

HOUSING PROPERTY PRICE ESTIMATION IN LONDON

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```
#Loading libraries
suppressMessages(suppressWarnings(library(tidyverse)))
suppressMessages(suppressWarnings(library(ggplot2)))
suppressMessages(suppressWarnings(library(gridExtra)))
suppressMessages(suppressWarnings(library(MASS)))
suppressMessages(suppressWarnings(library(randomForest)))
suppressMessages(suppressWarnings(library("PerformanceAnalytics")))
```

Introduction:

Loading Data:

```
#Loading the data
LondonData <- suppressMessages(suppressWarnings(read_csv("data/DataScienceProj.csv")))
head(LondonData)
```

```
## # A tibble: 6 x 31
##       X1 Easting Northing Purprice BldIntWr BldPostW Bld60s Bld70s Bld80s
##   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1    53  545500   173000   85000     0     0     1     0     0
## 2    73  525000   177800   71000     0     0     0     0     1
## 3    78  531100   183400   60000     0     0     0     0     0
## 4    95  538500   169400   64000     0     0     0     0     1
## 5   125  534000   168400  260000     0     0     0     0     1
## 6   153  528700   168800   48500     0     0     0     0     0
## # ... with 22 more variables: TypDetch <dbl>, TypSemiD <dbl>, TypFlat <dbl>,
## #   GarSingl <dbl>, GarDoubl <dbl>, Tenfree <dbl>, CenHeat <dbl>,
## #   BathTwo <dbl>, BedTwo <dbl>, BedThree <dbl>, BedFour <dbl>, BedFive <dbl>,
## #   NewPropD <dbl>, FlorArea <dbl>, NoCarHh <dbl>, CarspP <dbl>, ProfPct <dbl>,
## #   UnskPct <dbl>, RetiPct <dbl>, Saleunem <dbl>, Unemploy <dbl>,
## #   PopnDnsy <dbl>
```

```
#Checking for correlation
M <- cor(LondonData[,c(4,23:31)])
head(round(M,2))
```

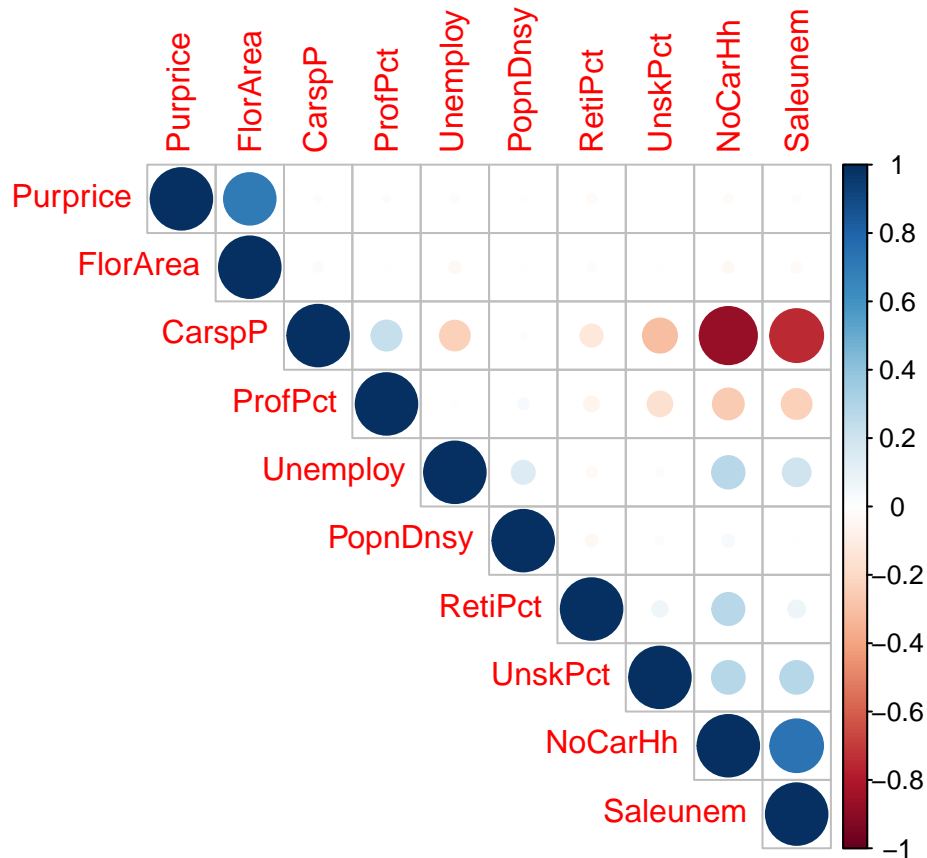
```
##           Purprice FlorArea NoCarHh CarspP ProfPct UnskPct RetiPct Saleunem
## Purprice      1.00      0.70   -0.02   0.01   0.01   0.00   -0.02   -0.01
## FlorArea      0.70      1.00   -0.03   0.02   0.00   0.01   -0.02   -0.03
## NoCarHh     -0.02     -0.03    1.00  -0.86  -0.25   0.28   0.27    0.73
## CarspP       0.01      0.02  -0.86    1.00   0.24  -0.31  -0.13   -0.74
## ProfPct      0.01      0.00  -0.25   0.24    1.00  -0.16  -0.06   -0.24
```

```
## UnskPct      0.00      0.01      0.28 -0.31 -0.16      1.00      0.06      0.28
##              Unemploy PopnDnsy
## Purprice     -0.02      0.01
## FlorArea     -0.04      0.00
## NoCarHh       0.28      0.04
## CarspP       -0.23     -0.01
## ProfPct       0.01      0.03
## UnskPct       0.02     -0.02
```

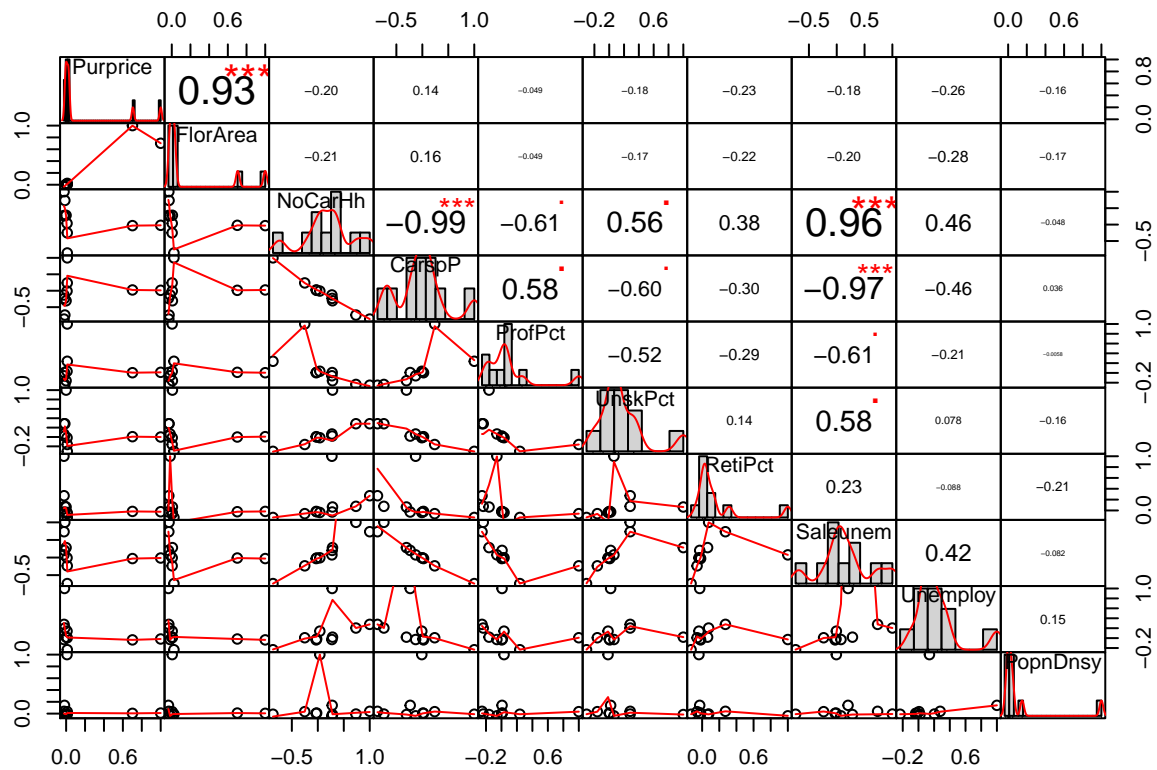
```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

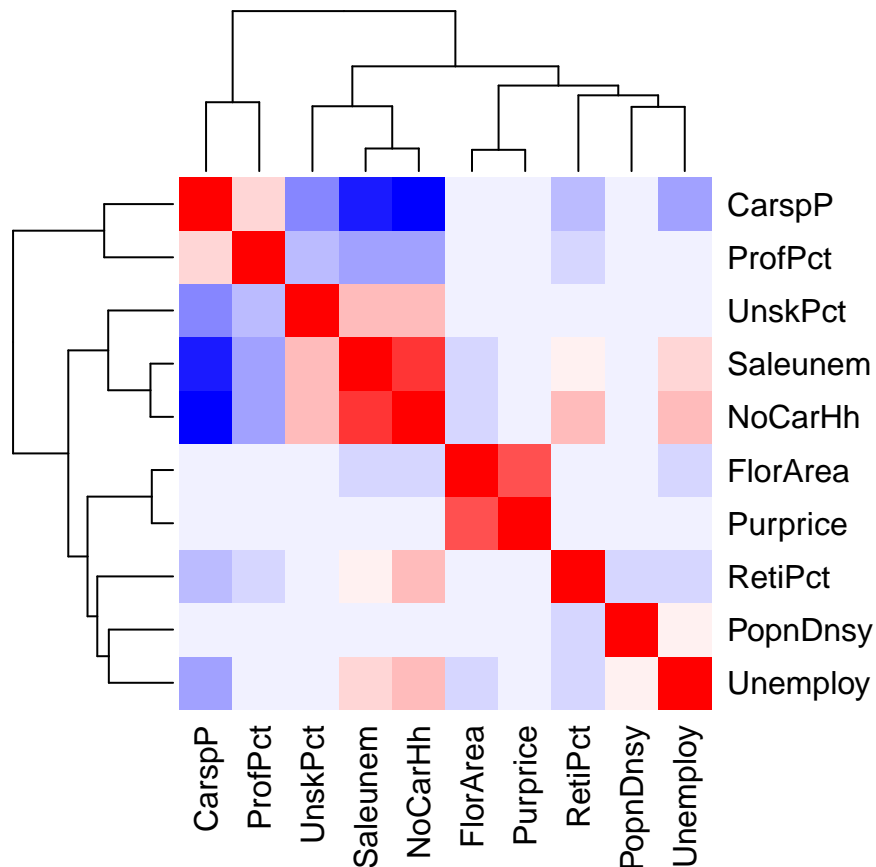
```
corrplot(M, method="circle", type = "upper", order="hclust", sig.level = 0.01)
```



```
chart.Correlation(M, histogram=TRUE, pch=19)
```



```
col<- colorRampPalette(c("blue", "white", "red"))(20)
heatmap(x = M, col = col, symm = TRUE)
```



Data Cleanup:

Convert dummies to factors

```
Dummy2Factor <- function(mat,lev1="Level1") {  
  mat <- as.matrix(mat)  
  factor((mat %*% (1:ncol(mat))) + 1,  
    labels = c(lev1, colnames(mat)))  
}  
  
Age      <- Dummy2Factor(LondonData[,5:9], "PreWW1")  
Type     <- Dummy2Factor(LondonData[,10:12], "Others")  
Garage   <- Dummy2Factor(LondonData[,13:14], "HardStnd")  
Bedrooms <- Dummy2Factor(LondonData[,18:21], "BedOne")  
  
MyData <- data.frame(LondonData[,c(2:4,15:17,22,23,26)], Age, Type, Garage, Bedrooms)  
summary(MyData)
```

```
##      Easting      Northing      Purprice      Tenfree  
## Min.   :504400   Min.   :157200   Min.    : 8500   Min.    :0.0000  
## 1st Qu.:517800   1st Qu.:172700   1st Qu.: 55000   1st Qu.:0.0000  
## Median :527600   Median :181200   Median : 70000   Median :1.0000  
## Mean   :527926   Mean   :180009   Mean    : 80018   Mean    :0.6835  
## 3rd Qu.:536700   3rd Qu.:187400   3rd Qu.: 90000   3rd Qu.:1.0000  
## Max.   :558000   Max.   :200100   Max.    :850000   Max.    :1.0000  
##      CenHeat      BathTwo      NewPropD      FlorArea  
## Min.   :0.0000   Min.   :0.00000   Min.    :0.00000   Min.    : 23.22  
## 1st Qu.:1.0000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.: 71.77  
## Median :1.0000   Median :0.00000   Median :0.00000   Median : 91.02  
## Mean   :0.8789   Mean   :0.05392   Mean    :0.03638   Mean    : 96.49  
## 3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:112.11  
## Max.   :1.0000   Max.   :1.00000   Max.    :1.00000   Max.    :278.00  
##      ProfPct      Age      Type      Garage  
## Min.    : 0.000   PreWW1 :4261   Others :3791   HardStnd:8306  
## 1st Qu.: 0.000   BldIntWr:4365   TypDetch:1168   GarSingl:3923  
## Median : 5.556   BldPostW:1054   TypSemiD:3260   GarDoubl: 307  
## Mean    : 7.640   Bld60s  : 789   TypFlat :4317  
## 3rd Qu.:12.500   Bld70s  : 679  
## Max.    :100.000   Bld80s  :1388  
##      Bedrooms  
## BedOne  :1713  
## BedTwo  :3785  
## BedThree:5723  
## BedFour :1100  
## BedFive : 215  
##
```

```
MyData$Tenfree <- factor(MyData$Tenfree)  
MyData$CenHeat <- factor(MyData$CenHeat)  
MyData$BathTwo <- factor(MyData$BathTwo)  
MyData$NewPropD <- factor(MyData$NewPropD)
```

```
levels(MyData$Tenfree) <- c("no", "yes")  
levels(MyData$CenHeat) <- c("no", "yes")
```

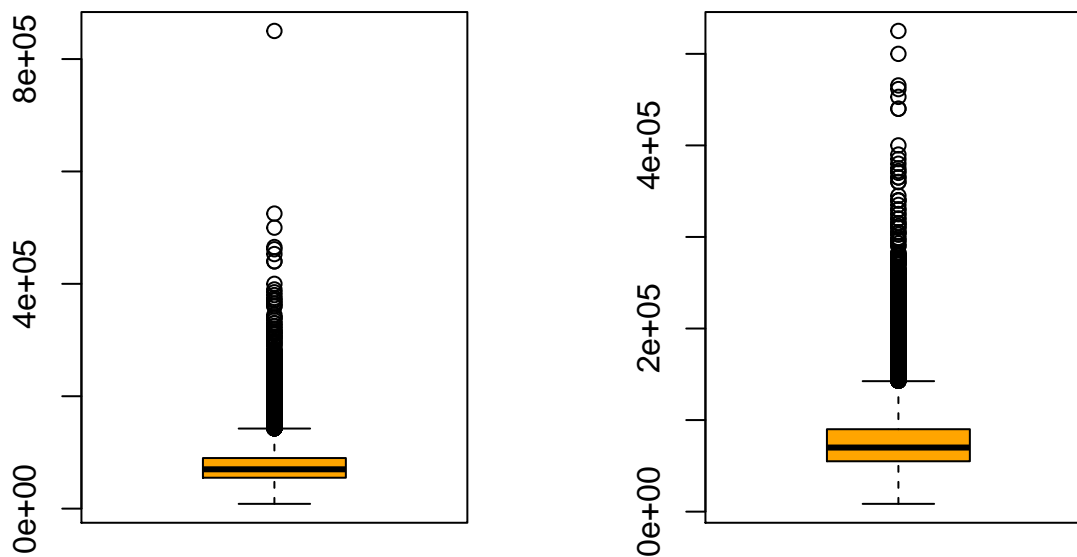
```
levels(MyData$BathTwo) <- c("no", "yes")
levels(MyData$NewPropD) <- c("no", "yes")
```

```
head(MyData)
```

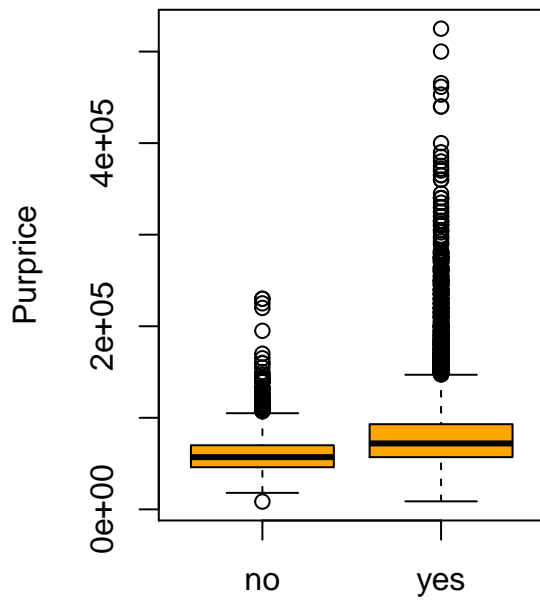
```
##   Easting Northing Purprice Tenfree CenHeat BathTwo NewPropD FlorArea ProfPct
## 1  545500  173000   85000    yes    yes    no      no   76.16146  0.0000
## 2  525000  177800   71000    yes    yes    no      no   98.45262  6.2500
## 3  531100  183400   60000    yes    yes    yes     no  124.73761  0.0000
## 4  538500  169400   64000    yes    yes    no      yes  127.00000  0.0000
## 5  534000  168400  260000    yes    yes    yes     no  190.40366  9.0909
## 6  528700  168800   48500    yes    yes    no      no   87.00000 16.6667
##      Age      Type  Garage Bedrooms
## 1 Bld60s TypDetch GarSingl BedThree
## 2 Bld80s TypDetch GarSingl BedThree
## 3 PreWW1 TypSemiD HardStnd  BedFour
## 4 Bld80s TypDetch GarSingl BedThree
## 5 Bld80s TypDetch GarDoubl  BedFour
## 6 PreWW1 TypFlat  HardStnd BedThree
```

