', 'batik',
                               labels = c(0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17))

attribset_$Decoration = factor(attribset_$Decoration,
                               levels = c('ruffles', 'null', 'embroidery', 'bow', 'lace', 'beading', 'sa
                               labels = c(0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23

attribset_$`Pattern Type` = factor(attribset_$`Pattern Type`,
                                   levels = c('animal', 'print', 'dot', 'solid', 'null', 'patchwork', 's
                                   labels = c(0,1,2,3,4,5,6,7,8,9,10,11,12))

attribset_$Recommendation = sapply(attribset_$Recommendation, factor)

# count of missing values in attribset_ dataset
colSums(is.na(attribset_))
```

```
##          Style          Price         Rating           Size         Season
##              0              2              0              0              2
##       NeckLine   SleeveLength      waiseline       Material     FabricType
##              1              0              1              1              1
##     Decoration   Pattern Type Recommendation
##              1              1              0
```

```r
# Create the function.
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

# fill missing Value with mode
attribset_$Price[is.na(attribset_$Price) ==TRUE] <- getmode(attribset_$Price)
attribset_$Season[is.na(attribset_$Season) ==TRUE] <- getmode(attribset_$Season)
attribset_$NeckLine[is.na(attribset_$NeckLine) ==TRUE] <- getmode(attribset_$NeckLine)
attribset_$waiseline[is.na(attribset_$waiseline) ==TRUE] <- getmode(attribset_$waiseline)
attribset_$Material[is.na(attribset_$Material) ==TRUE] <- getmode(attribset_$Material)
attribset_$FabricType[is.na(attribset_$FabricType) ==TRUE] <- getmode(attribset_$FabricType)
attribset_$Decoration[is.na(attribset_$Decoration) ==TRUE] <- getmode(attribset_$Decoration)
attribset_$`Pattern Type`[is.na(attribset_$`Pattern Type`) ==TRUE] <- getmode(attribset_$`Pattern Type`

attribset_data <- data.frame(attribset_)
str(attribset_data)
```

```
## 'data.frame':    500 obs. of  13 variables:
##  $ Style         : Factor w/ 12 levels "0","1","2","3",..: 1 2 3 4 5 6 2 7 8 6 ...
##  $ Price         : Factor w/ 5 levels "0","1","2","3",..: 1 1 2 3 1 1 3 3 3 1 ...
##  $ Rating        : num  4.6 0 0 4.6 4.5 0 0 0 0 0 ...
##  $ Size          : Factor w/ 5 levels "0","1","2","3",..: 1 2 2 2 1 1 3 4 4 4 ...
##  $ Season        : Factor w/ 4 levels "0","1","2","3": 1 1 2 3 1 1 1 2 3 1 ...
##  $ NeckLine      : Factor w/ 16 levels "0","1","2","3",..: 1 1 1 1 1 2 1 1 2 2 ...
##  $ SleeveLength  : Factor w/ 13 levels "0","1","2","3",..: 1 2 3 3 4 1 3 5 5 1 ...
##  $ waiseline     : Factor w/ 5 levels "0","1","2","3",..: 1 2 2 2 2 1 3 2 1 2 ...
##  $ Material      : Factor w/ 24 levels "0","1","2","3",..: 1 2 3 4 5 1 6 3 6 7 ...
##  $ FabricType    : Factor w/ 18 levels "0","1","2","3",..: 1 2 2 1 1 2 2 3 3 1 ...
##  $ Decoration    : Factor w/ 24 levels "0","1","2","3",..: 1 1 2 3 4 2 2 5 6 2 ...
##  $ Pattern.Type  : Factor w/ 13 levels "0","1","2","3",..: 1 1 2 2 3 2 4 5 4 5 ...
##  $ Recommendation: Factor w/ 2 levels "1","0": 1 2 2 1 2 2 2 2 1 1 ...
```

```r
# Update columns name in dresssale_ dataset

dresssale_ = rename(dresssale_,c('41314'= '2/9/2013'))
dresssale_ = rename(dresssale_,c('41373'='4/9/2013'))
dresssale_ = rename(dresssale_,c('41434'='6/9/2013'))
dresssale_ = rename(dresssale_,c('41495'='8/9/2013'))
dresssale_ = rename(dresssale_,c('41556'='10/9/2013'))
dresssale_ = rename(dresssale_,c('41617'='12/9/2013'))
dresssale_ = rename(dresssale_,c('41315'='2/10/2013'))
dresssale_ = rename(dresssale_,c('41374'='4/10/2013'))
dresssale_ = rename(dresssale_,c('41435'='6/10/2013'))
dresssale_ = rename(dresssale_,c('40400'='8/10/2013'))
dresssale_ = rename(dresssale_,c('41557'='10/10/2013'))
dresssale_ = rename(dresssale_,c('41618'='12/10/2013'))

# Convert all variable types to numeric
dresssale_ <- as.data.frame(apply(dresssale_, 2, as.numeric))
```

```
## Warning in apply(dresssale_, 2, as.numeric): NAs introduced by coercion
```

