Store Sales Prediction

In [27]:
```
library(ggplot2)
library(caret)
library(gridExtra)
library(dplyr)
library(stringr)
```

...

Data Exploration and Cleaning

In [5]:
```
df <- read.csv('C:/Datasets/SalesTrain.txt',na.strings='')
head(df,5)
length(df[,1])
```

Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	O
FDA15	9.30	Low Fat	0.01604730	Dairy	249.8092	OUT049	
DRC01	5.92	Regular	0.01927822	Soft Drinks	48.2692	OUT018	
FDN15	17.50	Low Fat	0.01676007	Meat	141.6180	OUT049	
FDX07	19.20	Regular	0.00000000	Fruits and Vegetables	182.0950	OUT010	
NCD19	8.93	Low Fat	0.00000000	Household	53.8614	OUT013	

8523

Check for duplicates

In [6]:
```
sum(duplicated(df))
```

0

Summarize Data

In [7]:
```
summary(df)
```

```
 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
```

In [8]:
```
names(df)[1]
length(unique(df[,1]))
names(df)[5]
length(unique(df[,5]))
names(df)[7]
length(unique(df[,7]))
```

'Item_Identifier'

1559

'Item_Type'

16

'Outlet_Identifier'

10

Item identifier has many levels and likely cannot be included as a feature as is. Prefixes are explored.

In [9]:
```
itemprefix <- unique(substring(df[,1],1,3))
paste(length(itemprefix),'levels')
itemprefix


itemprefix2 <- unique(substring(df[,1],1,2))
itemprefix2
```

'71 levels'

'FDA' 'DRC' 'FDN' 'FDX' 'NCD' 'FDP' 'FDO' 'FDH' 'FDU' 'FDY' 'FDS' 'FDF' 'NCB'
'DRI' 'FDW' 'FDC' 'FDR' 'FDV' 'DRJ' 'FDE' 'NCS' 'DRH' 'NCX' 'DRZ' 'FDB' 'FDK'
'FDL' 'FDM' 'NCP' 'NCL' 'DRK' 'FDI' 'FDZ' 'NCI' 'FDJ' 'FDG' 'NCZ' 'FDQ' 'FDD'
'DRG' 'NCR' 'FDT' 'DRB' 'DRE' 'DRA' 'NCF' 'NCH' 'NCO' 'NCN' 'NCC' 'DRD' 'DRF'
'DRL' 'NCM' 'NCU' 'DRY' 'NCW' 'DRM' 'NCT' 'NCQ' 'DRP' 'DRQ' 'NCK' 'NCY' 'DRN'
'NCA' 'NCE' 'NCJ' 'NCV' 'NCG' 'DRO'

'FD' 'DR' 'NC'

2 letter prefix only has 3 levels. 3 level prefix has 71 levels. Overfitting will be evaluated before deciding which prefix to keep in the model. For now both will be added to the data frame.

In [10]:
```
df$ItemPrefix2 <- factor(substring(df[,1],1,2))
df$ItemPrefix3 <- factor(substring(df[,1],1,3))
df$ItemNumber <- as.numeric(substring(df[,1],4,5))
df<-df[,-1]
head(df,5)
```

Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishm
9.30	Low Fat	0.01604730	Dairy	249.8092	OUT049	
5.92	Regular	0.01927822	Soft Drinks	48.2692	OUT018	
17.50	Low Fat	0.01676007	Meat	141.6180	OUT049	
19.20	Regular	0.00000000	Fruits and Vegetables	182.0950	OUT010	
8.93	Low Fat	0.00000000	Household	53.8614	OUT013	

The fat content should only have 2 levels. This is corrected below.

In [11]:
```
df$Item_Fat_Content <- factor(ifelse(df$Item_Fat_Content %in% c('reg','Regular'), 'r
head(df,5)
```

Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishm
9.30	low	0.01604730	Dairy	249.8092	OUT049	
5.92	reg	0.01927822	Soft Drinks	48.2692	OUT018	
17.50	low	0.01676007	Meat	141.6180	OUT049	
19.20	reg	0.00000000	Fruits and Vegetables	182.0950	OUT010	
8.93	low	0.00000000	Household	53.8614	OUT013	

Summary of data after cleaning

In [12]:
```
summary(df)
```

```
 Item_Weight     Item_Fat_Content Item_Visibility
Min.   : 4.555   low:5517         Min.   :0.00000
1st Qu.: 8.774   reg:3006         1st Qu.:0.02699
Median :12.600                    Median :0.05393
Mean   :12.858                    Mean   :0.06613
3rd Qu.:16.850                    3rd Qu.:0.09459
Max.   :21.350                    Max.   :0.32839
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  ItemPrefix2  ItemPrefix3
Grocery Store    :1083   Min.   :   33.29   DR: 799     FDX    : 295
Supermarket Type1:5577   1st Qu.:  834.25   FD:6125     FDT    : 281
Supermarket Type2: 928   Median : 1794.33   NC:1599     FDS    : 279
Supermarket Type3: 935   Mean   : 2181.29               FDR    : 275
                         3rd Qu.: 3101.30               FDW    : 271
                         Max.   :13086.97               FDY    : 271
                                                        (Other):6851
  ItemNumber
Min.   : 1.00
1st Qu.:15.00
Median :30.00
Mean   :30.33
3rd Qu.:45.00
Max.   :60.00
```

Check for near zero variance.

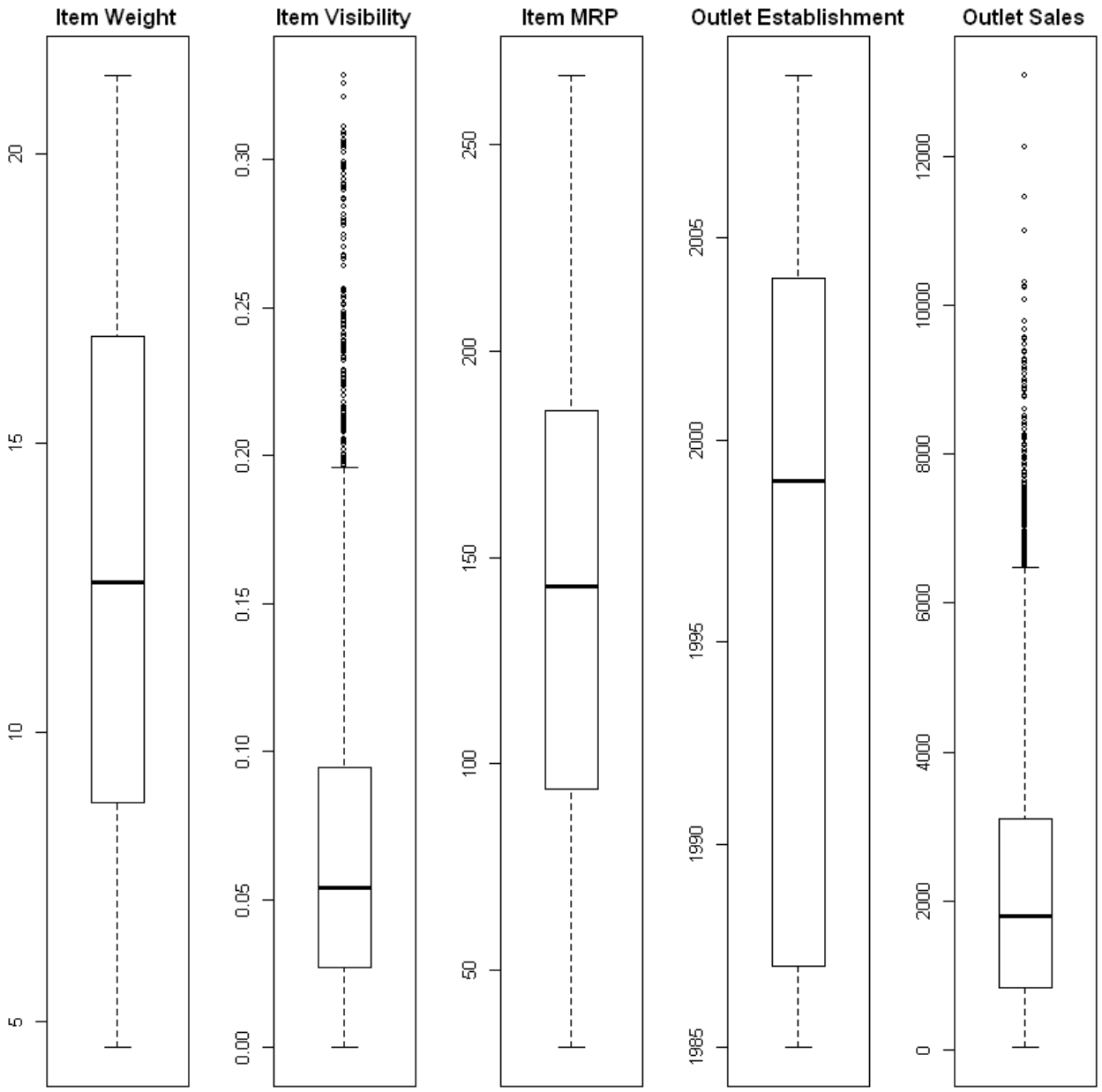
In [13]:
```
nearZeroVar(df, saveMetrics=TRUE)
```