Remove Outliers:

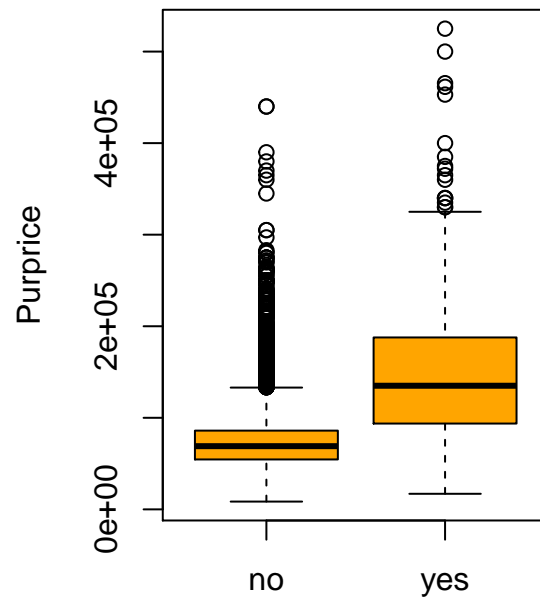
```
par(mfrow= c(1,2))
boxplot(MyData$Purprice, col = 'orange')
# From boxplot we can see that purprice greater then 600000 is an outlier so we will remove that
MyData <- MyData[MyData$Purprice<600000,]
boxplot(MyData$Purprice, col = 'orange')
```



```
boxplot(Purprice~CenHeat,data=MyData, col = 'orange')
boxplot(Purprice~BathTwo,data=MyData, col = 'orange')
```

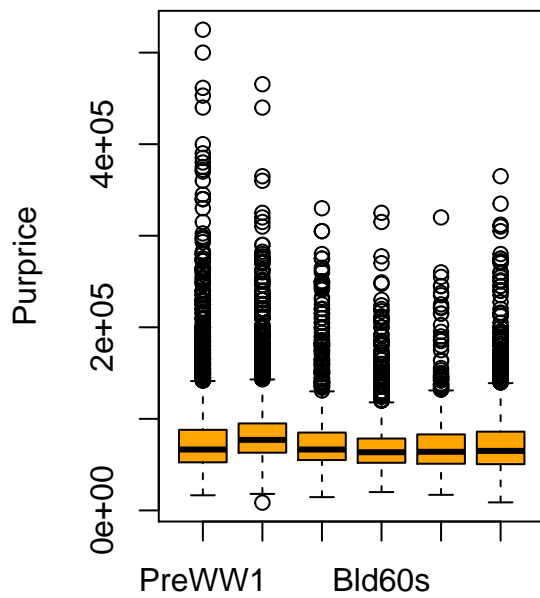


CenHeat

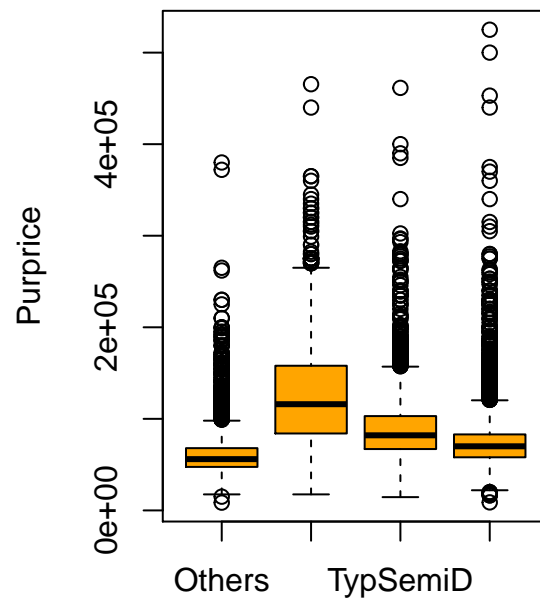


BathTwo

```
boxplot(Purprice~Age,data=MyData, col = 'orange')
boxplot(Purprice~Type,data=MyData, col = 'orange')
```

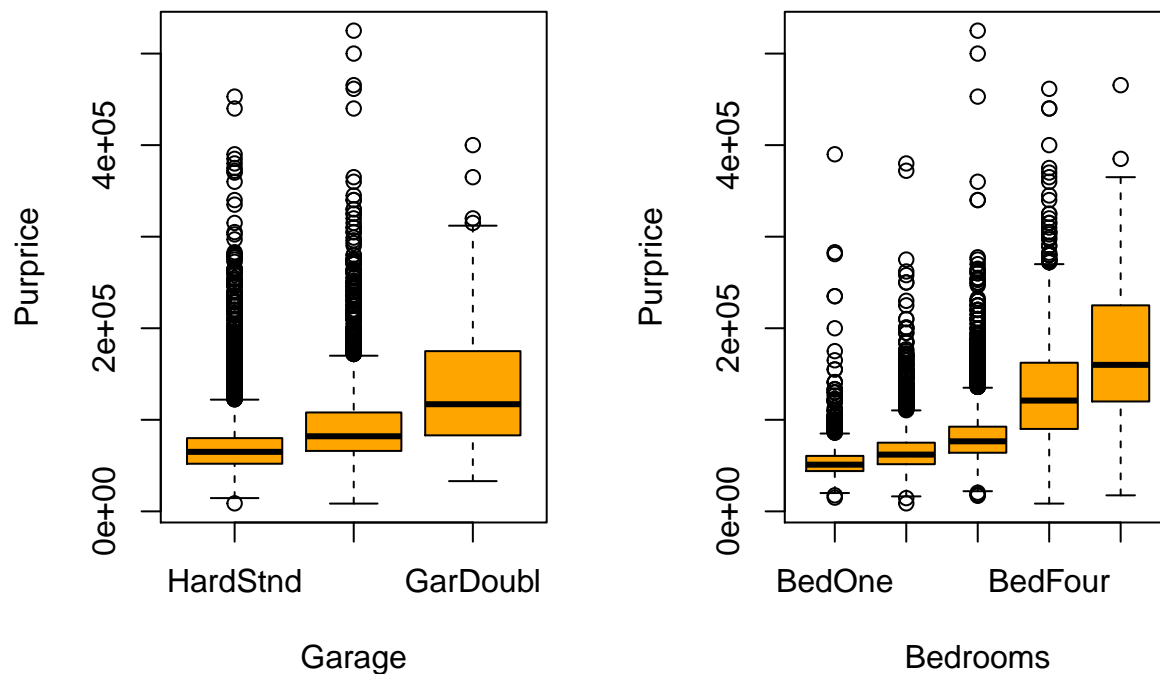


Age



Type

```
boxplot(Purprice~Garage,data=MyData, col = 'orange')
boxplot(Purprice~Bedrooms,data=MyData, col = 'orange')
```



```
par(mfrow= c(1,1))
```

Exploratory Analysis:

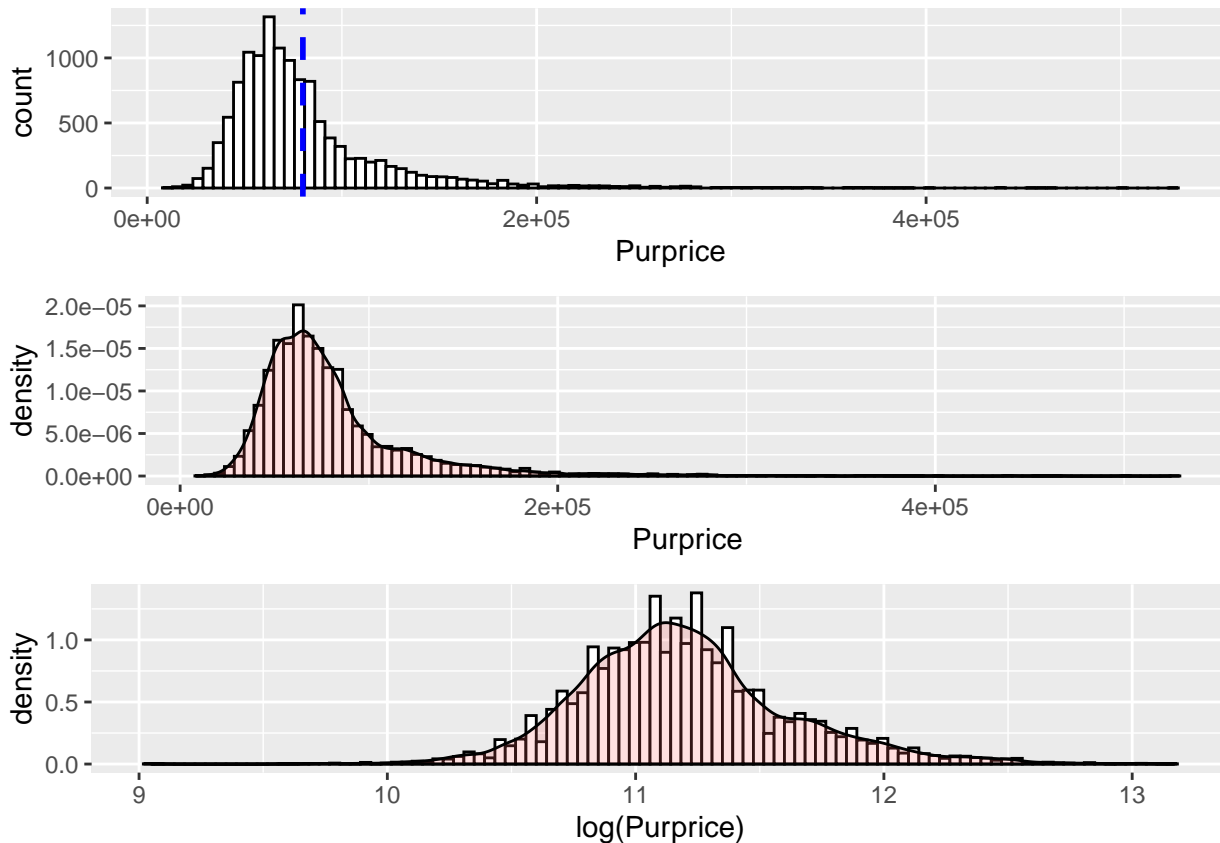
Checking for price:

```
p1 <- ggplot(MyData, aes(x=Purprice)) + geom_histogram(bins = 100, color="black", fill="white")+
  geom_vline(aes(xintercept=mean(Purprice)),
    color="blue", linetype="dashed", size=1)

p2 <- ggplot(MyData, aes(x=Purprice)) +
  geom_histogram(bins = 100, aes(y=..density..), colour="black", fill="white")+
  geom_density(alpha=.2, fill="#FF6666")

p3 <- ggplot(MyData, aes(x=log(Purprice))) +
  geom_histogram(bins = 100, aes(y=..density..), colour="black", fill="white")+
  geom_density(alpha=.2, fill="#FF6666")

grid.arrange(p1, p2, p3, nrow=3)
```



From the plots we can see that it is skewed towards the left so we can say that to make it a normal distribution we have to apply some transformation. After applying log transformation on purprice we see that purprice is normally distributed.

```
p4 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$CenHeat)) +
  geom_histogram(bins = 50, fill= "white", alpha=0.5, position="identity")+
  theme(legend.position = "top")

p5 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$CenHeat)) +
  geom_freqpoly()+
  theme(legend.position = "top")

p6 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$Tenfree)) +
  geom_freqpoly()+
  theme(legend.position = "top")

p7 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$NewPropD)) +
  geom_freqpoly()+
  theme(legend.position = "top")

p8 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$Age)) +
  geom_freqpoly()+
  theme(legend.position = "top")

p9 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$Type)) +
  geom_freqpoly()+
  theme(legend.position = "top")
```



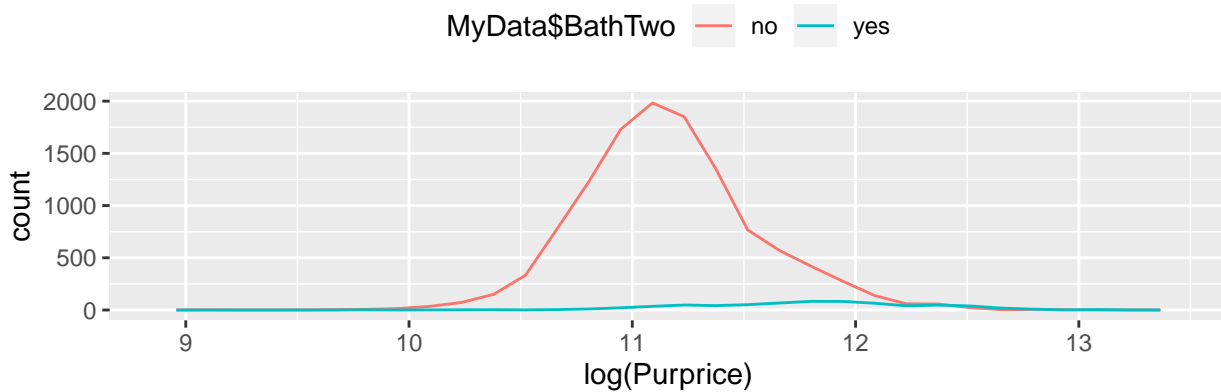
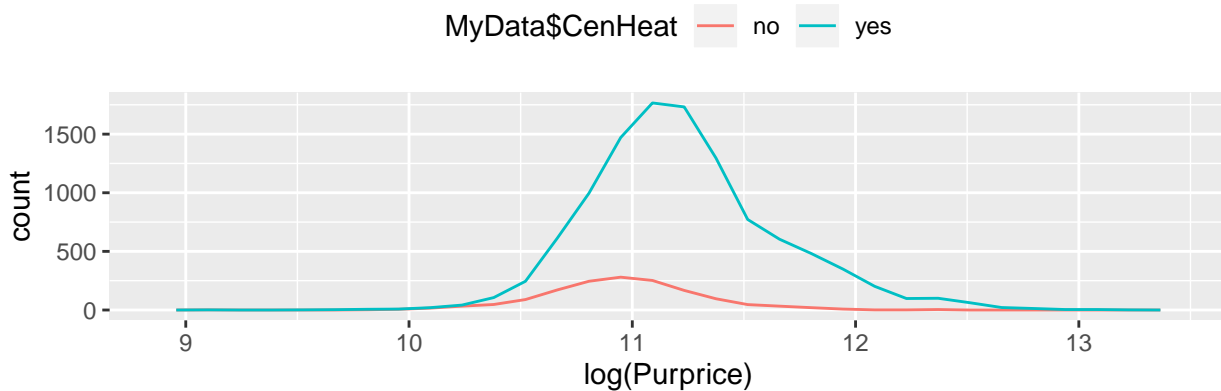
```
p10 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$Garage)) +
  geom_freqpoly()+
  theme(legend.position = "top")

p11 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$Bedrooms)) +
  geom_freqpoly()+
  theme(legend.position = "top")

p12 <- ggplot(MyData, aes(x=log(Purprice), color=MyData$BathTwo)) +
  geom_freqpoly()+
  theme(legend.position = "top")

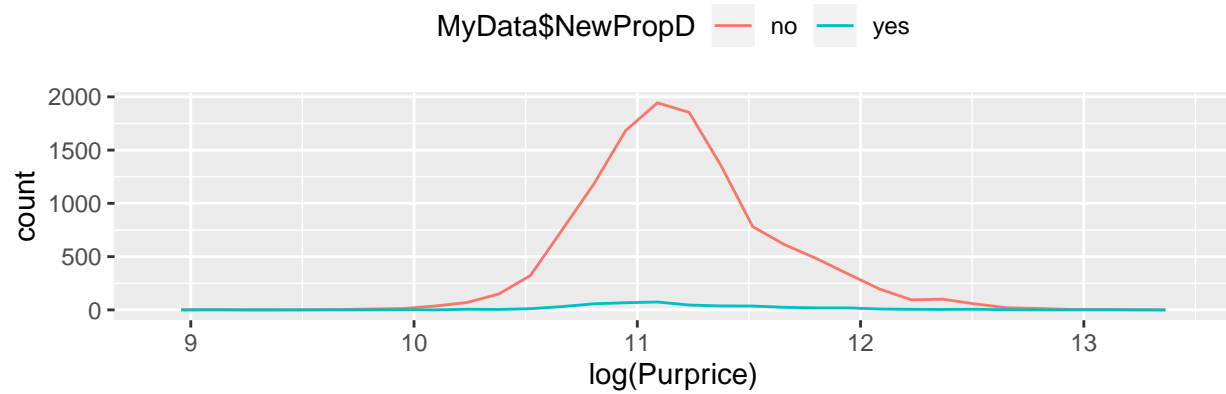
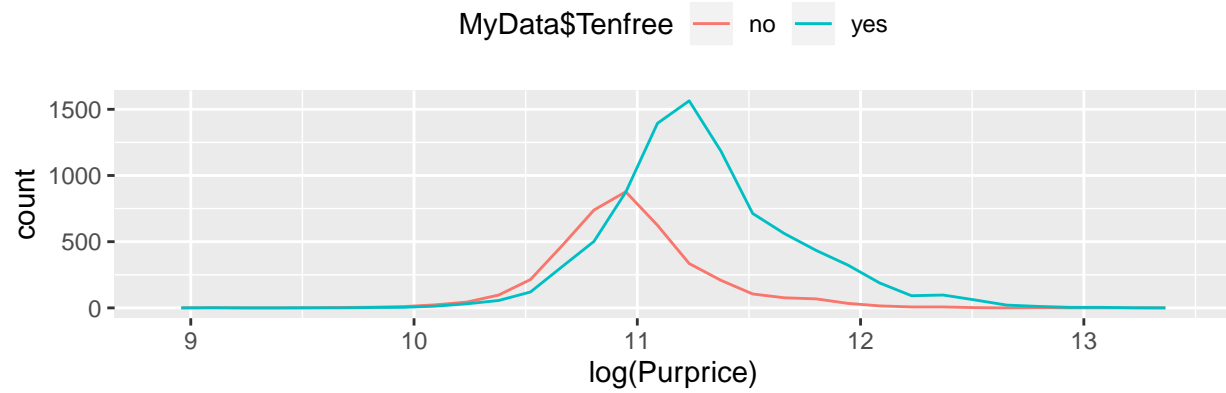
grid.arrange(p5, p12, nrow=2)
```