```
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```

```
# mean row
dresssale_ = as.matrix(dresssale_)
k <- which(is.na(dresssale_), arr.ind=TRUE)
dresssale_[k] <- rowMeans(dresssale_, na.rm=TRUE)[k[,1]]
dresssale_ = as.data.frame(dresssale_)

# sum all values on row on (total sales)
dresssale_$total_sales = rowSums(dresssale_)
head(dresssale_)
```

```
##   29/8/2013 31/8/2013 2/9/2013 4/9/2013 6/9/2013 8/9/2013 10/9/2013 12/9/2013
## 1      2114      2274     2491     2660     2727     2887      2930      3119
## 2       151       275      570      750      813     1066      1164      1558
## 3         6         7        7        7        8        8         9        10
## 4      1005      1128     1326     1455     1507     1621      1637      1723
## 5       996      1175     1304     1396     1432     1559      1570      1638
## 6         4         5       11       13       13       13        16        18
##   14/9/2013 16/9/2013 18/9/2013 20/9/2013 22/9/2013 24/9/2013 26/9/2013
## 1      3204      3277      3321      3386      3479      3554      3624
## 2      1756      1878      1985      2106      2454      2710      2942
## 3        10        10        10        10        11        11        11
## 4      1746      1783      1796      1812      1845      1878      1892
## 5      1655      1681      1743      1824      1919      2032      2156
## 6        19        20        20        21        22        25        25
##   28/9/2013 30/9/2013 2/10/2013 4/10/2013 6/10/2013 8/10/2013 10/10/2013
## 1      3706      3746      3795      3832      3897      3923       3985
## 2      3258      3354      3475      3654      3911      4024       4125
## 3        11        11        11        11        11        11         11
## 4      1914      1924      1929      1941      1952      1955       1959
## 5      2252      2312      2387      2459      2544      2614       2693
## 6        26        26        26        26        27        27         27
##   12/10/2013 total_sales
## 1       4048       75979
## 2       4277       52256
## 3         11         223
## 4       1963       39691
## 5       2736       44077
## 6         27         457
```

```
#merge data
merged_data <- data.frame(attribset_ ,dresssale_)
head(merged_data)
```

```
##   Style Price Rating Size Season NeckLine SleeveLength waiseline Material
```

```
## 1     0     0    4.6    0      0        0            0         0         0
## 2     1     0    0.0    1      0        0            1         1         1
## 3     2     1    0.0    1      1        0            2         1         2
## 4     3     2    4.6    1      2        0            2         1         3
## 5     4     0    4.5    0      0        0            3         1         4
## 6     5     0    0.0    0      0        1            0         0         0
##   FabricType Decoration Pattern.Type Recommendation X29.8.2013 X31.8.2013
## 1          0          0            0              1       2114       2274
## 2          1          0            0              0        151        275
## 3          1          1            1              0          6          7
## 4          0          2            1              1       1005       1128
## 5          0          3            2              0        996       1175
## 6          1          1            1              0          4          5
##   X2.9.2013 X4.9.2013 X6.9.2013 X8.9.2013 X10.9.2013 X12.9.2013 X14.9.2013
## 1      2491      2660      2727      2887       2930       3119       3204
## 2       570       750       813      1066       1164       1558       1756
## 3         7         7         8         8          9         10         10
## 4      1326      1455      1507      1621       1637       1723       1746
## 5      1304      1396      1432      1559       1570       1638       1655
## 6        11        13        13        13         16         18         19
##   X16.9.2013 X18.9.2013 X20.9.2013 X22.9.2013 X24.9.2013 X26.9.2013 X28.9.2013
## 1       3277       3321       3386       3479       3554       3624       3706
## 2       1878       1985       2106       2454       2710       2942       3258
## 3         10         10         10         11         11         11         11
## 4       1783       1796       1812       1845       1878       1892       1914
## 5       1681       1743       1824       1919       2032       2156       2252
## 6         20         20         21         22         25         25         26
##   X30.9.2013 X2.10.2013 X4.10.2013 X6.10.2013 X8.10.2013 X10.10.2013
## 1       3746       3795       3832       3897       3923        3985
## 2       3354       3475       3654       3911       4024        4125
## 3         11         11         11         11         11          11
## 4       1924       1929       1941       1952       1955        1959
## 5       2312       2387       2459       2544       2614        2693
## 6         26         26         26         27         27          27
##   X12.10.2013 total_sales
## 1        4048       75979
## 2        4277       52256
## 3          11         223
## 4        1963       39691
## 5        2736       44077
## 6          27         457
```

```
str(merged_data)
```

```
## 'data.frame':    500 obs. of  37 variables:
##  $ Style         : Factor w/ 12 levels "0","1","2","3",..: 1 2 3 4 5 6 2 7 8 6 ...
##  $ Price         : Factor w/ 5 levels "0","1","2","3",..: 1 1 2 3 1 1 3 3 3 1 ...
##  $ Rating        : num  4.6 0 0 4.6 4.5 0 0 0 0 0 ...
##  $ Size          : Factor w/ 5 levels "0","1","2","3",..: 1 2 2 2 1 1 3 4 4 4 ...
##  $ Season        : Factor w/ 4 levels "0","1","2","3": 1 1 2 3 1 1 1 2 3 1 ...
##  $ NeckLine      : Factor w/ 16 levels "0","1","2","3",..: 1 1 1 1 1 2 1 1 2 2 ...
##  $ SleeveLength  : Factor w/ 13 levels "0","1","2","3",..: 1 2 3 3 4 1 3 5 5 1 ...
##  $ waiseline     : Factor w/ 5 levels "0","1","2","3",..: 1 2 2 2 2 1 3 2 1 2 ...
##  $ Material      : Factor w/ 24 levels "0","1","2","3",..: 1 2 3 4 5 1 6 3 6 7 ...
```

```
## $ FabricType    : Factor w/ 18 levels "0","1","2","3",..: 1 2 2 1 1 2 2 3 3 1 ...
## $ Decoration    : Factor w/ 24 levels "0","1","2","3",..: 1 1 2 3 4 2 2 5 6 2 ...
## $ Pattern.Type  : Factor w/ 13 levels "0","1","2","3",..: 1 1 2 2 3 2 4 5 4 5 ...
## $ Recommendation: Factor w/ 2 levels "1","0": 1 2 2 1 2 2 2 2 1 1 ...
## $ X29.8.2013    : num  2114 151 6 1005 996 ...
## $ X31.8.2013    : num  2274 275 7 1128 1175 ...
## $ X2.9.2013     : num  2491 570 7 1326 1304 ...
## $ X4.9.2013     : num  2660 750 7 1455 1396 ...
## $ X6.9.2013     : num  2727 813 8 1507 1432 ...
## $ X8.9.2013     : num  2887 1066 8 1621 1559 ...
## $ X10.9.2013    : num  2930 1164 9 1637 1570 ...
## $ X12.9.2013    : num  3119 1558 10 1723 1638 ...
## $ X14.9.2013    : num  3204 1756 10 1746 1655 ...
## $ X16.9.2013    : num  3277 1878 10 1783 1681 ...
## $ X18.9.2013    : num  3321 1985 10 1796 1743 ...
## $ X20.9.2013    : num  3386 2106 10 1812 1824 ...
## $ X22.9.2013    : num  3479 2454 11 1845 1919 ...
## $ X24.9.2013    : num  3554 2710 11 1878 2032 ...
## $ X26.9.2013    : num  3624 2942 11 1892 2156 ...
## $ X28.9.2013    : num  3706 3258 11 1914 2252 ...
## $ X30.9.2013    : num  3746 3354 11 1924 2312 ...
## $ X2.10.2013    : num  3795 3475 11 1929 2387 ...
## $ X4.10.2013    : num  3832 3654 11 1941 2459 ...
## $ X6.10.2013    : num  3897 3911 11 1952 2544 ...
## $ X8.10.2013    : num  3923 4024 11 1955 2614 ...
## $ X10.10.2013   : num  3985 4125 11 1959 2693 ...
## $ X12.10.2013   : num  4048 4277 11 1963 2736 ...
## $ total_sales   : num  75979 52256 223 39691 44077 ...
```

```r
# spliting dataset
set.seed(100)

spl = sample.split(merged_data$Recommendation, SplitRatio = 0.7)
train = subset(merged_data, spl==TRUE)
test = subset(merged_data, spl==FALSE)

print(dim(train)); print(dim(test))
```

```
## [1] 350  37
```

```
## [1] 150  37
```

```r
# naive bayes model
naive_model = naiveBayes(Recommendation ~.,data = train) # build model
confusionMatrix(train$Recommendation,predict(naive_model,train),positive = '1') # create confusion Matr
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   0
##          1 106  41
##          0  67 136
```

```
##
##                Accuracy : 0.6914
##                  95% CI : (0.6401, 0.7394)
##     No Information Rate : 0.5057
##     P-Value [Acc > NIR] : 1.409e-12
##
##                   Kappa : 0.3817
##
##  Mcnemar's Test P-Value : 0.01614
##
##             Sensitivity : 0.6127
##             Specificity : 0.7684
##          Pos Pred Value : 0.7211
##          Neg Pred Value : 0.6700
##              Prevalence : 0.4943
##          Detection Rate : 0.3029
##    Detection Prevalence : 0.4200
##       Balanced Accuracy : 0.6905
##
##        'Positive' Class : 1
##
```

```
print('---------------')
```

```
## [1] "---------------"
```

```
naive_predict = predict(naive_model,test) # predict test set
table(naive_predict,test$Recommendation) # create table
```

```
##
## naive_predict  1  0
##             1 33 37
##             0 30 50
```

```
# Support vector machine
svm_model = svm(Recommendation ~.,train) # build model
confusionMatrix(train$Recommendation,predict(svm_model),positive = '1')# create confusion Matrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   0
##          1   6 141
##          0   0 203
##
##                Accuracy : 0.5971
##                  95% CI : (0.5437, 0.6489)
##     No Information Rate : 0.9829
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.047
##
```

```
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 1.00000
##             Specificity : 0.59012
##          Pos Pred Value : 0.04082
##          Neg Pred Value : 1.00000
##              Prevalence : 0.01714
##          Detection Rate : 0.01714
##    Detection Prevalence : 0.42000
##       Balanced Accuracy : 0.79506
##
##        'Positive' Class : 1
##
```

```
print('---------------')
```

```
## [1] "---------------"
```

```
svm_predict = predict(svm_model,test) # predict test set
table(svm_predict,test$Recommendation) # create table
```

```
##
## svm_predict  1  0
##           1  0  2
##           0 63 85
```

```
# Random Forest
randomForest_model = randomForest(x = train, y = train$Recommendation,ntree =800)# build model
confusionMatrix(train$Recommendation,predict(randomForest_model),positive = '1') # create confusion Mat
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   0
##          1 147   0
##          0   0 203
##
##                Accuracy : 1
##                  95% CI : (0.9895, 1)
##     No Information Rate : 0.58
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##
##  Mcnemar's Test P-Value : NA
##
##             Sensitivity : 1.00
##             Specificity : 1.00
##          Pos Pred Value : 1.00
##          Neg Pred Value : 1.00
##              Prevalence : 0.42
##          Detection Rate : 0.42
```

```
##    Detection Prevalence : 0.42
##       Balanced Accuracy : 1.00
##
##        'Positive' Class : 1
##
```

```r
print('---------------')
```

```
## [1] "---------------"
```

```r
randomForest_predict = predict(randomForest_model,test) # predict test set
table(randomForest_predict,test$Recommendation )# create table
```

```
##
## randomForest_predict  1  0
##                    1 63  0
##                    0  0 87
```