	freqRatio	percentUnique	zeroVar	nzv
Item_Weight	1.048780	4.86917752	FALSE	FALSE
Item_Fat_Content	1.835329	0.02346592	FALSE	FALSE
Item_Visibility	175.333333	92.45570808	FALSE	FALSE
Item_Type	1.026667	0.18772733	FALSE	FALSE
Item_MRP	1.166667	69.67030388	FALSE	FALSE
Outlet_Identifier	1.003219	0.11732958	FALSE	FALSE
Outlet_Establishment_Year	1.569742	0.10559662	FALSE	FALSE
Outlet_Size	1.169598	0.03519887	FALSE	FALSE
Outlet_Location_Type	1.202873	0.03519887	FALSE	FALSE
Outlet_Type	5.149584	0.04693183	FALSE	FALSE
Item_Outlet_Sales	1.062500	40.98322187	FALSE	FALSE
ItemPrefix2	3.830519	0.03519887	FALSE	FALSE
ItemPrefix3	1.049822	0.83304001	FALSE	FALSE
ItemNumber	1.006410	0.70397747	FALSE	FALSE

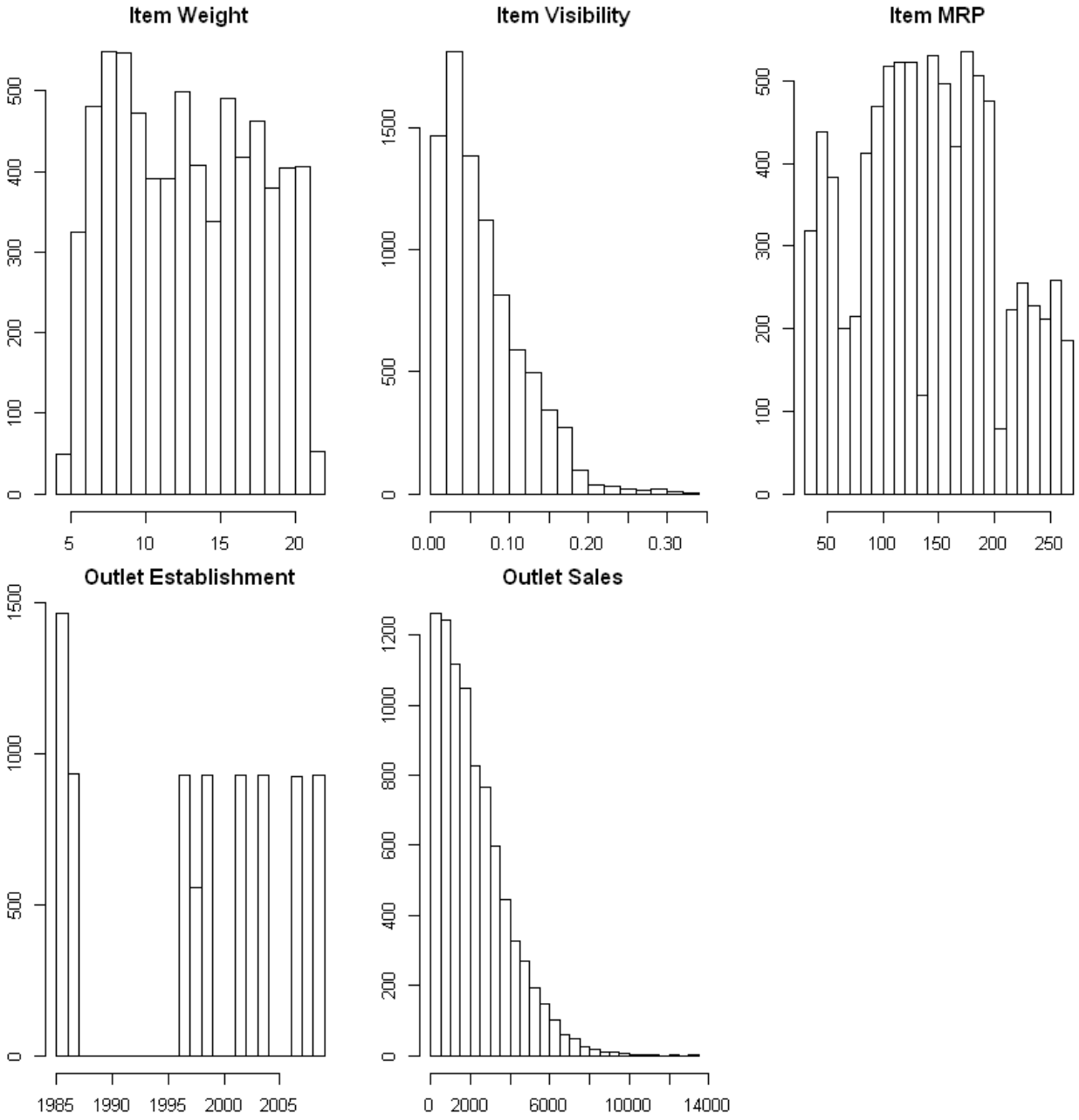
Check for outliers

In [14]:

```
par(mfrow=c(1,5), mar=c(2,2,2,2))
boxplot(df$Item_Weight,main='Item Weight')
boxplot(df$Item_Visibility,main='Item Visibility')
boxplot(df$Item_MRP,main='Item MRP')
boxplot(df$Outlet_Establishment_Year,main='Outlet Establishment')
boxplot(df$Item_Outlet_Sales,main='Outlet Sales')
```



In [15]:
```
par(mfrow=c(2,3), mar=c(2,2,2,2))
hist(df$Item_Weight,main='Item Weight',breaks=20)
hist(df$Item_Visibility,main='Item Visibility',breaks=20)
hist(df$Item_MRP,main='Item MRP',breaks=20)
hist(df$Outlet_Establishment_Year,main='Outlet Establishment',breaks=20)
hist(df$Item_Outlet_Sales,main='Outlet Sales',breaks=20)
```



The two variables with extreme values are item visibility and outlet sales. However, the extreme values are numerous and are consistent with the skewed distributions observed in the histogram. Therefore they are not considered outliers.

