

Ensemble Methods on the Ames Housing dataset

```
install_tensorflow() install.packages("tensorflow") library(tensorflow) install_tensorflow()
library(tensorflow) tf$constant("Hellow Tensorflow")
```

Predicting house prices using Ensemble methods

Reading in the dataset

```
dataHouse <- read.csv("housing.csv", colClasses = c(MSSubClass = 'factor', MoSold = 'factor'))
dataHouse$Id <- NULL
```

Section 1 - Data Cleaning

Overall structure and summary statistics of variables.

```
summary(dataHouse)
```

```
##      MSSubClass      MSZoning      LotFrontage      LotArea      Street
## 20      :536      C (all): 10      Min.      : 21.00      Min.      : 1300      Grvl: 6
## 60      :299      FV      : 65      1st Qu.: 59.00      1st Qu.: 7554      Pave:1454
## 50      :144      RH      : 16      Median : 69.00      Median : 9478
## 120     : 87      RL      :1151      Mean   : 70.05      Mean   : 10517
## 30      : 69      RM      : 218      3rd Qu.: 80.00      3rd Qu.: 11602
## 160     : 63                      Max.   :313.00      Max.   :215245
## (Other):262                      NA's   :259
## Alley      LotShape LandContour Utilities      LotConfig      LandSlope
## Grvl: 50    IR1:484   Bnk: 63    AllPub:1459   Corner : 263    Gtl:1382
## Pave: 41    IR2: 41   HLS: 50    NoSeWa: 1     CulDSac: 94    Mod: 65
## NA's:1369   IR3: 10   Low: 36                      FR2      : 47    Sev: 13
##                      Reg:925   Lvl:1311                      FR3      : 4
##                                                    Inside :1052
##
##
## Neighborhood Condition1 Condition2 BldgType HouseStyle
## Names :225 Norm :1260 Norm :1445 1Fam :1220 1Story :726
## CollgCr:150 Feedr : 81 Feedr : 6 2fmCon: 31 2Story :445
## OldTown:113 Artery : 48 Artery : 2 Duplex: 52 1.5Fin :154
## Edwards:100 RRAn : 26 PosN : 2 Twnhs : 43 SLvl : 65
## Somerst: 86 PosN : 19 RRNn : 2 TwnhsE: 114 SFoyer : 37
## Gilbert: 79 RRAe : 11 PosA : 1 1.5Unf : 14
## (Other):707 (Other): 15 (Other): 2 (Other): 19
## OverallQual OverallCond YearBuilt YearRemodAdd RoofStyle
## Min. : 1.000 Min. :1.000 Min. :1872 Min. :1950 Flat : 13
```

```