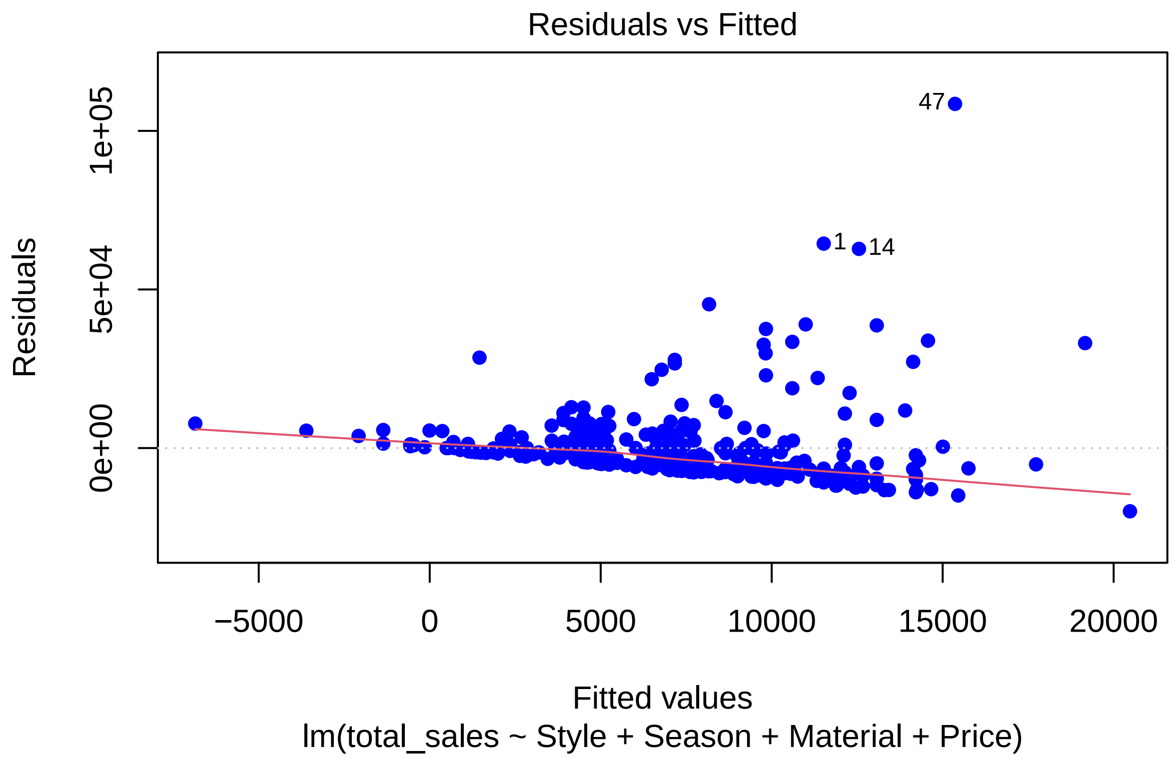
```r
# regression (total sales and (Style+Season+Material+Price))
regressor_Sales = lm(formula = total_sales ~ Style+Season+Material+Price, data = train) # build model
summary(regressor_Sales) # print model summary
```