Next, check for correlations.

In [16]:
```
cor(df[,c(1,3,5,7,14)],use='complete.obs')
```

	Item_Weight	Item_Visibility	Item_MRP	Outlet_Establishment_Year	ItemNu
Item_Weight	1.00000000	-0.014047726	0.027141154	-0.011588290	0.0252
Item_Visibility	-0.01404773	1.000000000	-0.006061148	-0.016935201	-0.0265
Item_MRP	0.02714115	-0.006061148	1.000000000	-0.001656520	-0.0188
Outlet_Establishment_Year	-0.01158829	-0.016935201	-0.001656520	1.000000000	0.0011
ItemNumber	0.02528662	-0.026579321	-0.018875820	0.001171761	1.0000

In [17]:
```
chisqfun <- function(a,b){
    if(a==b) return(0)
    else return(round(chisq.test(table(df[,a],df[,b]))$p.value,2))
}
matrix(mapply(chisqfun,rep(c(2,4,6,8:10,12:13),8),rep(c(2,4,6,8:10,12:13),rep(8,8))))
```

```
f[, a], df[, b])):
"Chi-squared approximation may be incorrect"Warning message in chisq.test(table(d
f[, a], df[, b])):
"Chi-squared approximation may be incorrect"
```

	Item_Fat_Content	Item_Type	Outlet_Identifier	Outlet_Size	Outlet_Location_Typ
Item_Fat_Content	0.00	0	1	0.91	0.9
Item_Type	0.00	0	1	1.00	1.0
Outlet_Identifier	1.00	1	0	NaN	0.0
Outlet_Size	0.91	1	NaN	0.00	0.0
Outlet_Location_Type	0.94	1	0	0.00	0.0
Outlet_Type	0.99	1	0	0.00	0.0
ItemPrefix2	0.00	0	1	0.96	0.9

Some of the factors are not independent. The strength of correlation will be evaluated after dummy coding.

Next, factors will be coded and pre-processing will be performed.

In [18]:
```
X <- predict(dummyVars(Item_Outlet_Sales~.,df,fullRank=TRUE),df)
dimnames(X)[[2]] <- gsub(' ','',dimnames(X)[[2]])
head(X,5)
```

	Item_Weight	Item_Fat_Content.reg	Item_Visibility	Item_Type.Breads	Item_Type.Breakfast	Item_Type.C
1	9.30	0	0.01604730	0	0	
2	5.92	1	0.01927822	0	0	
3	17.50	0	0.01676007	0	0	
4	19.20	1	0.00000000	0	0	
5	8.93	0	0.00000000	0	0	

In [19]:
```
preprocessparams <- preProcess(X,method=c('center','scale','bagImpute'))
processedX <- predict(preprocessparams, X)
head(processedX,5)
```

	Item_Weight	Item_Fat_Content.reg	Item_Visibility	Item_Type.Breads	Item_Type.Breakfast	Item_Type.C
1	-0.7661631	-0.7381039	-0.9706752	-0.1741831	-0.1143393	-0.2
2	-1.4940692	1.3546638	-0.9080580	-0.1741831	-0.1143393	-0.2
3	0.9997627	-0.7381039	-0.9568612	-0.1741831	-0.1143393	-0.2
4	1.3658693	1.3546638	-1.2816826	-0.1741831	-0.1143393	-0.2
5	-0.8458452	-0.7381039	-1.2816826	-0.1741831	-0.1143393	-0.2

Check for and remove any correlated dummy variables

In [20]:
```
cormatrix <-cor(X,use='complete.obs')
cormatrix[is.na(cormatrix)] <- 0
findCorrelation(cormatrix,0.9,names=TRUE, exact=FALSE)
findCorrelation(cormatrix,0.9, exact=FALSE)
```

```
Warning message in cor(X, use = "complete.obs"):
"the standard deviation is zero"
```

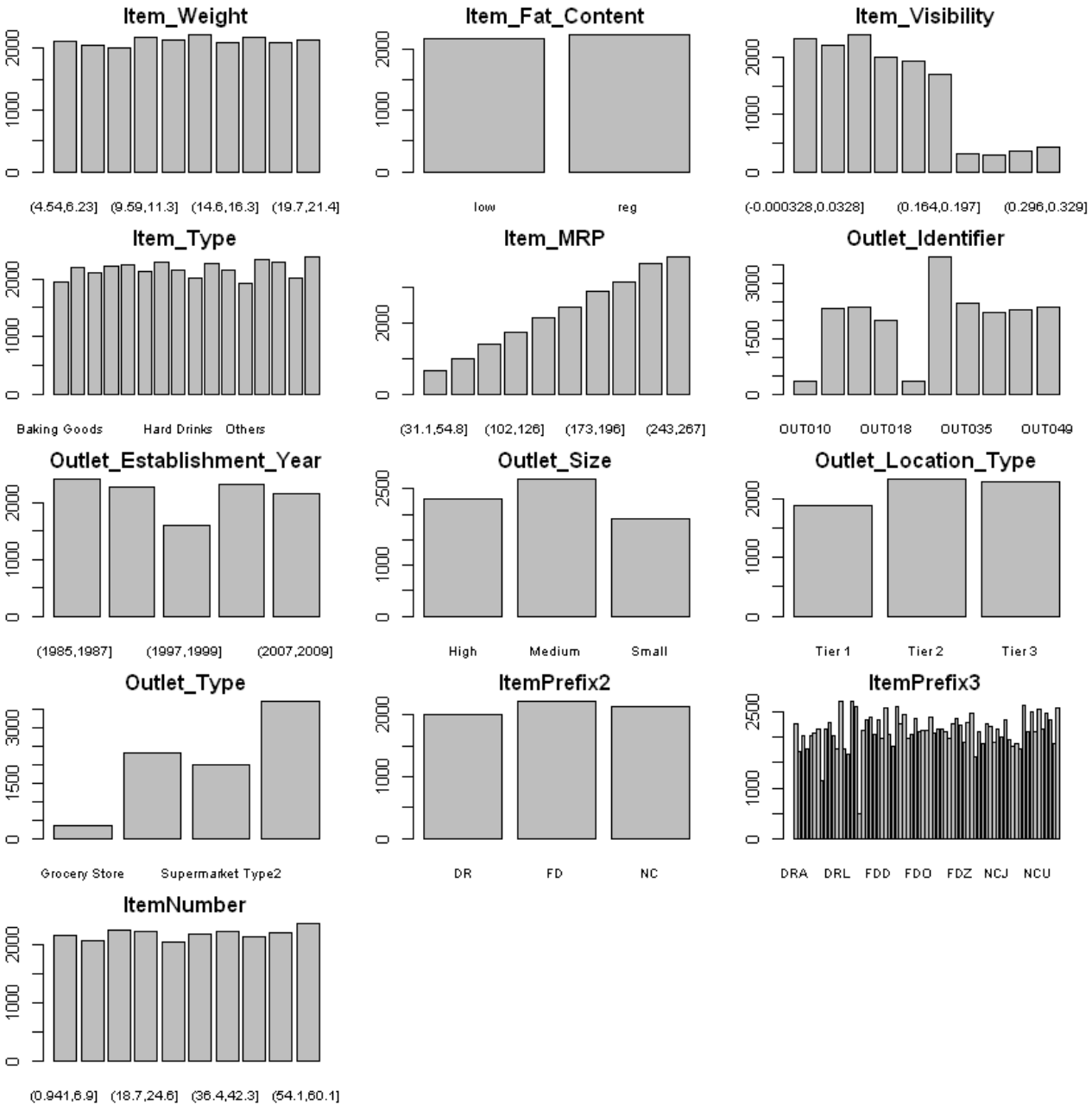
'Outlet_Identifier.OUT035' 'Outlet_Identifier.OUT018' 'Outlet_Type.SupermarketType1'