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



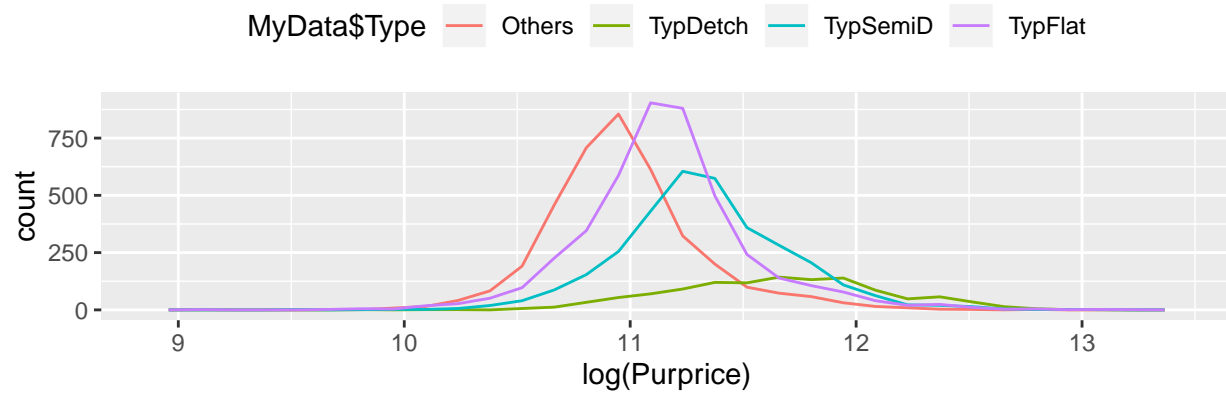
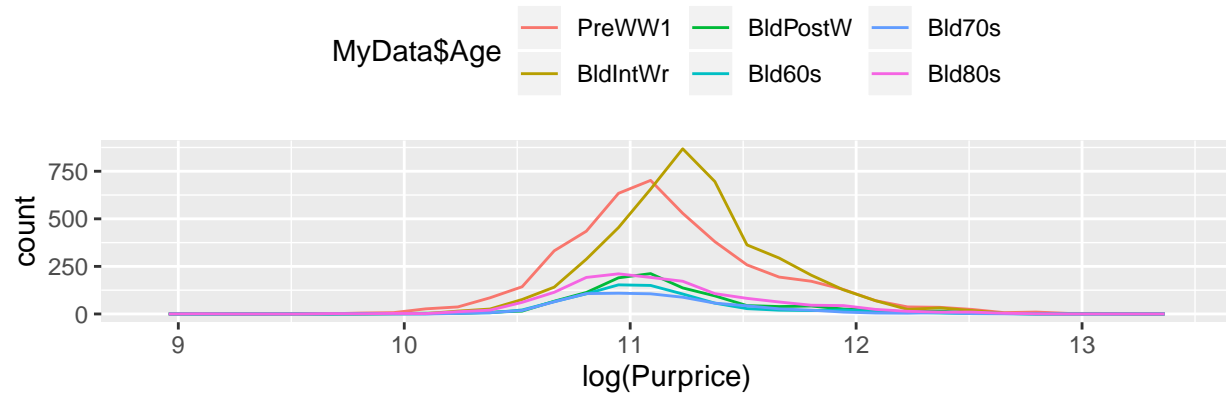
```
grid.arrange(p6, p7, nrow=2)
```

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



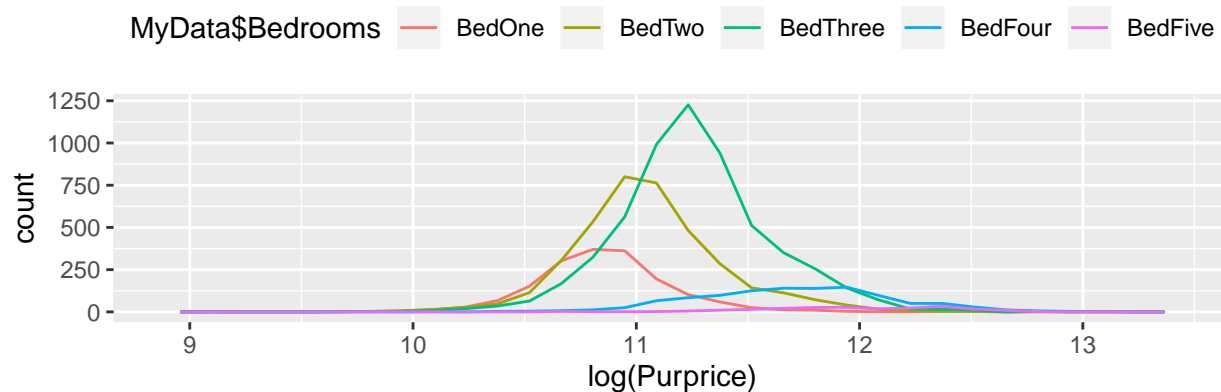
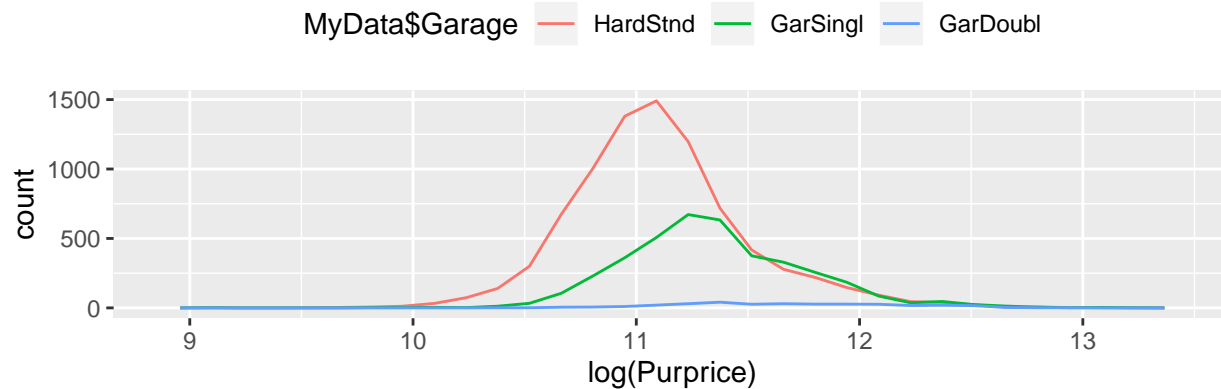
```
grid.arrange(p8, p9, nrow=2)
```

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



```
grid.arrange(p10, p11, nrow=2)
```

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



```
ld_model <- lm(Purprice~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+Bedrooms, data=MyData)
step <- stepAIC(ld_model, direction="both")
```

```
## Start: AIC=255965.1
## Purprice ~ Tenfree + CenHeat + BathTwo + NewPropD + FlorArea +
## ProfPct + Age + Type + Garage + Bedrooms
##
##           Df Sum of Sq      RSS      AIC
## - NewPropD  1 1.1105e+09 9.2263e+12 255965
## <none>                                9.2252e+12 255965
## - ProfPct   1 2.6037e+09 9.2278e+12 255967
## - Tenfree   1 1.5377e+10 9.2406e+12 255984
## - Garage    2 4.1633e+10 9.2669e+12 256018
## - Bedrooms  4 8.6698e+10 9.3119e+12 256074
## - Age       5 1.3264e+11 9.3579e+12 256134
## - CenHeat   1 1.8185e+11 9.4071e+12 256208
## - Type      3 2.4028e+11 9.4655e+12 256281
## - BathTwo   1 2.9356e+11 9.5188e+12 256356
## - FlorArea  1 2.6197e+12 1.1845e+13 259096
##
## Step: AIC=255964.6
## Purprice ~ Tenfree + CenHeat + BathTwo + FlorArea + ProfPct +
## Age + Type + Garage + Bedrooms
##
##           Df Sum of Sq      RSS      AIC
## <none>                                9.2263e+12 255965
## + NewPropD  1 1.1105e+09 9.2252e+12 255965
## - ProfPct   1 2.6641e+09 9.2290e+12 255966
```

```
## - Tenfree    1 1.5170e+10 9.2415e+12 255983
## - Garage     2 4.1396e+10 9.2677e+12 256017
## - Bedrooms   4 8.6713e+10 9.3131e+12 256074
## - Age        5 1.3364e+11 9.3600e+12 256135
## - CenHeat    1 1.8197e+11 9.4083e+12 256207
## - Type       3 2.4081e+11 9.4671e+12 256282
## - BathTwo    1 2.9504e+11 9.5214e+12 256357
## - FlorArea   1 2.6199e+12 1.1846e+13 259096
```

```
step$anova
```

```
## Stepwise Model Path
## Analysis of Deviance Table
##
## Initial Model:
## Purprice ~ Tenfree + CenHeat + BathTwo + NewPropD + FlorArea +
##   ProfPct + Age + Type + Garage + Bedrooms
##
## Final Model:
## Purprice ~ Tenfree + CenHeat + BathTwo + FlorArea + ProfPct +
##   Age + Type + Garage + Bedrooms
##
##
##           Step Df   Deviance Resid. Df   Resid. Dev       AIC
## 1                                12514 9.225229e+12 255965.1
## 2 - NewPropD  1 1110546555      12515 9.226339e+12 255964.6
```

```
library(leaps)
```

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

```
sample <- sample(c(TRUE, FALSE), nrow(MyData), replace = T, prob = c(0.6,0.4))
train <- MyData[sample, ]
test <- MyData[!sample, ]
```

```
#Best subsets plots for Purprice and log(Purprice)
```

```
# ld_orgnl <- regsubsets(Purprice~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+Bed
```

```
# ld_model <- regsubsets(log(Purprice)~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garag
```

```
# results <- summary(ld_model)
```

```
# plot(ld_orgnl,scale="adjr2")
```

```
# title(main= "Best subsets plot for Purprice")
```

```
# plot(ld_model,scale="adjr2")
```

```
# title(main= "Best subsets plot for Log Purprice")
```

```
#
```

```
# # extract and plot results
```

```
# tibble(predictors = 1:10,
```

```
#   adj_R2 = results$adjr2,
```

```
#   Cp = results$cp,
```

```
#   BIC = results$bic) %>%
```

```
#   gather(statistic, value, ~predictors) %>%
```

```
#   ggplot(aes(predictors, value, color = statistic)) +
```

```
#   geom_line(show.legend = F) +
```

```
#   geom_point(show.legend = F) +
```

```
#   facet_wrap(~ statistic, scales = "free")
```

```
#
```

```
# which.max(results$adjr2)
```

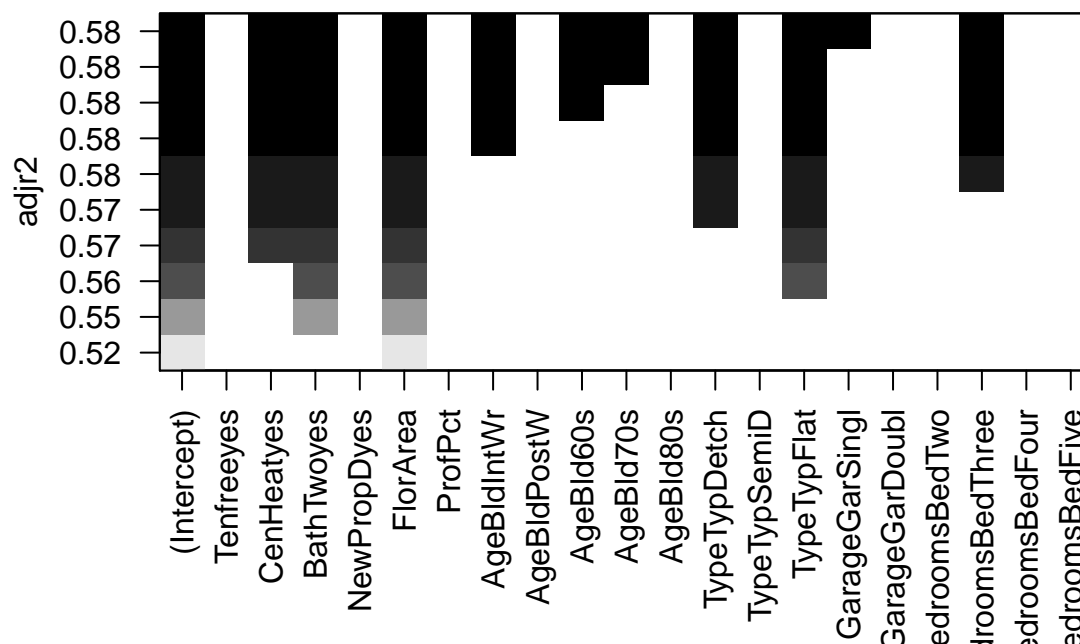
```

# which.min(results$bic)
# which.min(results$cp)

#Best subsets with Forward selection
ld_orgnl_frwd <- regsubsets(Purprice~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+
ld_frwd <- regsubsets(log(Purprice)~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+B
results <- summary(ld_orgnl_frwd)
# results <- summary(ld_frwd)
plot(ld_orgnl_frwd,scale="adjr2")
title(main= "Best subsets Forward selection plot for Purprice")

```

Best subsets Forward selection plot for Purprice

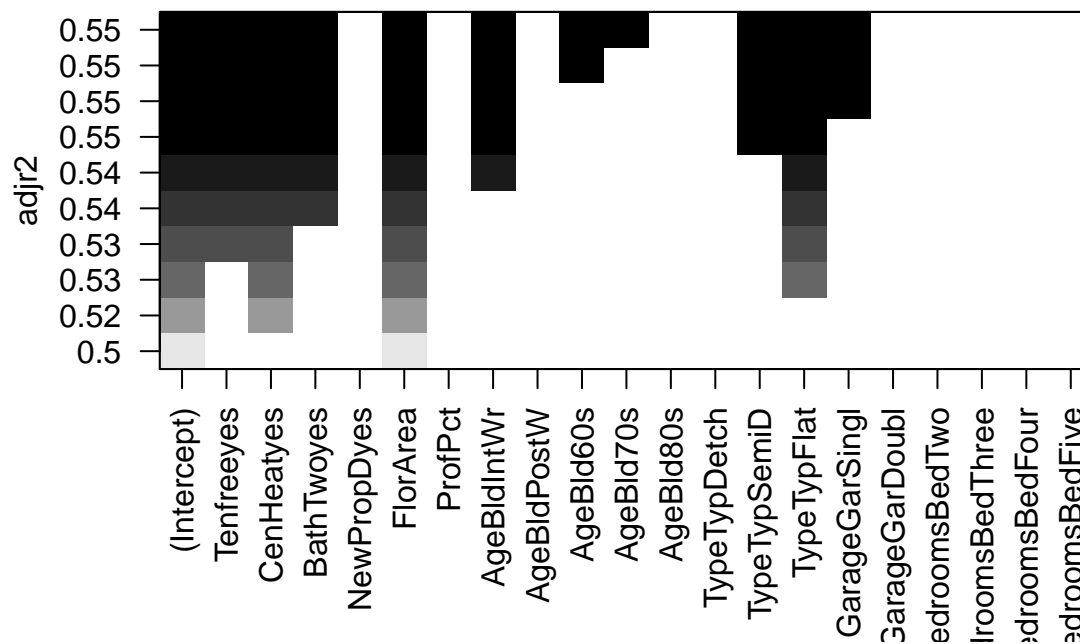


```

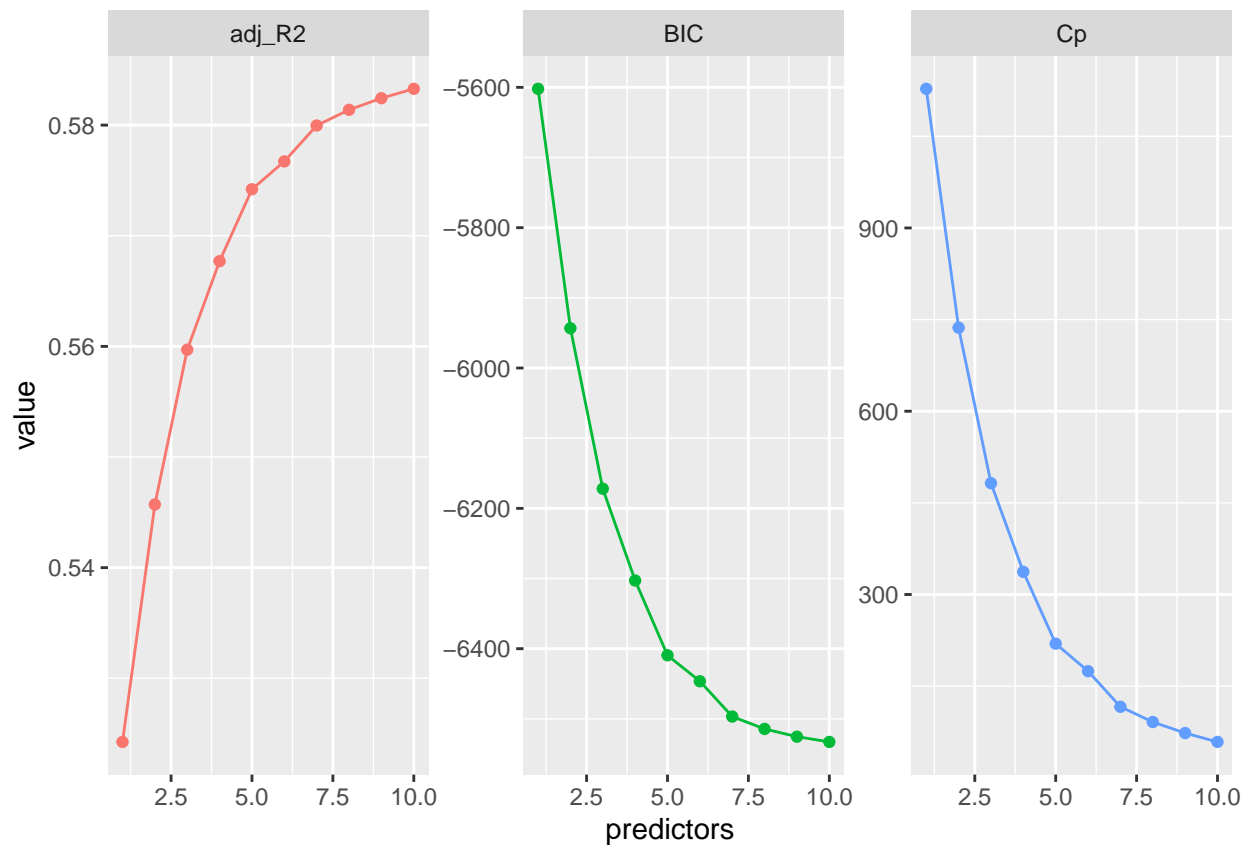
plot(ld_frwd,scale="adjr2")
title(main= "Best subsets Forward selection plot for Log Purprice")

