Predicting Sales Volume for 4 Different Product Types

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The purpose of this project is to predict sales of four different product types and assess the impact of service reviews and customer reviews have on sales.

Target variable: 'Volume' for the product types: PC, Laptops, Netbooks, and Smartphones

```r
library(tidyverse)
library(caret)
library(ggplot2)
library(corrplot)
library(openxlsx)
library(h2o)
library(kableExtra)
```

```r
existing <- read.csv(file.path('C:/Users/jlbro/OneDrive/C3T3', 'existing.csv'),
                     stringsAsFactors = TRUE)
```

Checking structure

```r
str(existing)
```

```
## 'data.frame':    80 obs. of  18 variables:
##  $ ProductType          : Factor w/ 12 levels "Accessories",..: 7 7 7 5 5 1 1 1 1 1 ...
##  $ ProductNum           : int  101 102 103 104 105 106 107 108 109 110 ...
##  $ Price                : num  949 2250 399 410 1080 ...
##  $ x5StarReviews        : int  3 2 3 49 58 83 11 33 16 10 ...
##  $ x4StarReviews        : int  3 1 0 19 31 30 3 19 9 1 ...
##  $ x3StarReviews        : int  2 0 0 8 11 10 0 12 2 1 ...
##  $ x2StarReviews        : int  0 0 0 3 7 9 0 5 0 0 ...
##  $ x1StarReviews        : int  0 0 0 9 36 40 1 9 2 0 ...
##  $ PositiveServiceReview: int  2 1 1 7 7 12 3 5 2 2 ...
##  $ NegativeServiceReview: int  0 0 0 8 20 5 0 3 1 0 ...
##  $ Recommendproduct     : num  0.9 0.9 0.9 0.8 0.7 0.3 0.9 0.7 0.8 0.9 ...
##  $ BestSellersRank      : int  1967 4806 12076 109 268 64 NA 2 NA 18 ...
##  $ ShippingWeight       : num  25.8 50 17.4 5.7 7 1.6 7.3 12 1.8 0.75 ...
##  $ ProductDepth         : num  23.9 35 10.5 15 12.9 ...
```

```
##  $ ProductWidth         : num  6.62 31.75 8.3 9.9 0.3 ...
##  $ ProductHeight        : num  16.9 19 10.2 1.3 8.9 ...
##  $ ProfitMargin         : num  0.15 0.25 0.08 0.08 0.09 0.05 0.05 0.05 0.05 0.05 ...
##  $ Volume               : int  12 8 12 196 232 332 44 132 64 40 ...
```

Because regression algorithms can easily misinterpret categorical variables in which there are more than 2 values, we will dummify categorical data for regression modeling to binarize the values.

```
existingDummy <- dummyVars(' ~ .', data = existing)
existing2 <- data.frame(predict(existingDummy, newdata = existing))
```

Check structure again

```
str(existing2)
```

```
## 'data.frame':    80 obs. of  29 variables:
##  $ ProductType.Accessories     : num  0 0 0 0 0 1 1 1 1 1 ...
##  $ ProductType.Display         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.ExtendedWarranty: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.GameConsole     : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Laptop          : num  0 0 0 1 1 0 0 0 0 0 ...
##  $ ProductType.Netbook         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.PC              : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ ProductType.Printer         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.PrinterSupplies : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Smartphone      : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Software        : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Tablet          : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductNum                  : num  101 102 103 104 105 106 107 108 109 110 ...
##  $ Price                       : num  949 2250 399 410 1080 ...
##  $ x5StarReviews               : num  3 2 3 49 58 83 11 33 16 10 ...
##  $ x4StarReviews               : num  3 1 0 19 31 30 3 19 9 1 ...
##  $ x3StarReviews               : num  2 0 0 8 11 10 0 12 2 1 ...
##  $ x2StarReviews               : num  0 0 0 3 7 9 0 5 0 0 ...
##  $ x1StarReviews               : num  0 0 0 9 36 40 1 9 2 0 ...
##  $ PositiveServiceReview       : num  2 1 1 7 7 12 3 5 2 2 ...
##  $ NegativeServiceReview       : num  0 0 0 8 20 5 0 3 1 0 ...
##  $ Recommendproduct            : num  0.9 0.9 0.9 0.8 0.7 0.3 0.9 0.7 0.8 0.9 ...
##  $ BestSellersRank             : num  1967 4806 12076 109 268 ...
##  $ ShippingWeight              : num  25.8 50 17.4 5.7 7 1.6 7.3 12 1.8 0.75 ...
##  $ ProductDepth                : num  23.9 35 10.5 15 12.9 ...
##  $ ProductWidth                : num  6.62 31.75 8.3 9.9 0.3 ...
##  $ ProductHeight               : num  16.9 19 10.2 1.3 8.9 ...
##  $ ProfitMargin                : num  0.15 0.25 0.08 0.08 0.09 0.05 0.05 0.05 0.05 0.05 ...
##  $ Volume                      : num  12 8 12 196 232 332 44 132 64 40 ...
```

Check summary for descriptive and NAs

```r
summary(existing2)
```

```
##  ProductType.Accessories ProductType.Display ProductType.ExtendedWarranty
##  Min.   :0.000           Min.   :0.0000      Min.   :0.000
##  1st Qu.:0.000           1st Qu.:0.0000      1st Qu.:0.000
##  Median :0.000           Median :0.0000      Median :0.000
##  Mean   :0.325           Mean   :0.0625      Mean   :0.125
##  3rd Qu.:1.000           3rd Qu.:0.0000      3rd Qu.:0.000
##  Max.   :1.000           Max.   :1.0000      Max.   :1.000
##
##  ProductType.GameConsole ProductType.Laptop ProductType.Netbook ProductType.PC
##  Min.   :0.000           Min.   :0.0000     Min.   :0.000       Min.   :0.00
##  1st Qu.:0.000           1st Qu.:0.0000     1st Qu.:0.000       1st Qu.:0.00
##  Median :0.000           Median :0.0000     Median :0.000       Median :0.00
##  Mean   :0.025           Mean   :0.0375     Mean   :0.025       Mean   :0.05
##  3rd Qu.:0.000           3rd Qu.:0.0000     3rd Qu.:0.000       3rd Qu.:0.00
##  Max.   :1.000           Max.   :1.0000     Max.   :1.000       Max.   :1.00
##
##  ProductType.Printer ProductType.PrinterSupplies ProductType.Smartphone
##  Min.   :0.00        Min.   :0.0000              Min.   :0.00
##  1st Qu.:0.00        1st Qu.:0.0000              1st Qu.:0.00
##  Median :0.00        Median :0.0000              Median :0.00
##  Mean   :0.15        Mean   :0.0375              Mean   :0.05
##  3rd Qu.:0.00        3rd Qu.:0.0000              3rd Qu.:0.00
##  Max.   :1.00        Max.   :1.0000              Max.   :1.00
##
##  ProductType.Software ProductType.Tablet   ProductNum        Price
##  Min.   :0.000        Min.   :0.0000     Min.   :101.0   Min.   :   3.60
##  1st Qu.:0.000        1st Qu.:0.0000     1st Qu.:120.8   1st Qu.:  52.66
##  Median :0.000        Median :0.0000     Median :140.5   Median : 132.72
##  Mean   :0.075        Mean   :0.0375     Mean   :142.6   Mean   : 247.25
##  3rd Qu.:0.000        3rd Qu.:0.0000     3rd Qu.:160.2   3rd Qu.: 352.49
##  Max.   :1.000        Max.   :1.0000     Max.   :200.0   Max.   :2249.99
##
##  x5StarReviews    x4StarReviews    x3StarReviews    x2StarReviews
##  Min.   :   0.0   Min.   :  0.00   Min.   :  0.00   Min.   :  0.00
##  1st Qu.:  10.0   1st Qu.:  2.75   1st Qu.:  2.00   1st Qu.:  1.00
##  Median :  50.0   Median : 22.00   Median :  7.00   Median :  3.00
##  Mean   : 176.2   Mean   : 40.20   Mean   : 14.79   Mean   : 13.79
##  3rd Qu.: 306.5   3rd Qu.: 33.00   3rd Qu.: 11.25   3rd Qu.:  7.00
##  Max.   :2801.0   Max.   :431.00   Max.   :162.00   Max.   :370.00
##
##  x1StarReviews     PositiveServiceReview NegativeServiceReview Recommendproduct
##  Min.   :   0.00   Min.   :  0.00        Min.   :  0.000       Min.   :0.100
##  1st Qu.:   2.00   1st Qu.:  2.00        1st Qu.:  1.000       1st Qu.:0.700
##  Median :   8.50   Median :  5.50        Median :  3.000       Median :0.800
##  Mean   :  37.67   Mean   : 51.75        Mean   :  6.225       Mean   :0.745
##  3rd Qu.:  15.25   3rd Qu.: 42.00        3rd Qu.:  6.250       3rd Qu.:0.900
##  Max.   :1654.00   Max.   :536.00        Max.   :112.000       Max.   :1.000
##
##  BestSellersRank ShippingWeight     ProductDepth      ProductWidth
```

```
##  Min.   :    1   Min.   : 0.0100   Min.   :  0.000   Min.   : 0.000
##  1st Qu.:    7   1st Qu.: 0.5125   1st Qu.:  4.775   1st Qu.: 1.750
##  Median :   27   Median : 2.1000   Median :  7.950   Median : 6.800
##  Mean   : 1126   Mean   : 9.6681   Mean   : 14.425   Mean   : 7.819
##  3rd Qu.:  281   3rd Qu.:11.2050   3rd Qu.: 15.025   3rd Qu.:11.275
##  Max.   :17502   Max.   :63.0000   Max.   :300.000   Max.   :31.750
##  NA's   :15
##  ProductHeight     ProfitMargin        Volume
##  Min.   : 0.000   Min.   :0.0500   Min.   :    0
##  1st Qu.: 0.400   1st Qu.:0.0500   1st Qu.:   40
##  Median : 3.950   Median :0.1200   Median :  200
##  Mean   : 6.259   Mean   :0.1545   Mean   :  705
##  3rd Qu.:10.300   3rd Qu.:0.2000   3rd Qu.: 1226
##  Max.   :25.800   Max.   :0.4000   Max.   :11204
##
```

Reveals 15 NA's for 'BestSellersRank'

Deleting BestSellersRank, only variable with NAs

```r
existing2$BestSellersRank <- NULL
```

Correlation matrix of all variables

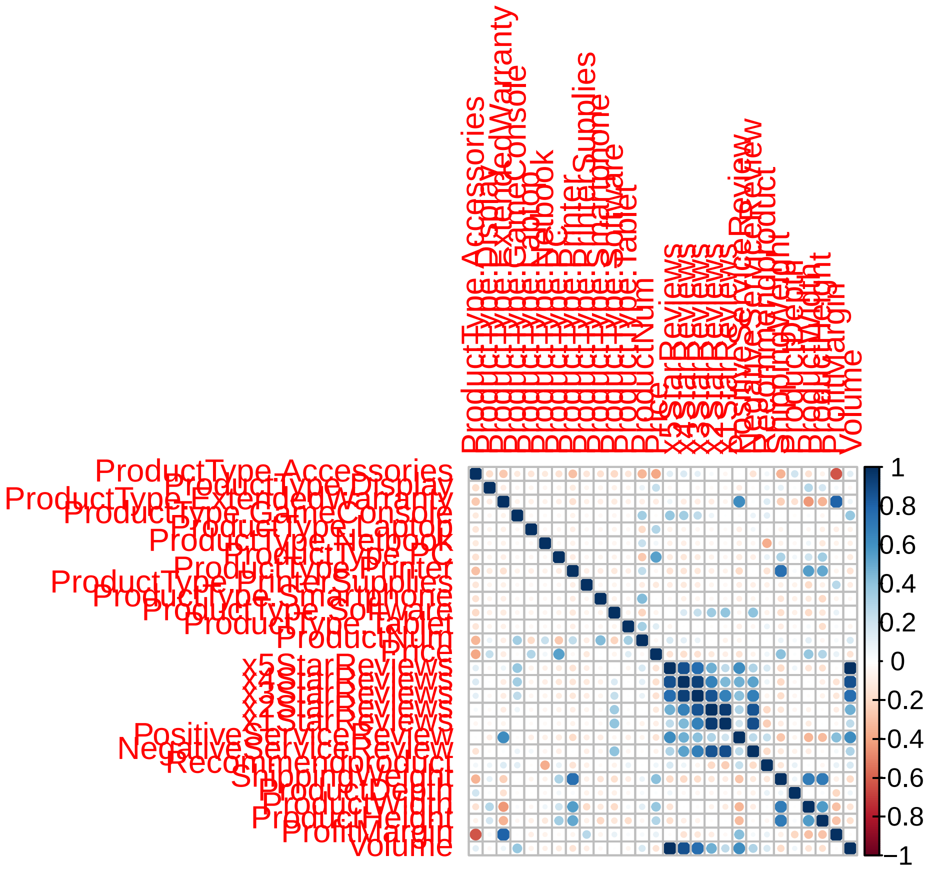
```r
corrData <- cor(existing2)
```

Exporting correlation to excel

```r
write.xlsx(corrData, file = "corrData.xlsx", row.names=TRUE)
write.xlsx(existing2, file = 'existing2.xlsx')
```