25 22 34

In [21]:
```
processedX <- processedX[,-c(25,22,34)]
```

Data Visualization

In [22]:
```
par(mfrow=c(5,3),mar=c(2,2,2,2))
for(i in 1:14){
    if(i %in% c(2,4,6,8:10,12:13)) heightmatrix <- as.matrix(aggregate(df[,11],list(
    else if(i != 11) heightmatrix <- as.matrix(aggregate(df[,11],list(cut(df[,i],10)
    if(i!=11){
        heights <- as.numeric(heightmatrix[,2])
        names(heights) <- heightmatrix[,1]
        barplot(heights, beside=TRUE, main=names(df)[i],cex.names=0.75)
    }
}
```



Item visibility, MRP, outlet indentifier, and outlet type seem to have the largest effects on sales.

Linear Model

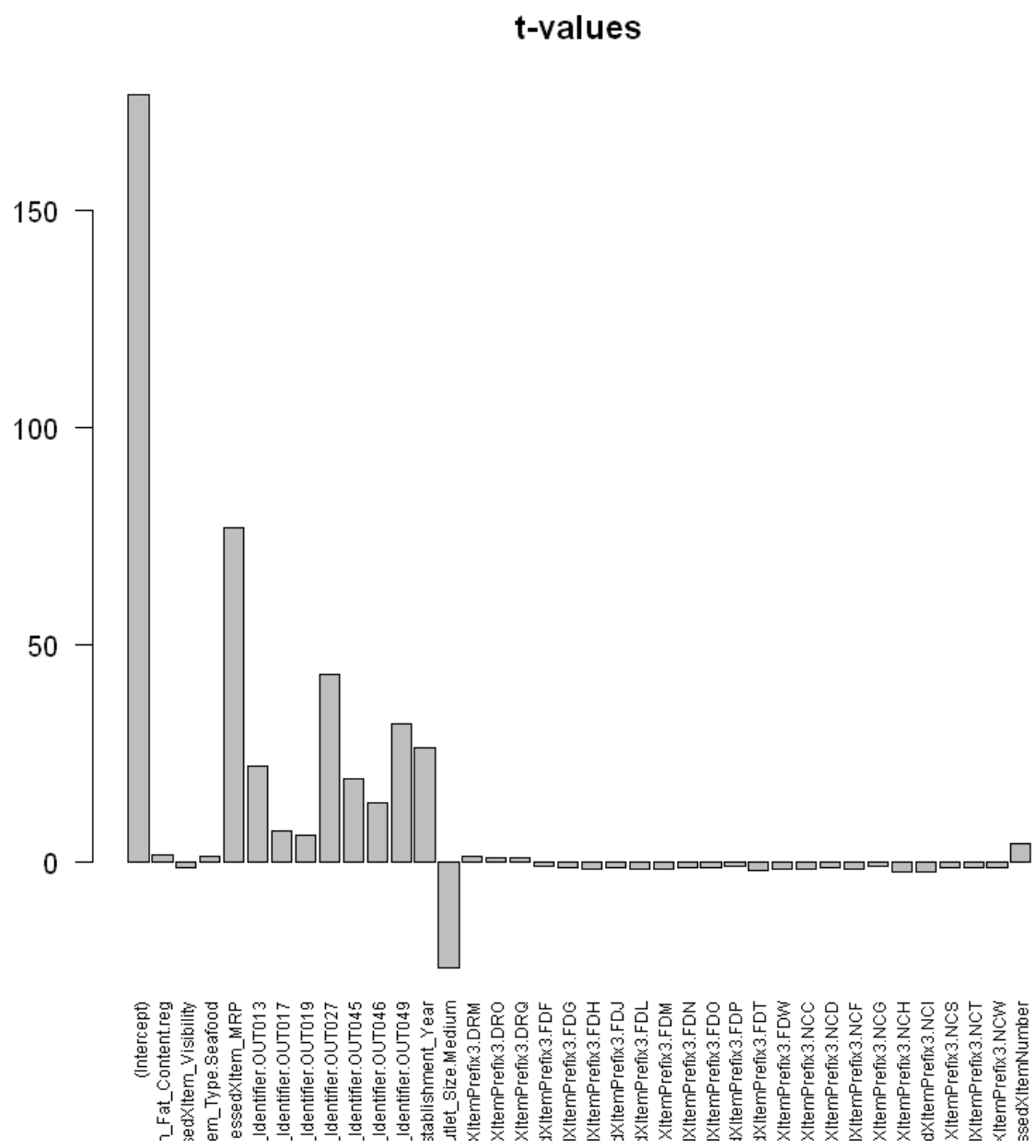
First model with all the current features.

In [23]:
```
linearmod <-lm(df[,11]~processedX)
lmsummary <- summary(linearmod)
lmsummary
```

```
Call:
lm(formula = df[, 11] ~ processedX)

Residuals:
    Min      1Q  Median      3Q     Max 
-4372.4  -682.0   -87.0   571.3  7880.6 

Coefficients: (8 not defined because of singularities)
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                           2283.7186    12.9386 176.505  < 2e-16
processedXItem_Weight                   -2.3546    13.8642  -0.170   0.8651
processedXItem_Fat_Content.reg          24.2491    13.8339   1.753   0.0797
processedXItem_Visibility              -15.8401    13.0961  -1.210   0.2265
processedXItem_Type.Breads               0.1974    14.4324   0.014   0.9891
processedXItem_Type.Breakfast            9.1583    13.5397   0.676   0.4988
processedXItem_Type.Canned              14.2974    16.8406   0.849   0.3959
processedXItem_Type.Dairy              -11.7418    18.2689  -0.643   0.5204
processedXItem_Type.FrozenFoods         -2.3343    17.9588  -0.130   0.8966
```

Significance of features is summarized below.

In [24]:
```
barplot(lmsummary$coefficients[abs(lmsummary$coefficients[,3])>=1,3],main='t-values'
```



In [25]:
```
sigfeatures <- lmsummary$coefficients[abs(lmsummary$coefficients[,4])<=0.05,]
sigfeatures
```

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2283.71861	12.93858	176.504568	0.000000e+00
processedXItem_MRP	970.89650	12.63025	76.870748	0.000000e+00
processedXOutlet_Identifier.OUT013	750.78317	33.93937	22.121307	1.900360e-105
processedXOutlet_Identifier.OUT017	102.15748	14.27344	7.157173	8.926718e-13
processedXOutlet_Identifier.OUT019	188.08163	29.37974	6.401745	1.618243e-10
processedXOutlet_Identifier.OUT027	1649.66946	38.07139	43.330953	0.000000e+00
processedXOutlet_Identifier.OUT045	278.83950	14.50041	19.229768	1.099017e-80
processedXOutlet_Identifier.OUT046	278.17601	20.44095	13.608759	9.792648e-42
processedXOutlet_Identifier.OUT049	578.17295	18.15598	31.844759	3.124907e-210
processedXOutlet_Establishment_Year	1239.59742	46.90286	26.429038	6.045229e-148
processedXOutlet_Size.Medium	-578.03530	23.82113	-24.265652	8.720852e-126
processedXItemPrefix3.NCH	-37.35915	17.17607	-2.175070	2.965258e-02
processedXItemPrefix3.NCI	-36.40136	17.91378	-2.032031	4.218181e-02
processedXItemNumber	53.04357	12.53284	4.232366	2.336990e-05

Add interactions of significant features to design matrix.

