

Bigmart Sales

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```
library(caret)
library(plyr)
library(dplyr)
library(dummies)
library(mlr)
library(rpart)
library(rpart.plot)
library(caret)
library(e1071)
library(Metrics)
library(randomForest)
```

Loading data and exploration

```
train = read.csv("train.csv",na.strings = c("", " ",NA,"NA"))
test = read.csv("test.csv",na.strings = c("", " ",NA,"NA"))

summary(train)
```

```

## Item_Identifier Item_Weight Item_Fat_Content Item_Visibility
## FDG33 : 10 Min. : 4.555 LF : 316 Min. :0.00000
## FDW13 : 10 1st Qu.: 8.774 low fat: 112 1st Qu.:0.02699
## DRE49 : 9 Median :12.600 Low Fat:5089 Median :0.05393
## DRN47 : 9 Mean :12.858 reg : 117 Mean :0.06613
## FDD38 : 9 3rd Qu.:16.850 Regular:2889 3rd Qu.:0.09459
## FDF52 : 9 Max. :21.350 Max. :0.32839
## (Other):8467 NA's :1463
##
## Item_Type Item_MRP Outlet_Identifier
## Fruits and Vegetables:1232 Min. : 31.29 OUT027 : 935
## Snack Foods :1200 1st Qu.: 93.83 OUT013 : 932
## Household : 910 Median :143.01 OUT035 : 930
## Frozen Foods : 856 Mean :140.99 OUT046 : 930
## Dairy : 682 3rd Qu.:185.64 OUT049 : 930
## Canned : 649 Max. :266.89 OUT045 : 929
## (Other) :2994 (Other):2937
## Outlet_Establishment_Year Outlet_Size Outlet_Location_Type
## Min. :1985 High : 932 Tier 1:2388
## 1st Qu.:1987 Medium:2793 Tier 2:2785
## Median :1999 Small :2388 Tier 3:3350
## Mean :1998 NA's :2410
## 3rd Qu.:2004
## Max. :2009
##
## Outlet_Type Item_Outlet_Sales
## Grocery Store :1083 Min. : 33.29
## Supermarket Type1:5577 1st Qu.: 834.25
## Supermarket Type2: 928 Median : 1794.33
## Supermarket Type3: 935 Mean : 2181.29
## 3rd Qu.: 3101.30
## Max. :13086.97
##

```

```
str(train)
```

```
## 'data.frame': 8523 obs. of 12 variables:
## $ Item_Identifier : Factor w/ 1559 levels "DRA12","DRA24",...: 157 9 663 1122 1298 7
59 697 739 441 991 ...
## $ Item_Weight : num 9.3 5.92 17.5 19.2 8.93 ...
## $ Item_Fat_Content : Factor w/ 5 levels "LF","low fat",...: 3 5 3 5 3 5 5 3 5 5 ...
## $ Item_Visibility : num 0.016 0.0193 0.0168 0 0 ...
## $ Item_Type : Factor w/ 16 levels "Baking Goods",...: 5 15 11 7 10 1 14 14 6 6
...
## $ Item_MRP : num 249.8 48.3 141.6 182.1 53.9 ...
## $ Outlet_Identifier : Factor w/ 10 levels "OUT010","OUT013",...: 10 4 10 1 2 4 2 6 8 3
...
## $ Outlet_Establishment_Year: int 1999 2009 1999 1998 1987 2009 1987 1985 2002 2007 ...
## $ Outlet_Size : Factor w/ 3 levels "High","Medium",...: 2 2 2 NA 1 2 1 2 NA NA
...
## $ Outlet_Location_Type : Factor w/ 3 levels "Tier 1","Tier 2",...: 1 3 1 3 3 3 3 3 2 2
...
## $ Outlet_Type : Factor w/ 4 levels "Grocery Store",...: 2 3 2 1 2 3 2 4 2 2 ...
## $ Item_Outlet_Sales : num 3735 443 2097 732 995 ...
```

```
summary(test)
```

```

## Item_Identifier Item_Weight Item_Fat_Content Item_Visibility
## DRF48 : 8 Min. : 4.555 LF : 206 Min. :0.00000
## FDK57 : 8 1st Qu.: 8.645 low fat: 66 1st Qu.:0.02705
## FDN52 : 8 Median :12.500 Low Fat:3396 Median :0.05415
## FDP15 : 8 Mean :12.696 reg : 78 Mean :0.06568
## FDQ60 : 8 3rd Qu.:16.700 Regular:1935 3rd Qu.:0.09346
## FDW10 : 8 Max. :21.350 Max. :0.32364
## (Other):5633 NA's :976
## Item_Type Item_MRP Outlet_Identifier
## Snack Foods : 789 Min. : 31.99 OUT027 : 624
## Fruits and Vegetables: 781 1st Qu.: 94.41 OUT013 : 621
## Household : 638 Median :141.42 OUT035 : 620
## Frozen Foods : 570 Mean :141.02 OUT046 : 620
## Dairy : 454 3rd Qu.:186.03 OUT049 : 620
## Baking Goods : 438 Max. :266.59 OUT045 : 619
## (Other) :2011 (Other):1957
## Outlet_Establishment_Year Outlet_Size Outlet_Location_Type
## Min. :1985 High : 621 Tier 1:1592
## 1st Qu.:1987 Medium:1862 Tier 2:1856
## Median :1999 Small :1592 Tier 3:2233
## Mean :1998 NA's :1606
## 3rd Qu.:2004
## Max. :2009
##
## Outlet_Type
## Grocery Store : 722
## Supermarket Type1:3717
## Supermarket Type2: 618
## Supermarket Type3: 624
##
##
##

```