```

Best subsets Forward selection plot for Log Purprice



```
tibble(predictors = 1:10,
  adj_R2 = results$adjr2,
  Cp = results$cp,
  BIC = results$bic) %>%
  gather(statistic, value, -predictors) %>%
  ggplot(aes(predictors, value, color = statistic)) +
  geom_line(show.legend = F) +
  geom_point(show.legend = F) +
  facet_wrap(~ statistic, scales = "free")
```



```
which.min(results$cp)
```

```
## [1] 10
```

```
#Best subsets with Backward selection
```

```
ld_orgnl_bkwd <- regsubsets(Purprice~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+...
```

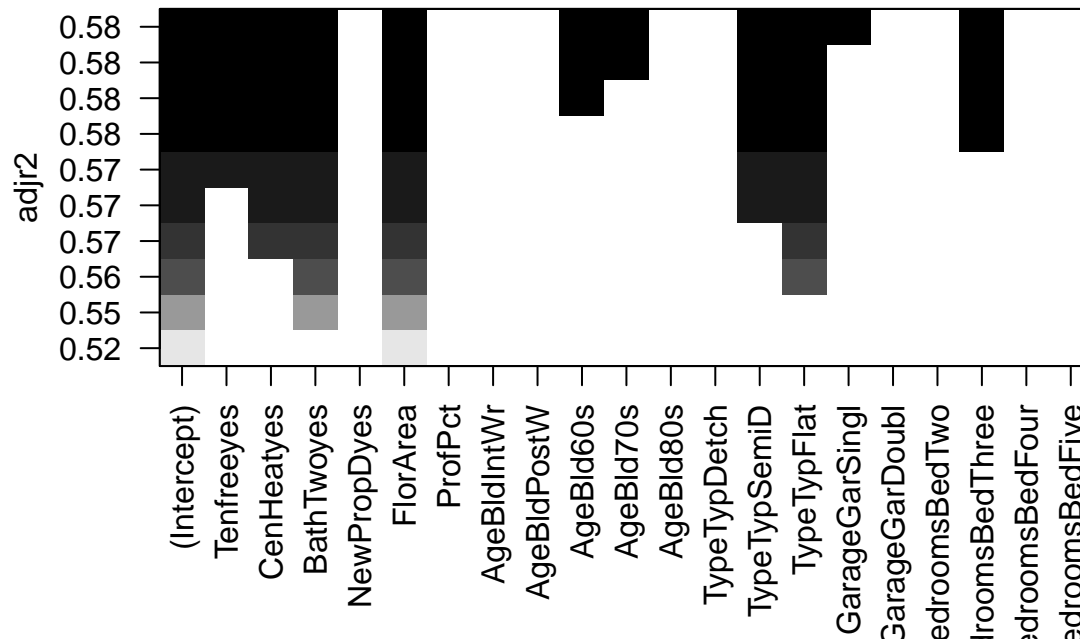
```
ld_bkwd <- regsubsets(log(Purprice)~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+...
```

```
results <- summary(ld_bkwd)
```

```
plot(ld_orgnl_bkwd,scale="adjr2")
```

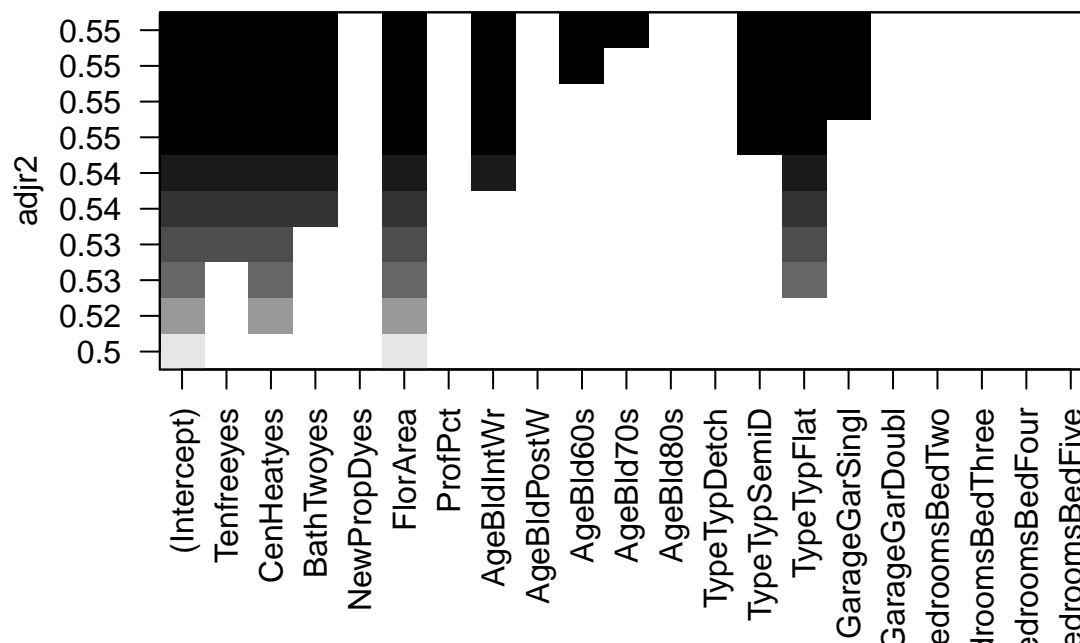
```
title(main= "Best subsets Backward selection plot for Purprice")
```


Best subsets Backward selection plot for Purprice



```
plot(ld_bkwd,scale="adjr2")
title(main= "Best subsets Backward selection plot for Log Purprice")
```

Best subsets Backward selection plot for Log Purprice

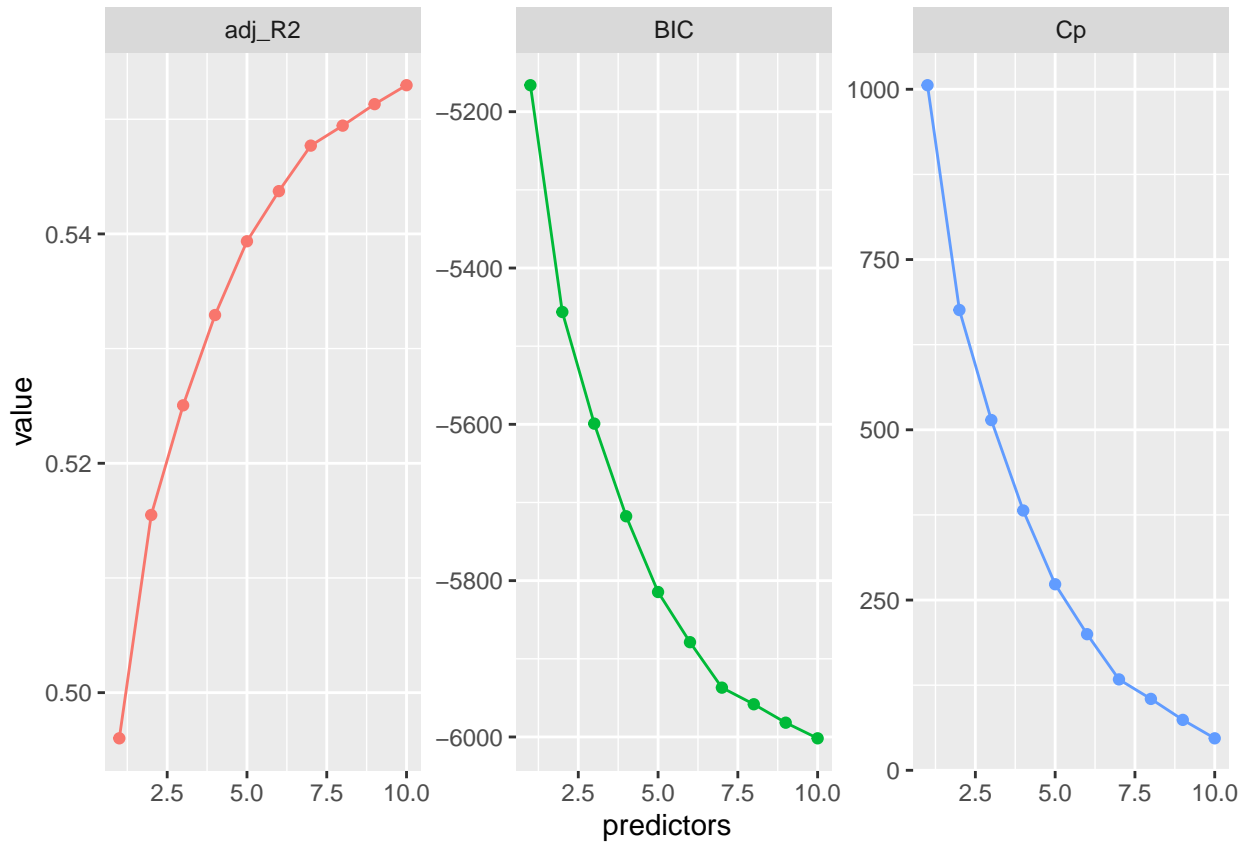


```
tibble(predictors = 1:10,
  adj_R2 = results$adjr2,
```

```

Cp = results$cp,
BIC = results$bic) %>%
gather(statistic, value, -predictors) %>%
ggplot(aes(predictors, value, color = statistic)) +
geom_line(show.legend = F) +
geom_point(show.legend = F) +
facet_wrap(~ statistic, scales = "free")

```



```
which.min(results$cp)
```

```
## [1] 10
```

```
#Plotting using models and required number of variables
```

```
coef(ld_model,10)
```

```
##      (Intercept)      Tenfreeeyes      CenHeatyes      BathTwoyes
##      6184.99958      6176.19785      11851.02315      24006.96253
##      NewPropDyes      FlorArea      ProfPct      AgeBldIntWr
##      1896.22846      677.99715      44.83954      4045.76814
##      AgeBldPostW      AgeBld60s      AgeBld70s      AgeBld80s
##      -1136.56704      -7346.42319      -6725.04819      307.19266
##      TypeTypDetch      TypeTypSemiD      TypeTypFlat      GarageGarSingl
##      5660.72489      -6701.98958      -11590.32066      3797.91709
##      GarageGarDoubl      BedroomsBedTwo      BedroomsBedThree      BedroomsBedFour
##      9288.54166      -3432.11465      -7874.67308      -1767.50740
##      BedroomsBedFive
##      3948.63829
```

```
coef(ld_frwd,10)
```

```
##      (Intercept)      Tenfreeyes      CenHeatyes      BathTwoyes      FlorArea
##  10.345570773      0.141601889      0.172871907      0.163571806      0.006712639
##      AgeBldIntWr      AgeBld60s      AgeBld70s      TypeTypSemiD      TypeTypFlat
##      0.050166334     -0.090246092     -0.079859427     -0.096002370     -0.171086108
## GarageGarSingl
##      0.054988865
```

```
coef(ld_bkwd,10)
```

```
##      (Intercept)      Tenfreeyes      CenHeatyes      BathTwoyes      FlorArea
##  10.345570773      0.141601889      0.172871907      0.163571806      0.006712639
##      AgeBldIntWr      AgeBld60s      AgeBld70s      TypeTypSemiD      TypeTypFlat
##      0.050166334     -0.090246092     -0.079859427     -0.096002370     -0.171086108
## GarageGarSingl
##      0.054988865
```

```
#Cross Validation with test data
```

```
test_m <- model.matrix(log(Purprice) ~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage
```

```
validation_errors <- vector("double", length = 10)
```

```
val_error <- function(myModel){
```

```
for(i in 1:10) {
```

```
  coef_x <- coef(myModel, id = i) # extract coefficients for model size i
```

```
  pred_x <- test_m[, names(coef_x)] %*% coef_x # predict salary using matrix algebra
```

```
  validation_errors[i] <- mean((test$Purprice - pred_x)^2) # compute test error btwn actual & predicted
```

```
}
```

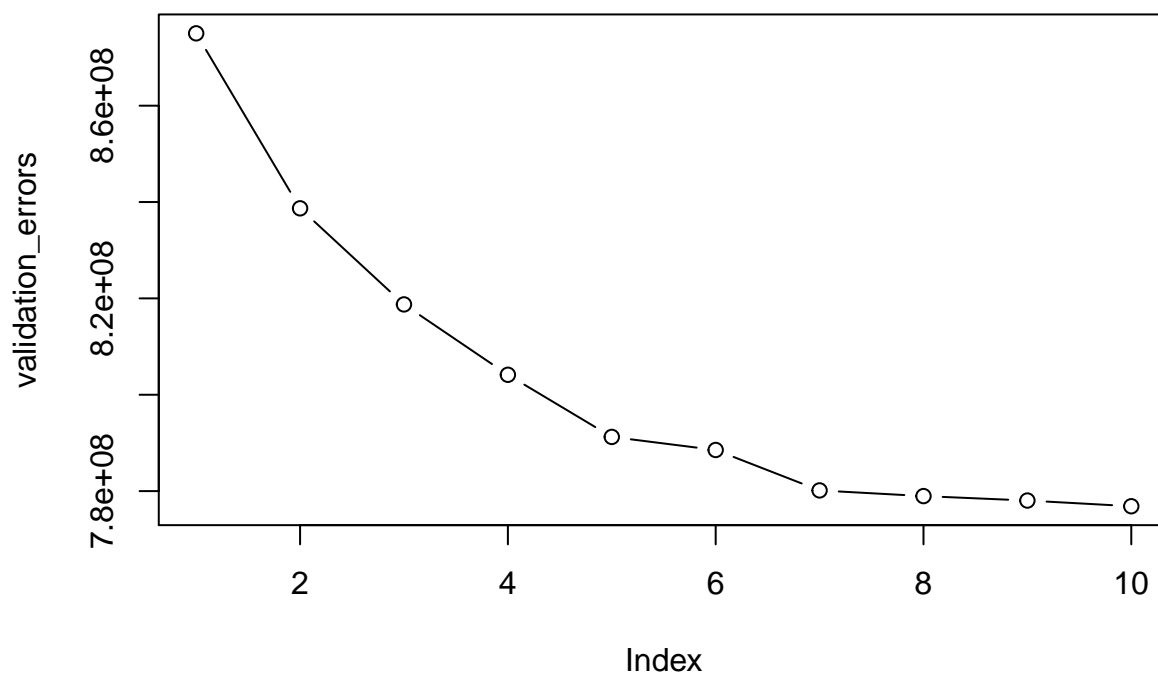
```
plot(validation_errors, type = "b")
```

```
}
```

```
val_error(myModel = ld_orgnl_frwd)
```

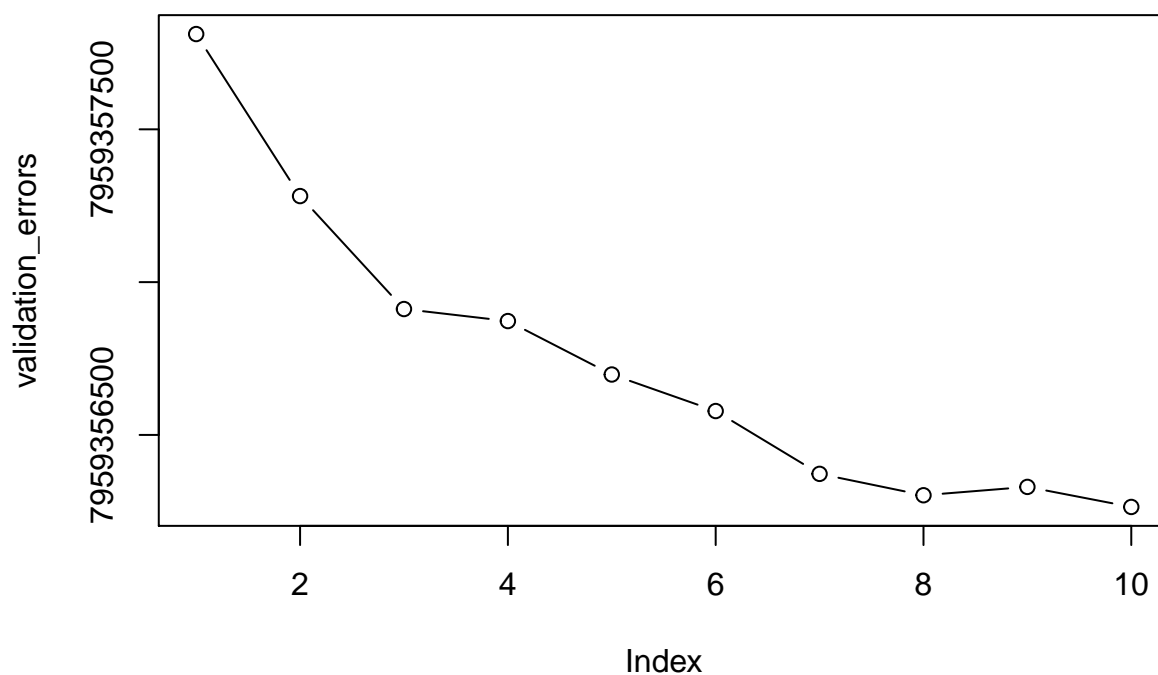
```
title(main = "CV plot for Purprice forward best subset selection")
```