In [28]:
```
sigfeaturelist <- str_replace_all(dimnames(sigfeatures)[[1]],'processedX','')[-1]
sigfeaturelist
```

'Item_MRP' 'Outlet_Identifier.OUT013' 'Outlet_Identifier.OUT017' 'Outlet_Identifier.OUT019' 'Outlet_Identifier.OUT027' 'Outlet_Identifier.OUT045' 'Outlet_Identifier.OUT046' 'Outlet_Identifier.OUT049' 'Outlet_Establishment_Year' 'Outlet_Size.Medium' 'ItemPrefix3.NCH' 'ItemPrefix3.NCI' 'ItemNumber'

In [29]:
```
InterX <- as.data.frame(processedX)
for(a in 1:12){
    for(b in (a+1):13){
        internname <- paste(sigfeaturelist[a],sigfeaturelist[b],sep='x')
        InterX <- mutate(InterX,!!internname := processedX[,sigfeaturelist[a]]*proces
    }
}
InterX <- as.matrix(InterX)
```

Check for and remove interactions that are highly correlated with other features.

In [30]:
```
intercormatrix <-cor(InterX,use='complete.obs')
intercormatrix[is.na(cormatrix)] <- 0
diag(intercormatrix) <- 0
maxcor <- apply(intercormatrix,1,max)
filteredindex <- 1:length(maxcor)
filteredindex <- filteredindex[(maxcor >= 0.9)&(filteredindex>98)]
filteredindex
```

125 126 135 144 145 153 165 170 171

In [31]:
```
InterX <-InterX[,-filteredindex]
```

Run linear model with interactions.

In [32]:
```
linearmodinter <-lm(df[,11]~InterX)
lmintersummary <- summary(linearmodinter)
lmintersummary
```

```
Call:
lm(formula = df[, 11] ~ InterX)

Residuals:
    Min      1Q  Median      3Q     Max
-5514.8  -534.7   -53.6   452.4  6873.6

Coefficients: (36 not defined because of singularities)
                                                    Estimate Std. Error
(Intercept)                                      2284.92041   12.28974
InterXItem_Weight                                  -6.06602   13.16625
InterXItem_Fat_Content.reg                         17.44366   13.12486
InterXItem_Visibility                             -13.72552   12.43355
InterXItem_Type.Breads                              1.64473   13.68194
InterXItem_Type.Breakfast                           8.65375   12.83275
InterXItem_Type.Canned                             10.90327   15.97262
InterXItem_Type.Dairy                              -9.23726   17.32069
InterXItem_Type.FrozenFoods                        -6.18434   17.02545
```

Filter out insignificant features.

In [33]:
```
siginter <-lmintersummary$coefficients[lmintersummary$coefficients[,4]<=0.05,]
siginterlist <- str_replace_all(dimnames(siginter)[[1]],'InterX','')[-1]
siginterlist <- siginterlist[13:25]
siginterlist
```

'Item_MRPxOutlet_Identifier.OUT013' 'Item_MRPxOutlet_Identifier.OUT017'
'Item_MRPxOutlet_Identifier.OUT019' 'Item_MRPxOutlet_Identifier.OUT027'
'Item_MRPxOutlet_Identifier.OUT045' 'Item_MRPxOutlet_Identifier.OUT046'
'Item_MRPxOutlet_Identifier.OUT049' 'Item_MRPxOutlet_Establishment_Year'
'Item_MRPxOutlet_Size.Medium' 'Item_MRPxItemPrefix3.NCH' 'Item_MRPxItemPrefix3.NCI'
'Item_MRPxItemNumber' 'Outlet_Identifier.OUT013xItemPrefix3.NCH'

In [34]:
```
fullX <- as.data.frame(processedX)
for(a in siginterlist){
        fullX <- mutate(fullX,!!a := InterX[,a])
}
fullX <- as.matrix(fullX)

linearmodfull <-lm(df[,11]~fullX)
lmfullsummary <- summary(linearmodfull)
lmfullsummary
```

```
Call:
lm(formula = df[, 11] ~ fullX)

Residuals:
    Min      1Q  Median      3Q     Max
-5548.3  -539.1   -51.3   455.9  6917.1

Coefficients: (8 not defined because of singularities)
                                              Estimate Std. Error t value
(Intercept)                                 2285.3341    12.2749 186.179
fullXItem_Weight                              -6.3010    13.1433  -0.479
fullXItem_Fat_Content.reg                     17.2192    13.1198   1.312
fullXItem_Visibility                         -12.4791    12.4140  -1.005
fullXItem_Type.Breads                          1.6217    13.6760   0.119
fullXItem_Type.Breakfast                       8.9046    12.8283   0.694
fullXItem_Type.Canned                         11.1434    15.9631   0.698
fullXItem_Type.Dairy                          -9.5597    17.3132  -0.552
fullXItem_Type.FrozenFoods                    -6.6393    17.0187  -0.390
```

Add square and cube features for continuous features.

In [35]:
```
nonlinX <- as.data.frame(fullX)
continuouslist <- c('Item_Weight','Item_MRP','Item_Visibility','Outlet_Establishment
for(a in continuouslist){
    sqname <- paste(a,'sqr',sep='.')
    cubname <- paste(a,'cub',sep='.')
    nonlinX <- mutate(nonlinX,!!sqname := fullX[,a]^2)
    nonlinX <- mutate(nonlinX,!!cubname := fullX[,a]^3)
}
nonlinX <- as.matrix(nonlinX)

nonlinearmod <-lm(df[,11]~nonlinX)
nlmsummary <- summary(nonlinearmod)
nlmsummary
```

```
Call:
lm(formula = df[, 11] ~ nonlinX)

Residuals:
    Min      1Q  Median      3Q     Max
-5451.3  -533.3   -50.9   456.1  6908.8

Coefficients: (10 not defined because of singularities)
                                                Estimate Std. Error t value
(Intercept)                                   2309.78682   24.45734  94.441
nonlinXItem_Weight                              47.52413   32.04466   1.483
nonlinXItem_Fat_Content.reg                     16.73881   13.12263   1.276
nonlinXItem_Visibility                         -19.48536   15.44958  -1.261
nonlinXItem_Type.Breads                          0.34177   13.68739   0.025
nonlinXItem_Type.Breakfast                       8.97961   12.85298   0.699
nonlinXItem_Type.Canned                         10.17210   15.97353   0.637
nonlinXItem_Type.Dairy                          -8.72684   17.34316  -0.503
nonlinXItem_Type.FrozenFoods                    -7.47347   17.04192  -0.439
```

Only the cube of item weight and MRP is significant (at alpha = 0.1), so other cube and square terms are removed.