```
str(test)
```

```
## 'data.frame': 5681 obs. of 11 variables:
## $ Item_Identifier : Factor w/ 1543 levels "DRA12","DRA24",...: 1104 1068 1407 810 11
85 462 605 267 669 171 ...
## $ Item_Weight : num 20.75 8.3 14.6 7.32 NA ...
## $ Item_Fat_Content : Factor w/ 5 levels "LF","low fat",...: 3 4 3 3 5 5 5 3 5 3 ...
## $ Item_Visibility : num 0.00756 0.03843 0.09957 0.01539 0.1186 ...
## $ Item_Type : Factor w/ 16 levels "Baking Goods",...: 14 5 12 14 5 7 1 1 14 1
...
## $ Item_MRP : num 107.9 87.3 241.8 155 234.2 ...
## $ Outlet_Identifier : Factor w/ 10 levels "OUT010","OUT013",...: 10 3 1 3 6 9 4 6 8 3
...
## $ Outlet_Establishment_Year: int 1999 2007 1998 2007 1985 1997 2009 1985 2002 2007 ...
## $ Outlet_Size : Factor w/ 3 levels "High","Medium",...: 2 NA NA NA 2 3 2 2 NA NA
...
## $ Outlet_Location_Type : Factor w/ 3 levels "Tier 1","Tier 2",...: 1 2 3 2 3 1 3 3 2 2
...
## $ Outlet_Type : Factor w/ 4 levels "Grocery Store",...: 2 2 1 2 4 2 3 4 2 2 ...
```

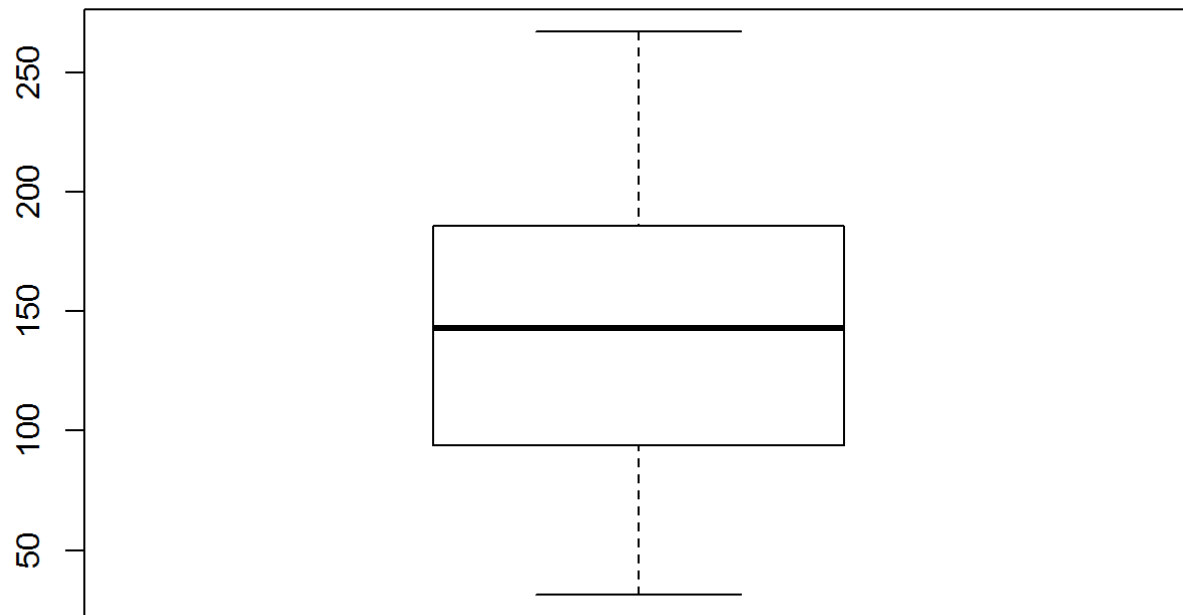
Inferences drawn from data exploration :-

1. Factor mismatch in Item_Fat_Content.
2. Missing values in Item_Weight and Outlet_Size.
3. Minimum value of Item_Visibility is 0, which is not practically possible. Hence, we'll deal them as missing values.

Univariate Analysis

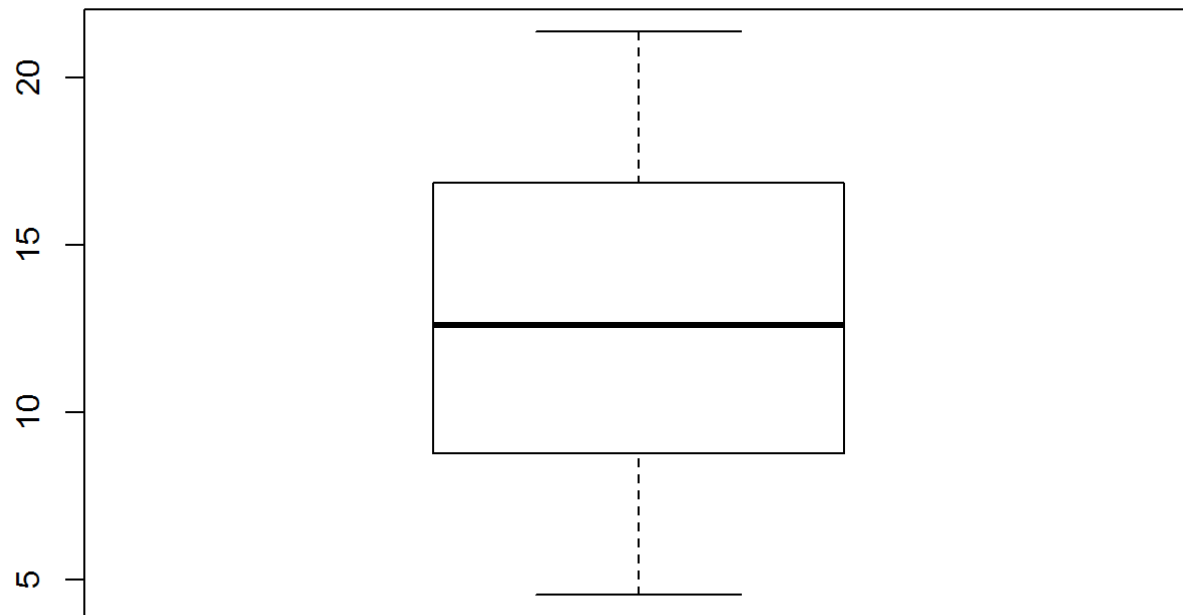
```
boxplot(train$Item_MRP, main = "Boxplot of Item MRP")
```

Boxplot of Item MRP



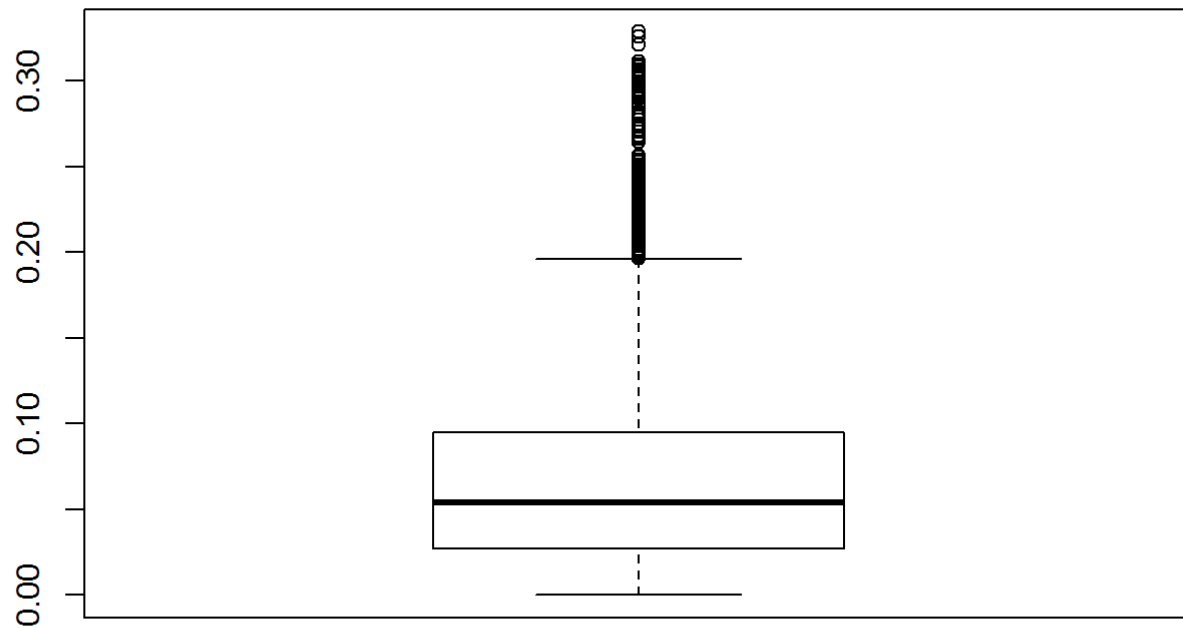
```
boxplot(train$Item_Weight,main = "Boxplot of Item Weight")
```

Boxplot of Item Weight