## 1st Qu.: 5.000    1st Qu.:5.000    1st Qu.:1954    1st Qu.:1967    Gable :1141
## Median : 6.000    Median :5.000    Median :1973    Median :1994    Gambrel: 11
## Mean : 6.099    Mean :5.575    Mean :1971    Mean :1985    Hip : 286
## 3rd Qu.: 7.000    3rd Qu.:6.000    3rd Qu.:2000    3rd Qu.:2004    Mansard: 7
## Max. :10.000    Max. :9.000    Max. :2010    Max. :2010    Shed : 2
##
## RoofMatl Exterior1st Exterior2nd MasVnrType MasVnrArea
## CompShg:1434 VinylSd:515 VinylSd:504 BrkCmn : 15 Min. : 0.0
## Tar&Grv: 11 HdBoard:222 MetalSd:214 BrkFace:445 1st Qu.: 0.0
## WdShngl: 6 MetalSd:220 HdBoard:207 None :864 Median : 0.0
## WdShake: 5 Wd Sdng:206 Wd Sdng:197 Stone :128 Mean : 103.7
## ClyTile: 1 Plywood:108 Plywood:142 NA's : 8 3rd Qu.: 166.0
## Membran: 1 CemntBd: 61 CmentBd: 60 Max. :1600.0
## (Other): 2 (Other):128 (Other):136 NA's :8
## ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure
## Ex: 52 Ex: 3 BrkTil:146 Ex :121 Fa : 45 Av :221
## Fa: 14 Fa: 28 CBlock:634 Fa : 35 Gd : 65 Gd :134
## Gd:488 Gd: 146 PConc :647 Gd :618 Po : 2 Mn :114
## TA:906 Po: 1 Slab : 24 TA :649 TA :1311 No :953
## TA:1282 Stone : 6 NA's: 37 NA's: 37 NA's: 38
## Wood : 3
##
## BsmtFinType1 BsmtFinSF1 BsmtFinType2 BsmtFinSF2 BsmtUnfSF
## ALQ :220 Min. : 0.0 ALQ : 19 Min. : 0.00 Min. : 0.0
## BLQ :148 1st Qu.: 0.0 BLQ : 33 1st Qu.: 0.00 1st Qu.: 223.0
## GLQ :418 Median : 383.5 GLQ : 14 Median : 0.00 Median : 477.5
## LwQ : 74 Mean : 443.6 LwQ : 46 Mean : 46.55 Mean : 567.2
## Rec :133 3rd Qu.: 712.2 Rec : 54 3rd Qu.: 0.00 3rd Qu.: 808.0
## Unf :430 Max. :5644.0 Unf :1256 Max. :1474.00 Max. :2336.0
## NA's: 37 NA's: 38
## TotalBsmtSF Heating HeatingQC CentralAir Electrical X1stFlrSF
## Min. : 0.0 Floor: 1 Ex:741 N: 95 FuseA: 94 Min. : 334
## 1st Qu.: 795.8 GasA :1428 Fa: 49 Y:1365 FuseF: 27 1st Qu.: 882
## Median : 991.5 GasW : 18 Gd:241 FuseP: 3 Median :1087
## Mean :1057.4 Grav : 7 Po: 1 Mix : 1 Mean :1163
## 3rd Qu.:1298.2 OthW : 2 TA:428 SBrkr:1334 3rd Qu.:1391
## Max. :6110.0 Wall : 4 NA's : 1 Max. :4692
##
## X2ndFlrSF LowQualFinSF GrLivArea BsmtFullBath
## Min. : 0 Min. : 0.000 Min. : 334 Min. :0.0000
## 1st Qu.: 0 1st Qu.: 0.000 1st Qu.:1130 1st Qu.:0.0000
## Median : 0 Median : 0.000 Median :1464 Median :0.0000
## Mean : 347 Mean : 5.845 Mean :1515 Mean :0.4253
## 3rd Qu.: 728 3rd Qu.: 0.000 3rd Qu.:1777 3rd Qu.:1.0000
## Max. :2065 Max. :572.000 Max. :5642 Max. :3.0000
##
## BsmtHalfBath FullBath HalfBath BedroomAbvGr
## Min. :0.00000 Min. :0.000 Min. :0.0000 Min. :0.000
## 1st Qu.:0.00000 1st Qu.:1.000 1st Qu.:0.0000 1st Qu.:2.000
## Median :0.00000 Median :2.000 Median :0.0000 Median :3.000
## Mean :0.05753 Mean :1.565 Mean :0.3829 Mean :2.866
## 3rd Qu.:0.00000 3rd Qu.:2.000 3rd Qu.:1.0000 3rd Qu.:3.000
## Max. :2.00000 Max. :3.000 Max. :2.0000 Max. :8.000
##