Viewing correlation heatmap, as you can see, it's unreadable with so many variables

```r
corrplot(corrData)
```



Removing 5 Star since perfect correlation of 1 to target variable, risks overfitting

Also removing low correlated variables

```r
existing3 <- subset(existing2, select = -c(1:4, 8:9, 11:12, 15, 24:27))
str(existing3)
```

```
## 'data.frame':    80 obs. of  15 variables:
##  $ ProductType.Laptop    : num  0 0 0 1 1 0 0 0 0 0 ...
##  $ ProductType.Netbook   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.PC        : num  1 1 1 0 0 0 0 0 0 0 ...
##  $ ProductType.Smartphone: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductNum            : num  101 102 103 104 105 106 107 108 109 110 ...
##  $ Price                 : num  949 2250 399 410 1080 ...
##  $ x4StarReviews         : num  3 1 0 19 31 30 3 19 9 1 ...
##  $ x3StarReviews         : num  2 0 0 8 11 10 0 12 2 1 ...
##  $ x2StarReviews         : num  0 0 0 3 7 9 0 5 0 0 ...
##  $ x1StarReviews         : num  0 0 0 9 36 40 1 9 2 0 ...
##  $ PositiveServiceReview : num  2 1 1 7 7 12 3 5 2 2 ...
##  $ NegativeServiceReview : num  0 0 0 8 20 5 0 3 1 0 ...
##  $ Recommendproduct      : num  0.9 0.9 0.9 0.8 0.7 0.3 0.9 0.7 0.8 0.9 ...
##  $ ShippingWeight        : num  25.8 50 17.4 5.7 7 1.6 7.3 12 1.8 0.75 ...
##  $ Volume                : num  12 8 12 196 232 332 44 132 64 40 ...
```

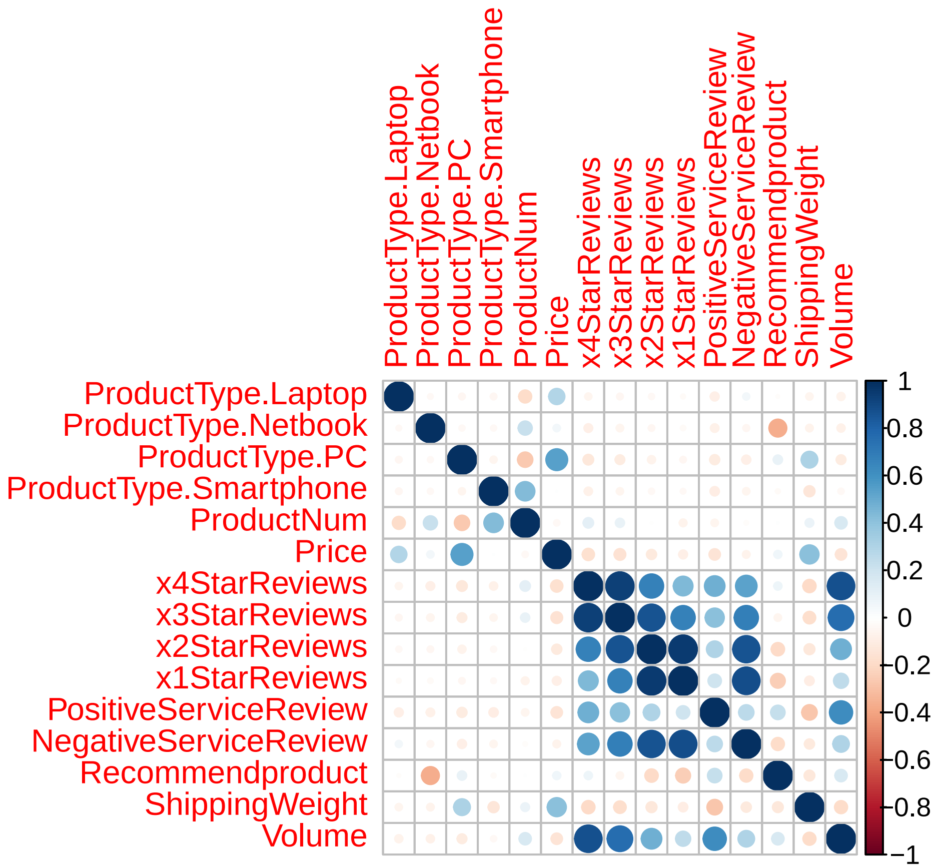
Transmute new column that is average of all Star Reviews to try as form of PCA

```
existing4 <- existing3 %>%
  rowwise() %>% mutate(AvgStarReviews = (mean(c(x4StarReviews, x3StarReviews, x2StarReviews, x1StarRevie
```

EDA

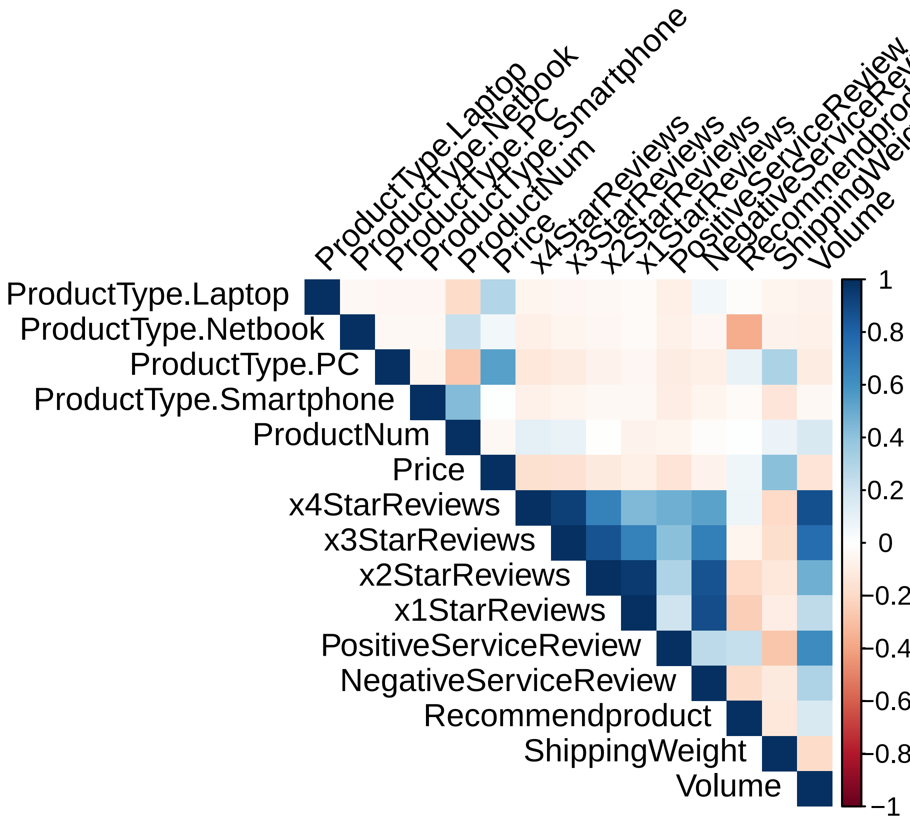
viewing correlation heatmap

```
corrData3 <- cor(existing3)
corrplot(corrData3)
```



Enhancing the correlation heatmap

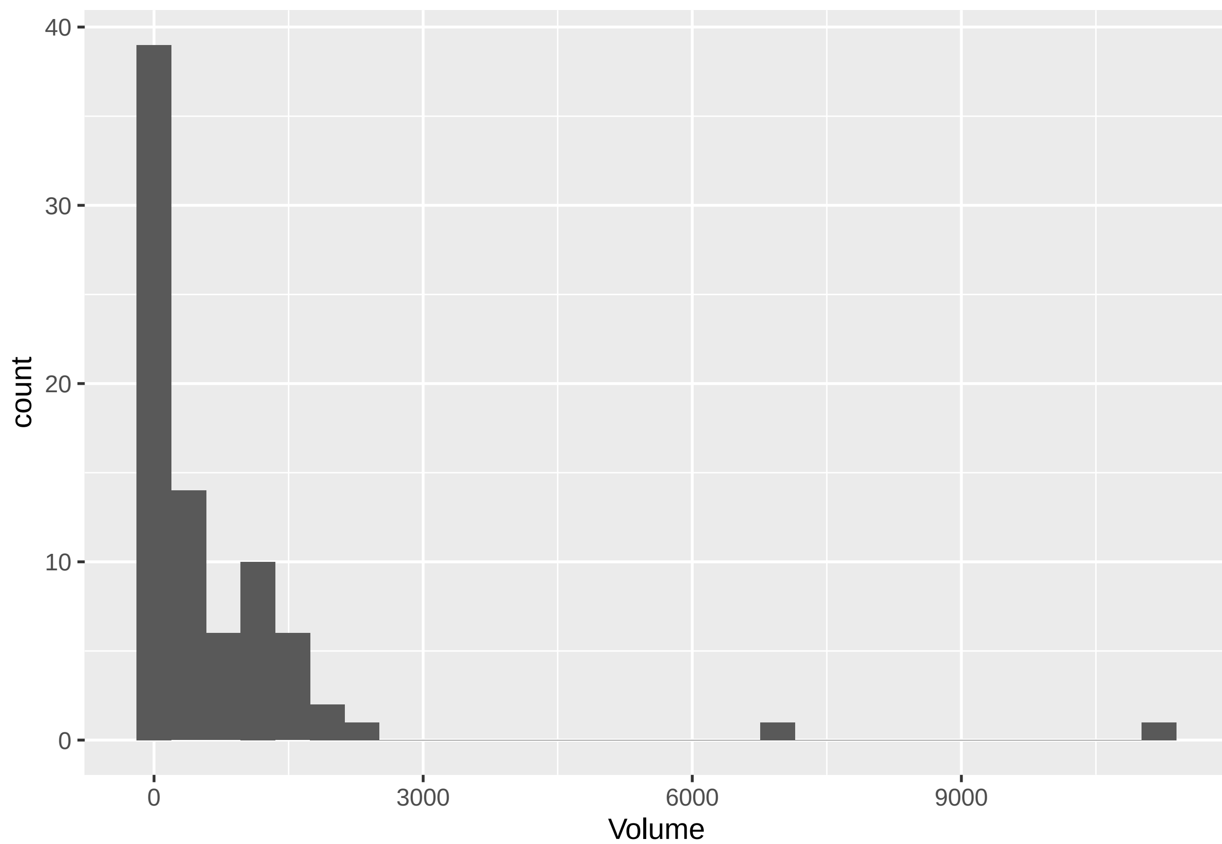
```
color <- colorRampPalette(c('#BB4444','#EE9988','#FFFFFF','#77AADD','#4477AA'))
corrplot(corrData3, method = 'shade', shade.col = NA, tl.col = 'black',
         type = 'upper', tl.srt = 45)
```