```
boxplot(train$Item_Visibility,main = "Boxplot of Item Visibility")
```

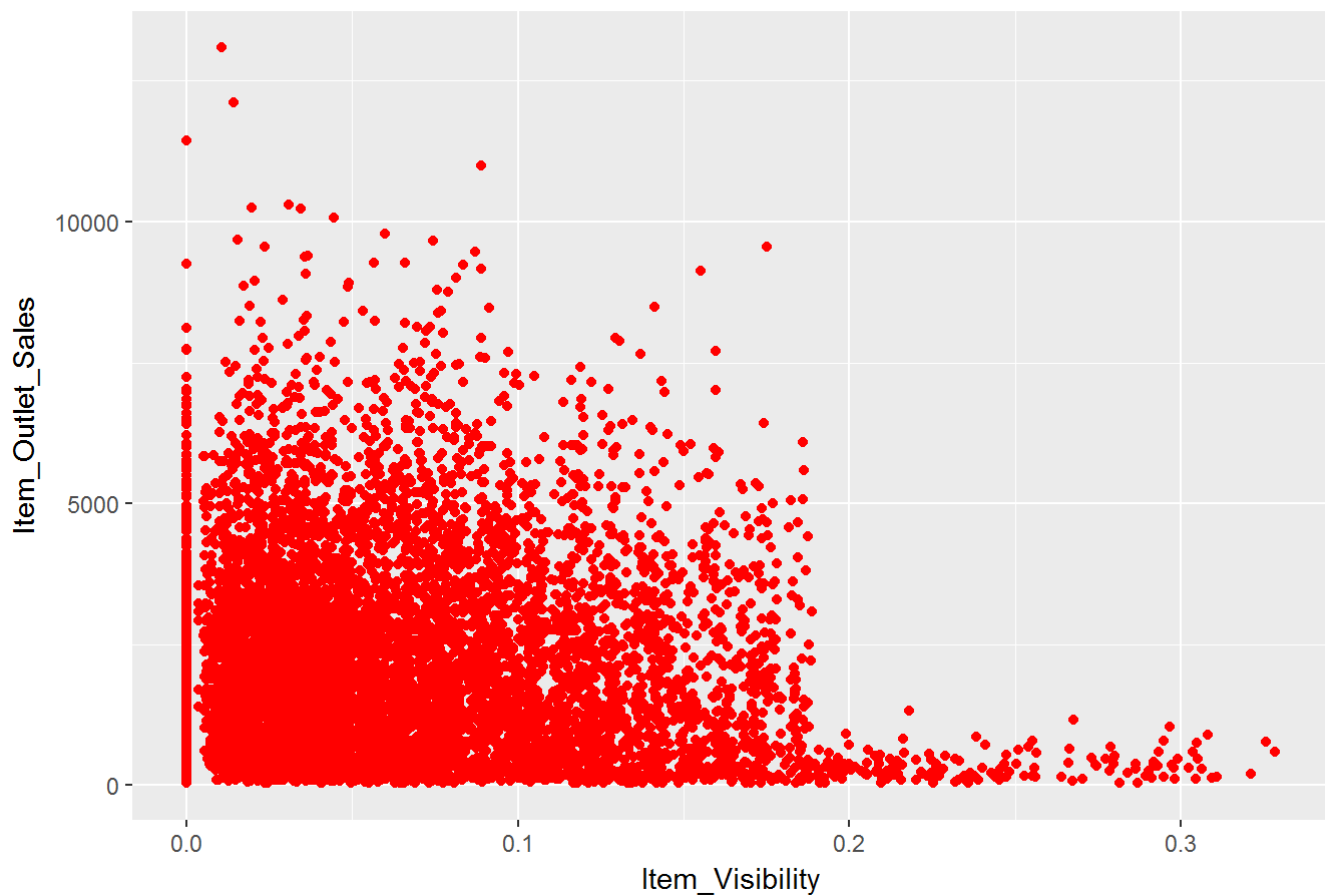
Boxplot of Item Visibility



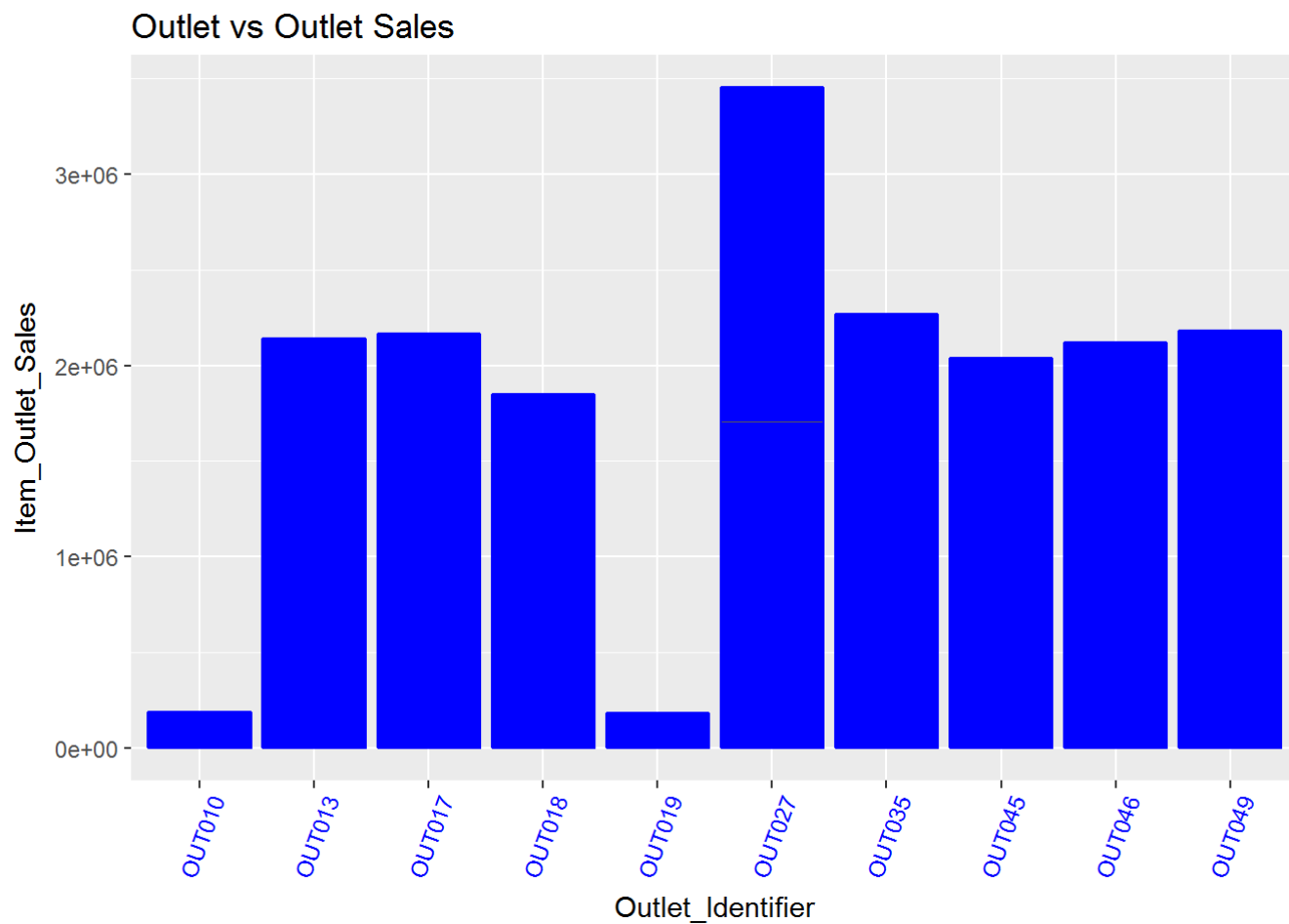
Bivariate Analysis