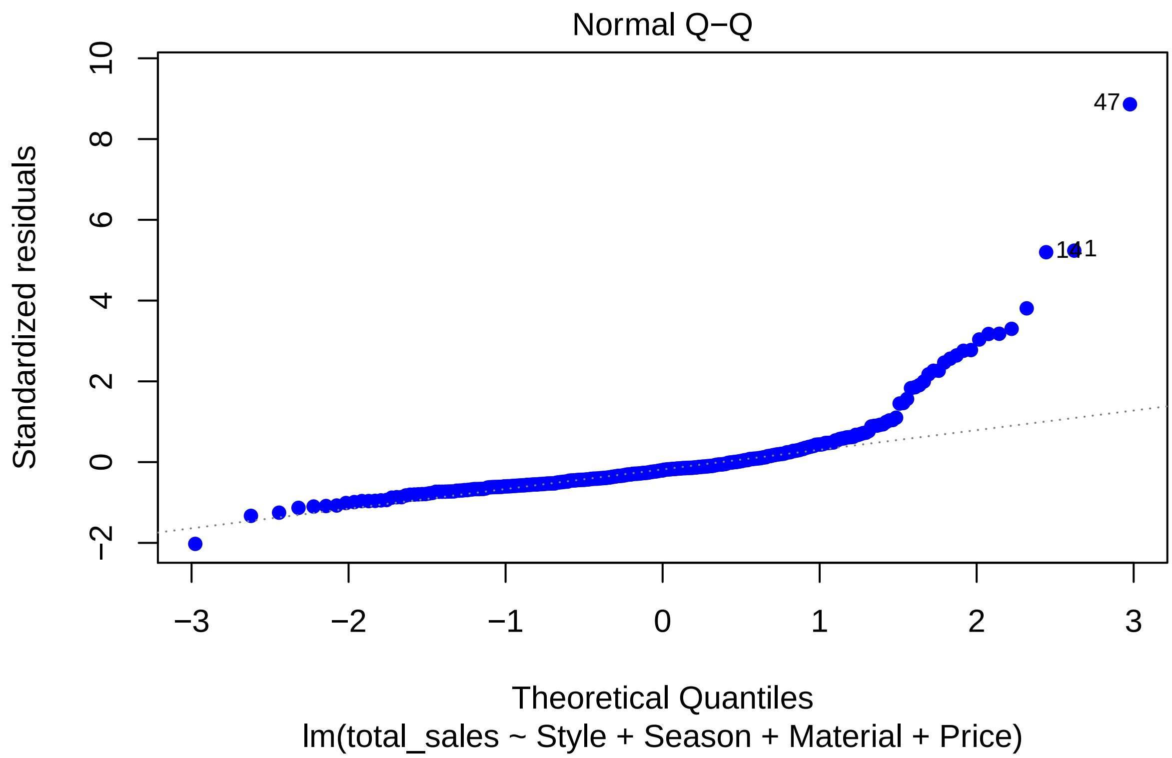
```
##
## Call:
## lm(formula = total_sales ~ Style + Season + Material + Price,
##     data = train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -19936  -6113  -2230   1381 108508
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  11521.7     2460.7   4.682 4.24e-06 ***
## Style1       -4739.3     2018.1  -2.348   0.0195 *
## Style2        2786.7     3731.1   0.747   0.4557
## Style3       -2293.6     3957.3  -0.580   0.5626
## Style4       -4514.3     3037.8  -1.486   0.1383
## Style5       -7057.2     3738.5  -1.888   0.0600 .
## Style6       -6905.0     6052.5  -1.141   0.2548
## Style7      -11965.4    12808.3  -0.934   0.3509
## Style8       -4017.0     3208.8  -1.252   0.2116
## Style9       -3254.6     4066.9  -0.800   0.4242
## Style11      -9220.8    12763.8  -0.722   0.4706
## Season1       -761.5     2339.6  -0.325   0.7450
## Season2       2694.3     1915.0   1.407   0.1604
## Season3       -527.7     1944.7  -0.271   0.7863
## Material1    12382.7     7516.0   1.648   0.1005
## Material2      790.2     2243.6   0.352   0.7249
## Material3    -2454.3     3316.7  -0.740   0.4599
## Material4     3595.3     3141.2   1.145   0.2533
## Material5    -2111.8     1884.6  -1.121   0.2633
```