CV plot for Purprice forward best subset selection



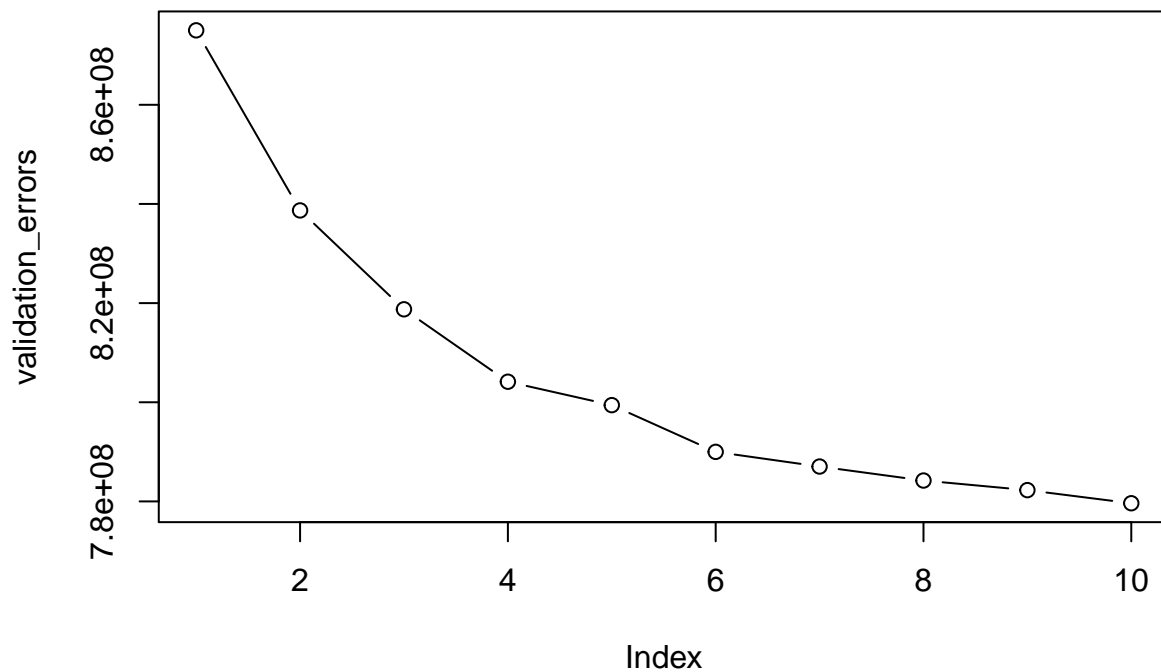
```
val_error(myModel = ld_frwd)
title(main = "CV plot for Log Purprice forward best subset selection")
```

CV plot for Log Purprice forward best subset selection



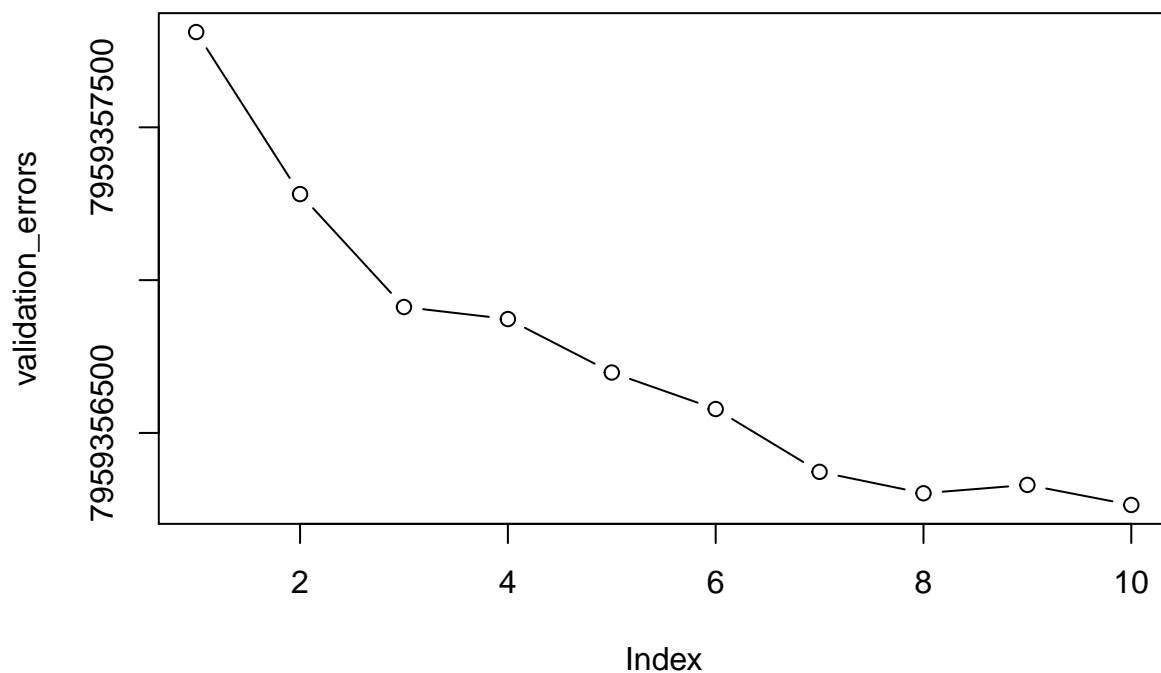
```
val_error(myModel = ld_orgnl_bkwd)
title(main = "CV plot for Purprice backward best subset selection")
```

CV plot for Purprice backward best subset selection



```
val_error(myModel = ld_bkwd)
title(main = "CV plot for Log Purprice backward best subset selection")
```

CV plot for Log Purprice backward best subset selection



```
# ld_model <- lm(Purprice~FlorArea+BathTwo+CenHeat+Type,data = MyData)
# # ld_model <- lm(Purprice~FlorArea+BathTwo+CenHeat+Type+Easting+Bedrooms+Age,data = MyData)
# summary(ld_model)
```

```

predict.regsbsets <- function(object, newdata, id ,...) {
  form <- as.formula(object$call[[2]])
  mat <- model.matrix(form, newdata)
  coefi <- coef(object, id = id)
  xvars <- names(coefi)
  mat[, xvars] %*% coefi
}

k <- 10
set.seed(1)
folds <- sample(1:k, nrow(MyData), replace = TRUE)
cv_errors <- matrix(NA, k, 15, dimnames = list(NULL, paste(1:15)))

for(j in 1:k) {

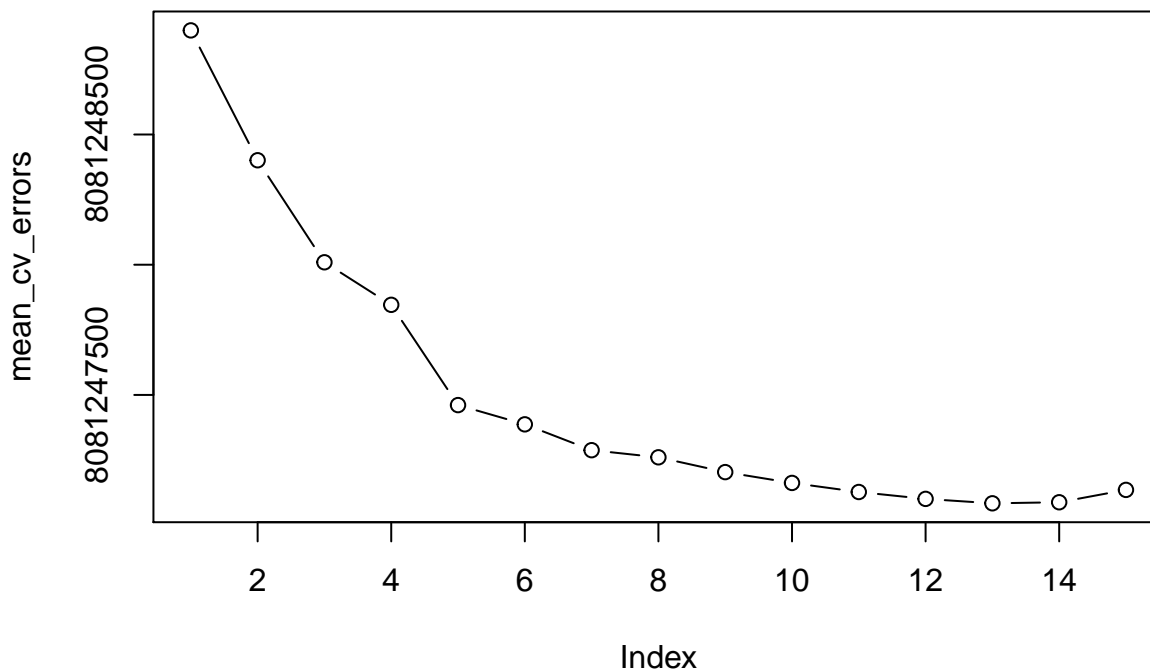
  # perform best subset on rows not equal to j
  ld_model <- regsubsets(log(Purprice) ~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage,
                        data=MyData,
                        nbest=15,
                        method="cv",
                        folds=folds,
                        id=j)

  # perform cross-validation
  for( i in 1:15) {
    pred_x <- predict.regsbsets(ld_model, MyData[folds == j, ], id = i)
    cv_errors[j, i] <- mean((MyData$Purprice[folds == j] - pred_x)^2)
  }
}

mean_cv_errors <- colMeans(cv_errors)

plot(mean_cv_errors, type = "b")

```



```

final_best <- regsubsets(log(Purprice) ~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage,
                        data=MyData,
                        nbest=15,
                        method="cv",
                        folds=folds,
                        id=j)
coef(final_best, 15)

```

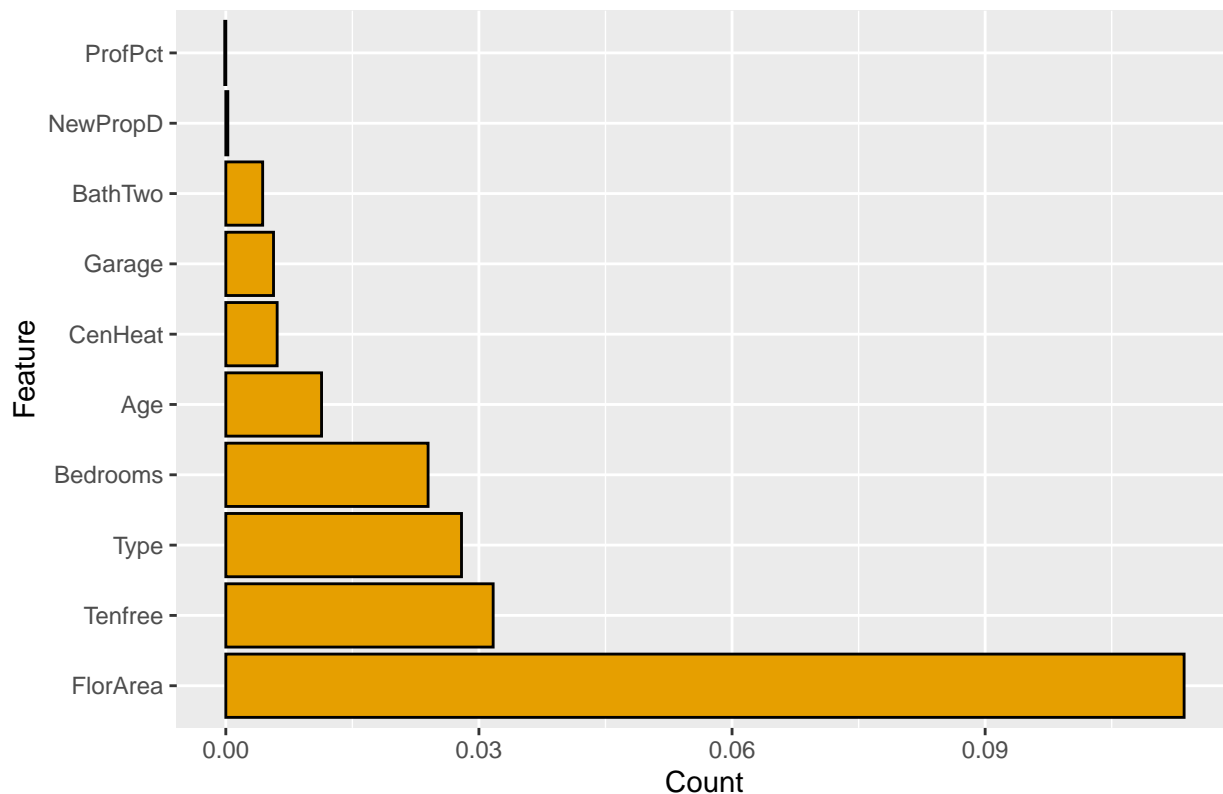
```
##      (Intercept)      Tenfreeyes      CenHeatyes      BathTwoyes
##      10.353520267      0.131989007      0.172189237      0.157698257
##      FlorArea      AgeBldIntWr      AgeBldPostW      AgeBld60s
##      0.006400832      0.046193006      -0.035729546      -0.092546361
##      AgeBld70s      TypeTypSemiD      TypeTypFlat      GarageGarSingl
##      -0.083574547      -0.094678432      -0.168521161      0.060540511
##      GarageGarDoubl      BedroomsBedTwo      BedroomsBedThree      BedroomsBedFour
##      0.084110135      0.033080239      0.031098321      0.065597488
```

```
fit <- randomForest(log(Purprice) ~Tenfree+CenHeat+BathTwo+NewPropD+FlorArea+ProfPct+Age+Type+Garage+Be
                      data = train,importance=TRUE,ntree=60)
```

```
importance.features <- tibble::rownames_to_column(data.frame(fit$importance[,c(1)]))
colnames(importance.features) <- c("rowname", "value")
```

```
ggplot(importance.features, aes(x = reorder(rowname, -value), y = value)) +
  geom_bar(stat = "identity", position = "dodge", fill="#E69F00", colour="black") +
  xlab("Feature") + ylab("Count") + ggtitle("Importance of a feature: Simple Random Forest classifier")
coord_flip()
```

Importance of a feature: Simple Random Forest classifier



```
#printing the final model
```

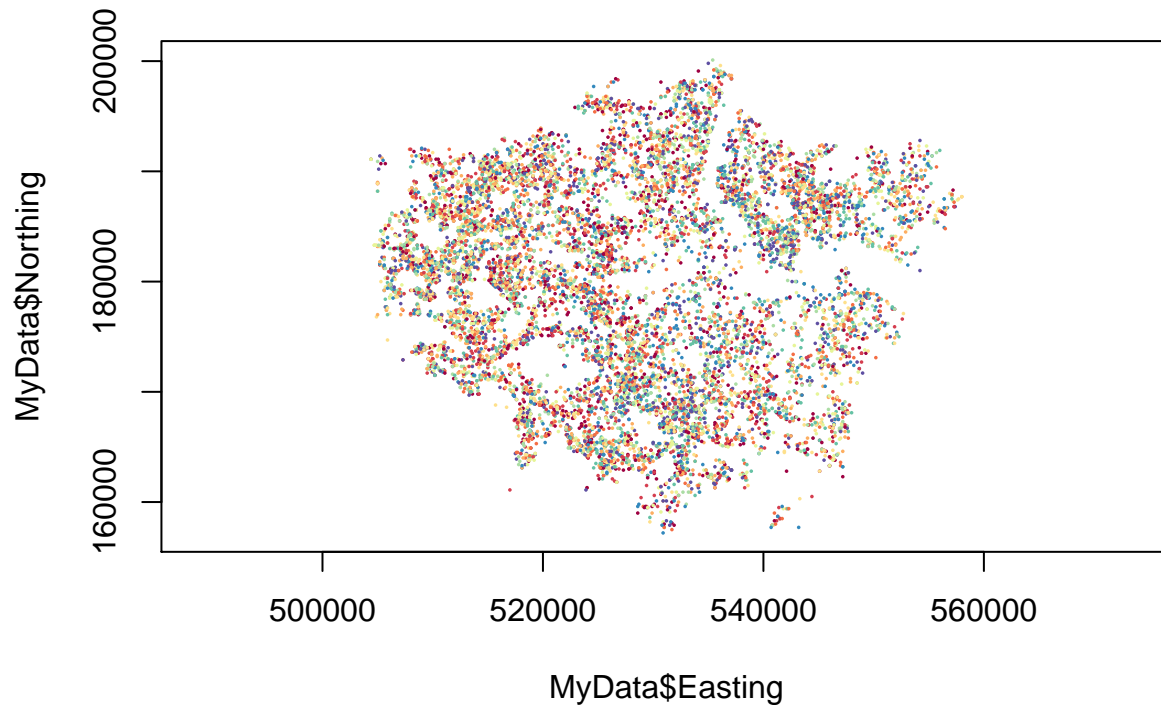
```
model.9v <- lm(Purprice~FlorArea+Bedrooms+Type+BathTwo+Garage+Tenfree+CenHeat+Age+ProfPct,data=MyData)
summary(model.9v)
```

```
##
## Call:
## lm(formula = Purprice ~ FlorArea + Bedrooms + Type + BathTwo +
##      Garage + Tenfree + CenHeat + Age + ProfPct, data = MyData)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -136550  -13463   -1378   10388  371517
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6183.51    1187.85   5.206 1.96e-07 ***
## FlorArea       678.01      11.37  59.613 < 2e-16 ***
## BedroomsBedTwo -3434.19     869.05  -3.952 7.80e-05 ***
## BedroomsBedThree -7872.74    1068.10  -7.371 1.80e-13 ***
## BedroomsBedFour -1749.22    1541.74  -1.135 0.256574
## BedroomsBedFive  3937.03    2504.03   1.572 0.115911
## TypeTypDetch    5715.04    1657.99   3.447 0.000569 ***
## TypeTypSemiD   -6671.47    1440.82  -4.630 3.69e-06 ***
## TypeTypFlat   -11564.76    1395.83  -8.285 < 2e-16 ***
## BathTwoyes     24054.83    1202.43  20.005 < 2e-16 ***
## GarageGarSingl  3784.77     614.42   6.160 7.50e-10 ***
## GarageGarDoubl  9266.06    1676.12   5.528 3.30e-08 ***
## Tenfreeyes     6132.37    1351.89   4.536 5.78e-06 ***
## CenHeatyes     11855.05     754.57  15.711 < 2e-16 ***
## AgeBldIntWr     4052.62     656.80   6.170 7.03e-10 ***
## AgeBldPostW    -1135.27     975.05  -1.164 0.244316
## AgeBld60s      -7345.56    1089.66  -6.741 1.64e-11 ***
## AgeBld70s     -6721.82    1164.33  -5.773 7.97e-09 ***
## AgeBld80s       915.55     898.67   1.019 0.308325
## ProfPct         45.35      23.86   1.901 0.057327 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27150 on 12515 degrees of freedom
## Multiple R-squared:  0.5648, Adjusted R-squared:  0.5641
## F-statistic: 854.8 on 19 and 12515 DF, p-value: < 2.2e-16
```

```
library(classInt)
library(RColorBrewer)

nClass = 10
Palette <- rev(brewer.pal(nClass,"Spectral"))
Classes <- classIntervals(MyData$Purprice,nClass,"quantile")
Colours <- findColours(Classes,Palette)
plot(MyData$Easting,MyData$Northing,pch=16,cex=0.25,col=Colours,asp=1)
```