```
ggplot(train,aes(x=Item_Visibility,y=Item_Outlet_Sales)) + geom_point(color = "red") +  
ggtitle("Item Visibility vs Item Outlet Sales")
```


Item Visibility vs Item Outlet Sales

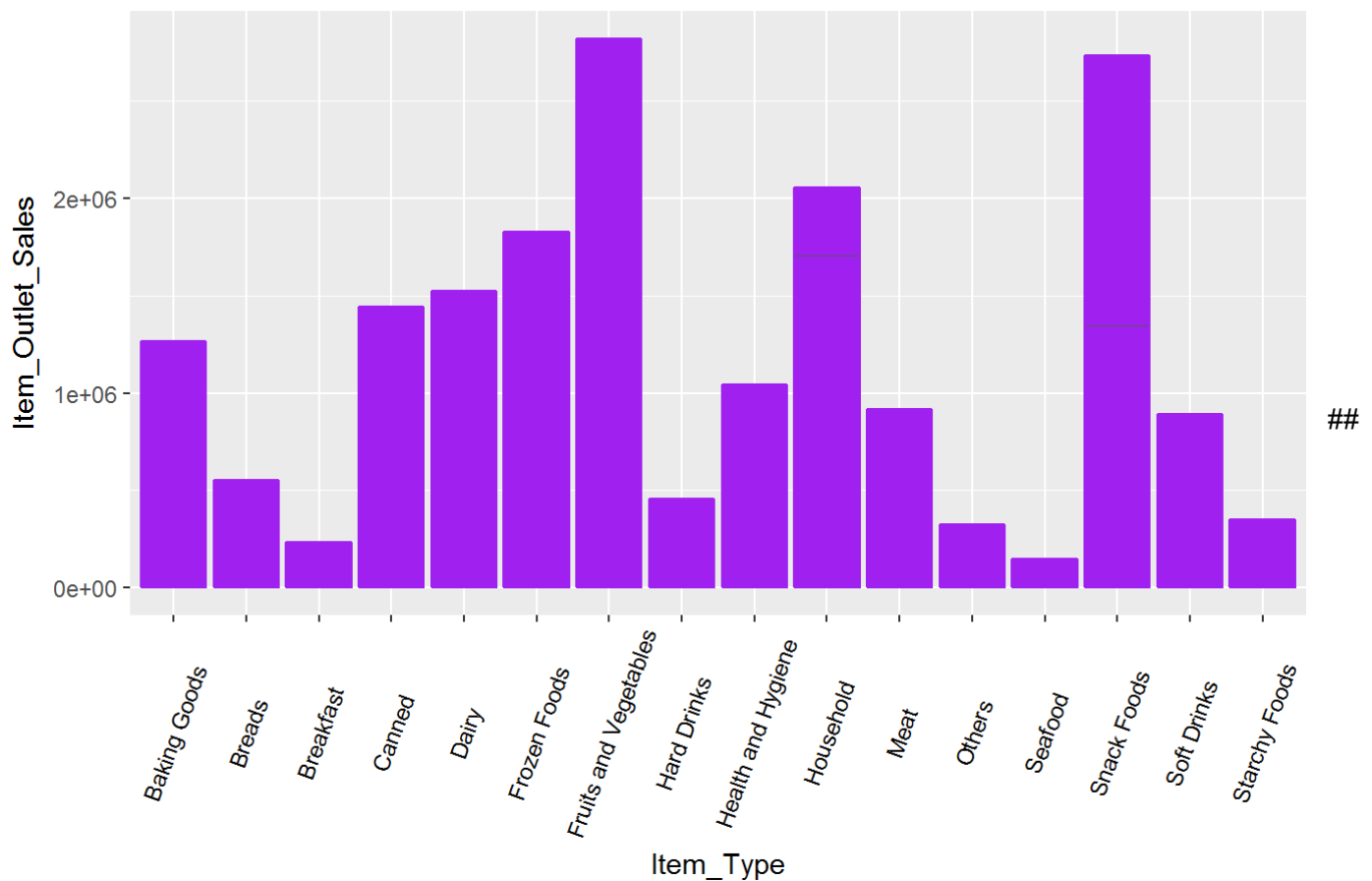