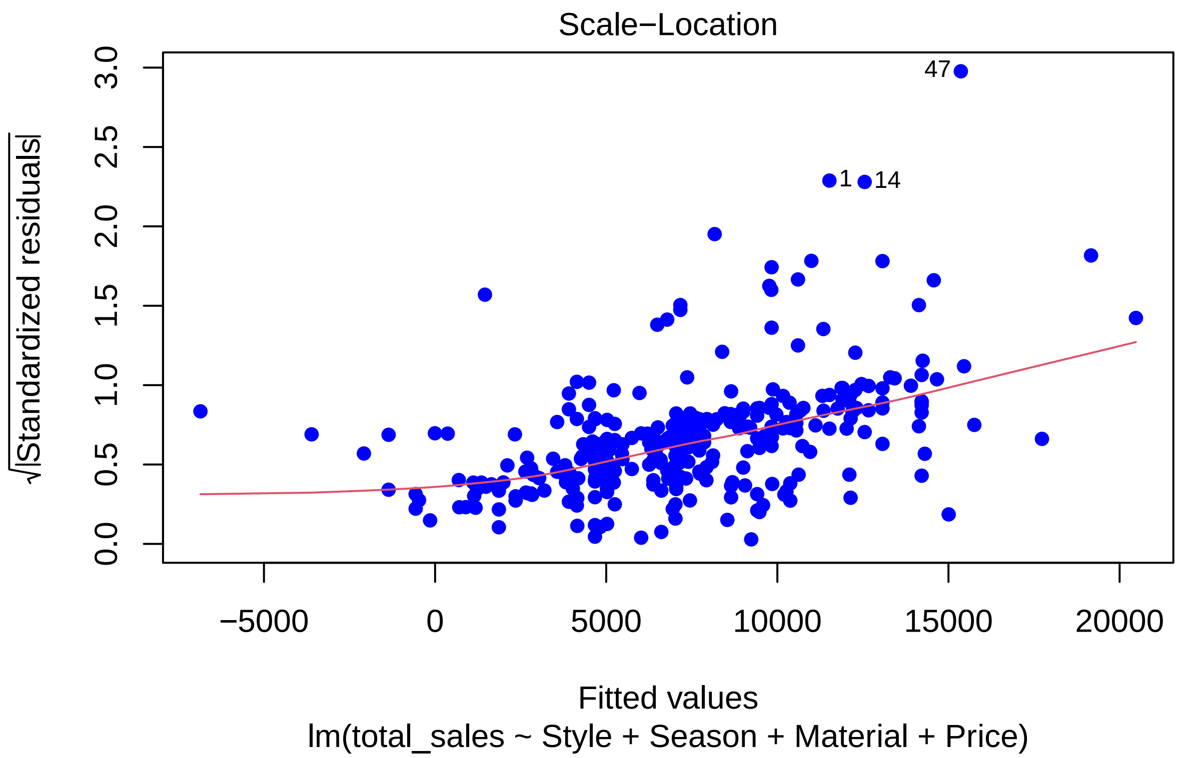
```
## Material6    -3568.7     5518.6  -0.647   0.5183
## Material7    -2426.9     9130.3  -0.266   0.7906
## Material8    -2429.2     9068.5  -0.268   0.7890
## Material9     2010.3     7588.1   0.265   0.7912
## Material10   -6025.8     5056.8  -1.192   0.2343
## Material11    -637.5     7475.0  -0.085   0.9321
## Material12   -1602.8     4285.8  -0.374   0.7087
## Material13   -2853.4     7500.8  -0.380   0.7039
## Material14   -7213.0    12932.0  -0.558   0.5774
## Material15   -2242.1    12843.7  -0.175   0.8615
## Material16   -6416.6    12731.2  -0.504   0.6146
## Material17   -5257.7     9108.9  -0.577   0.5642
## Material19   -1842.8    12767.8  -0.144   0.8853
## Material20   -7843.1    12790.6  -0.613   0.5402
## Material23   -3215.7     9269.8  -0.347   0.7289
## Price1       -2030.6     3912.1  -0.519   0.6041
## Price2         355.2     1627.8   0.218   0.8274
## Price3       -4172.0     3571.0  -1.168   0.2436
## Price4       -8335.1     4055.2  -2.055   0.0407 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12550 on 312 degrees of freedom
## Multiple R-squared:  0.09296,    Adjusted R-squared:  -0.01461
## F-statistic: 0.8642 on 37 and 312 DF,  p-value: 0.6971
```

```r
plot(regressor_Sales, pch = 16, col = "blue") # Plot the results
```

```
## Warning: not plotting observations with leverage one:
##   8, 68, 153, 162, 202, 257, 271
```