Histogram of Volume, reveals couple outliers

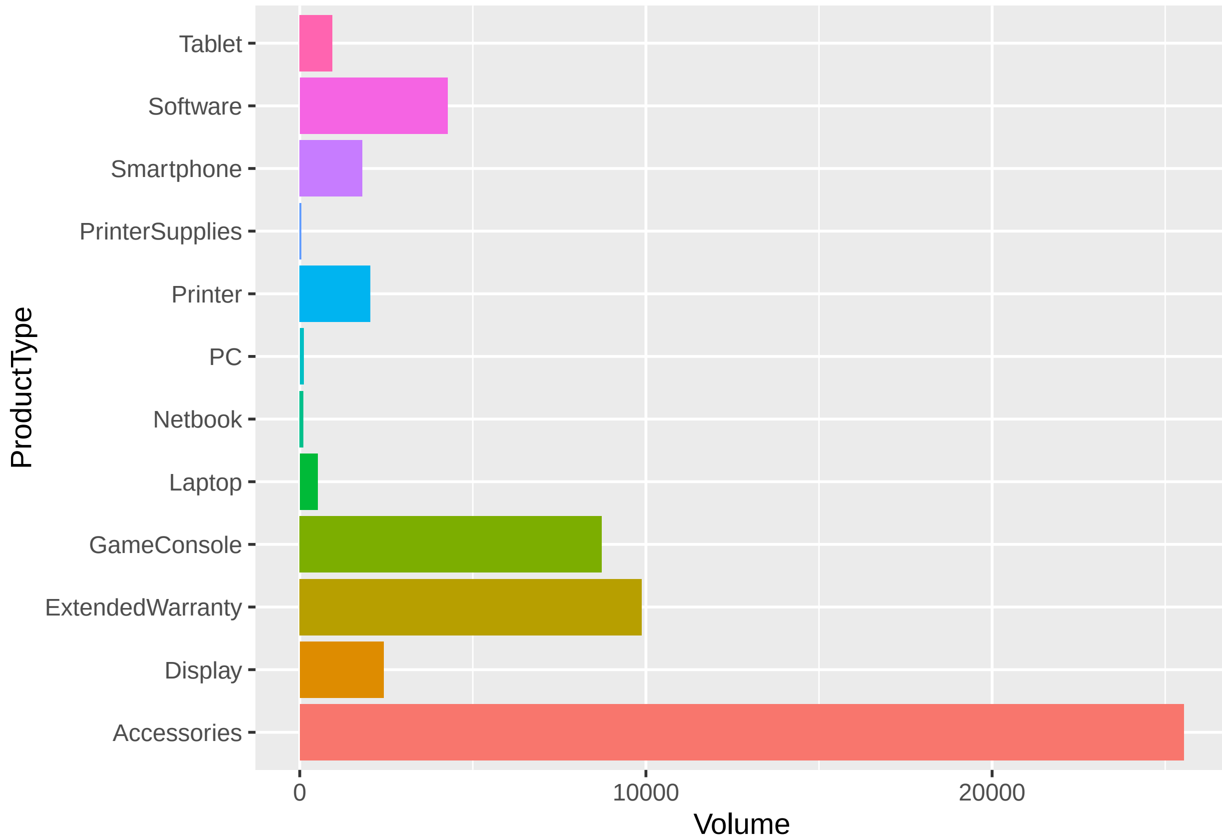
```
ggplot(data = existing3, mapping = aes(x = Volume)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



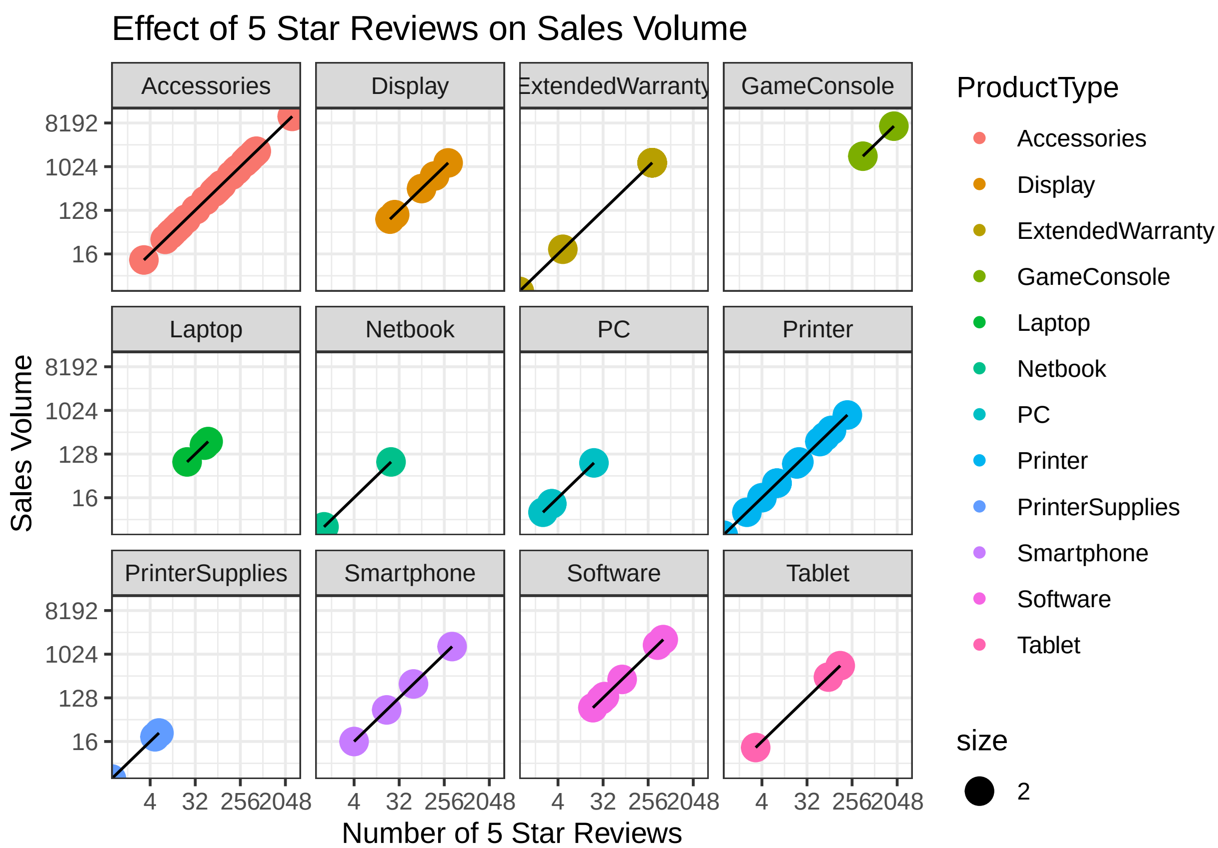
Plotting Sales Volume by Product Type

```
ggplot(data = existing, aes(x = ProductType, y = Volume, fill = ProductType)) +
  geom_bar(stat = 'identity') +
  guides(fill=FALSE) +
  coord_flip()
```



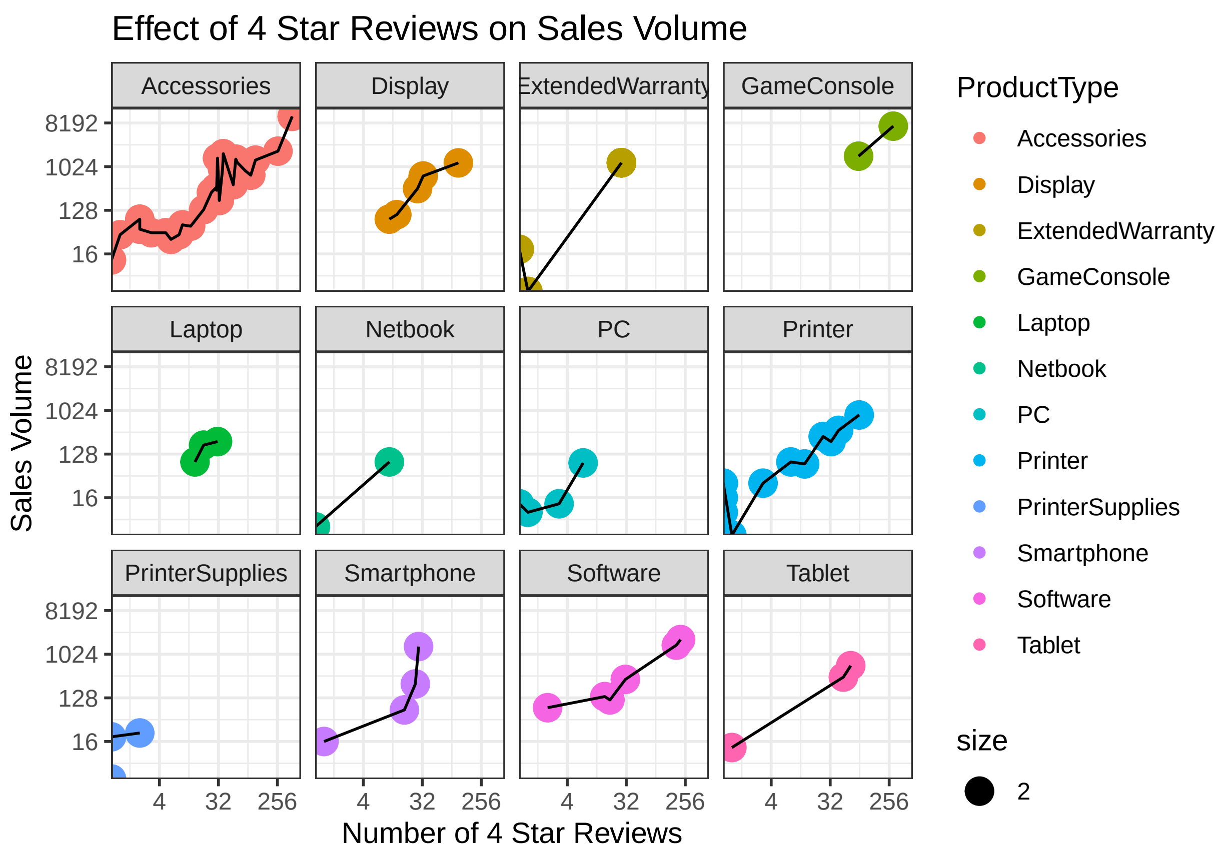
Plotting the impact 5 Star Reviews have on Sales Volume

```
ggplot(data=existing, aes(x=x5StarReviews, y=Volume)) +
  geom_point(aes(color=ProductType, size=2)) +
  theme_bw() +
  scale_x_continuous(trans = 'log2') +
  scale_y_continuous(trans = 'log2') +
  geom_line() +
  facet_wrap(~ProductType) +
  xlab('Number of 5 Star Reviews') +
  ylab('Sales Volume') +
  ggtitle('Effect of 5 Star Reviews on Sales Volume')
```

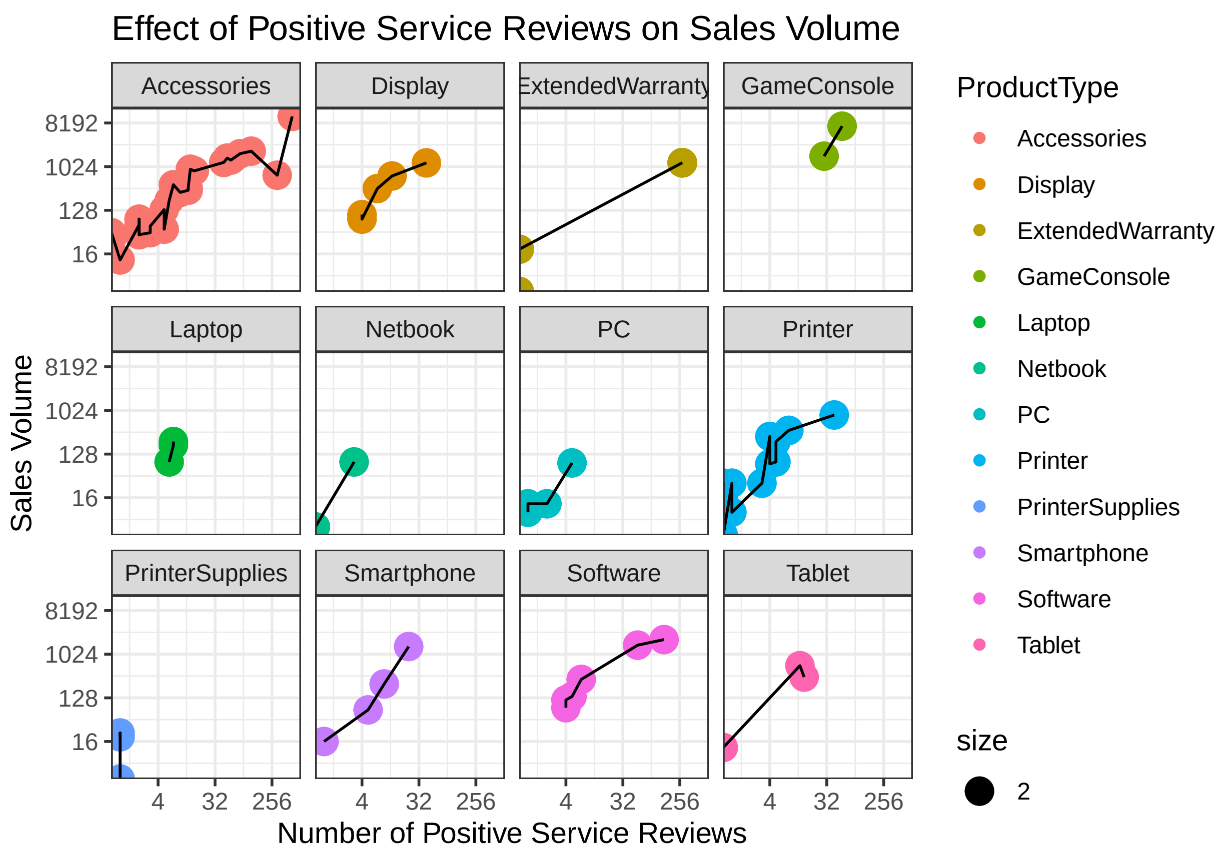


Now plotting the impact of 4 Star Reviews on Sales Volume