```
ggplot(train,aes(x=Outlet_Identifier,y= Item_Outlet_Sales)) + geom_bar(stat="identity",color =  
"blue") + ggtitle("Outlet vs Outlet Sales") + theme(axis.text.x = element_text(angle = 70,vjust  
= 0.5,color = "blue"))
```



```
ggplot(train,aes(x=Item_Type,y= Item_Outlet_Sales)) + geom_bar(stat="identity",color = "purple")  
+ ggtitle("Item Type vs Item Sales") + theme(axis.text.x = element_text(angle = 70,vjust =  
0.5,color = "black"))
```

Item Type vs Item Sales



Dealing with categorical and continuous variables

We will use median imputation to deal with continuous missing values

```
test$Item_Outlet_Sales = 1
comb = rbind(train,test)

comb$Item_Weight[is.na(comb$Item_Weight)] = median(comb$Item_Weight,na.rm = T)

comb$Item_Visibility = ifelse(comb$Item_Visibility==0,median(comb$Item_Visibility),comb$Item_Visibility)

comb$Outlet_Size = ifelse(is.na(comb$Outlet_Size),"Others",comb$Outlet_Size)
comb$Outlet_Size = as.factor(comb$Outlet_Size)
levels(comb$Outlet_Size)[1] = "High"
levels(comb$Outlet_Size)[2] = "Medium"
levels(comb$Outlet_Size)[3] = "Low"

table(comb$Item_Fat_Content)
```

```
##
##      LF low fat Low Fat      reg Regular
##      522      178   8485      195   4824
```

```
comb$Item_Fat_Content = revalue(comb$Item_Fat_Content,c("LF" = "Low Fat","reg"="Regular"))
comb$Item_Fat_Content = revalue(comb$Item_Fat_Content,c("low fat"="Low Fat"))

table(comb$Item_Fat_Content)
```

```
##
## Low Fat Regular
##      9185      5019
```

Feature Engineering

```
temp = comb%>%group_by(Outlet_Identifier)%>%tally()
names(temp)[2] = "Outlet_Count"
comb = full_join(comb,temp,by = "Outlet_Identifier")

temp1 = comb%>%group_by(Item_Identifier)%>%tally()
names(temp1)[2] = "Item_Count"
comb = merge(comb,temp1,by = "Item_Identifier")

temp2 = comb%>%select(Outlet_Establishment_Year)%>%mutate(Outlet_Year = 2013 - comb$Outlet_Establishment_Year)
temp2$Outlet_Establishment_Year = NULL
comb = cbind(comb,temp2 )

items = substr(comb$Item_Identifier,1,2)
items = gsub("FD","Food",items)
items = gsub("DR","Drinks",items)
items = gsub("NC","Non Consumable",items)
comb$Item_Type_New = factor(items)

str(comb)
```

```
## 'data.frame': 14204 obs. of 16 variables:
## $ Item_Identifier : Factor w/ 1559 levels "DRA12","DRA24",...: 1 1 1 1 1 1 1 1 1 2
## ...
## $ Item_Weight : num 11.6 11.6 11.6 11.6 12.6 ...
## $ Item_Fat_Content : Factor w/ 2 levels "Low Fat","Regular": 1 1 1 1 1 1 1 1 1 2 ...
## $ Item_Visibility : num 0.054 0.041 0.054 0.0409 0.0407 ...
## $ Item_Type : Factor w/ 16 levels "Baking Goods",...: 15 15 15 15 15 15 15 15 15
15 15 ...
## $ Item_MRP : num 142 141 142 143 140 ...
## $ Outlet_Identifier : Factor w/ 10 levels "OUT010","OUT013",...: 7 10 8 9 6 4 1 2 3 9
## ...
## $ Outlet_Establishment_Year: int 2004 1999 2002 1997 1985 2009 1998 1987 2007 1997 ...
## $ Outlet_Size : Factor w/ 4 levels "High","Medium",...: 3 2 4 3 2 2 4 1 4 3 ...
## $ Outlet_Location_Type : Factor w/ 3 levels "Tier 1","Tier 2",...: 2 1 2 1 3 3 3 3 2 1
## ...
## $ Outlet_Type : Factor w/ 4 levels "Grocery Store",...: 2 2 2 2 4 3 1 2 2 2 ...
## $ Item_Outlet_Sales : num 993 1 3829 1 1 ...
## $ Outlet_Count : int 1550 1550 1548 1550 1559 1546 925 1553 1543 1550 ...
## $ Item_Count : int 9 9 9 9 9 9 9 9 9 10 ...
## $ Outlet_Year : num 9 14 11 16 28 4 15 26 6 16 ...
## $ Item_Type_New : Factor w/ 3 levels "Drinks","Food",...: 1 1 1 1 1 1 1 1 1 1 ...
```

One Hot Encoding

```
comb = dummy.data.frame(comb,names = c("Outlet_Size","Outlet_Location_Type","Outlet_Type","Item_
Type_New","Item_Fat_Content"),sep='_')
str(comb)
```