In [36]:
```
finalX <- as.data.frame(fullX)
continuouslist <- c('Item_Weight','Item_MRP')
for(a in continuouslist){
    cubname <- paste(a,'cub',sep='.')
    finalX <- mutate(finalX,!!cubname := fullX[,a]^3)
}
finalX <- as.matrix(finalX)
finallinearmod <-lm(df[,11]~finalX)
finallmsummary <- summary(finallinearmod)
finallmsummary
```

```
Call:
lm(formula = df[, 11] ~ finalX)

Residuals:
    Min      1Q  Median      3Q     Max 
-5459.4  -531.9   -53.0   452.7  6914.5 

Coefficients: (8 not defined because of singularities)
                                            Estimate Std. Error t value
(Intercept)                                2290.3463    12.3960 184.765
finalXItem_Weight                            52.2886    31.8723   1.641
finalXItem_Fat_Content.reg                   16.4154    13.1180   1.251
finalXItem_Visibility                       -13.3536    12.4133  -1.076
finalXItem_Type.Breads                        0.3820    13.6849   0.028
finalXItem_Type.Breakfast                     8.8011    12.8506   0.685
finalXItem_Type.Canned                       10.5802    15.9649   0.663
finalXItem_Type.Dairy                        -8.8606    17.3183  -0.512
finalXItem_Type.FrozenFoods                  -7.2372    17.0190  -0.425
```

The singularities are caused by features that are linear combinations of other features. These are filtered out by taking only features listed in the linear model coefficient summary.

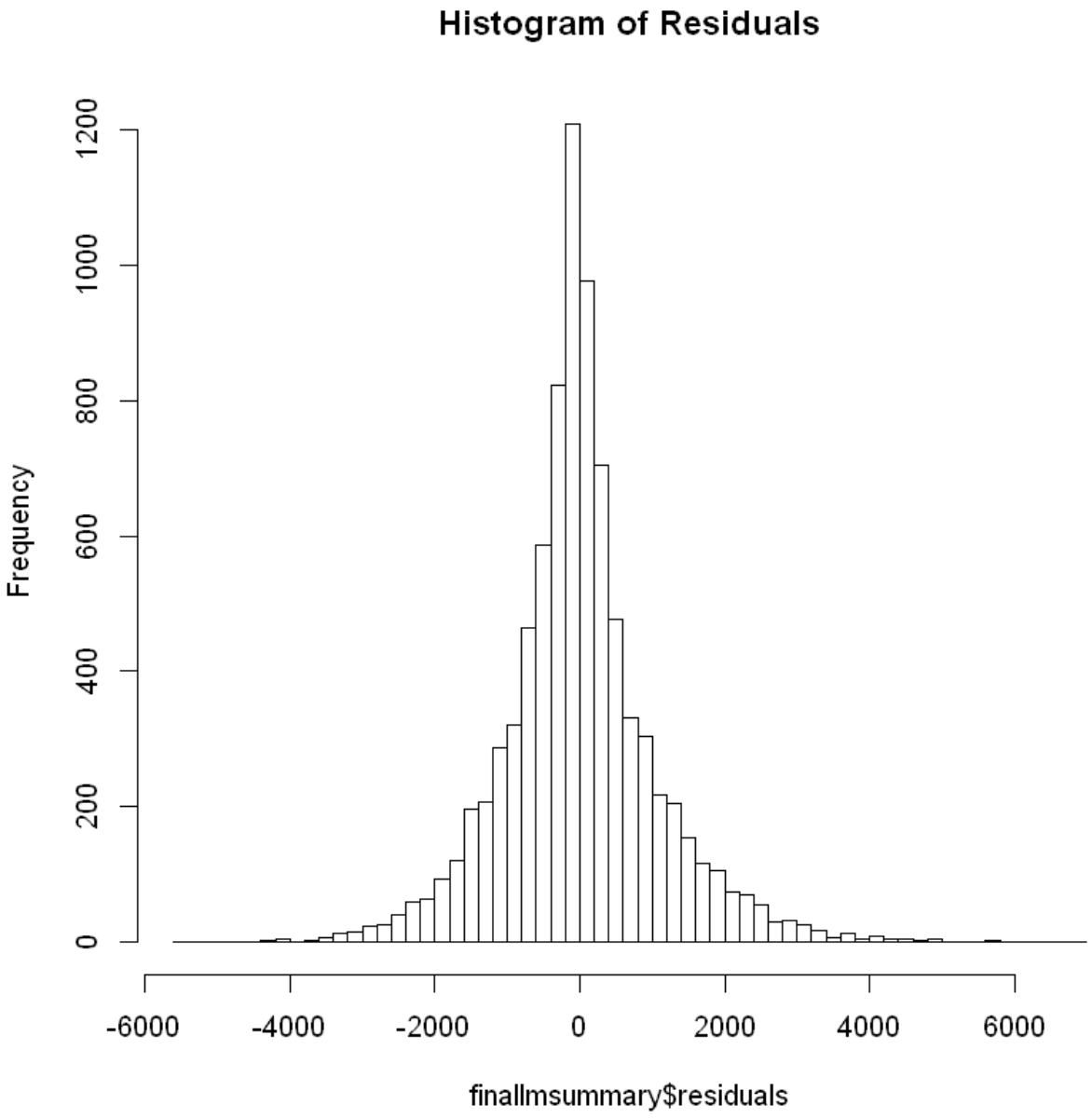
In [46]:
```
finalfeaturelist <- str_replace_all(dimnames(finallmsummary$coefficients)[[1]],'fina
finalX <- finalX[,finalfeaturelist]
finallinearmod <-lm(df[,11]~finalX)
finallmsummary <- summary(finallinearmod)
finallmsummary
```

```
Call:
lm(formula = df[, 11] ~ finalX)

Residuals:
    Min      1Q  Median      3Q     Max
-5459.4  -531.9   -53.0   452.7  6914.5

Coefficients:
                                            Estimate Std. Error t value
(Intercept)                                2290.3463    12.3960 184.765
finalXItem_Weight                            52.2886    31.8723   1.641
finalXItem_Fat_Content.reg                   16.4154    13.1180   1.251
finalXItem_Visibility                       -13.3536    12.4133  -1.076
finalXItem_Type.Breads                        0.3820    13.6849   0.028
finalXItem_Type.Breakfast                     8.8011    12.8506   0.685
finalXItem_Type.Canned                       10.5802    15.9649   0.663
finalXItem_Type.Dairy                        -8.8606    17.3183  -0.512
finalXItem_Type.FrozenFoods                  -7.2372    17.0190  -0.425
```

Check for normality of residuals

In [47]:
```
hist(finallmsummary$residuals,50, main='Histogram of Residuals')
shapiro.test(sample(finallmsummary$residuals,5000))
```