```

```

## KitchenAbvGr KitchenQual TotRmsAbvGrd Functional Fireplaces
## Min. :0.000 Ex:100 Min. : 2.000 Maj1: 14 Min. :0.000
## 1st Qu.:1.000 Fa: 39 1st Qu.: 5.000 Maj2: 5 1st Qu.:0.000
## Median :1.000 Gd:586 Median : 6.000 Min1: 31 Median :1.000
## Mean :1.047 TA:735 Mean : 6.518 Min2: 34 Mean :0.613
## 3rd Qu.:1.000 3rd Qu.: 7.000 Mod : 15 3rd Qu.:1.000
## Max. :3.000 Max. :14.000 Sev : 1 Max. :3.000
## Typ :1360
## FireplaceQu GarageType GarageYrBltd GarageFinish GarageCars
## Ex : 24 2Types : 6 Min. :1900 Fin :352 Min. :0.000
## Fa : 33 Attchd :870 1st Qu.:1961 RFn :422 1st Qu.:1.000
## Gd :380 Basment: 19 Median :1980 Unf :605 Median :2.000
## Po : 20 BuiltIn: 88 Mean :1979 NA's: 81 Mean :1.767
## TA :313 CarPort: 9 3rd Qu.:2002 3rd Qu.:2.000
## NA's:690 Detchd :387 Max. :2010 Max. :4.000
## NA's : 81 NA's :81
## GarageArea GarageQual GarageCond PavedDrive WoodDeckSF
## Min. : 0.0 Ex : 3 Ex : 2 N: 90 Min. : 0.00
## 1st Qu.: 334.5 Fa : 48 Fa : 35 P: 30 1st Qu.: 0.00
## Median : 480.0 Gd : 14 Gd : 9 Y:1340 Median : 0.00
## Mean : 473.0 Po : 3 Po : 7 Mean : 94.24
## 3rd Qu.: 576.0 TA :1311 TA :1326 3rd Qu.:168.00
## Max. :1418.0 NA's: 81 NA's: 81 Max. :857.00
##
## OpenPorchSF EnclosedPorch X3SsnPorch ScreenPorch
## Min. : 0.00 Min. : 0.00 Min. : 0.00 Min. : 0.00
## 1st Qu.: 0.00 1st Qu.: 0.00 1st Qu.: 0.00 1st Qu.: 0.00
## Median : 25.00 Median : 0.00 Median : 0.00 Median : 0.00
## Mean : 46.66 Mean : 21.95 Mean : 3.41 Mean : 15.06
## 3rd Qu.: 68.00 3rd Qu.: 0.00 3rd Qu.: 0.00 3rd Qu.: 0.00
## Max. :547.00 Max. :552.00 Max. :508.00 Max. :480.00
##
## PoolArea PoolQC Fence MiscFeature MiscVal
## Min. : 0.000 Ex : 2 GdPrv: 59 Gar2: 2 Min. : 0.00
## 1st Qu.: 0.000 Fa : 2 GdWo : 54 Othr: 2 1st Qu.: 0.00
## Median : 0.000 Gd : 3 MnPrv: 157 Shed: 49 Median : 0.00
## Mean : 2.759 NA's:1453 MnWw : 11 TenC: 1 Mean : 43.49
## 3rd Qu.: 0.000 NA's :1179 NA's:1406 3rd Qu.: 0.00
## Max. :738.000 Max. :15500.00
##
## MoSold YrSold SaleType SaleCondition SalePrice
## 6 :253 Min. :2006 WD :1267 Abnorml: 101 Min. : 34900
## 7 :234 1st Qu.:2007 New : 122 AdjLand: 4 1st Qu.:129975
## 5 :204 Median :2008 COD : 43 Alloca : 12 Median :163000
## 4 :141 Mean :2008 ConLD : 9 Family : 20 Mean :180921
## 8 :122 3rd Qu.:2009 ConLI : 5 Normal :1198 3rd Qu.:214000
## 3 :106 Max. :2010 ConLw : 5 Partial: 125 Max. :755000
## (Other):400 (Other): 9