```
ggplot(data=existing, aes(x=x4StarReviews, y=Volume)) +
  geom_point(aes(color=ProductType, size=2)) +
  theme_bw() +
  scale_x_continuous(trans = 'log2') +
  scale_y_continuous(trans = 'log2') +
  geom_line() +
  facet_wrap(~ProductType) +
  xlab('Number of 4 Star Reviews') +
  ylab('Sales Volume') +
  ggtitle('Effect of 4 Star Reviews on Sales Volume')
```




```r
ggplot(data=existing, aes(x=PositiveServiceReview, y=Volume)) +
  geom_point(aes(color=ProductType, size=2)) +
  theme_bw() +
  scale_x_continuous(trans = 'log2') +
  scale_y_continuous(trans = 'log2') +
  geom_line() +
  facet_wrap(~ProductType) +
  xlab('Number of Positive Service Reviews') +
  ylab('Sales Volume') +
  ggtitle('Effect of Positive Service Reviews on Sales Volume')
```



Modeling

Creating data partition and setting cross validation

Two rows eventually were removed due to outlier volumes

```
set.seed(123)

# CreateDataPartition() 75% and 25%
index1 <- createDataPartition(existing3$Volume, p=0.75, list = FALSE)
train1 <- existing3[ index1,]
test1 <- existing3[-index1,]

# Removing 2 outlier rows #18 and #48 from test set
test1_rem_out <- test1[!rownames(test1) %in% c('18', '48'), ]

# Checking structure of train1
str(train1)
```

```
## 'data.frame':    61 obs. of  15 variables:
##  $ ProductType.Laptop    : num  0 0 0 1 0 0 0 0 0 0 ...
##  $ ProductType.Netbook   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.PC        : num  1 1 1 0 0 0 0 0 0 0 ...
```

```
##  $ ProductType.Smartphone: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductNum            : num  101 102 103 104 106 107 108 109 110 111 ...
##  $ Price                 : num  949 2250 399 410 114 ...
##  $ x4StarReviews         : num  3 1 0 19 30 3 19 9 1 2 ...
##  $ x3StarReviews         : num  2 0 0 8 10 0 12 2 1 2 ...
##  $ x2StarReviews         : num  0 0 0 3 9 0 5 0 0 4 ...
##  $ x1StarReviews         : num  0 0 0 9 40 1 9 2 0 15 ...
##  $ PositiveServiceReview : num  2 1 1 7 12 3 5 2 2 2 ...
##  $ NegativeServiceReview : num  0 0 0 8 5 0 3 1 0 1 ...
##  $ Recommendproduct      : num  0.9 0.9 0.9 0.8 0.3 0.9 0.7 0.8 0.9 0.5 ...
##  $ ShippingWeight        : num  25.8 50 17.4 5.7 1.6 7.3 12 1.8 0.75 1 ...
##  $ Volume                : num  12 8 12 196 332 44 132 64 40 84 ...
```

```
# Setting cross validation
control1 <- trainControl(method = 'repeatedcv',
                         number = 10,
                         repeats = 1)
```

Random forest model and tuning

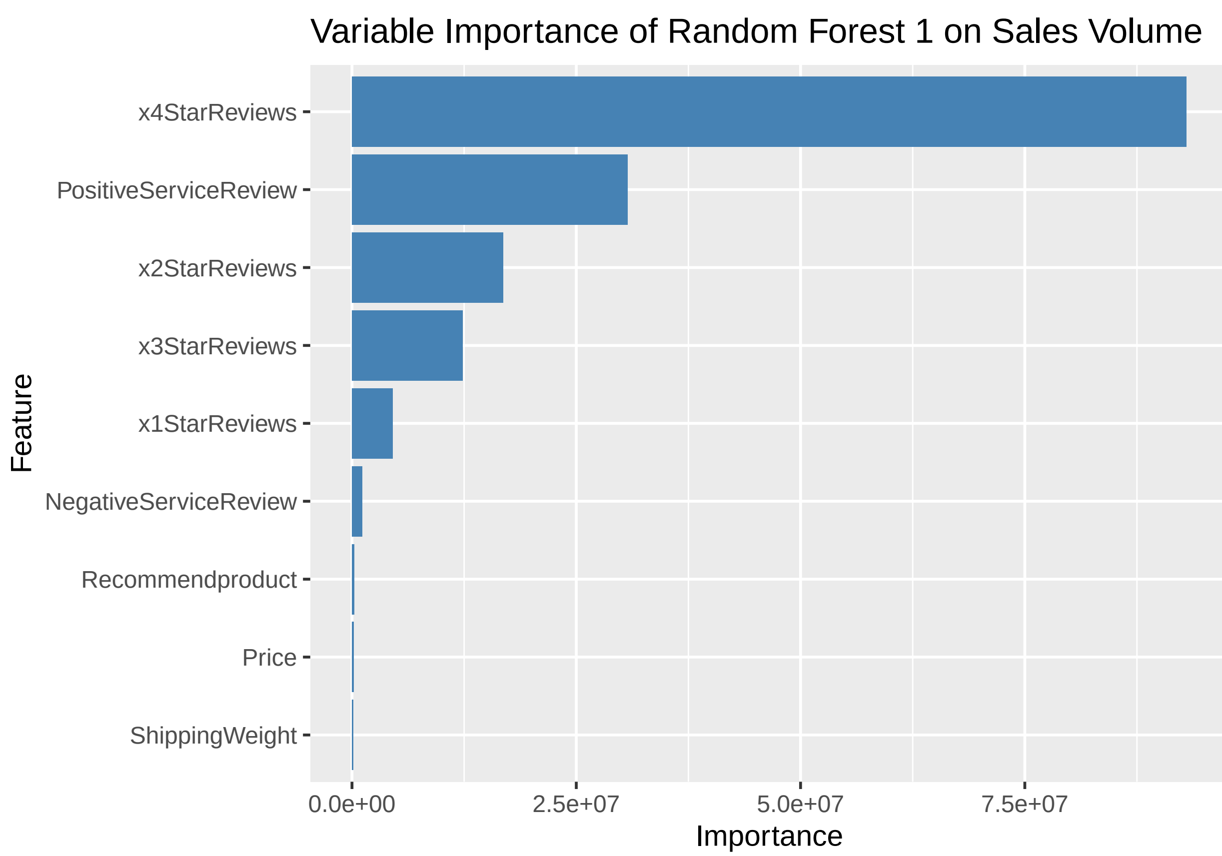
```
# set seed
set.seed(123)

# Creating dataframe for manual tuning
rfGrid <- expand.grid(mtry = c(2,3,4,5,6,7,8))

rf1 <- train(Volume ~ x4StarReviews + PositiveServiceReview + x2StarReviews + x3StarReviews +
               x1StarReviews + NegativeServiceReview + Recommendproduct + ShippingWeight + Price,
             data = train1,
             method = 'rf',
             trControl = control1,
             tuneGrid = rfGrid)

rf1
```

```
## Random Forest
##
## 61 samples
##  9 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     869.2921  0.8755901  416.0646
##   3     849.5229  0.8871013  400.1741
##   4     824.7775  0.8939530  386.7741
##   5     827.7373  0.8980015  384.5929
##   6     801.6069  0.9043345  372.1979
```

```
##    7      802.9288   0.9073910   372.2425
##    8      788.6419   0.9081729   365.2084
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 8.
```

Level of importance for variables in model

```r
ggplot(varImp(rf1, scale=FALSE)) +
  geom_bar(stat = 'identity', fill = 'steelblue') +
  ggtitle('Variable Importance of Random Forest 1 on Sales Volume')
```

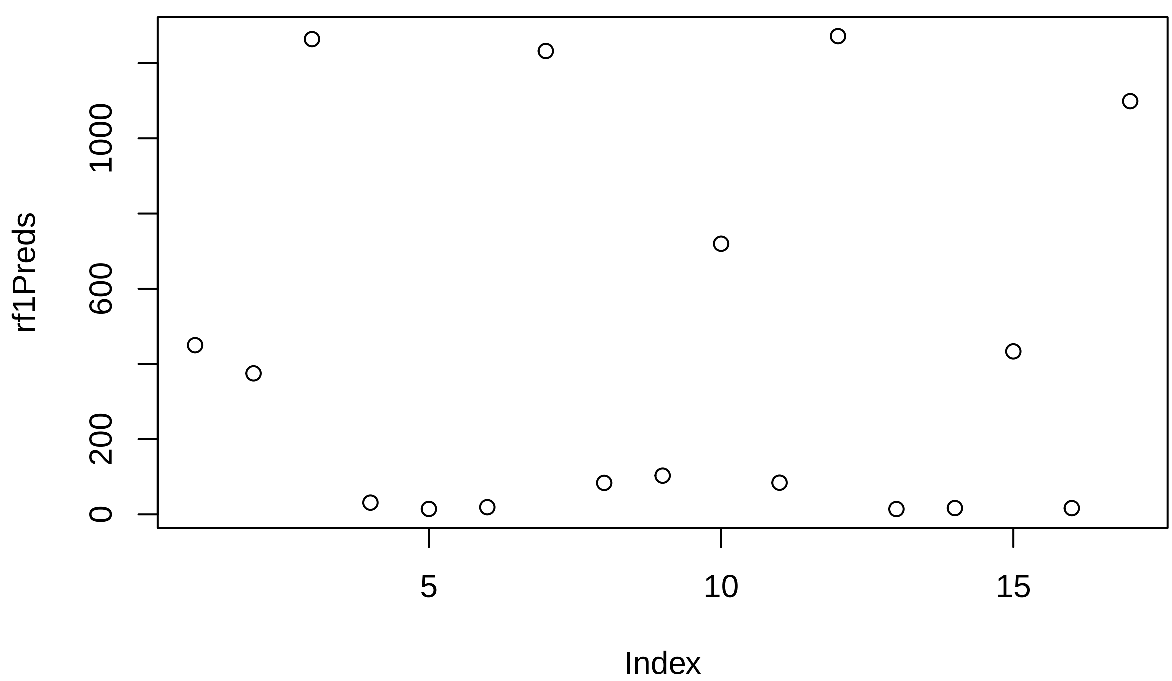


Predicting rf on test1

```r
rf1Preds <- predict(rf1, newdata = test1_rem_out)
summary(rf1Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   14.11   19.05  102.97  425.15  719.71 1271.74
```