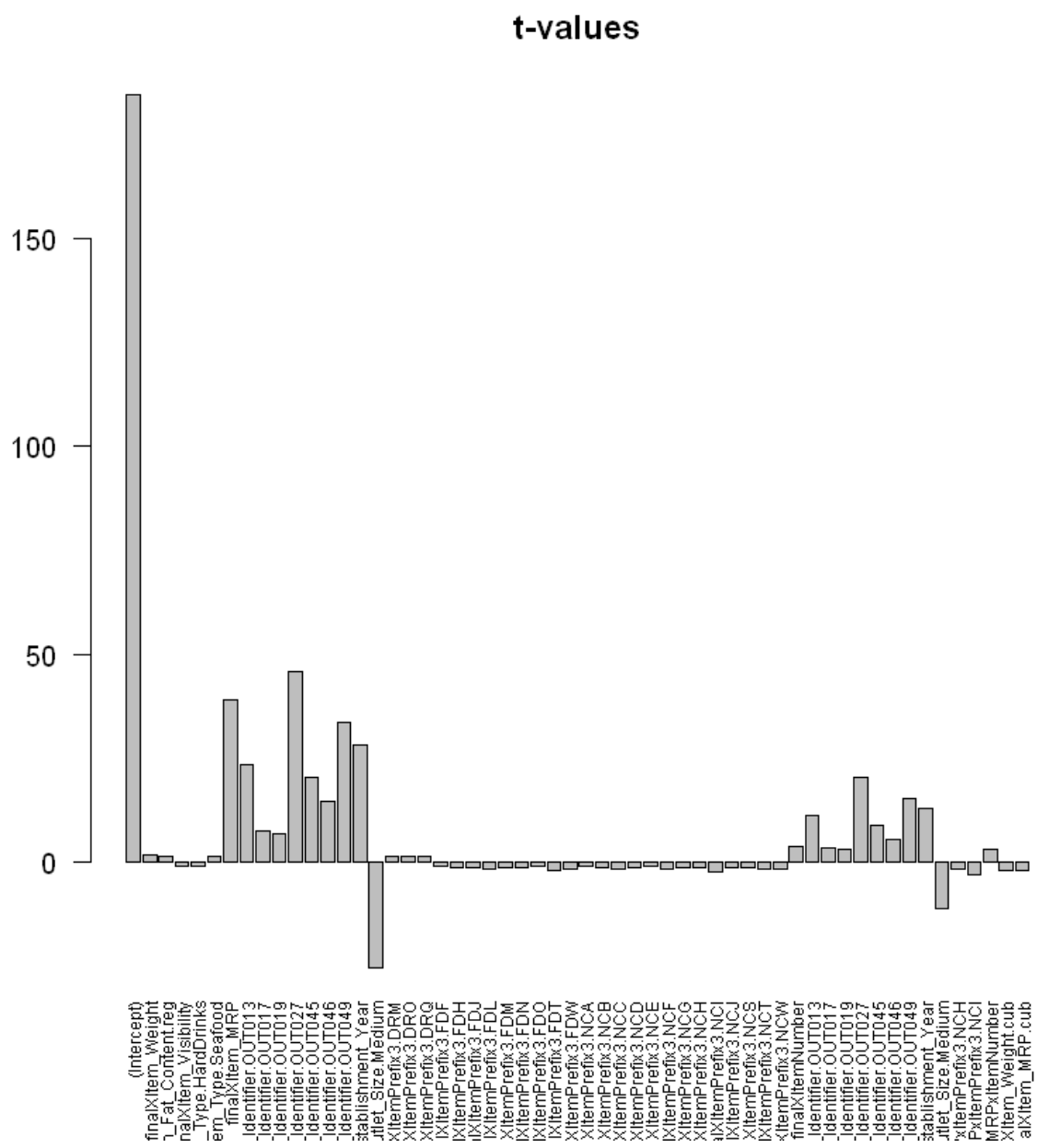
```
        Shapiro-Wilk normality test

data:  sample(finallmsummary$residuals, 5000)
W = 0.95835, p-value < 2.2e-16
```



The residual distribution has heavy tails, possibly indicating a large influence of features not captured in the model or in the data set.

The significance of features in the model is summarized below.

In [48]:
```
barplot(finallmsummary$coefficients[abs(finallmsummary$coefficients[,3])>=1,3],main=
```



In [49]:
```
finallmsummary$coefficients[finallmsummary$coefficients[,4]<=0.1,]
```

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2290.34625	12.39601	184.764729	0.000000e+00
finalXItem_MRP	1066.70848	27.22300	39.184090	1.302347e-308
finalXOutlet_Identifier.OUT013	757.53434	32.14573	23.565630	5.852413e-119
finalXOutlet_Identifier.OUT017	102.78752	13.51861	7.603411	3.194981e-14
finalXOutlet_Identifier.OUT019	188.75018	27.82621	6.783181	1.255057e-11
finalXOutlet_Identifier.OUT027	1657.92788	36.05383	45.984797	0.000000e+00
finalXOutlet_Identifier.OUT045	280.17338	13.73227	20.402561	2.382812e-90
finalXOutlet_Identifier.OUT046	282.81046	19.36473	14.604412	1.007887e-47
finalXOutlet_Identifier.OUT049	580.33109	17.19359	33.752763	2.506709e-234
finalXOutlet_Establishment_Year	1247.30512	44.41542	28.082702	6.066573e-166
finalXOutlet_Size.Medium	-575.99995	22.56530	-25.525916	1.726855e-138
finalXItemPrefix3.FDT	-33.18683	16.42859	-2.020065	4.340826e-02
finalXItemPrefix3.FDW	-28.90952	16.27265	-1.776571	7.567502e-02
finalXItemPrefix3.NCC	-27.80474	15.79873	-1.759935	7.845516e-02
finalXItemPrefix3.NCI	-39.57200	16.97821	-2.330752	1.978995e-02
finalXItemPrefix3.NCT	-27.45584	15.69773	-1.749033	8.032187e-02
finalXItemNumber	42.89486	11.89430	3.606338	3.123483e-04
finalXItem_MRPxOutlet_Identifier.OUT013	358.82433	31.75561	11.299556	2.146993e-29
finalXItem_MRPxOutlet_Identifier.OUT017	43.16997	13.43739	3.212676	1.320001e-03
finalXItem_MRPxOutlet_Identifier.OUT019	85.70648	27.86869	3.075368	2.109179e-03
finalXItem_MRPxOutlet_Identifier.OUT027	718.87112	35.43004	20.289877	2.129859e-89
finalXItem_MRPxOutlet_Identifier.OUT045	119.19688	13.65513	8.729091	3.061507e-18
finalXItem_MRPxOutlet_Identifier.OUT046	106.75557	19.24694	5.546625	3.000675e-08
finalXItem_MRPxOutlet_Identifier.OUT049	260.89385	17.07128	15.282615	4.975527e-52
finalXItem_MRPxOutlet_Establishment_Year	569.37033	43.67207	13.037402	1.767222e-38
finalXItem_MRPxOutlet_Size.Medium	-253.85440	22.59335	-11.235804	4.380714e-29
finalXItem_MRPxItemPrefix3.NCH	-24.23002	13.45744	-1.800493	7.181867e-02
finalXItem_MRPxItemPrefix3.NCI	-31.60884	10.79118	-2.929137	3.408177e-03
finalXItem_MRPxItemNumber	37.53014	11.95861	3.138337	1.704971e-03
finalXItem_Weight.cub	-33.51879	16.37811	-2.046560	4.073228e-02
finalXItem_MRP.cub	-23.52734	11.49696	-2.046396	4.074845e-02

Cross validation is performed to check for overfitting.

In [51]:
```
fulllinearmodel <- train(finalX,df[,11],method='lm',trControl=trainControl(method='r
fulllinearmodel
```

```
Linear Regression

8523 samples
 113 predictor

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 6819, 6817, 6819, 6819, 6818, 6819, ...
Resampling results:

  RMSE      Rsquared   MAE
  1077.878  0.6014958  759.3767

Tuning parameter 'intercept' was held constant at a value of TRUE
```

The RMSE is comparable to that of the model fit to the entire data set, indicating overfitting is minimal. Therefore the model will not be reduced further, nor will any regularization penalties be added.