```

There are 45 categorical features, and 35 numerical features. Of which, 19 features have missing values.

```
colMeans(is.na(dataHouse))
```

```
## MSSubClass MSZoning LotFrontage LotArea Street
```

```
## 0.0000000000 0.0000000000 0.1773972603 0.0000000000 0.0000000000
## Alley LotShape LandContour Utilities LotConfig
## 0.9376712329 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## LandSlope Neighborhood Condition1 Condition2 BldgType
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## HouseStyle OverallQual OverallCond YearBuilt YearRemodAdd
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0054794521
## MasVnrArea ExterQual ExterCond Foundation BsmtQual
## 0.0054794521 0.0000000000 0.0000000000 0.0000000000 0.0253424658
## BsmtCond BsmtExposure BsmtFinType1 BsmtFinSF1 BsmtFinType2
## 0.0253424658 0.0260273973 0.0253424658 0.0000000000 0.0260273973
## BsmtFinSF2 BsmtUnfSF TotalBsmtSF Heating HeatingQC
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## CentralAir Electrical X1stFlrSF X2ndFlrSF LowQualFinSF
## 0.0000000000 0.0006849315 0.0000000000 0.0000000000 0.0000000000
## GrLivArea BsmtFullBath BsmtHalfBath FullBath HalfBath
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## BedroomAbvGr KitchenAbvGr KitchenQual TotRmsAbvGrd Functional
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## Fireplaces FireplaceQu GarageType GarageYrBlt GarageFinish
## 0.0000000000 0.4726027397 0.0554794521 0.0554794521 0.0554794521
## GarageCars GarageArea GarageQual GarageCond PavedDrive
## 0.0000000000 0.0000000000 0.0554794521 0.0554794521 0.0000000000
## WoodDeckSF OpenPorchSF EnclosedPorch X3SsnPorch ScreenPorch
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
## PoolArea PoolQC Fence MiscFeature MiscVal
## 0.0000000000 0.9952054795 0.8075342466 0.9630136986 0.0000000000
## MoSold YrSold SaleType SaleCondition SalePrice
## 0.0000000000 0.0000000000 0.0000000000 0.0000000000 0.0000000000
```

Variables with Missing values %: LotFrontage(17.7%), Alley(93.8%), MasVnrType (0.6%), MasVnrArea (0.6%), BsmtQual (2.5%), BsmtCond (2.5%), BsmtExposure (2.6%), BsmtFinType1 (2.5%), BsmtFinType2 (2.6%), Electrical (0.06%), FireplaceQu (47.3%), GarageType (5.5%), GarageYrBlt (5.5%), GarageFinish (5.5%), GarageQual (5.5%), GarageCond (5.6%), PoolQC (99.5%), Fence (80.8%), MiscFeature (96.3%).

```
which(colMeans(is.na(dataHouse)) >= 0.30)
```

```
## Alley FireplaceQu PoolQC Fence MiscFeature
## 6 57 72 73 74
```

```
dataHouse$Alley <- NULL
dataHouse$FireplaceQu <- NULL
dataHouse$PoolQC <- NULL
dataHouse$Fence <- NULL
dataHouse$MiscFeature <- NULL
```

```
NROW(dataHouse[!complete.cases(dataHouse),])/NROW(dataHouse) * 100
```

```
## [1] 25.06849
```

Around 25% rows have one or more missing values now.

Imputing missing values using Random Forests

```
#install.packages("missForest")  
library(missForest)
```

```
## Warning: package 'missForest' was built under R version 3.6.3  
  
## Loading required package: randomForest  
  
## Warning: package 'randomForest' was built under R version 3.6.3  
  
## randomForest 4.6-14  
  
## Type rfNews() to see new features/changes/bug fixes.  
  
## Loading required package: foreach  
  
## Warning: package 'foreach' was built under R version 3.6.3  
  
## Loading required package: iterators  
  
## Warning: package 'iterators' was built under R version 3.6.3  
  
## Loading required package: iterators  
  
## Warning: package 'iterators' was built under R version 3.6.3
```

```
set.seed(1)
```

```
tempVar <- dataHouse$SalePrice  
dataHouse$SalePrice <- NULL  
  
data_Imp <- missForest(dataHouse)
```

```
## missForest iteration 1 in progress...done!  
## missForest iteration 2 in progress...done!  
## missForest iteration 3 in progress...done!
```