```
## 'data.frame':      14204 obs. of      27 variables:
## $ Item_Identifier      : Factor w/ 1559 levels "DRA12","DRA24",...: 1 1 1 1 1 1 1 1 1 1
## 2 ...
## $ Item_Weight          : num  11.6 11.6 11.6 11.6 12.6 ...
## $ Item_Fat_Content_Low Fat : int  1 1 1 1 1 1 1 1 1 0 ...
## $ Item_Fat_Content_Regular : int  0 0 0 0 0 0 0 0 0 1 ...
## $ Item_Visibility      : num  0.054 0.041 0.054 0.0409 0.0407 ...
## $ Item_Type            : Factor w/ 16 levels "Baking Goods",...: 15 15 15 15 15 15 15
## 15 15 15 ...
## $ Item_MRP             : num  142 141 142 143 140 ...
## $ Outlet_Identifier     : Factor w/ 10 levels "OUT010","OUT013",...: 7 10 8 9 6 4 1 2
## 3 9 ...
## $ Outlet_Establishment_Year : int  2004 1999 2002 1997 1985 2009 1998 1987 2007 1997 ...
## $ Outlet_Size_High       : int  0 0 0 0 0 0 0 1 0 0 ...
## $ Outlet_Size_Medium     : int  0 1 0 0 1 1 0 0 0 0 ...
## $ Outlet_Size_Low        : int  1 0 0 1 0 0 0 0 0 1 ...
## $ Outlet_Size_Others     : int  0 0 1 0 0 0 1 0 1 0 ...
## $ Outlet_Location_Type_Tier 1 : int  0 1 0 1 0 0 0 0 0 1 ...
## $ Outlet_Location_Type_Tier 2 : int  1 0 1 0 0 0 0 0 1 0 ...
## $ Outlet_Location_Type_Tier 3 : int  0 0 0 0 1 1 1 1 0 0 ...
## $ Outlet_Type_Grocery Store : int  0 0 0 0 0 0 1 0 0 0 ...
## $ Outlet_Type_Supermarket Type1: int  1 1 1 1 0 0 0 1 1 1 ...
## $ Outlet_Type_Supermarket Type2: int  0 0 0 0 0 1 0 0 0 0 ...
## $ Outlet_Type_Supermarket Type3: int  0 0 0 0 1 0 0 0 0 0 ...
## $ Item_Outlet_Sales      : num  993 1 3829 1 1 ...
## $ Outlet_Count           : int  1550 1550 1548 1550 1559 1546 925 1553 1543 1550 ...
## $ Item_Count             : int  9 9 9 9 9 9 9 9 9 10 ...
## $ Outlet_Year            : num  9 14 11 16 28 4 15 26 6 16 ...
## $ Item_Type_New_Drinks   : int  1 1 1 1 1 1 1 1 1 1 ...
## $ Item_Type_New_Food     : int  0 0 0 0 0 0 0 0 0 0 ...
## $ Item_Type_New_Non Consumable : int  0 0 0 0 0 0 0 0 0 0 ...
## - attr(*, "dummies")=List of 5
## ..$ Item_Fat_Content      : int  3 4
## ..$ Outlet_Size           : int  10 11 12 13
## ..$ Outlet_Location_Type: int  14 15 16
## ..$ Outlet_Type           : int  17 18 19 20
## ..$ Item_Type_New        : int  25 26 27
```

Predictive Modelling

```
comb = select(comb,-c(Item_Identifier,Outlet_Identifier,Item_Type,Outlet_Establishment_Year))

new_train = comb[1:nrow(train),]
new_test = comb[-(1:nrow(train)),]
names(new_train) = make.names(names(new_train))
names(new_test) = make.names(names(new_test))
```

1. Linear Regression

```
linear_model = lm(Item_Outlet_Sales ~ . ,data = new_train)
summary(linear_model)
```

```
##
## Call:
## lm(formula = Item_Outlet_Sales ~ ., data = new_train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3436.9 -1096.4   -43.0    791.8   8883.7
##
## Coefficients: (7 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.611e+04  2.202e+04   1.640   0.1011
## Item_Weight     2.461e+00  3.980e+00   0.618   0.5363
## Item_Fat_Content_Low.Fat -5.059e+01  3.508e+01  -1.442   0.1493
## Item_Fat_Content_Regular      NA         NA      NA      NA
## Item_Visibility  -1.572e+02  3.501e+02  -0.449   0.6535
## Item_MRP         9.524e+00  2.631e-01  36.204 < 2e-16 ***
## Outlet_Size_High  -9.254e+02  6.064e+02  -1.526   0.1270
## Outlet_Size_Medium  2.335e+02  1.132e+02   2.063   0.0392 *
## Outlet_Size_Low    1.868e+02  8.841e+01   2.113   0.0346 *
## Outlet_Size_Others      NA         NA      NA      NA
## Outlet_Location_Type_Tier.1 -1.222e+03  7.101e+02  -1.721   0.0854 .
## Outlet_Location_Type_Tier.2 -1.083e+03  7.101e+02  -1.525   0.1274
## Outlet_Location_Type_Tier.3      NA         NA      NA      NA
## Outlet_Type_Grocery.Store  -1.628e+04  8.919e+03  -1.825   0.0680 .
## Outlet_Type_Supermarket.Type1  2.058e+02  5.888e+02   0.350   0.7267
## Outlet_Type_Supermarket.Type2 -1.314e+03  1.972e+02  -6.661 2.89e-11 ***
## Outlet_Type_Supermarket.Type3      NA         NA      NA      NA
## Outlet_Count      -2.285e+01  1.417e+01  -1.613   0.1068
## Item_Count        1.781e+01  2.327e+01   0.765   0.4441
## Outlet_Year         NA         NA      NA      NA
## Item_Type_New_Drinks  -1.663e+01  4.787e+01  -0.347   0.7283
## Item_Type_New_Food      NA         NA      NA      NA
## Item_Type_New_Non.Consumable    NA         NA      NA      NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1526 on 8507 degrees of freedom
## Multiple R-squared:  0.2097, Adjusted R-squared:  0.2083
## F-statistic: 150.5 on 15 and 8507 DF,  p-value: < 2.2e-16
```

```
pred_lm = predict(linear_model,type = "response")
rmse(new_train$Item_Outlet_Sales,pred_lm)
```

```
## [1] 1524.375
```

2. Decision Trees

```
tree_model = rpart(Item_Outlet_Sales ~ . ,data = new_test)
summary(tree_model)
```