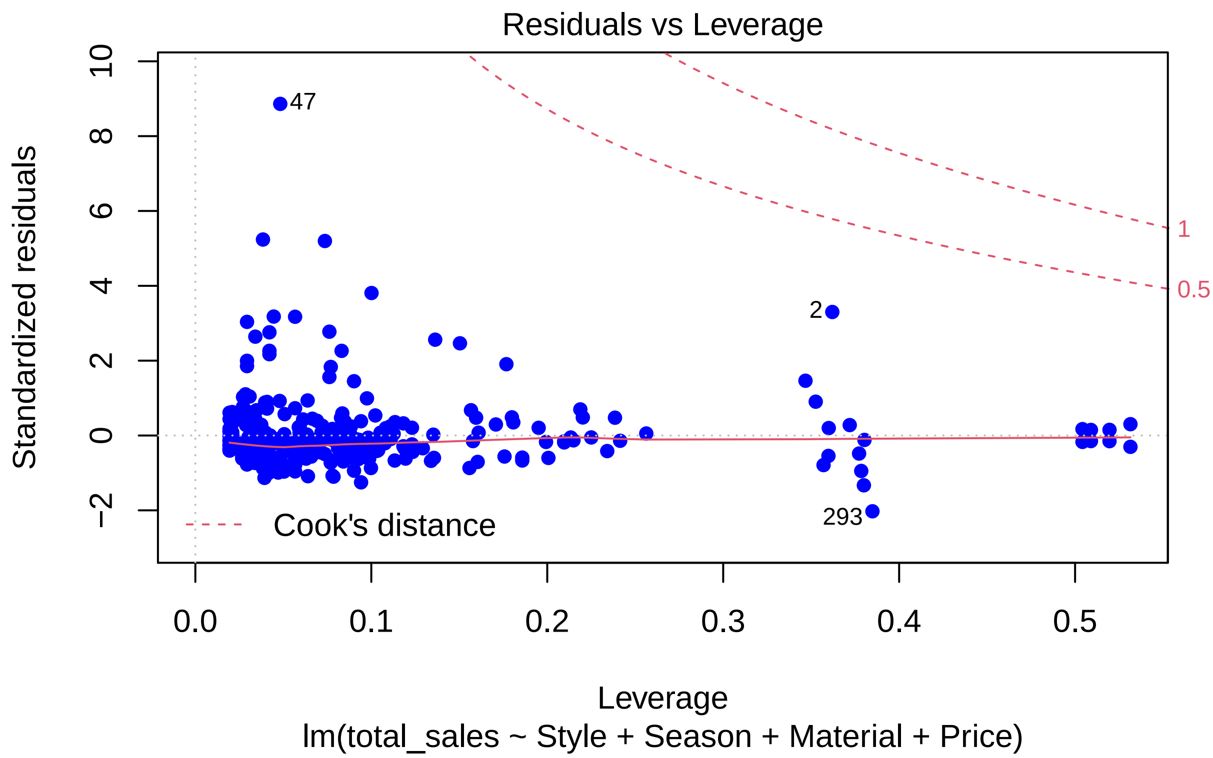

Residuals vs Fitted
Residuals
1e+05
5e+04
0e+00
47
1
14
−5000
0
5000
10000
15000
20000
Fitted values
lm(total_sales ~ Style + Season + Material + Price)


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(total_sales ~ Style + Season + Material + Price)
47
141
−2
0
2
4
6
8
10
−3
−2
−1
0
1
2
3




```
abline(regressor_Sales) # Add regression line
```

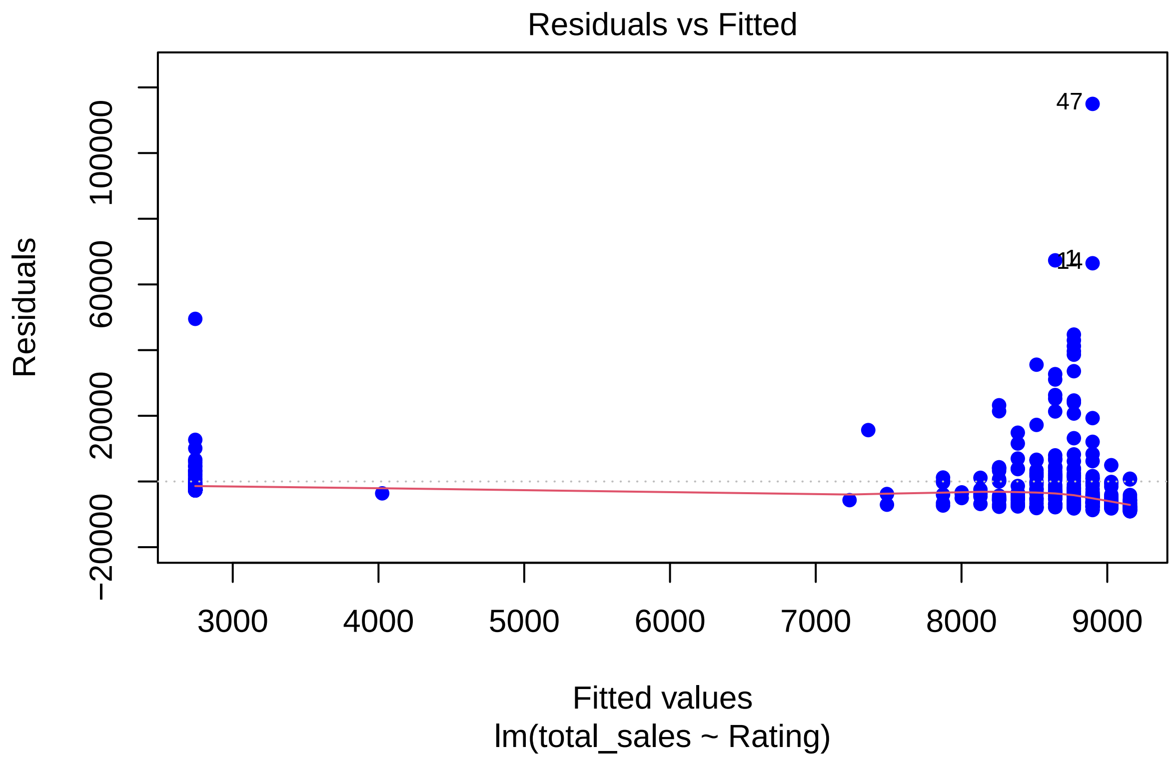
```
## Warning in abline(regressor_Sales): only using the first two of 38 regression
## coefficients
```