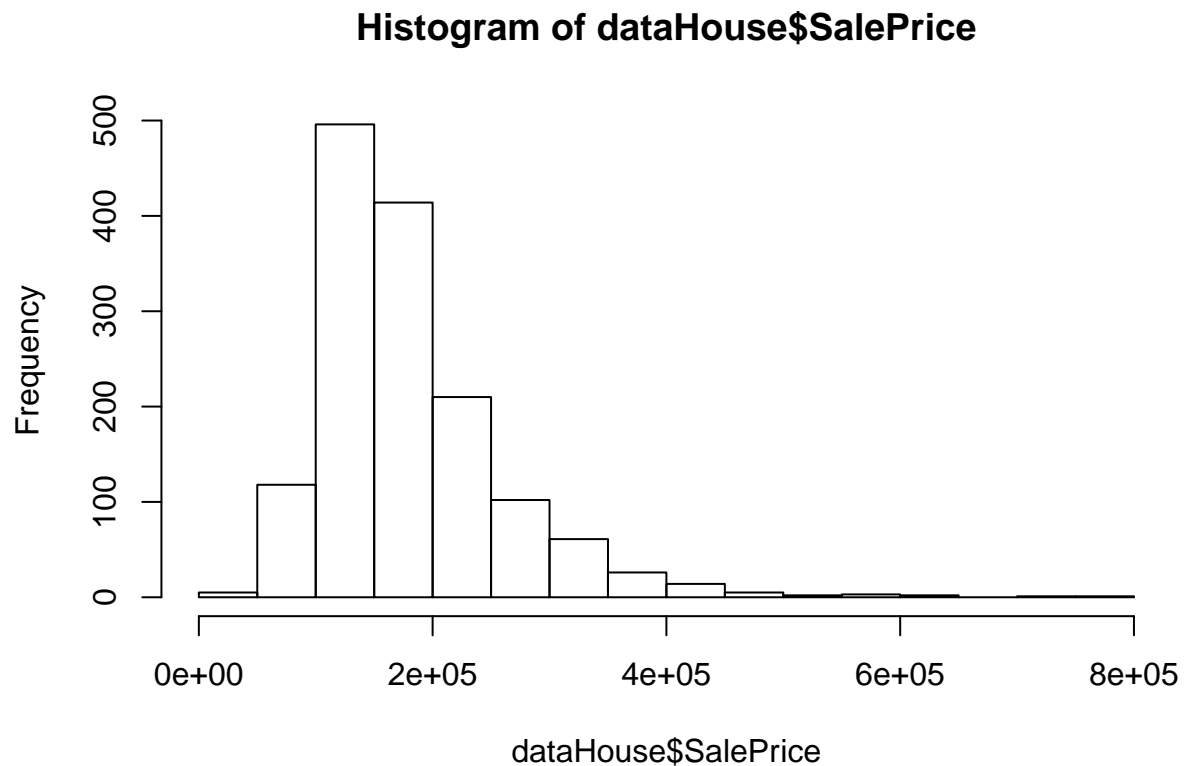
```
data_Imp$OOBerror
```

```
##          NRMSE          PFC  
## 0.008078283 0.039729589
```

```
dataHouse <- data_Imp$ximp  
dataHouse$SalePrice <- tempVar
```