```
## Call:
## rpart(formula = Item_Outlet_Sales ~ ., data = new_test)
## n= 5681
##
##          CP nsplit rel error   xerror   xstd
## 1 0.08646909      0 1.0000000 1.0001613 0.02827382
## 2 0.05420419      1 0.9135309 0.9141970 0.02420009
## 3 0.02443891      2 0.8593267 0.8597872 0.02284921
## 4 0.01316430      3 0.8348878 0.8366061 0.02050304
## 5 0.01224056      4 0.8217235 0.8246613 0.02025643
## 6 0.01210477      5 0.8094829 0.8229437 0.02023515
## 7 0.01000000      6 0.7973782 0.8076124 0.01986044
##
## Variable importance
##                Item_MRP                Outlet_Count
##                   33                   27
## Outlet_Type_Grocery.Store Outlet_Type_Supermarket.Type3
##                   20                   7
##                Outlet_Year                Item_Visibility
##                   7                   3
##                Item_Weight                Item_Count
##                   1                   1
##
## Node number 1: 5681 observations,   complexity param=0.08646909
## mean=1293.524, MSE=2809010
## left son=2 (2896 obs) right son=3 (2785 obs)
## Primary splits:
##      Item_MRP                < 143.797   to the left, improve=0.08646909, (0 missin
g)
##      Outlet_Count            < 1234      to the left, improve=0.06113592, (0 missin
g)
##      Outlet_Type_Grocery.Store < 0.5     to the right, improve=0.06113592, (0 missin
g)
##      Outlet_Type_Supermarket.Type3 < 0.5 to the left, improve=0.03814215, (0 missin
g)
##      Outlet_Size_Medium        < 0.5     to the left, improve=0.01847886, (0 missin
g)
## Surrogate splits:
##      Item_Weight              < 13.05     to the left, agree=0.533, adj=0.047, (0 split)
##      Item_Visibility          < 0.05837035 to the left, agree=0.522, adj=0.025, (0 split)
##      Item_Count               < 8.5       to the right, agree=0.520, adj=0.021, (0 split)
##      Item_Fat_Content_Low.Fat < 0.5       to the right, agree=0.515, adj=0.010, (0 split)
##      Item_Fat_Content_Regular < 0.5       to the left, agree=0.515, adj=0.010, (0 split)
##
## Node number 2: 2896 observations,   complexity param=0.0131643
## mean=810.2202, MSE=1049318
## left son=4 (386 obs) right son=5 (2510 obs)
## Primary splits:
##      Outlet_Type_Grocery.Store < 0.5     to the right, improve=0.06913057, (0 missin
g)
##      Outlet_Count            < 1234      to the left, improve=0.06913057, (0 missin
g)
##      Item_MRP                < 76.6512   to the left, improve=0.05935699, (0 missin
```

```

g)
##      Outlet_Type_Supermarket.Type3 < 0.5      to the left,  improve=0.04433924, (0 missin
g)
##      Outlet_Size_Medium      < 0.5      to the left,  improve=0.02583729, (0 missin
g)
##      Surrogate splits:
##      Outlet_Count      < 1234      to the left,  agree=1.000, adj=1.000, (0 split)
##      Item_Visibility < 0.1756642 to the right, agree=0.885, adj=0.135, (0 split)
##
## Node number 3: 2785 observations,      complexity param=0.05420419
##      mean=1796.091, MSE=4143372
##      left son=6 (349 obs) right son=7 (2436 obs)
##      Primary splits:
##      Outlet_Count      < 1234      to the left,  improve=0.07496041, (0 missin
g)
##      Outlet_Type_Grocery.Store < 0.5      to the right, improve=0.07496041, (0 missin
g)
##      Outlet_Type_Supermarket.Type3 < 0.5      to the left,  improve=0.04774003, (0 missin
g)
##      Outlet_Size_Medium      < 0.5      to the left,  improve=0.02061265, (0 missin
g)
##      Item_MRP      < 220.0456 to the left,  improve=0.01811604, (0 missin
g)
##      Surrogate splits:
##      Outlet_Type_Grocery.Store < 0.5      to the right, agree=1.000, adj=1.000, (0 split)
##      Item_Visibility < 0.1896654 to the right, agree=0.889, adj=0.112, (0 split)
##
## Node number 4: 386 observations
##      mean=123.4176, MSE=23738.38
##
## Node number 5: 2510 observations,      complexity param=0.01210477
##      mean=915.84, MSE=1123341
##      left son=10 (1020 obs) right son=11 (1490 obs)
##      Primary splits:
##      Item_MRP      < 88.6185 to the left,  improve=0.06850924, (0 missin
g)
##      Outlet_Type_Supermarket.Type3 < 0.5      to the left,  improve=0.03339728, (0 missin
g)
##      Outlet_Count      < 1556 to the left,  improve=0.03339728, (0 missin
g)
##      Outlet_Year      < 27 to the left,  improve=0.03339728, (0 missin
g)
##      Outlet_Type_Supermarket.Type1 < 0.5      to the right, improve=0.01175536, (0 missin
g)
##      Surrogate splits:
##      Item_Visibility < 0.01236591 to the left, agree=0.599, adj=0.013, (0 split)
##      Item_Count      < 7.5 to the left, agree=0.596, adj=0.007, (0 split)
##
## Node number 6: 349 observations
##      mean=323.7147, MSE=113127.9
##
## Node number 7: 2436 observations,      complexity param=0.02443891
##      mean=2007.035, MSE=4365689
##      left son=14 (2132 obs) right son=15 (304 obs)