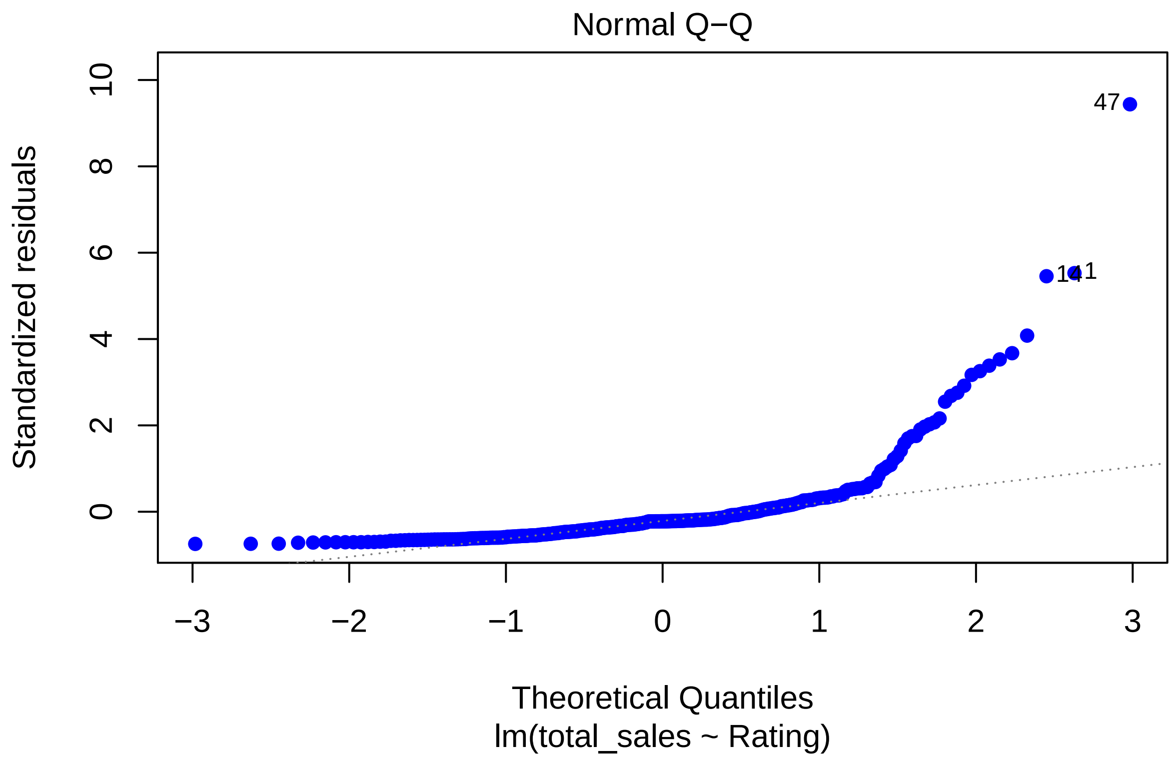

```r
# regression (total sales and Rating)
regressor_Rating = lm(formula = total_sales ~ Rating, data = train) # build model
summary(regressor_Rating) # print model summary
```

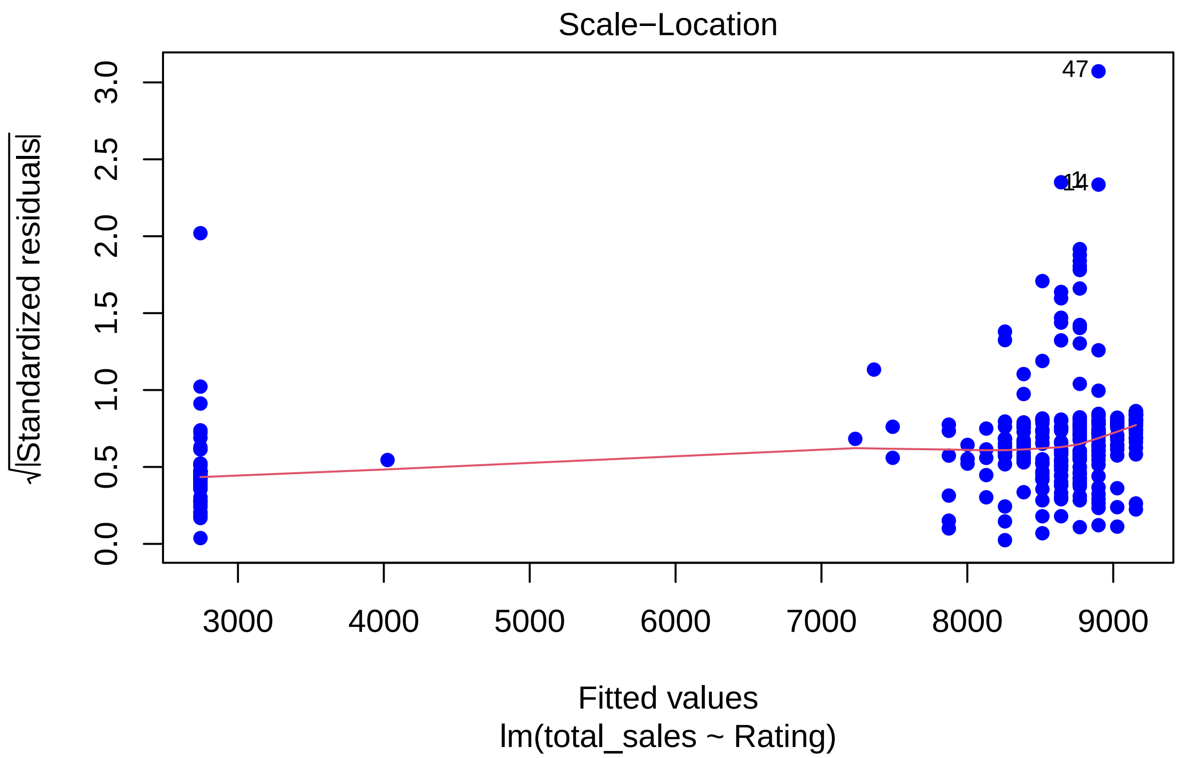
```
##
## Call:
## lm(formula = total_sales ~ Rating, data = train)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##  -9076  -6020  -2686    812 114971
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2742.8     1305.0   2.102   0.0363 *
## Rating        1282.6      323.7   3.962 9.02e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12210 on 348 degrees of freedom
## Multiple R-squared:  0.04316,    Adjusted R-squared:  0.04041
## F-statistic:  15.7 on 1 and 348 DF,  p-value: 9.022e-05
```

```r
plot(regressor_Rating, pch = 16, col = "blue") # Plot the results
```