Section 2 - Data Exploration

```
hist(dataHouse$SalePrice)
```

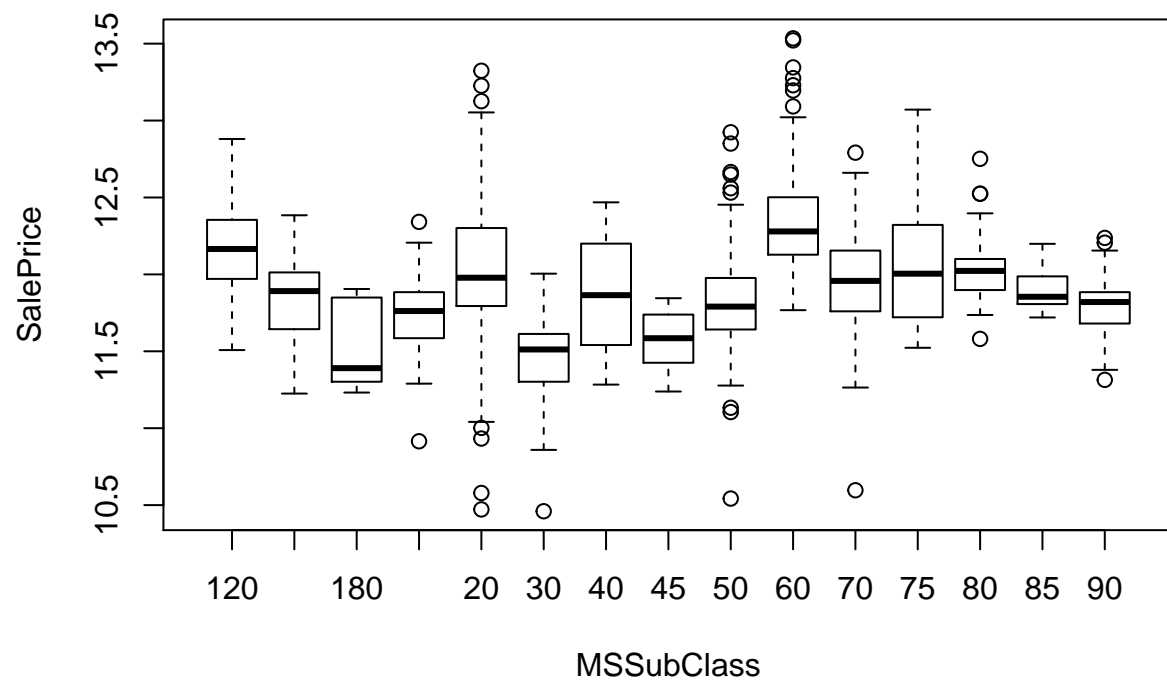


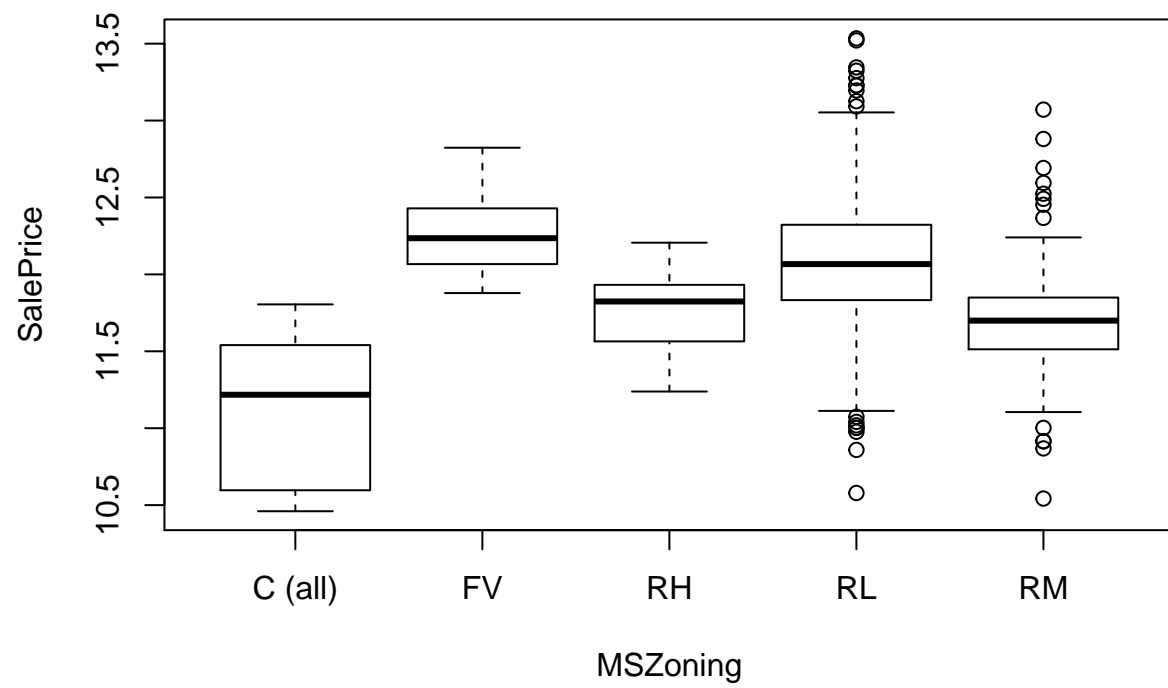
Eyeballing the distribution, we can see that the distribution is positively skewed, with most of the houses being in the lower price range.