Geography - look at trends with linear and quadratic trend surfaces

```
x <- MyData$Easting/1000
y <- MyData$Northing/1000
m.tr1 <- lm(Purprice~x+y,data=MyData)
AIC(m.tr1)
```

```
## [1] 301910.2
```

```
m.tr2 <- lm(Purprice~x+y+I(x^2)+I(y^2)+I(x*y),data=MyData)
AIC(m.tr2)
```

```
## [1] 301887.1
```

```
summary(m.tr1) # lower prices as we move east, slightly lower as w move south
```

```
##
## Call:
## lm(formula = Purprice ~ x + y, data = MyData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -72863 -24957 -10018   9714 443417
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 165151.00   17668.70   9.347  < 2e-16 ***
## x           -135.10     30.42  -4.441 9.03e-06 ***
## y            -77.06     40.45  -1.905  0.0568 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 41090 on 12532 degrees of freedom
## Multiple R-squared:  0.001854,    Adjusted R-squared:  0.001694
## F-statistic: 11.64 on 2 and 12532 DF,  p-value: 8.937e-06
```

```
summary(m.tr2) # lower AIC # higher price as we move west
```

```
##
## Call:
## lm(formula = Purprice ~ x + y + I(x^2) + I(y^2) + I(x * y), data = MyData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -73924 -24782  -9828   9862 444261
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.153e+06  8.741e+05  -3.607 0.000311 ***
## x             1.225e+04  2.793e+03   4.387 1.16e-05 ***
## y             3.525e+02  2.916e+03   0.121 0.903766
## I(x^2)       -1.074e+01  2.555e+00  -4.203 2.66e-05 ***
## I(y^2)        7.372e+00  4.717e+00   1.563 0.118080
## I(x * y)     -5.727e+00  4.323e+00  -1.325 0.185350
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 41050 on 12529 degrees of freedom
## Multiple R-squared:  0.004172,    Adjusted R-squared:  0.003774
## F-statistic: 10.5 on 5 and 12529 DF,  p-value: 4.507e-10
```

```
stepAIC(m.tr2)
```

```
## Start:  AIC=266312.3
## Purprice ~ x + y + I(x^2) + I(y^2) + I(x * y)
##
##              Df Sum of Sq      RSS      AIC
## - y           1 2.4632e+07 2.1111e+13 266310
## - I(x * y)    1 2.9561e+09 2.1114e+13 266312
## <none>                2.1111e+13 266312
## - I(y^2)      1 4.1163e+09 2.1115e+13 266313
## - I(x^2)      1 2.9761e+10 2.1141e+13 266328
## - x           1 3.2429e+10 2.1143e+13 266330
##
## Step:  AIC=266310.3
## Purprice ~ x + I(x^2) + I(y^2) + I(x * y)
##
##              Df Sum of Sq      RSS      AIC
## <none>                2.1111e+13 266310
## - I(y^2)      1 7.3282e+09 2.1118e+13 266313
## - I(x * y)    1 7.5460e+09 2.1119e+13 266313
## - I(x^2)      1 3.0205e+10 2.1141e+13 266326
## - x           1 3.7066e+10 2.1148e+13 266330
##
## Call:
## lm(formula = Purprice ~ x + I(x^2) + I(y^2) + I(x * y), data = MyData)
##
```

```
## Coefficients:
## (Intercept)          x          I(x^2)          I(y^2)          I(x * y)
## -3.087e+06    1.213e+04   -1.069e+01    7.725e+00   -5.300e+00
```

Explore variation by borough - first load the data

```
library(rgdal)
```

```
## Loading required package: sp
## rgdal: version: 1.4-8, (SVN revision 845)
##   Geospatial Data Abstraction Library extensions to R successfully loaded
##   Loaded GDAL runtime: GDAL 2.2.3, released 2017/11/20
##   Path to GDAL shared files: /usr/share/gdal/2.2
##   GDAL binary built with GEOS: TRUE
##   Loaded PROJ.4 runtime: Rel. 4.9.3, 15 August 2016, [PJ_VERSION: 493]
##   Path to PROJ.4 shared files: (autodetected)
##   Linking to sp version: 1.3-2
```

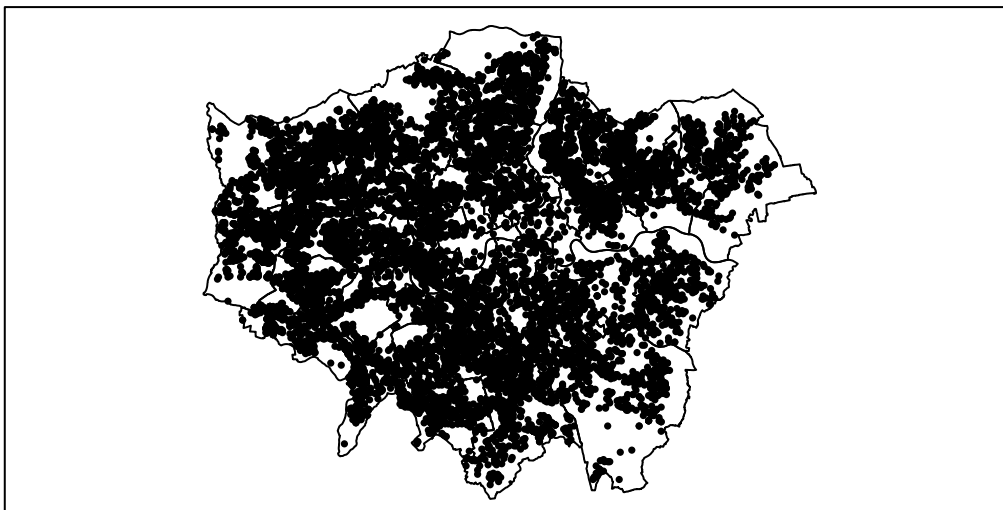
```
library(rgeos)
```

```
## rgeos version: 0.5-2, (SVN revision 621)
##   GEOS runtime version: 3.6.2-CAPI-1.10.2
##   Linking to sp version: 1.3-1
##   Polygon checking: TRUE
```

```
LB <- readOGR(dsn="LondonBoroughs",layer="LondonBoroughs",stringsAsFactors=FALSE) # Boroughs
```

```
## OGR data source with driver: ESRI Shapefile
## Source: "/users/students/19251101/HousingProject/LondonBoroughs", layer: "LondonBoroughs"
## with 33 features
## It has 15 fields
## Integer64 fields read as strings:  NUMBER NUMERO POLYGON_ID UNIT_ID
```

```
LH <- SpatialPointsDataFrame(MyData[,1:2],MyData) # Houses
proj4string(LH) <- CRS(proj4string(LB)) # copy CRS
plot(LB)
points(LH,pch=16,cex=0.5)
box()
```



Add Brough names to data - explore by type and borough - we'll need to do an overlay

```
LHLB <- over(LH,LB) # spatial join: points first, then polygons
dim(LHLB)
```

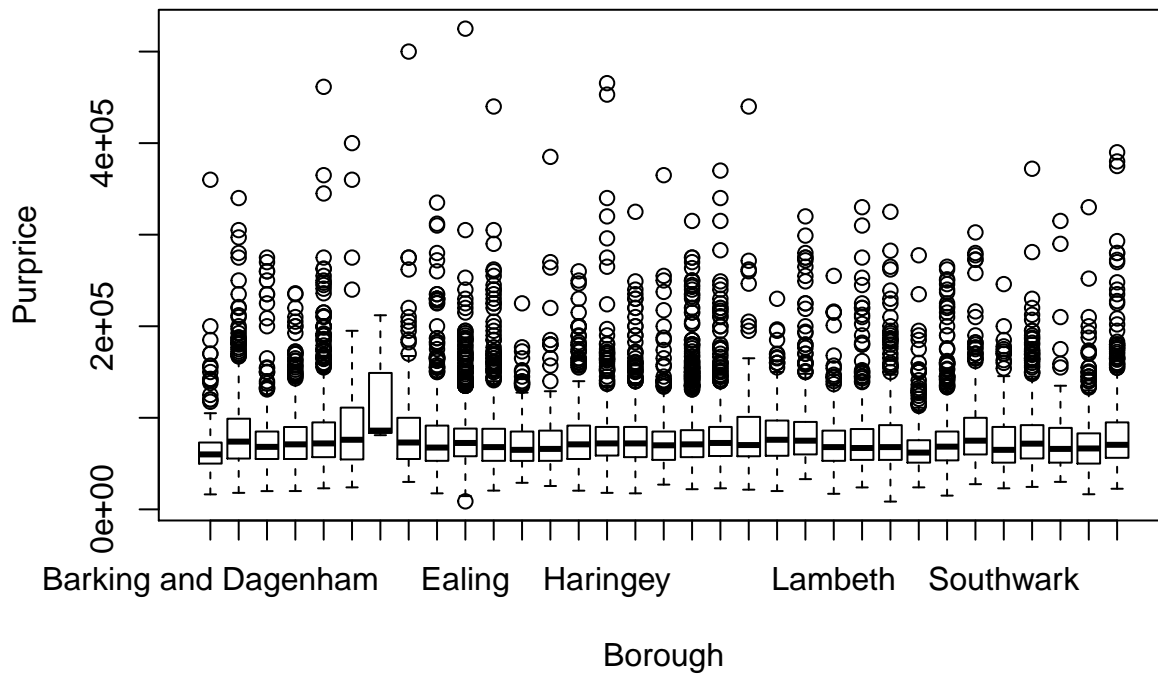
```
## [1] 12535      15
```

```
head(LHLB) # data frame has LB attributes in LH order
```

```
##              NAME AREA_CODE    DESCRIPTIO
## 1      Bexley London Boro      LBO London Borough
## 2 Hammersmith and Fulham London Boro      LBO London Borough
## 3      Islington London Boro      LBO London Borough
## 4      Bromley London Boro      LBO London Borough
## 5      Croydon London Boro      LBO London Borough
## 6      Merton London Boro      LBO London Borough
##              FILE_NAME NUMBER NUMBERO POLYGON_ID UNIT_ID      CODE
## 1 GREATER_LONDON_AUTHORITY      42      1080      50891      10759 E09000004
## 2 GREATER_LONDON_AUTHORITY      70      1254      50647      11259 E09000013
## 3 GREATER_LONDON_AUTHORITY      84      1357      50581      11281 E09000019
## 4 GREATER_LONDON_AUTHORITY       9       805      50904      10772 E09000006
## 5 GREATER_LONDON_AUTHORITY       6       781      51330      10896 E09000008
## 6 GREATER_LONDON_AUTHORITY      59      1213      122401      10995 E09000024
##      HECTARES      AREA TYPE_CODE      DESCRIPTO TYPE_CODO DESCRIPT1
## 1  6428.649 371.119      AA CIVIL ADMINISTRATION AREA      <NA>      <NA>
## 2  1715.409  75.648      AA CIVIL ADMINISTRATION AREA      <NA>      <NA>
## 3  1485.664   0.000      AA CIVIL ADMINISTRATION AREA      <NA>      <NA>
## 4 15013.487   0.000      AA CIVIL ADMINISTRATION AREA      <NA>      <NA>
## 5   8649.441   0.000      AA CIVIL ADMINISTRATION AREA      <NA>      <NA>
## 6   3762.466   0.000      AA CIVIL ADMINISTRATION AREA      <NA>      <NA>
```

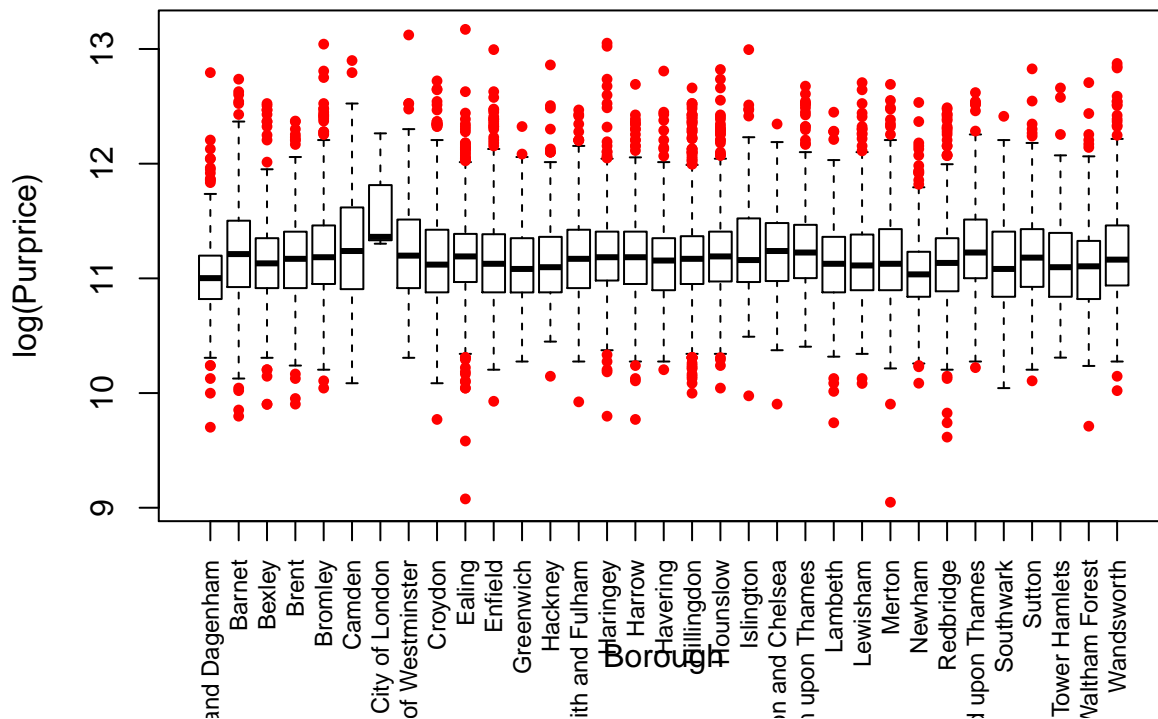
```
MyData$Borough <- gsub(" London Boro","",LHLB$NAME) # get the borough name
```

```
boxplot(Purprice~Borough,data=MyData)
```