```r
plot(rf1Preds)
```



A symmetrical pattern means a good residual plot!

postResample to test if it will do well on new data or if overfitting

```r
postResample(rf1Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 190.4253816   0.9452884  98.7387608
```

CV RMSE=788, R2=.908

PostResample RMSE=190, R2=.945

Random Forest using feature selection

```r
set.seed(123)

rf2 <- train(Volume ~ x4StarReviews + PositiveServiceReview + x2StarReviews,
```

```r
              data = train1,
              method = 'rf',
              trControl = control1)
```

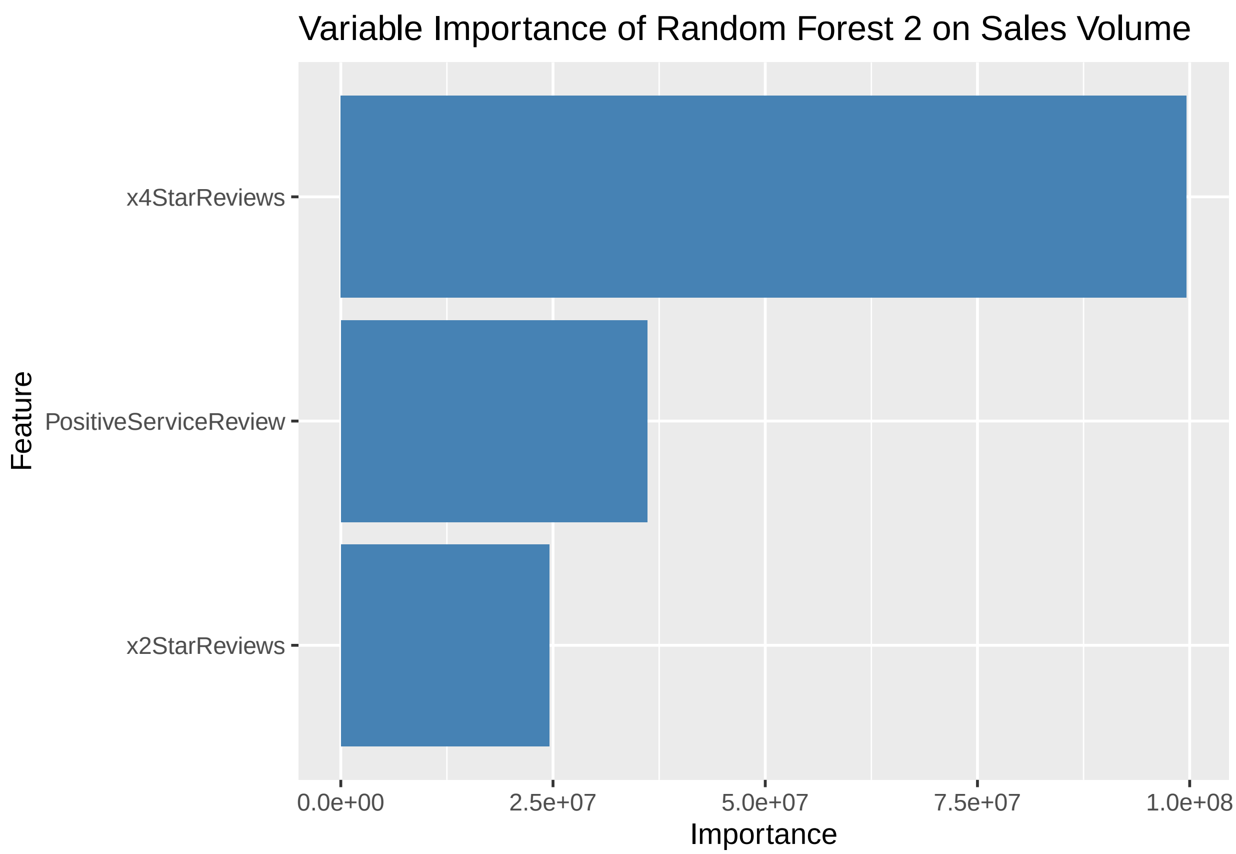
```
## note: only 2 unique complexity parameters in default grid. Truncating the grid to 2 .
```

```r
rf2
```

```
## Random Forest
##
## 61 samples
##  3 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     771.2710  0.9218973  349.2301
##   3     745.3771  0.9284383  338.8776
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 3.
```

Variable importance

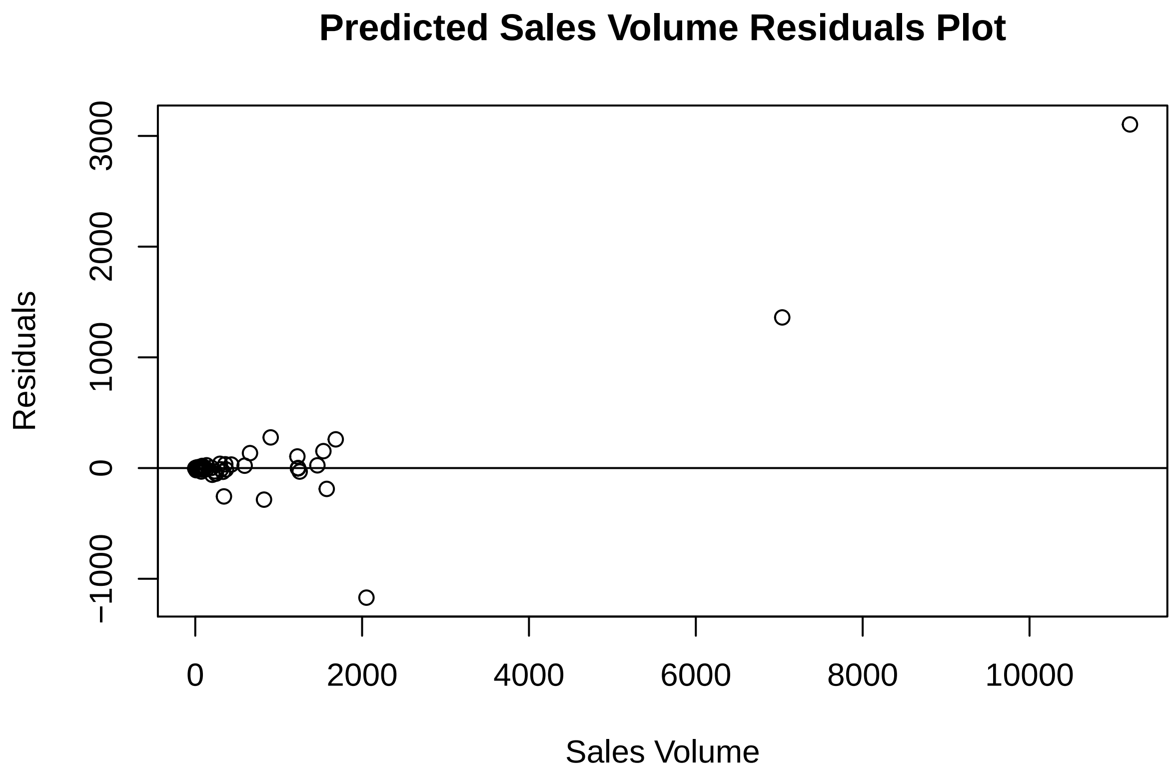
```r
ggplot(varImp(rf2, scale=FALSE)) +
  geom_bar(stat = 'identity', fill = 'steelblue') +
  ggtitle('Variable Importance of Random Forest 2 on Sales Volume')
```



Plotting the residuals against the actual values for Volume

This graph shows volume outlier, further research reveals both outliers are for accessories, which are not products of interest.

```
resid_rf2 <- residuals(rf2)
plot(train1$Volume, resid_rf2,
     xlab = 'Sales Volume',
     ylab = 'Residuals',
     main ='Predicted Sales Volume Residuals Plot',
     abline(0,0))
```

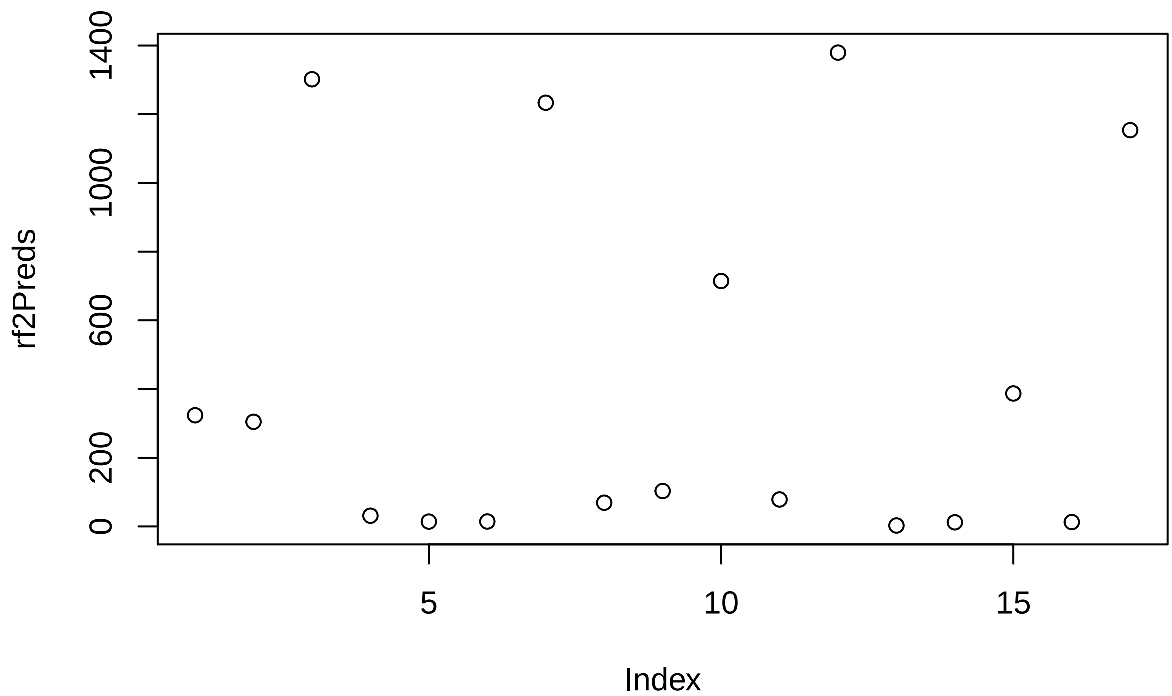


Predicting rf2 on test1

```r
rf2Preds <- predict(rf2, newdata = test1_rem_out)
summary(rf2Preds)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##    2.742   14.336  103.066  419.753  714.428 1379.420
```

```r
plot(rf2Preds)
```



Another excellent residual plot, showing our predictions are consistent with regression

postResample to test if it will do well on new data or if overfitting

```
postResample(rf2Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 153.8183544   0.9718405  74.7555212
```

CV RMSE = 745, R2=.928

PostResample RMSE=153, R2=.972

The postResample R2 and RMSE for a regression model is excellent. This is our top model!

Random Forest using feature selection

```
set.seed(123)

rf3 <- train(Volume ~ x4StarReviews + PositiveServiceReview + x3StarReviews,
             data = train1,
```