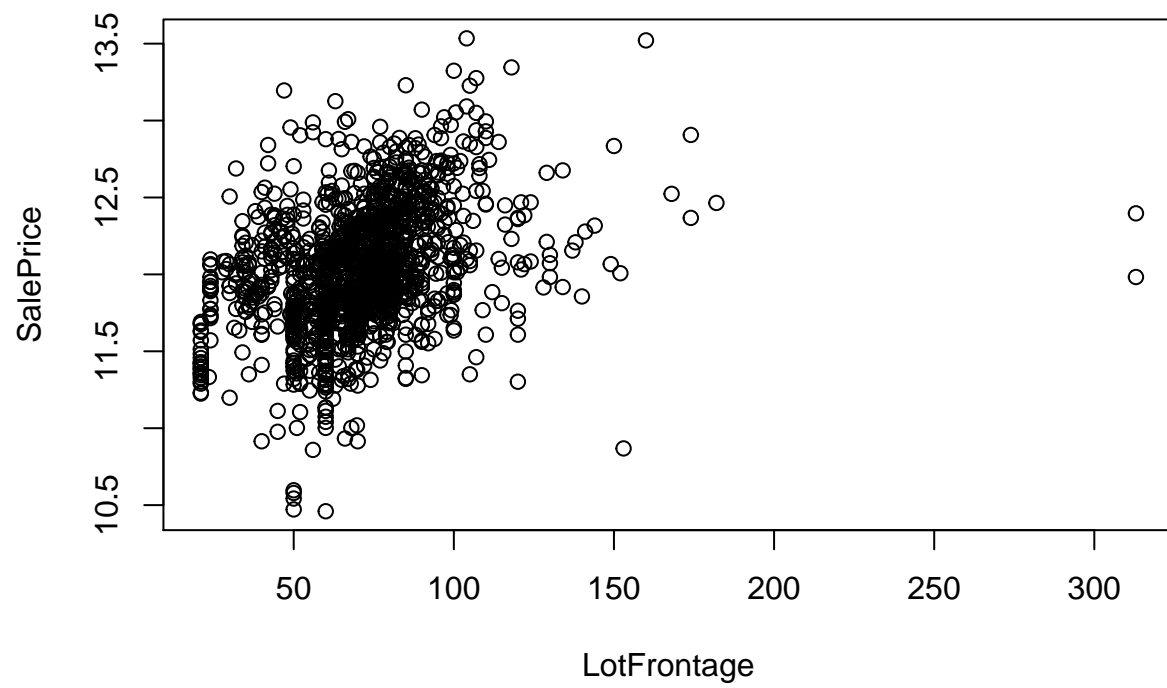
```
# Log transformation of target variable
```