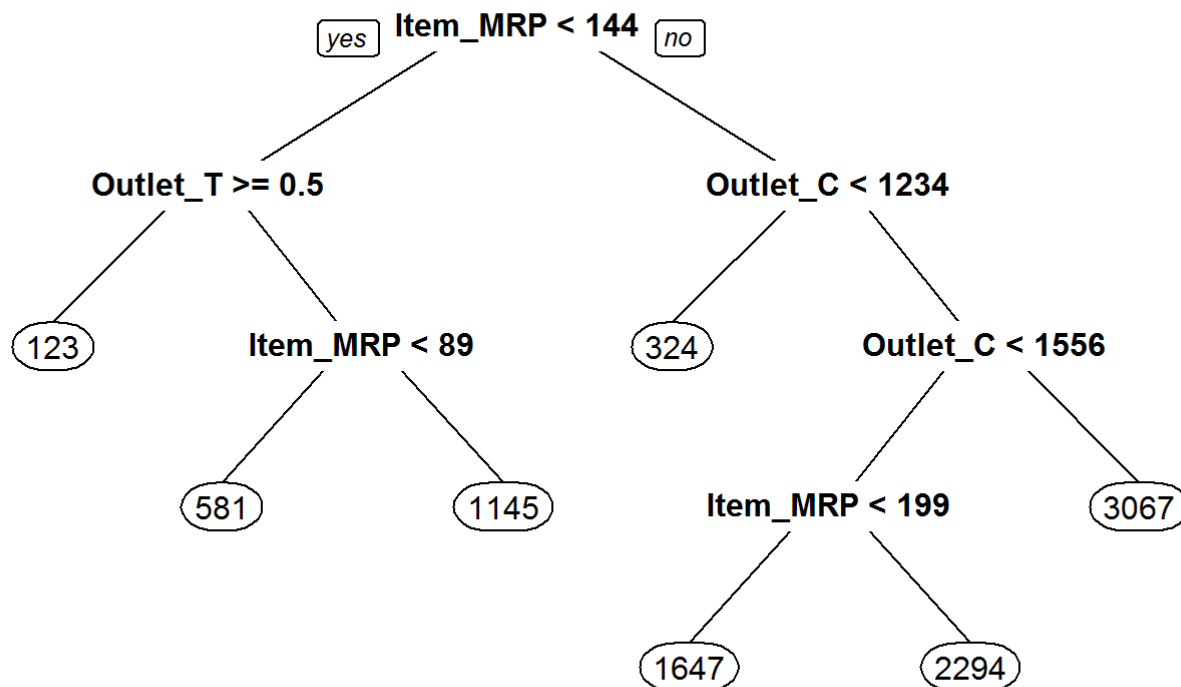
```

```

## Primary splits:
## Outlet_Count < 1556 to the left, improve=0.036671610, (0 missin
g)
## Outlet_Year < 27 to the left, improve=0.036671610, (0 missin
g)
## Outlet_Type_Supermarket.Type3 < 0.5 to the left, improve=0.036671610, (0 missin
g)
## Item_MRP < 220.3285 to the left, improve=0.021380880, (0 missin
g)
## Outlet_Type_Supermarket.Type1 < 0.5 to the right, improve=0.009034658, (0 missin
g)
## Surrogate splits:
## Outlet_Type_Supermarket.Type3 < 0.5 to the left, agree=1.000, adj=1.00, (0 spli
t)
## Outlet_Year < 27 to the left, agree=1.000, adj=1.00, (0 spli
t)
## Outlet_Type_Supermarket.Type1 < 0.5 to the right, agree=0.876, adj=0.01, (0 spli
t)
##
## Node number 10: 1020 observations
## mean=580.5478, MSE=431194.4
##
## Node number 11: 1490 observations
## mean=1145.369, MSE=1467517
##
## Node number 14: 2132 observations, complexity param=0.01224056
## mean=1855.945, MSE=3569990
## left son=28 (1443 obs) right son=29 (689 obs)
## Primary splits:
## Item_MRP < 199.0584 to the left, improve=0.025664040, (0 missing)
## Item_Weight < 6.6925 to the left, improve=0.003830461, (0 missing)
## Outlet_Count < 1549 to the left, improve=0.003305032, (0 missing)
## Item_Visibility < 0.1859728 to the left, improve=0.003216576, (0 missing)
## Outlet_Year < 7.5 to the left, improve=0.002334160, (0 missing)
## Surrogate splits:
## Item_Weight < 5.0725 to the right, agree=0.684, adj=0.023, (0 split)
## Item_Count < 7.5 to the right, agree=0.682, adj=0.017, (0 split)
## Item_Visibility < 0.1806009 to the left, agree=0.680, adj=0.010, (0 split)
##
## Node number 15: 304 observations
## mean=3066.65, MSE=8663172
##
## Node number 28: 1443 observations
## mean=1646.788, MSE=2745550
##
## Node number 29: 689 observations
## mean=2293.991, MSE=5013142

```

```
prp(tree_model)
```



```

pred_tree = predict(tree_model,type= "vector")
rmse(new_train$Item_Outlet_Sales,pred_tree)

```

```

## Warning in actual - predicted: longer object length is not a multiple of
## shorter object length

```

```

## [1] 1899.484

```

3. Random Forest

```

rf_model = randomForest(Item_Outlet_Sales ~ . ,data = new_train,mtry = 2 ,ntree = 1000)
summary(rf_model)

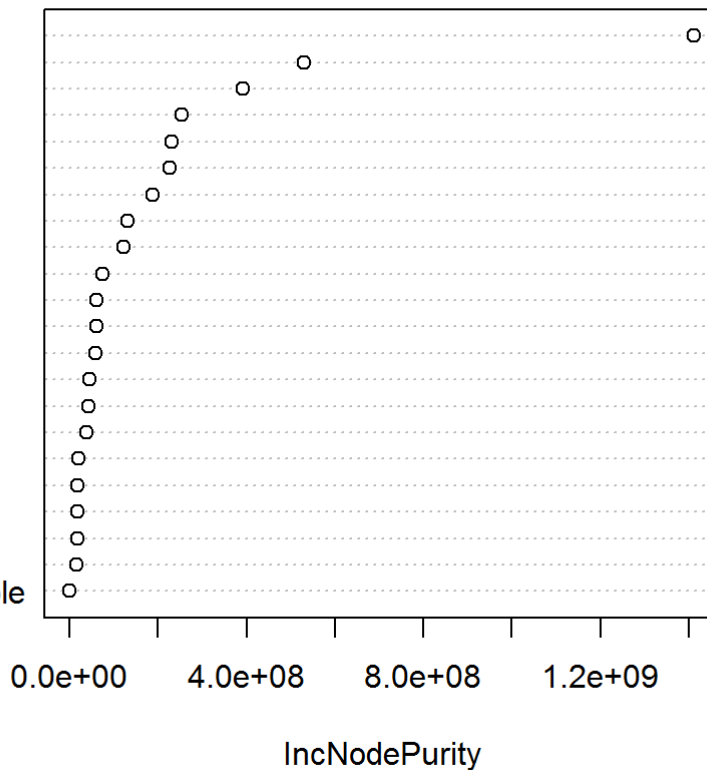
```

```
##          Length Class  Mode
## call           5  -none-  call
## type           1  -none- character
## predicted     8523  -none-  numeric
## mse           1000  -none-  numeric
## rsq           1000  -none-  numeric
## oob.times     8523  -none-  numeric
## importance      22  -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             8523  -none-  numeric
## test          0  -none-  NULL
## inbag          0  -none-  NULL
## terms          3  terms  call
```

```
varImpPlot(rf_model)
```

rf_model

```
Item_MRP
Outlet_Count
Outlet_Type_Grocery.Store
Outlet_Type_Supermarket.Type3
Outlet_Year
Item_Visibility
Item_Weight
Outlet_Type_Supermarket.Type1
Outlet_Size_Medium
Outlet_Size_Others
Outlet_Location_Type_Tier.1
Item_Count
Outlet_Location_Type_Tier.3
Outlet_Size_Low
Outlet_Location_Type_Tier.2
Outlet_Type_Supermarket.Type2
Item_Type_New_Drinks
Item_Type_New_Food
Item_Fat_Content_Low.Fat
Item_Fat_Content_Regular
Outlet_Size_High
Item_Type_New_Non-Consumable
```



```
pred_rf = predict(rf_model,type="response")
rmse(new_train$Item_Outlet_Sales,pred_rf)
```

```
## [1] 1566.205
```