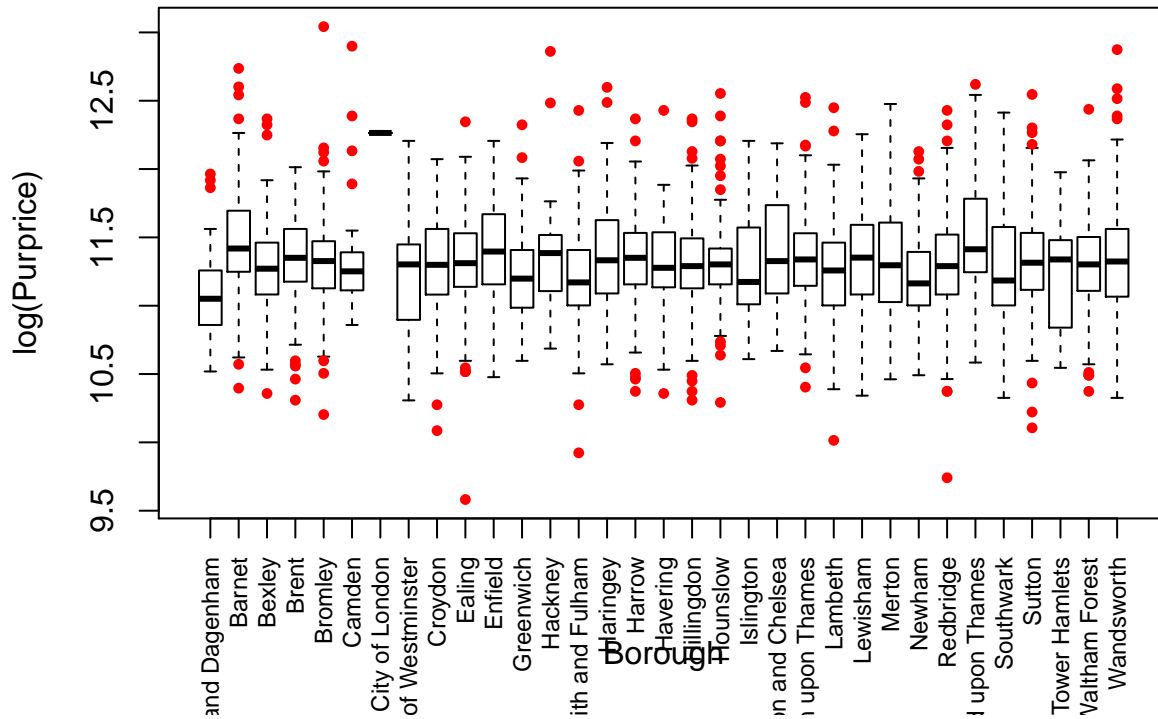
```
Boroughs <- names(table(MyData$Borough))
NB <- length(Boroughs)
boxplot(log(Purprice)~Borough,data=MyData,outpch=16,outcol="red",outcex=0.75,xaxt="n")
axis(1,labels=Boroughs,at=1:NB,cex.axis=0.75,las=2)
title("Log(Price) by Borough")
```

Log(Price) by Borough



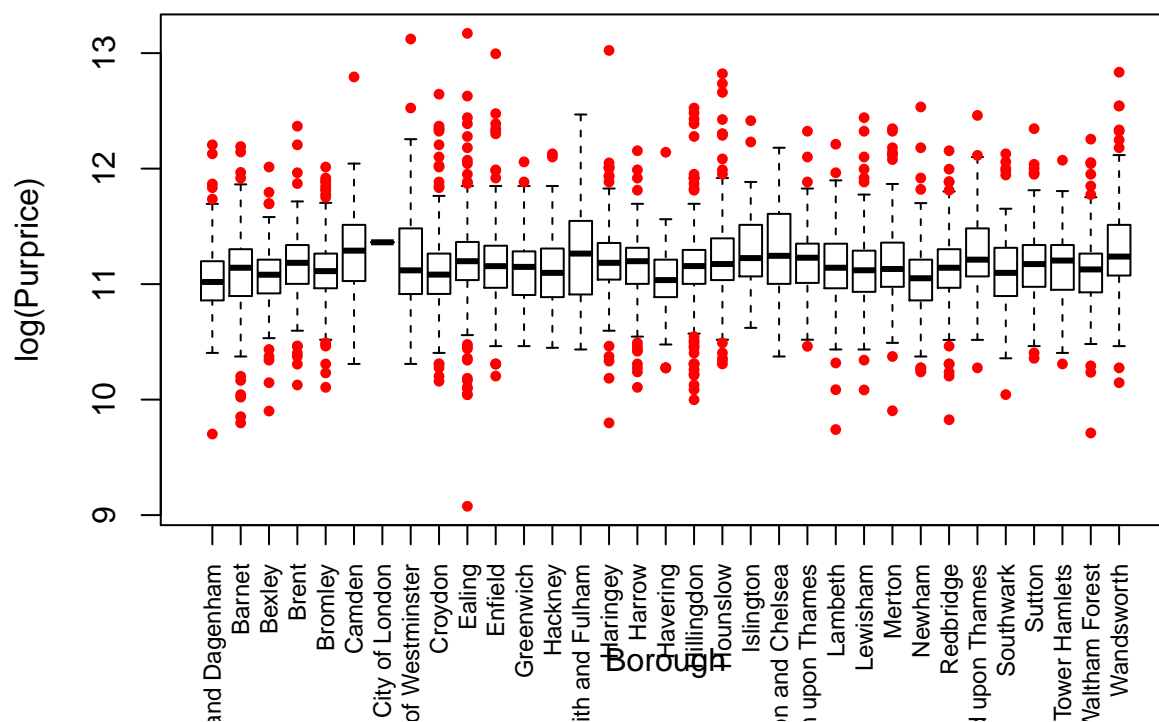
```
boxplot(log(Purprice)~Borough,data=MyData[MyData$Type=="TypSemiD",],outpch=16,outcol="red",outcex=0.75,
axis(1,labels=Boroughs,at=1:NB,cex.axis=0.75,las=2)
title("Log(Price) by Borough (Semi Detached only)")
```

Log(Price) by Borough (Semi Detached only)



```
boxplot(log(Purprice)~Borough,data=MyData[MyData$Type=="TypFlat",],outpch=16,outcol="red",outcex=0.75,x
axis(1,labels=Boroughs,at=1:NB,cex.axis=0.75,las=2)
title("Log(Price) by Borough (Flats only)")
```

Log(Price) by Borough (Flats only)

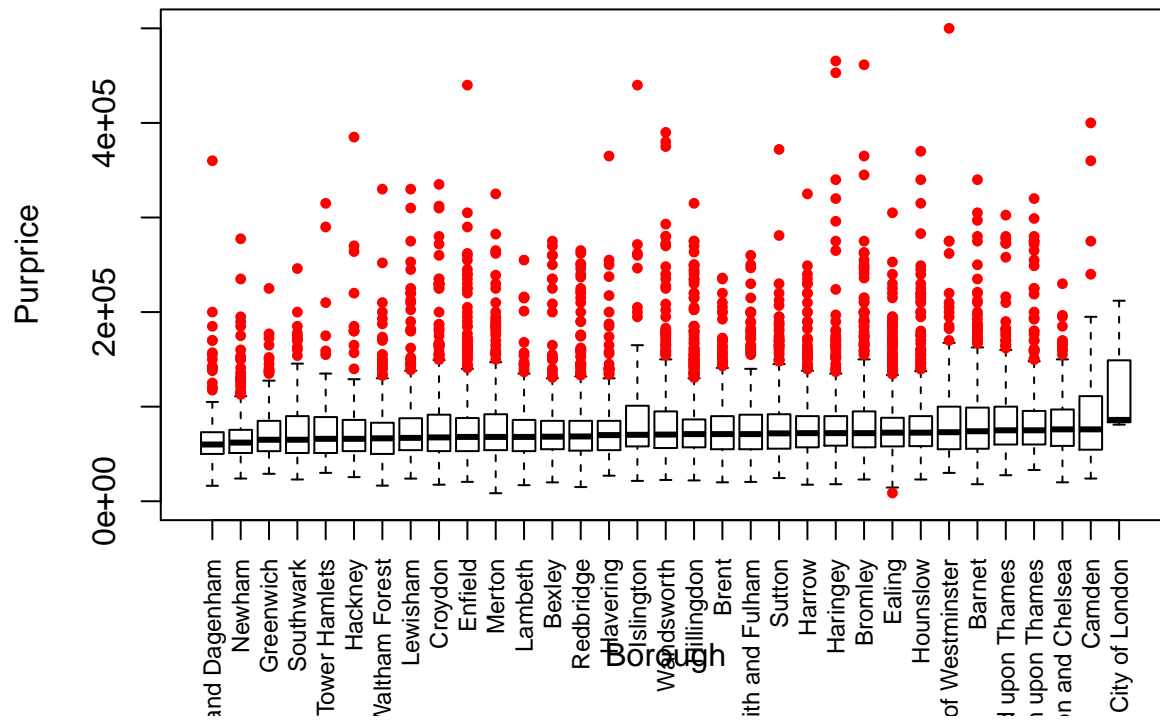


Ordered boxplot

```
b.order <- rank(tapply(MyData$Purprice+runif(nrow(MyData))),MyData$Borough,median))
```

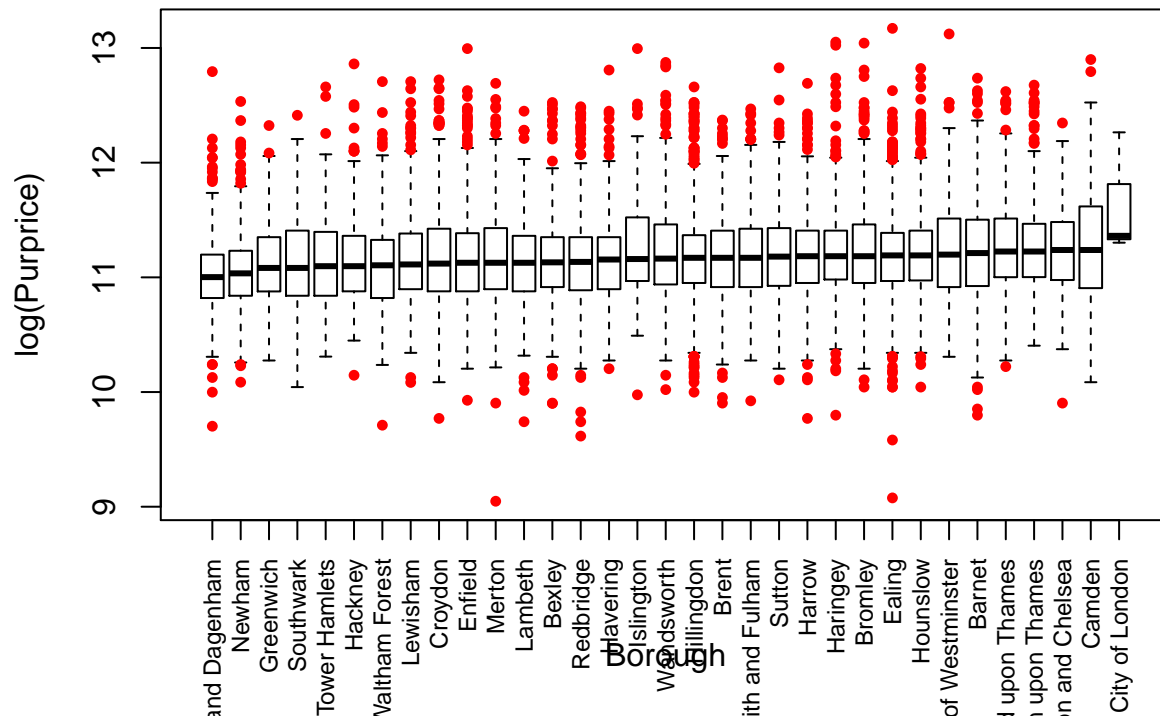
```
boxplot(Purprice~Borough,data=MyData,outpch=16,outcol="red",outcex=0.75,xaxt="n",at=b.order,ylim=c(0,500000))
axis(1,labels=Boroughs,at=b.order,cex.axis=0.75,las=2)
title("Price by Borough")
```

Price by Borough



```
boxplot(log(Purprice)~Borough,data=MyData,outpch=16,outcol="red",outcex=0.75,xaxt="n",at=b.order)
axis(1,labels=Boroughs,at=b.order,cex.axis=0.75,las=2)
title("Log(Price) by Borough")
```

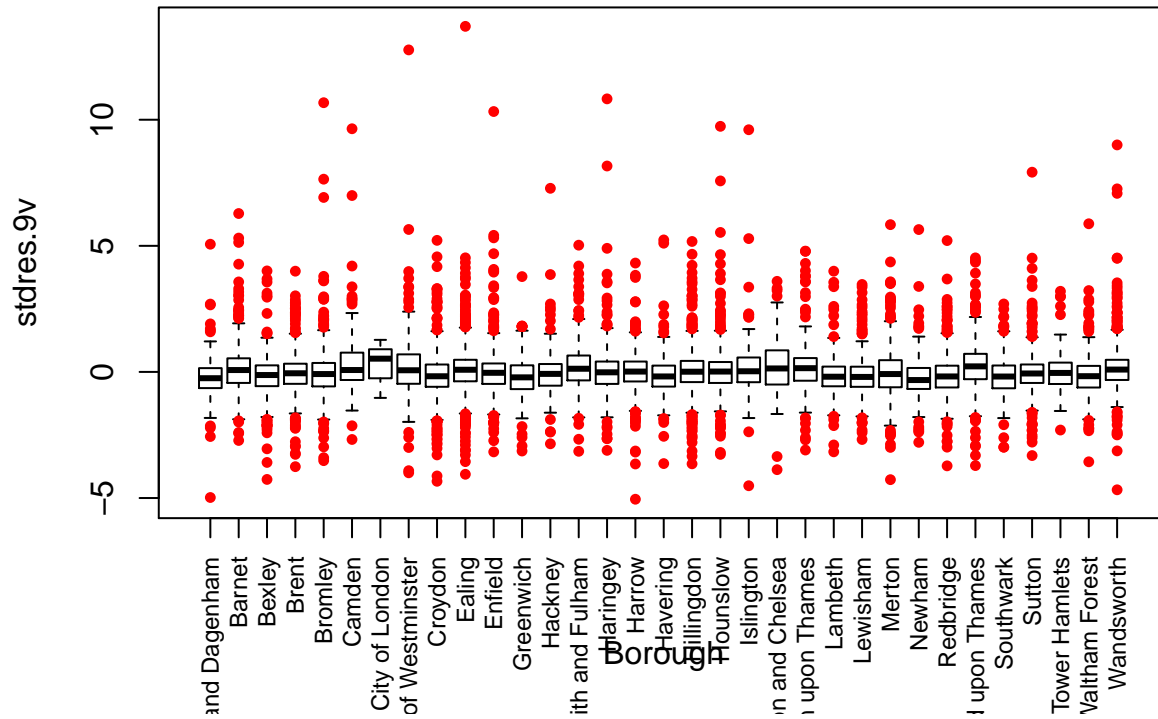

Log(Price) by Borough



standardised residuals - is there a pattern

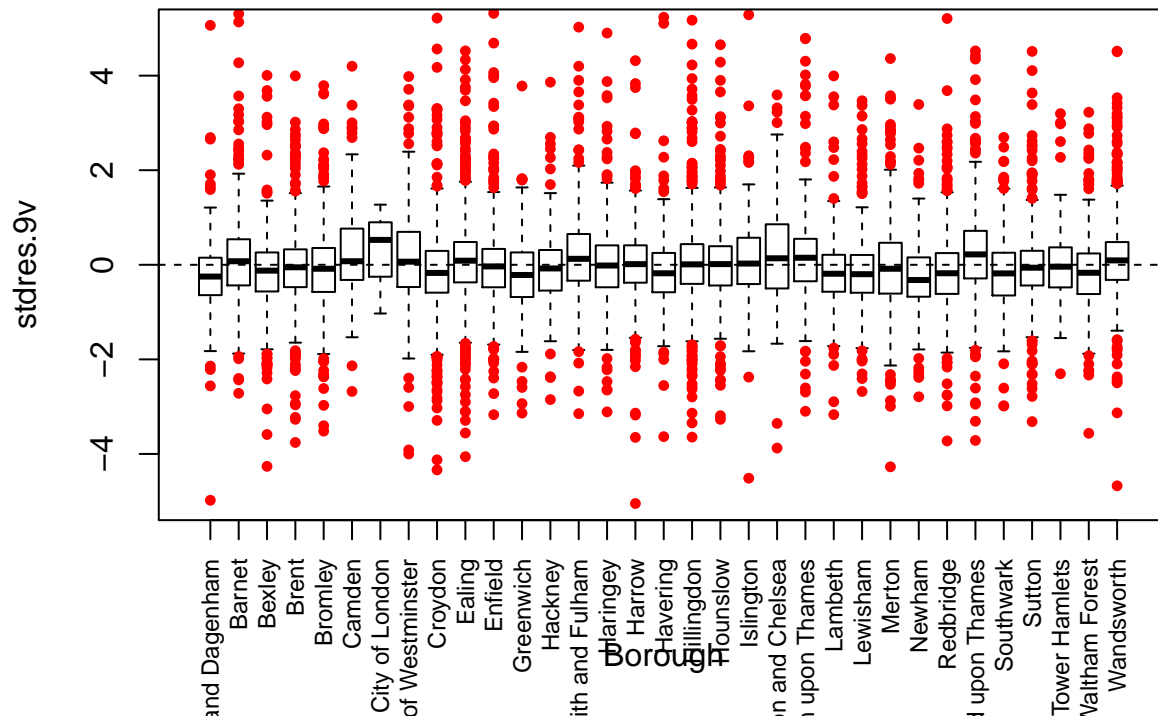
```
MyData$stdres.9v <- stdres(model.9v)
boxplot(stdres.9v~Borough,data=MyData,outpch=16,outcol="red",outcex=0.75,xaxt="n")
axis(1,labels=Boroughs,at=1:NB,cex.axis=0.75,las=2)
title("Standardised Residual by Borough")
```

Standardised Residual by Borough



```
boxplot(stdres.9v~Borough,data=MyData,outpch=16,outcol="red",outcex=0.75,xaxt="n",ylim=c(-5,5))
axis(1,labels=Boroughs,at=1:NB,cex.axis=0.75,las=2)
title("Standardised Residual by Borough")
abline(h=0,lty=2)
```