```r
             method = 'rf',
             trControl = control1)
```

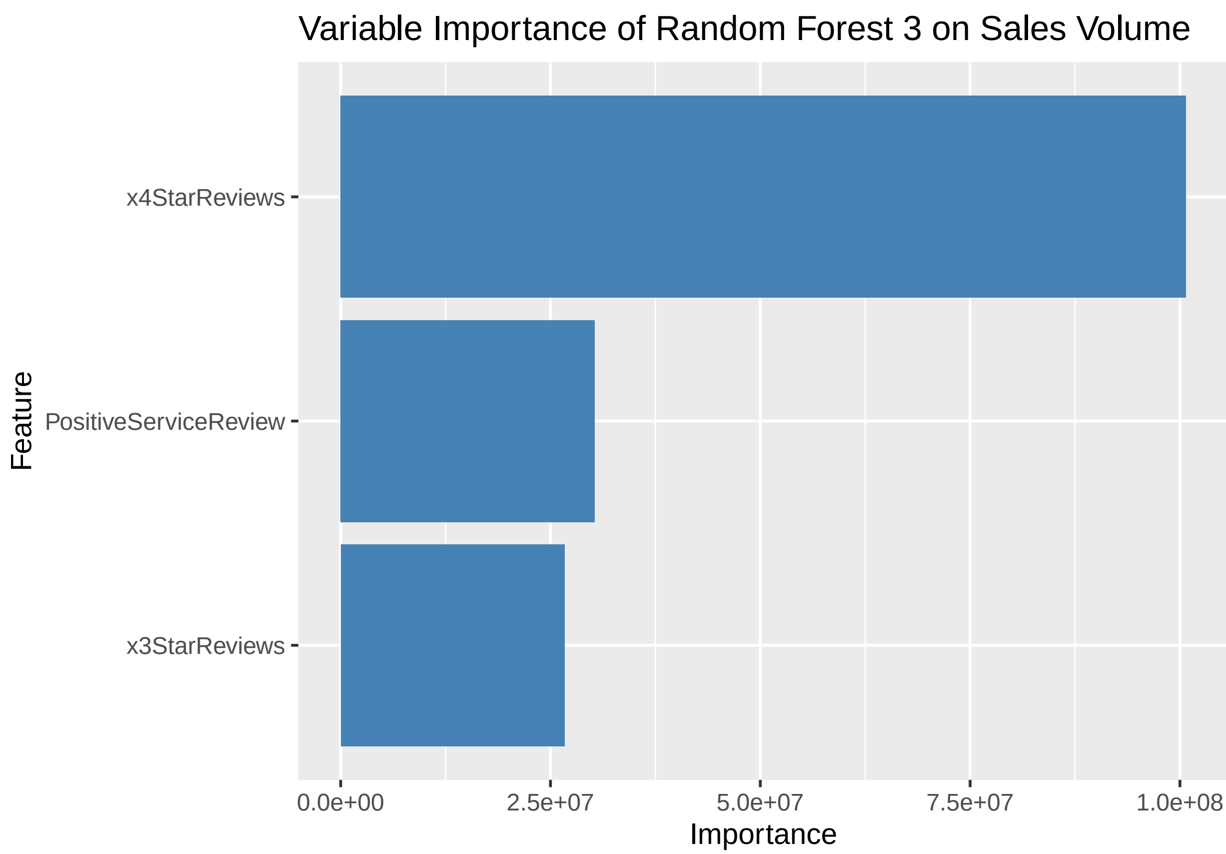
```
## note: only 2 unique complexity parameters in default grid. Truncating the grid to 2 .
```

```r
rf3
```

```
## Random Forest
##
## 61 samples
##  3 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     710.5834  0.9285459  323.8009
##   3     684.5642  0.9346194  313.5800
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 3.
```

Variable importance

```r
ggplot(varImp(rf3, scale=FALSE)) +
  geom_bar(stat = 'identity', fill = 'steelblue') +
  ggtitle('Variable Importance of Random Forest 3 on Sales Volume')
```



Predicting rf3 on test1

```
rf3Preds <- predict(rf3, newdata = test1_rem_out)
summary(rf3Preds)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##    5.789   11.959   94.221  425.461  737.133 1358.924
```

postResample to test if it will do well on new data or if overfitting

```
postResample(rf3Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 167.7971733   0.9549701  83.4029171
```

CV RMSe=648, R2=.934

PostResample RMSE=167, R2=.954

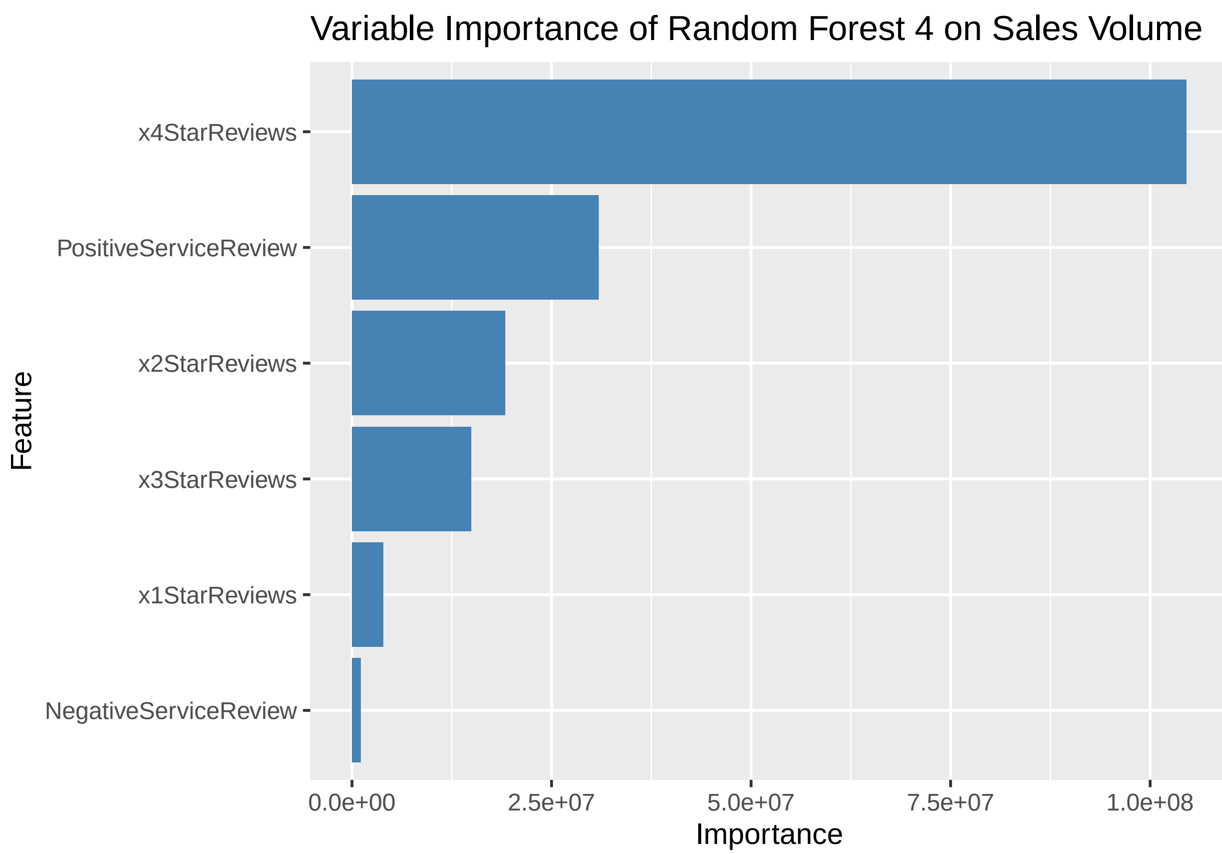
Random Forest using feature selection

```
set.seed(123)
rf4 <- train(Volume ~ x4StarReviews + PositiveServiceReview + x3StarReviews + x2StarReviews +
               x1StarReviews + NegativeServiceReview,
             data = train1,
             method = 'rf',
             trControl = control1)

rf4
```

```
## Random Forest
##
## 61 samples
##  6 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     844.5227  0.8864850  396.6254
##   4     801.2553  0.9052961  370.6409
##   6     790.8997  0.9072861  362.8766
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 6.
```

Variable importance using ggplot

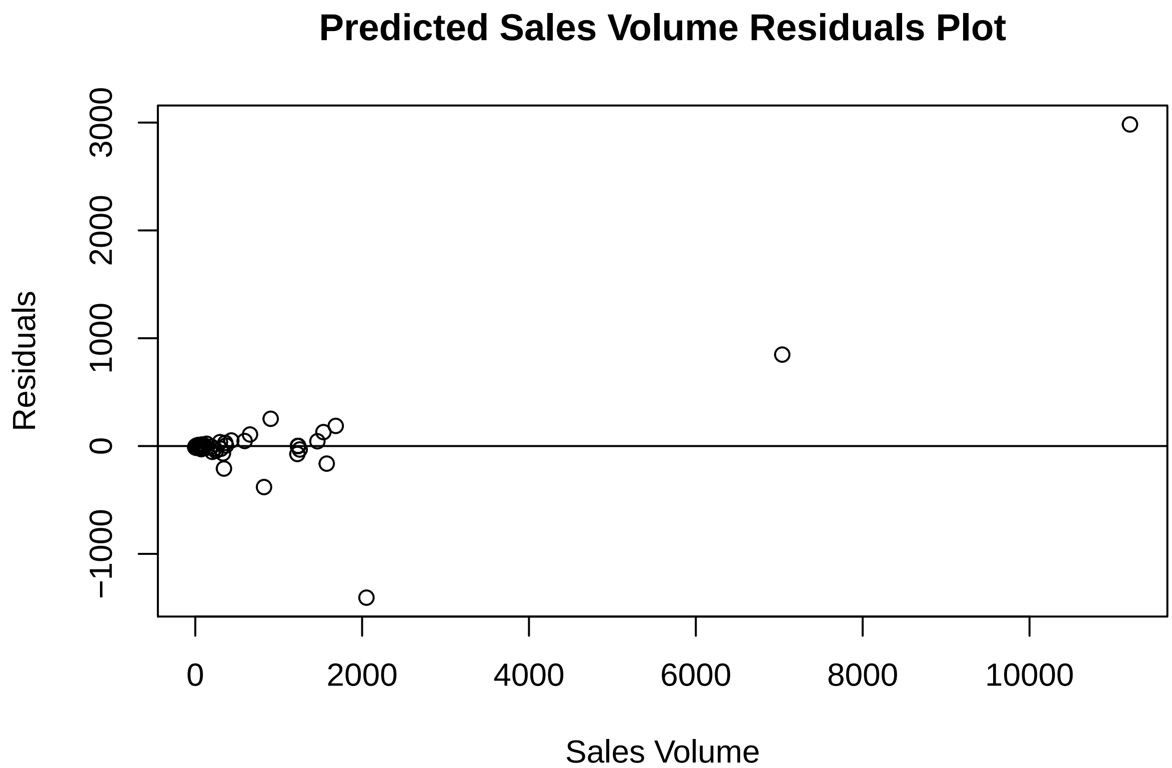
```
ggplot(varImp(rf4, scale=FALSE)) +
  geom_bar(stat = 'identity', fill = 'steelblue') +
  ggtitle('Variable Importance of Random Forest 4 on Sales Volume')
```



Plotting the residuals against the actual values for Volume

Graph shows outlier

```
resid_rf4 <- residuals(rf4)
plot(train1$Volume, resid_rf4, xlab = 'Sales Volume', ylab = 'Residuals',
     main='Predicted Sales Volume Residuals Plot',
     abline(0,0))
```



Predicting rf4 on test1

```
rf4Preds <- predict(rf4, newdata = test1_rem_out)
summary(rf4Preds)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##    7.937   15.732   98.618  426.150  782.476 1304.662
```

postResample to test if it will do well on new data or if overfitting

```
postResample(rf4Preds, test1_rem_out$Volume)
```

```
##       RMSE   Rsquared        MAE
## 177.453911   0.952956  87.506546
```

CV RMSE=783, R2=.909

RMSE=177, R2=.952

Support Vector Machines – RBF Kernel

Set seed

```r
set.seed(123)

# Creating dataframe for manual tuning
rbfGrid <- expand.grid(sigma = c(.01, .015, .2),
                       C = c(10, 100, 1000))

rbf1 <- train(Volume ~ x4StarReviews + x3StarReviews + PositiveServiceReview,
              data = train1,
              method = 'svmRadial',
              trControl = control1,
              tuneGrid = rbfGrid,
              preProc = c('center','scale'))

rbf1
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 61 samples
##  3 predictor
##
## Pre-processing: centered (3), scaled (3)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   sigma  C     RMSE       Rsquared   MAE
##   0.010    10   944.2228  0.8594778  489.1231
##   0.010   100   930.7863  0.8149199  473.1634
##   0.010  1000  1190.2695  0.8309208  580.6230
##   0.015    10   986.8673  0.8419784  507.9508
##   0.015   100   940.5278  0.8123009  480.0726
##   0.015  1000  1236.2804  0.8613697  590.2852
##   0.200    10   913.7802  0.9182651  467.5324
##   0.200   100   879.2184  0.9194906  436.6931
##   0.200  1000   949.7834  0.9093674  462.1128
##
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were sigma = 0.2 and C = 100.
```

Predicting rbf on test1