Decision Tree

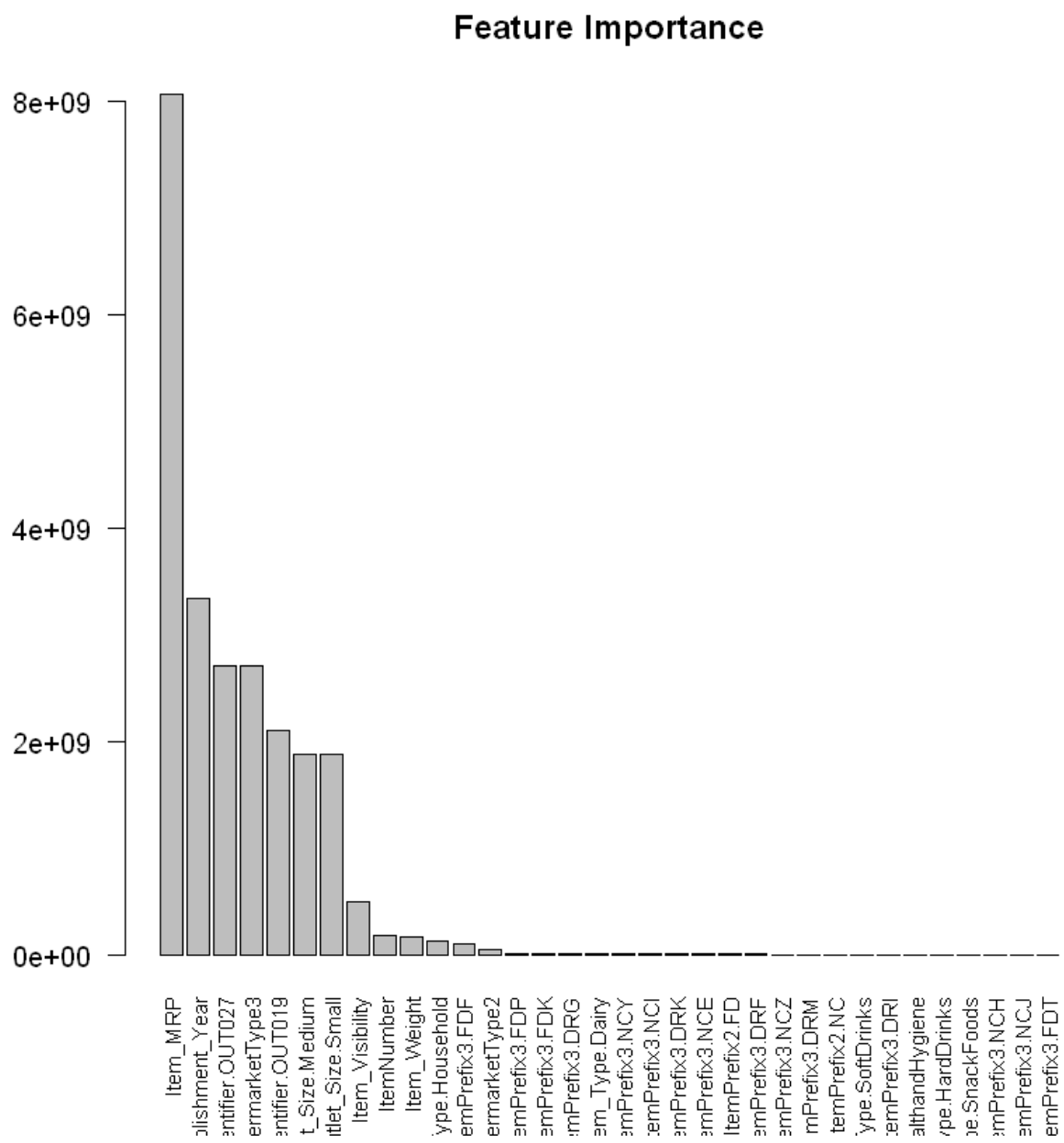
In [64]:
```
Grid <- expand.grid(cp=c(0.0005,0.001,0.002,0.003,0.004,0.005))
treemodel <- train(processedX,df[,11],method='rpart',trControl=trainControl(method='
treemodel
```

```
CART

8523 samples
 106 predictor

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 6817, 6818, 6819, 6820, 6818, 6818, ...
Resampling results across tuning parameters:

  cp     RMSE      Rsquared   MAE
  5e-04  1148.888  0.5520473  793.2892
  1e-03  1105.266  0.5813093  773.1895
  2e-03  1098.391  0.5859018  782.0021
  3e-03  1101.527  0.5835262  785.5887
  4e-03  1102.768  0.5825808  786.9578
  5e-03  1106.873  0.5794607  790.0889

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was cp = 0.002.
```

In [69]:
```
Grid <- expand.grid(cp=c(0.0016,0.0017,0.0018,0.0019,0.002))
treemodel <- train(processedX,df[,11],method='rpart',trControl=trainControl(method='
treemodel
```

```
CART

8523 samples
 106 predictor

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 6818, 6818, 6818, 6819, 6819, 6817, ...
Resampling results across tuning parameters:

  cp      RMSE      Rsquared   MAE
  0.0016  1097.356  0.5868223  779.9323
  0.0017  1097.245  0.5868887  780.0096
  0.0018  1097.269  0.5868148  780.4726
  0.0019  1097.308  0.5867609  780.5750
  0.0020  1098.377  0.5859599  781.1463

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was cp = 0.0017.
```

In [76]:
```
barplot(treemodel$finalModel$variable.importance,main='Feature Importance',cex.names
```



Model Selection

The linear model is slightly better than the decision tree model in terms of cros validation RMSE, therefore the linear model will be selected as the final model.

The test data set is processed the same way as the training set.

In [89]:
```
test <- read.csv('C:/Datasets/SalesTest.txt',na.strings='')
test$Item_Outlet_Sales <- 0
test$ItemPrefix2 <- factor(substring(test[,1],1,2))
test$ItemPrefix3 <- factor(substring(test[,1],1,3))
test$ItemNumber <- as.numeric(substring(test[,1],4,5))
itemID <- test[,1]
test<-test[,-1]
test$Item_Fat_Content <- factor(ifelse(test$Item_Fat_Content %in% c('reg','Regular')
testX <- predict(dummyVars(Item_Outlet_Sales~.,df,fullRank=TRUE),test)
dimnames(testX)[[2]] <- gsub(' ','',dimnames(testX)[[2]])
processedtestX <- predict(preprocessparams, testX)
processedtestX <- processedtestX[,-c(25,22,34)]
IntertestX <- as.data.frame(processedtestX)

for(a in 1:12){
    for(b in (a+1):13){
        internname <- paste(sigfeaturelist[a],sigfeaturelist[b],sep='x')
        IntertestX <- mutate(IntertestX,!!internname := processedtestX[,sigfeaturelis
    }
}
IntertestX <- as.matrix(IntertestX)
fulltestX <- as.data.frame(processedtestX)

for(a in siginterlist){
        fulltestX <- mutate(fulltestX,!!a := IntertestX[,a])
}
fulltestX <- as.matrix(fulltestX)

finaltestX <- as.data.frame(fulltestX)
for(a in continuouslist){
    cubname <- paste(a,'cub',sep='.')
    finaltestX <- mutate(finaltestX,!!cubname := fulltestX[,a]^3)
}
finaltestX <- as.matrix(finaltestX)
finaltestX <- finaltestX[,finalfeaturelist]
```

Then the model is used to predict sales for the test set.

In [90]:
```
results <- predict(fulllinearmodel,finaltestX)
```

In [94]:
```
resulttable <- as.data.frame(itemID)
resulttable$Outlet_Identifier <- test$Outlet_Identifier
resulttable$Item_Outlet_Sales <- results
write.csv(resulttable,'C:/Datasets/SalesTestPredict.csv')
```