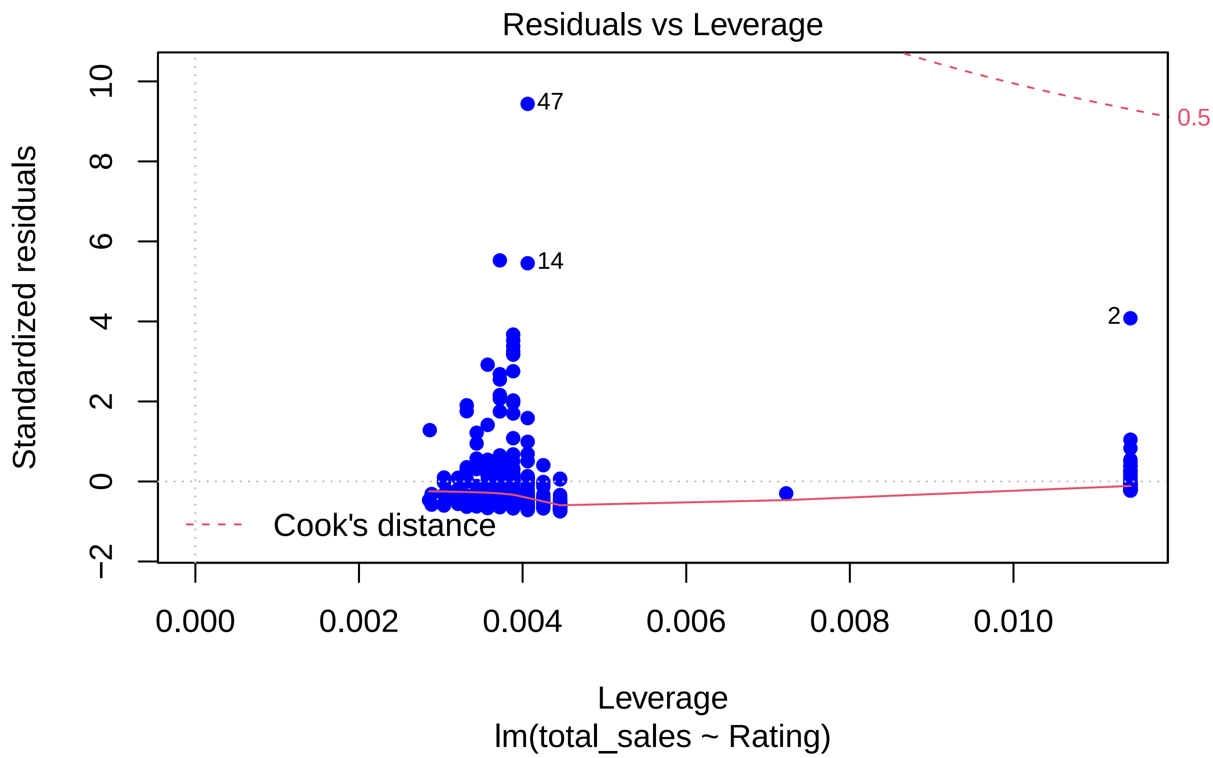


Residuals vs Fitted
Residuals
−20000
20000
60000
100000
3000
4000
5000
6000
7000
8000
9000
47
11
14
Fitted values
lm(total_sales ~ Rating)


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(total_sales ~ Rating)
47
14
41
−3
−2
−1
0
1
2
3
10
8
6
4
2
0




```
abline(regressor_Rating) # Add regression line
```




```r
# evaluation
original = test$total_sales
pred = predict(regressor_Rating,test)
predicted = pred
d = original-predicted

mse = mean((d)^2) # MSE
mae = mean(abs(d)) # MAE
rmse = sqrt(mse) # RMSE
R2 = 1-(sum((d)^2)/sum((original-mean(original))^2)) # R^2

cat(" MAE:", mae, "\n", "MSE:", mse, "\n", "RMSE:", rmse, "\n", "R-squared:", R2)
```

```
##  MAE: 7784.569
##  MSE: 274959077
##  RMSE: 16581.89
##  R-squared: 0.04042806
```