```r
rbf1Preds <- predict(rbf1, newdata = test1_rem_out)
summary(rbf1Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   29.81   94.91  267.83  463.59  552.12 2146.20
```

postResample to test if it will do well on new data or if overfitting

```r
postResample(rbf1Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 264.0730623   0.8148197 177.1172248
```

CV RMSE=879, R2=.919

PostResample RMSE=264, R2=.815

Support Vector Machines – RBF Kernel feature selection

Set seed

```r
set.seed(123)

# Creating dataframe for manual tuning
rbfGrid <- expand.grid(sigma = c(.01, .015, .2),
                       C = c(10, 100, 1000))

rbf2 <- train(Volume ~ x4StarReviews + PositiveServiceReview + x2StarReviews,
              data = train1,
              method = 'svmRadial',
              trControl = control1,
              tuneGrid = rbfGrid,
              preProc = c('center','scale'))

rbf2
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 61 samples
##  3 predictor
##
## Pre-processing: centered (3), scaled (3)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   sigma  C     RMSE      Rsquared   MAE
```

```
##   0.010    10  935.7611  0.8655808  465.7621
##   0.010   100  774.4498  0.8457538  408.1163
##   0.010  1000  729.0330  0.8563199  400.4417
##   0.015    10  879.8614  0.8620022  452.0967
##   0.015   100  761.7506  0.8470788  417.3052
##   0.015  1000  791.0228  0.8280795  418.6904
##   0.200    10  838.7191  0.9322844  436.6363
##   0.200   100  783.3714  0.9512888  398.3164
##   0.200  1000  657.2931  0.9099973  356.3912
##
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were sigma = 0.2 and C = 1000.
```

Predicting rbf on test1

```r
rbf2Preds <- predict(rbf2, newdata = test1_rem_out)
summary(rbf2Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -253.3    71.6   256.6   512.9   343.3  2499.2
```

```r
# postResample to test if it will do well on new data or if overfitting
postResample(rbf2Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 420.0433306   0.7040338 243.6208248
```

CV RMSE=657, R2=.909

PostResample RMSE=420, R2=.704

Negatives

Support Vector Machines – Linear

Set seed

```r
set.seed(123)

### Creating dataframe for manual tuning
linearGrid <- expand.grid(C = c(1, 10, 100, 1000))

linear1 <- train(Volume ~ x4StarReviews + x3StarReviews + PositiveServiceReview,
                 data = train1,
                 method = 'svmLinear',
                 trControl = control1,
                 tuneGrid = linearGrid,
                 preProc = c('center','scale'))

linear1
```

```
## Support Vector Machines with Linear Kernel
##
## 61 samples
##  3 predictor
##
## Pre-processing: centered (3), scaled (3)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   C     RMSE      Rsquared   MAE
##      1  873.4355  0.8664637  456.9757
##     10  843.0240  0.8585048  447.9310
##    100  848.6679  0.8571624  453.5503
##   1000  847.9066  0.8571915  452.4325
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was C = 10.
```

Predicting rbf on test1

```r
linearPreds <- predict(linear1, newdata = test1_rem_out)
summary(linearPreds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -196.9  -129.0   124.7   388.2   561.6  2364.1
```

postResample to test if it will do well on new data or if overfitting

```r
lin_PR <- postResample(linearPreds, test1_rem_out$Volume)
```

CV RMSE=843, R2=.858

PR RMSE=462, R2=.583

Negative predictions, move on

SVM – Linear

Changing features

Set seed

```r
set.seed(123)

# Creating dataframe for manual tuning
```

```r
linearGrid <- expand.grid(C = c(1, 10, 100, 1000))

linear2 <- train(Volume ~ x4StarReviews + x3StarReviews + PositiveServiceReview +
                   NegativeServiceReview + Price,
                 data = train1,
                 method = 'svmLinear',
                 trControl = control1,
                 tuneGrid = linearGrid,
                 preProc = c('center','scale'))

linear2
```

```
## Support Vector Machines with Linear Kernel
##
## 61 samples
##  5 predictor
##
## Pre-processing: centered (5), scaled (5)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   C     RMSE      Rsquared   MAE
##      1  553.1088  0.8300446  328.9984
##     10  538.0562  0.8151764  327.8059
##    100  538.1027  0.8148848  327.7453
##   1000  538.5593  0.8146058  327.9203
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was C = 10.
```

```r
# Predicting rbf on test1
linear2Preds <- predict(linear2, newdata = test1_rem_out)
summary(linear2Preds)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -155.3142 -102.7355    0.5217  435.3928  496.4102 2631.1579
```

postResample to test if it will do well on new data or if overfitting

```r
postResample(linear2Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 501.1605728   0.5858754 334.9077977
```

RMSE=1120, R2=56.9

Negative predictions, move on

Support Vector Machines – Polynomial

Set seed

```r
set.seed(123)

# Creating dataframe for manual tuning
polyGrid <- expand.grid(degree = c(2,3,4),
                        scale = c(1,2),
                        C = c(.1, 1, 10, 100))

poly1 <- train(Volume ~ x4StarReviews + x3StarReviews + PositiveServiceReview,
               data = train1,
               method = 'svmPoly',
               trControl = control1,
               tuneGrid = polyGrid,
               preProc = c('center','scale'))

poly1
```

```
## Support Vector Machines with Polynomial Kernel
##
## 61 samples
##  3 predictor
##
## Pre-processing: centered (3), scaled (3)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C      RMSE       Rsquared   MAE
##   2       1        0.1   1155.408  0.7966076    571.6401
##   2       1        1.0   4104.003  0.8301827   1770.0867
##   2       1       10.0   6987.814  0.8557033   2939.2082
##   2       1      100.0   9796.456  0.8389599   4083.3127
##   2       2        0.1   2104.421  0.8267500    966.7124
##   2       2        1.0   6491.915  0.8763071   2740.5152
##   2       2       10.0   9245.414  0.8522459   3859.6825
##   2       2      100.0  10042.438  0.8331194   4185.3819
##   3       1        0.1   1118.828  0.8898300    534.3918
##   3       1        1.0   3755.882  0.9381422   1597.5451
##   3       1       10.0   7095.492  0.9176351   2965.7635
##   3       1      100.0  39627.409  0.9024923  16252.9238
##   3       2        0.1   2667.568  0.8509251   1166.7636
##   3       2        1.0   4472.345  0.8879559   1896.1439
##   3       2       10.0  31802.988  0.9179907  13053.9787
##   3       2      100.0  86413.899  0.8848359  35365.6943
##   4       1        0.1   6877.359  0.8003001   2881.4997
```

```
##   4       1        1.0    54000.769  0.8216935  22115.1070
##   4       1       10.0   197327.453  0.9111491  80637.6759
##   4       1      100.0    25145.120  0.9146607  10346.8229
##   4       2        0.1    31923.943  0.8869538  13115.3285
##   4       2        1.0   167176.011  0.8980690  68329.9630
##   4       2       10.0    68279.157  0.9005098  27957.4632
##   4       2      100.0   157877.892  0.9005079  64537.4960
##
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were degree = 3, scale = 1 and C = 0.1.
```

Predicting rbf on test1

```
polyPreds <- predict(poly1, newdata = test1_rem_out)
summary(polyPreds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -31.78  -20.75  218.56  370.45  536.88 1240.00
```

postResample to test if it will do well on new data or if overfitting

```
postResample(polyPreds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 334.4330248   0.7687032 174.1454650
```

RMSE=688, R2=60.2

Negative predictions, move on

SVM – Polynomial

Set seed

```
set.seed(123)

# Creating dataframe for manual tuning
polyGrid <- expand.grid(degree = c(2,3,4),
                        scale = c(1,2),
                        C = c(.1, 1, 10, 100))

poly2 <- train(Volume ~ x4StarReviews + x2StarReviews + PositiveServiceReview +
                 NegativeServiceReview,
               data = train1,
               method = 'svmPoly',
               trControl = control1,
```

```r
             tuneGrid = polyGrid,
             preProc = c('center','scale'))

poly2
```

```
## Support Vector Machines with Polynomial Kernel
##
## 61 samples
##  4 predictor
##
## Pre-processing: centered (4), scaled (4)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C      RMSE         Rsquared   MAE
##   2       1        0.1     876.0226  0.8081674     469.4007
##   2       1        1.0    1532.8601  0.8154286     722.1496
##   2       1       10.0   14512.8090  0.8528996    6032.6490
##   2       1      100.0   11848.1045  0.9129566    4942.3458
##   2       2        0.1    1115.2333  0.8751110     559.6023
##   2       2        1.0    5251.8265  0.8636670    2247.9786
##   2       2       10.0   11368.9766  0.8529120    4751.2822
##   2       2      100.0   11354.9053  0.9063491    4732.0598
##   3       1        0.1   18313.5053  0.8935899    7558.3279
##   3       1        1.0   24882.0057  0.8523866   10250.6328
##   3       1       10.0   61551.6914  0.9182948   25214.9606
##   3       1      100.0   36782.7066  0.8210000   15136.3743
##   3       2        0.1   37470.6589  0.8460612   15381.2988
##   3       2        1.0   34037.7172  0.8417435   13992.1891
##   3       2       10.0   62873.4712  0.8259141   25775.7687
##   3       2      100.0  100280.0776  0.8102818   41118.1724
##   4       1        0.1   96870.0477  0.8372587   39632.3275
##   4       1        1.0    9912.6724  0.8582925    4146.7389
##   4       1       10.0  174996.0882  0.8816298   71529.9157
##   4       1      100.0  334667.4580  0.7981803  136752.8839
##   4       2        0.1  233541.8543  0.8434558   95446.7978
##   4       2        1.0  404176.1594  0.8485852  165110.5747
##   4       2       10.0  704939.6023  0.8342341  287898.1043
##   4       2      100.0  790317.3179  0.8342340  322758.2980
##
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were degree = 2, scale = 1 and C = 0.1.
```

Predicting rbf on test1

```r
poly2Preds <- predict(poly2, newdata = test1_rem_out)
summary(poly2Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   132.6   154.0   256.1   469.9   472.7  1710.2
```

postResample to test if it will do well on new data or if overfitting

```
postResample(poly2Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 402.3116913   0.5699793 256.8209379
```

RMSE=402, R2=0.57

Gradient Boosting

```
set.seed(123)

gbm1 <- train(Volume ~ x4StarReviews + x2StarReviews + PositiveServiceReview,
              data = train1,
              method = 'gbm',
              trControl = control1,
              preProc = c('center','scale'))
```

```
gbm1
```

```
## Stochastic Gradient Boosting
##
## 61 samples
##  3 predictor
##
## Pre-processing: centered (3), scaled (3)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   interaction.depth  n.trees  RMSE      Rsquared   MAE
##   1                   50      1010.966  0.8249911  571.2535
##   1                  100      1054.100  0.8371555  585.4725
##   1                  150      1024.901  0.8667286  552.3807
##   2                   50      1010.350  0.8575585  557.7797
##   2                  100      1046.985  0.8593534  568.5074
##   2                  150      1053.486  0.8588568  578.0264
##   3                   50      1010.362  0.8472539  564.3698
##   3                  100      1038.869  0.8615773  564.2031
##   3                  150      1055.289  0.8588360  567.2579
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were n.trees = 50, interaction.depth =
##  2, shrinkage = 0.1 and n.minobsinnode = 10.
```

Predicting gbm on test1

```
gbmPreds <- predict(gbm1, newdata = test1_rem_out)
summary(gbmPreds)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##    9.966   35.707   40.684  587.565 1340.268 2091.828
```

postResample to test if it will do well on new data or if overfitting

```
postResample(gbmPreds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 266.4904990   0.9105057 172.6952417
```

awesome step! provides comparison of predictions to actual within same DF!