Standardised Residual by Borough

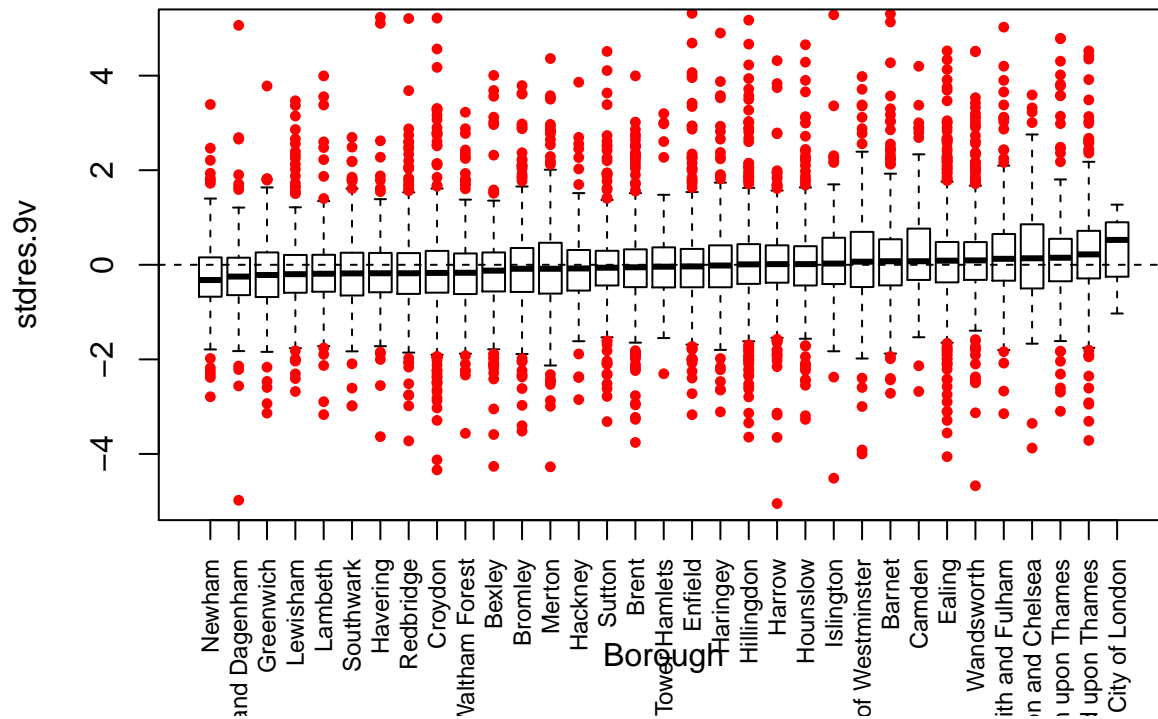


y-yhat negative : overprediction

y-yhat positive : underprediction

```
b.order.9v <- rank(tapply(MyData$stdres.9v+runif(nrow(MyData))*0.0001,MyData$Borough,median))
boxplot(stdres.9v~Borough,data=MyData,outpch=16,outcol="red",outcex=0.75,xaxt="n",at=b.order.9v,ylim=c(-4,4),
axis(1,labels=Boroughs,at=b.order.9v,cex.axis=0.75,las=2)
title("Standardised Residual by Borough")
abline(h=0,lty=2)
```

Standardised Residual by Borough



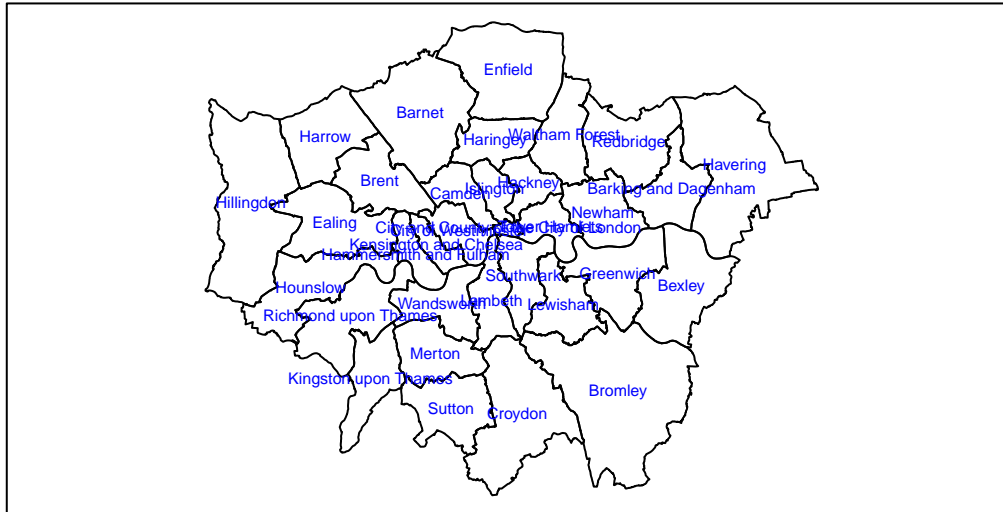
Map of Boroughs with names

```
head(LB$NAME)
```

```
## [1] "Camden London Boro"      "Tower Hamlets London Boro"
## [3] "Islington London Boro"   "Hackney London Boro"
## [5] "Haringey London Boro"    "Newham London Boro"
```

```
Bname <- gsub(" London Boro", "", LB$NAME)
xy <- coordinates(LB)
plot(LB)
text(xy[,1], xy[,2], Bname, col="blue", cex=0.5)
box()
title("London Borough Boundaries")
```

London Borough Boundaries



```
quickMap <- function(Var,nClass=10){
  require(classInt)
  require(RColorBrewer)
  Classes <- classIntervals(Var,nClass,method="quantile")
  Palette <- brewer.pal(nClass,"Reds")
  Colours <- findColours(Classes,Palette)
  plot(y)
  points(x.sdf2,cex=0.5,pch=16,col=Colours)
}
```

How about some borough specific models

```
data.frame(Bname, LB$NAME)
```

check ordering of names

| ## | Bname | LB.NAME |
|-------|---------------------------------------|---------------------------------------|
| ## 1 | Camden | Camden London Boro |
| ## 2 | Tower Hamlets | Tower Hamlets London Boro |
| ## 3 | Islington | Islington London Boro |
| ## 4 | Hackney | Hackney London Boro |
| ## 5 | Haringey | Haringey London Boro |
| ## 6 | Newham | Newham London Boro |
| ## 7 | Barking and Dagenham | Barking and Dagenham London Boro |
| ## 8 | City and County of the City of London | City and County of the City of London |
| ## 9 | Kingston upon Thames | Kingston upon Thames London Boro |
| ## 10 | Croydon | Croydon London Boro |
| ## 11 | Bromley | Bromley London Boro |
| ## 12 | Hounslow | Hounslow London Boro |
| ## 13 | Ealing | Ealing London Boro |
| ## 14 | Havering | Havering London Boro |
| ## 15 | Hillingdon | Hillingdon London Boro |
| ## 16 | Harrow | Harrow London Boro |
| ## 17 | Brent | Brent London Boro |
| ## 18 | Barnet | Barnet London Boro |

```
## 19 Lambeth Lambeth London Boro
## 20 Southwark Southwark London Boro
## 21 Lewisham Lewisham London Boro
## 22 Greenwich Greenwich London Boro
## 23 Bexley Bexley London Boro
## 24 Enfield Enfield London Boro
## 25 Waltham Forest Waltham Forest London Boro
## 26 Redbridge Redbridge London Boro
## 27 Sutton Sutton London Boro
## 28 Richmond upon Thames Richmond upon Thames London Boro
## 29 Merton Merton London Boro
## 30 Wandsworth Wandsworth London Boro
## 31 Hammersmith and Fulham Hammersmith and Fulham London Boro
## 32 Kensington and Chelsea Kensington and Chelsea London Boro
## 33 City of Westminster City of Westminster London Boro
```

```
head(MyData) # and MyData
```

```
## Easting Northing Purprice Tenfree CenHeat BathTwo NewPropD FlorArea ProfPct
## 1 545500 173000 85000 yes yes no no 76.16146 0.0000
## 2 525000 177800 71000 yes yes no no 98.45262 6.2500
## 3 531100 183400 60000 yes yes yes no 124.73761 0.0000
## 4 538500 169400 64000 yes yes no yes 127.00000 0.0000
## 5 534000 168400 260000 yes yes yes no 190.40366 9.0909
## 6 528700 168800 48500 yes yes no no 87.00000 16.6667
## Age Type Garage Bedrooms Borough stdres.9v
## 1 Bld60s TypDetch GarSingl BedThree Bexley 0.5498566
## 2 Bld80s TypDetch GarSingl BedThree Hammersmith and Fulham -0.8386380
## 3 PreWW1 TypSemiD HardStnd BedFour Islington -2.3747931
## 4 Bld80s TypDetch GarSingl BedThree Bromley -1.7998290
## 5 Bld80s TypDetch GarDoubl BedFour Croydon 2.5149597
## 6 PreWW1 TypFlat HardStnd BedThree Merton -0.5885948
```

```
NB <- length(LB) # number of boroughs
results <- matrix(0,NB,2) # storage for borough legfel coefficients
for(i in 1:NB) {
  m.x <- lm(Purprice~FlorArea,data=MyData[MyData$Borough == Bname[i],])
  results[i,] <- coef(m.x)
}
rownames(results) <- Bname # add in names
colnames(results) <- c("Intercept","FlorArea")
print(results)
```

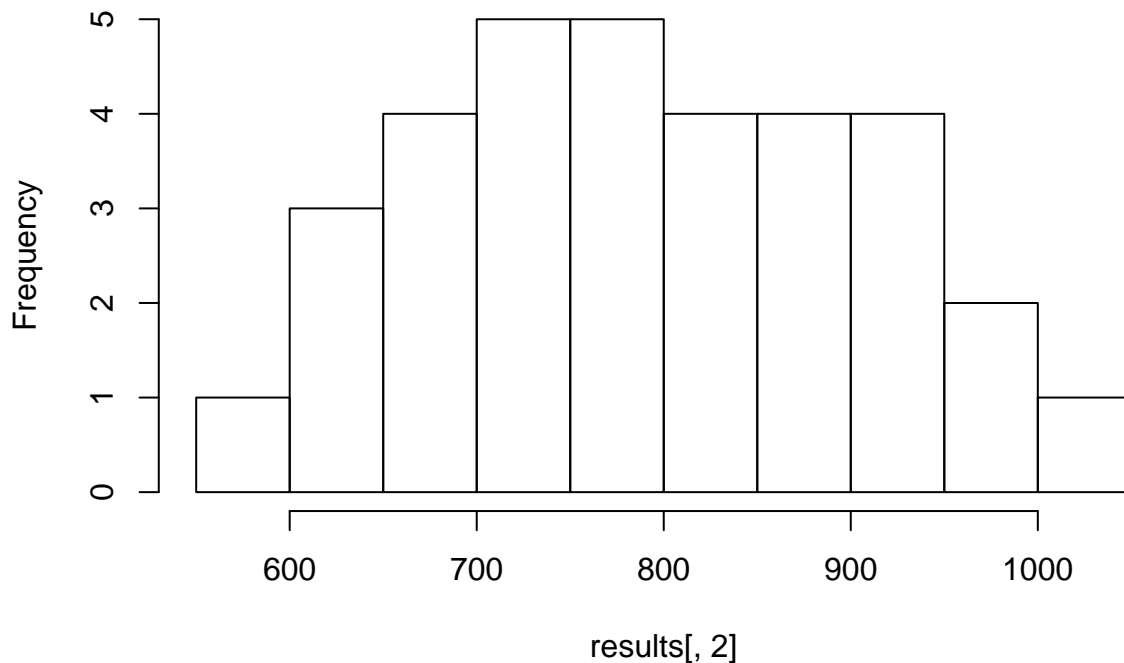
```
## Intercept FlorArea
## Camden 4193.591 912.5144
## Tower Hamlets -22055.905 1042.9070
## Islington -9756.782 976.7416
## Hackney -6427.270 888.3199
## Haringey -10165.200 941.1180
## Newham 8392.221 639.8260
## Barking and Dagenham 2833.098 714.4698
## City and County of the City of London -8934.581 926.4475
## Kingston upon Thames -7486.608 970.7183
## Croydon 2511.360 765.5992
## Bromley -1299.960 838.6432
```

| | | |
|---------------------------|-----------|----------|
| ## Hounslow | 2331.035 | 822.3698 |
| ## Ealing | 15196.698 | 691.0613 |
| ## Havering | -8434.152 | 875.8949 |
| ## Hillingdon | 6441.099 | 774.5079 |
| ## Harrow | 9438.779 | 737.1701 |
| ## Brent | 20595.103 | 598.9557 |
| ## Barnet | -1450.793 | 885.0956 |
| ## Lambeth | 10948.837 | 666.9039 |
| ## Southwark | 10211.971 | 689.2389 |
| ## Lewisham | -6768.227 | 860.6584 |
| ## Greenwich | 16655.867 | 600.0343 |
| ## Bexley | 6120.194 | 729.3274 |
| ## Enfield | -1612.182 | 844.1284 |
| ## Waltham Forest | 9317.256 | 669.1548 |
| ## Redbridge | 1371.890 | 757.0958 |
| ## Sutton | 10038.245 | 730.6204 |
| ## Richmond upon Thames | 13743.097 | 752.8587 |
| ## Merton | 7064.287 | 753.2699 |
| ## Wandsworth | -3590.767 | 919.3393 |
| ## Hammersmith and Fulham | 14952.080 | 736.6411 |
| ## Kensington and Chelsea | 24302.279 | 637.5807 |
| ## City of Westminster | 8260.768 | 830.7942 |

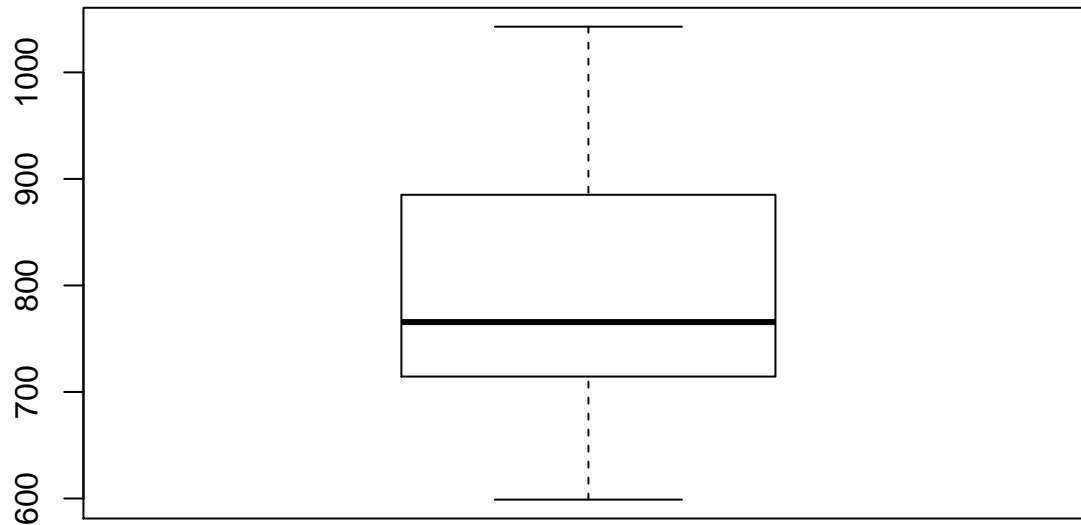
```
hist(results[,2])
```

look at FlorArea coefficient

Histogram of results[, 2]



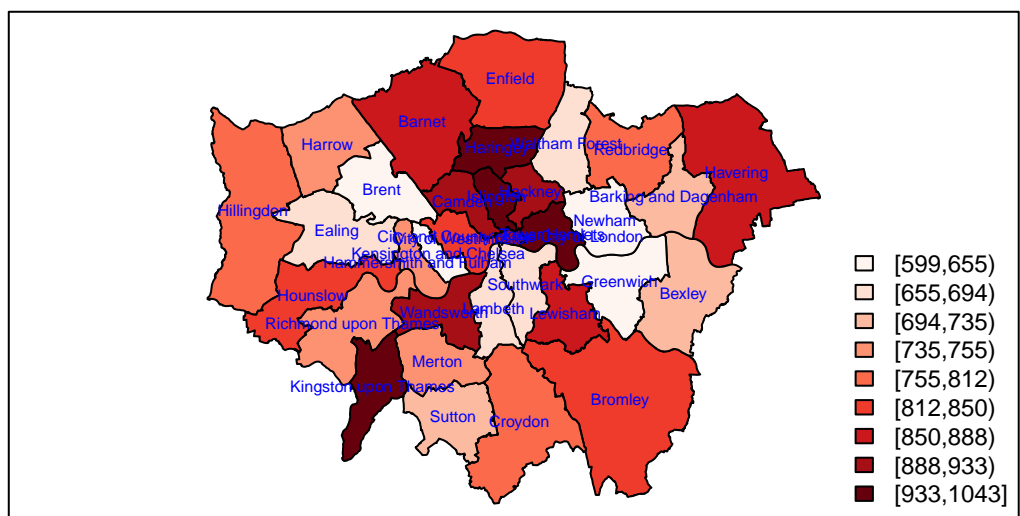
```
boxplot(results[,2])
```



borough levels plots with legend

```
quickMap2 <- function(Var,nClass=9,dp=0,plotNames=FALSE){
  require(classInt)
  require(RColorBrewer)
  Classes <- classIntervals(Var,nClass,method="quantile",dataPrecision=dp)
  Palette <- brewer.pal(nClass,"Reds")
  Colours <- findColours(Classes,Palette)
  plot(LB,col=Colours)
  legend("bottomright",
        legend=names(attr(Colours,"table")),
        fill=attr(Colours,"palette"),
        cex=0.75,bty="n")
  box()
  if(plotNames) {
    xy <- coordinates(LB)
    text(xy[,1],xy[,2],Bname,col="blue",cex=0.5)
  }
}

quickMap2(results[,2]) # without borough names
quickMap2(results[,2],plotNames=TRUE) # with borough names
```

and the residuals from the model? Plot the borough medians

```
quickMap2(tapply(MyData$stdres.9v,MyData$Borough,median),plotNames=TRUE,dp=3)
```