```
compare_gbm1 <- data.frame(test1_rem_out,gbmPreds)
```

CV RMSE=1010, R2=.858

PostResample RMSE=266, R2=.911

Gradient Boosting

```
set.seed(123)

gbm2 <- train(Volume ~ x4StarReviews + x3StarReviews + PositiveServiceReview,
              data = train1,
              method = 'gbm',
              trControl = control1,
              preProc = c('center','scale'))
```

```
gbm2
```

```
## Stochastic Gradient Boosting
##
## 61 samples
##  3 predictor
##
## Pre-processing: centered (3), scaled (3)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
```

```
##
##   interaction.depth  n.trees  RMSE      Rsquared   MAE
##   1                   50      1016.102  0.8326938  568.3590
##   1                  100      1063.431  0.8452965  576.8135
##   1                  150      1039.162  0.8622175  553.1044
##   2                   50      1021.436  0.8660802  555.2569
##   2                  100      1041.471  0.8672959  564.3505
##   2                  150      1053.235  0.8573396  580.2639
##   3                   50      1009.603  0.8574569  552.9631
##   3                  100      1056.474  0.8524858  573.3080
##   3                  150      1066.260  0.8481968  572.4470
##
## Tuning parameter 'shrinkage' was held constant at a value of 0.1
##
## Tuning parameter 'n.minobsinnode' was held constant at a value of 10
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were n.trees = 50, interaction.depth =
##  3, shrinkage = 0.1 and n.minobsinnode = 10.
```

Predicting gbm2 on test1

```
gbm2Preds <- predict(gbm2, newdata = test1_rem_out)
summary(gbm2Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -13.48   48.78   48.78  541.48 1105.80 2141.98
```

postResample to test if it will do well on new data or if overfitting

```
postResample(gbm2Preds, test1_rem_out$Volume)
```

```
##        RMSE    Rsquared         MAE
## 264.0765350   0.8822213 156.1233574
```

CV RMSE=813, R2=.962

PostResample RMSE=415, R2=.706

Bayesian Ridge Regression, L1

Set seed

```
set.seed(123)

bay1 <- train(Volume ~ x4StarReviews + PositiveServiceReview + x2StarReviews,
              data = train1,
```

```r
              method = 'blassoAveraged',
              trControl = control1,
              preProc = c('center','scale'))

bay1
```

Predicting bay1 on test1

```r
bay1Preds <- predict(bay1, newdata = test1_rem_out)
summary(bay1Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -211.99 -187.44   79.51  397.59  667.00 2491.79
```

postResample to test if it will do well on new data or if overfitting

```r
postResample(bay1Preds, test1$Volume)
```

```
##     RMSE Rsquared      MAE
## 925.6151       NA 716.4564
```

Negative predictions regardless of feature selection, high RMSE, doesn't work with this task

CV RMSE=1148, R2=.753

After deleting problem outlier rows in test set - 17 observations

Actual_vs_Predicted_NoOutlier <- data.frame(test1_rem_out %>% select(ProductNum, Volume), rf1Preds, rf2Preds, rf3Preds, rf4Preds, rbf1Preds, rbf2Preds, linearPreds, linear2Preds, polyPreds, poly2Preds, gbmPreds, gbm2Preds)

exporting to excel

write.xlsx(Actual_vs_Predicted_NoOutlier, file = "Actual_vs_Predicted_NoOutlier.xlsx", row.names=TRUE)

Now modeling with our transmuted column, AvgStarReviews to see if it helps with predictions

Set seed

```r
set.seed(123)

# CreateDataPartition() 75% and 25%
index2 <- createDataPartition(existing4$Volume, p=0.75, list = FALSE)
train2 <- existing4[ index2,]
test2 <- existing4[-index2,]
```

```r
# Checking structure of train1
str(train2)

# Setting cross validation
control1 <- trainControl(method = 'repeatedcv',
                         number = 10,
                         repeats = 1)
```

set seed

```r
set.seed(123)

# Creating dataframe for manual tuning
rfGrid <- expand.grid(mtry = c(2,3,4,5,6,7,8))

rf_1 <- train(Volume ~ .,
              data = train2,
              method = 'rf',
              trControl = control1,
              tuneGrid = rfGrid)

rf_1
```

```
## Random Forest
##
## 61 samples
## 15 predictors
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 55, 53, 55, 55, 55, 56, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##   2     890.2517  0.8684611  434.8184
##   3     860.1573  0.8812491  403.8704
##   4     869.6858  0.8853209  404.3859
##   5     877.7167  0.8894399  405.0399
##   6     833.4313  0.9025322  382.2740
##   7     858.2201  0.8943709  391.7704
##   8     841.2111  0.9013432  384.3876
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 6.
```

```r
summary(rf_1)
```

```
##                 Length Class      Mode
## call              4    -none-     call
## type              1    -none-     character
```

```
## predicted        61    -none-     numeric
## mse             500    -none-     numeric
## rsq             500    -none-     numeric
## oob.times        61    -none-     numeric
## importance       15    -none-     numeric
## importanceSD      0    -none-     NULL
## localImportance   0    -none-     NULL
## proximity         0    -none-     NULL
## ntree             1    -none-     numeric
## mtry              1    -none-     numeric
## forest           11    -none-     list
## coefs             0    -none-     NULL
## y                61    -none-     numeric
## test              0    -none-     NULL
## inbag             0    -none-     NULL
## xNames           15    -none-     character
## problemType       1    -none-     character
## tuneValue         1    data.frame list
## obsLevels         1    -none-     logical
## param             0    -none-     list
```

Predicting rf on test2

```r
rf_1Preds <- predict(rf_1, newdata = test2)
summary(rf_1Preds)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   12.40   28.42  258.18  758.58 1062.08 5708.03
```

postResample to test if it will do well on new data or if overfitting

```r
postResample(rf_1Preds, test2$Volume)
```

```
##        RMSE    Rsquared         MAE
## 867.1132444   0.6025625 341.3013774
```

RMSE=1545 and R2=.217, poor, it does not, move on.

Using Top Model rf2 algorithm to make predictions on new product data

Target variable: 'Volume' for PC, Laptops, Netbooks, and Smartphones product types

importing data

```r
new <- read.csv(file.path('C:/Users/jlbro/OneDrive/C3T3', 'new.csv'), stringsAsFactors = TRUE)
```

checking structure

```r
str(new)
```

```
## 'data.frame':    24 obs. of  18 variables:
##  $ ProductType          : Factor w/ 12 levels "Accessories",..: 7 7 5 5 5 6 6 6 6 12 ...
##  $ ProductNum           : int  171 172 173 175 176 178 180 181 183 186 ...
##  $ Price                : num  699 860 1199 1199 1999 ...
##  $ x5StarReviews        : int  96 51 74 7 1 19 312 23 3 296 ...
##  $ x4StarReviews        : int  26 11 10 2 1 8 112 18 4 66 ...
##  $ x3StarReviews        : int  14 10 3 1 1 4 28 7 0 30 ...
##  $ x2StarReviews        : int  14 10 3 1 3 1 31 22 1 21 ...
##  $ x1StarReviews        : int  25 21 11 1 0 10 47 18 0 36 ...
##  $ PositiveServiceReview: int  12 7 11 2 0 2 28 5 1 28 ...
##  $ NegativeServiceReview: int  3 5 5 1 1 4 16 16 0 9 ...
##  $ Recommendproduct     : num  0.7 0.6 0.8 0.6 0.3 0.6 0.7 0.4 0.7 0.8 ...
##  $ BestSellersRank      : int  2498 490 111 4446 2820 4140 2699 1704 5128 34 ...
##  $ ShippingWeight       : num  19.9 27 6.6 13 11.6 5.8 4.6 4.8 4.3 3 ...
##  $ ProductDepth         : num  20.63 21.89 8.94 16.3 16.81 ...
##  $ ProductWidth         : num  19.2 27 12.8 10.8 10.9 ...
##  $ ProductHeight        : num  8.39 9.13 0.68 1.4 0.88 1.2 0.95 1.5 0.97 0.37 ...
##  $ ProfitMargin         : num  0.25 0.2 0.1 0.15 0.23 0.08 0.09 0.11 0.09 0.1 ...
##  $ Volume               : int  0 0 0 0 0 0 0 0 0 0 ...
```

Making new dataframe same column wise as trained dataframes

```r
newDummy <- dummyVars(' ~ .', data = new)
```

```r
new2 <- data.frame(predict(newDummy, newdata = new))
```

check structure again

```r
str(new2)
```

```
## 'data.frame':    24 obs. of  29 variables:
##  $ ProductType.Accessories     : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Display         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.ExtendedWarranty: num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.GameConsole     : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Laptop          : num  0 0 1 1 1 0 0 0 0 0 ...
##  $ ProductType.Netbook         : num  0 0 0 0 0 1 1 1 1 0 ...
##  $ ProductType.PC              : num  1 1 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Printer         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.PrinterSupplies : num  0 0 0 0 0 0 0 0 0 0 ...
```

```
##  $ ProductType.Smartphone      : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Software        : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ ProductType.Tablet          : num  0 0 0 0 0 0 0 0 0 1 ...
##  $ ProductNum                  : num  171 172 173 175 176 178 180 181 183 186 ...
##  $ Price                       : num  699 860 1199 1199 1999 ...
##  $ x5StarReviews               : num  96 51 74 7 1 19 312 23 3 296 ...
##  $ x4StarReviews               : num  26 11 10 2 1 8 112 18 4 66 ...
##  $ x3StarReviews               : num  14 10 3 1 1 4 28 7 0 30 ...
##  $ x2StarReviews               : num  14 10 3 1 3 1 31 22 1 21 ...
##  $ x1StarReviews               : num  25 21 11 1 0 10 47 18 0 36 ...
##  $ PositiveServiceReview       : num  12 7 11 2 0 2 28 5 1 28 ...
##  $ NegativeServiceReview       : num  3 5 5 1 1 4 16 16 0 9 ...
##  $ Recommendproduct            : num  0.7 0.6 0.8 0.6 0.3 0.6 0.7 0.4 0.7 0.8 ...
##  $ BestSellersRank             : num  2498 490 111 4446 2820 ...
##  $ ShippingWeight              : num  19.9 27 6.6 13 11.6 5.8 4.6 4.8 4.3 3 ...
##  $ ProductDepth                : num  20.63 21.89 8.94 16.3 16.81 ...
##  $ ProductWidth                : num  19.2 27 12.8 10.8 10.9 ...
##  $ ProductHeight               : num  8.39 9.13 0.68 1.4 0.88 1.2 0.95 1.5 0.97 0.37 ...
##  $ ProfitMargin                : num  0.25 0.2 0.1 0.15 0.23 0.08 0.09 0.11 0.09 0.1 ...
##  $ Volume                      : num  0 0 0 0 0 0 0 0 0 0 ...
```

Removing 'BestSellersRank' since not in modeling dataset

```r
new2$BestSellersRank <- NULL

str(new2)
```

Removing same columns as training datasets

```r
new3 <- subset(new2, select = -c(1:4, 8:9, 11:12, 15, 24:27))

str(new3)
```

```r
set.seed(123)

# Predicting rbf1 on 'new3' product data
Predicted_Volume <- predict(rf2, newdata = new3)
```

Adding our predictions to the 'new' product dataframe

```r
Preds_rf2_df <- data.frame(new3 %>% select(ProductType.Laptop, ProductType.Netbook, ProductType.PC, Proc

TopModelPreds <- read.xlsx(file.path('C:/Users/jlbro/OneDrive/C3T3-3', 'newPreds_TopModel_rf2.xlsx'))
```

Finally viewing our predictions for Sales Volume for 4 product types on new dataset

```
kable(TopModelPreds) %>%
  kable_styling(bootstrap_options = c('striped','hover'))
```

Product.Type	ProductNum	Volume	Predicted_Volume
PC	171	0	478.64227
PC	172	0	157.28747
Laptop	173	0	187.16573
Laptop	175	0	36.68747
Laptop	176	0	14.43680
Netbook	178	0	55.57160
Netbook	180	0	1234.30893
Netbook	181	0	129.49760
Netbook	183	0	19.38773
Smartphone	193	0	444.73333
Smartphone	194	0	649.95707
Smartphone	195	0	87.20040
Smartphone	196	0	159.08307

Exporting to excel

```
write.xlsx(Preds_rf2_df,"TopModel_rf2_Preds.xlsx")
```