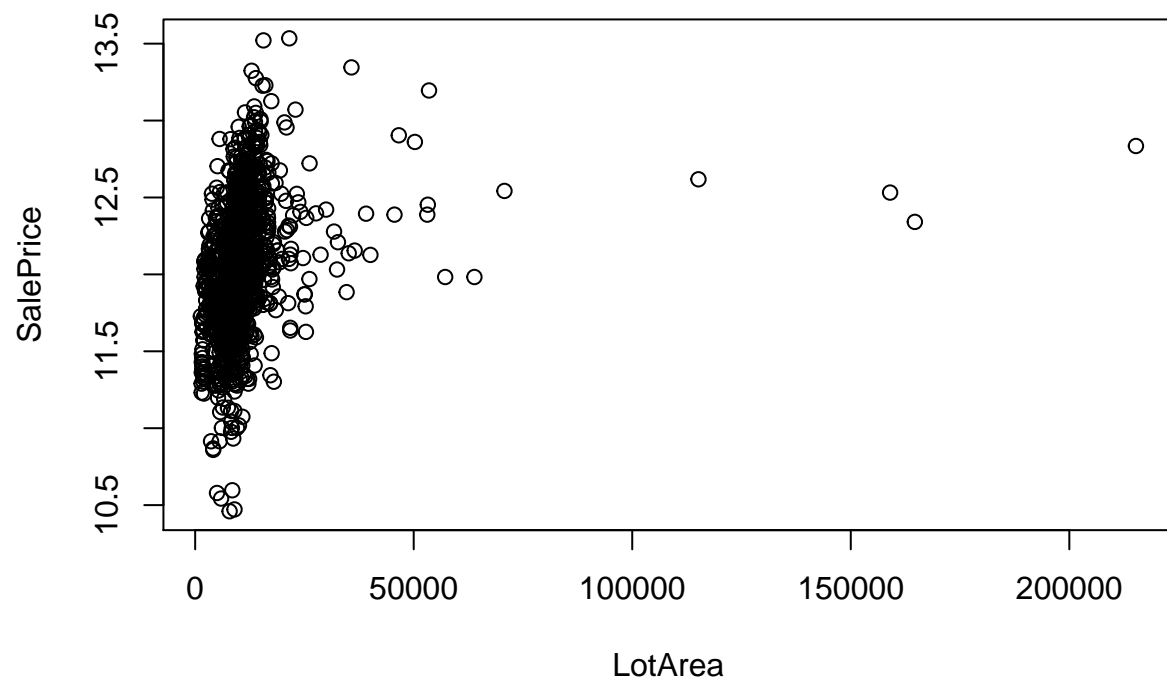
```
dataHouse$SalePrice <- log(dataHouse$SalePrice)
```

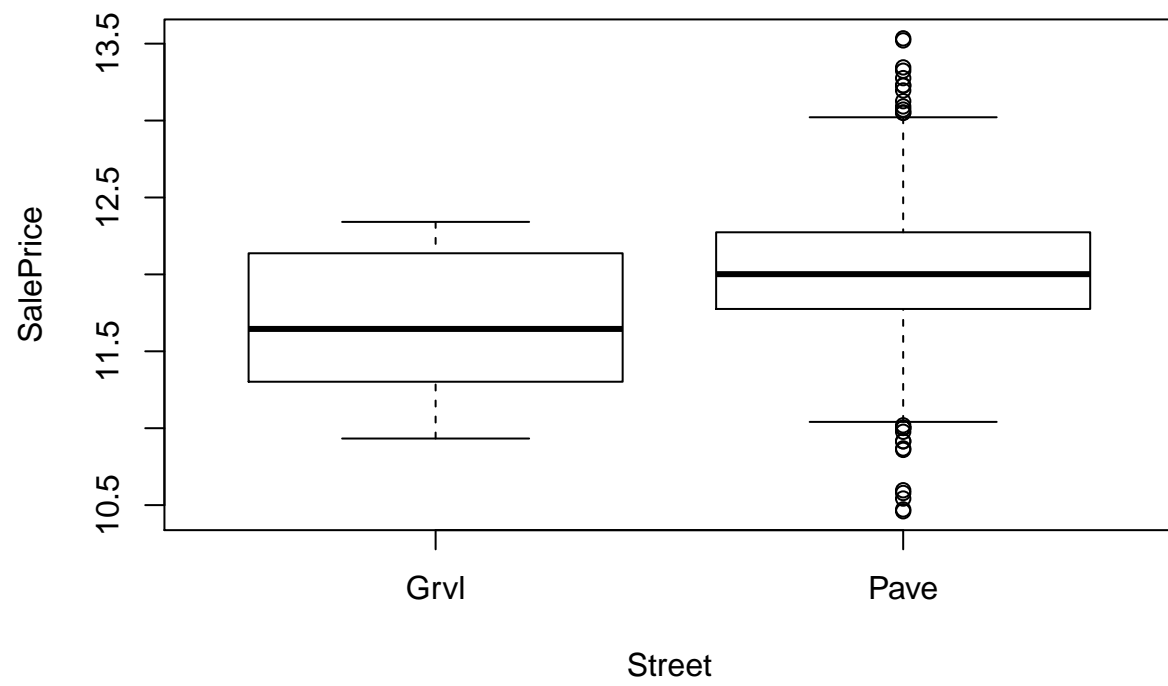
```
plot(SalePrice ~ ., data= dataHouse)
```

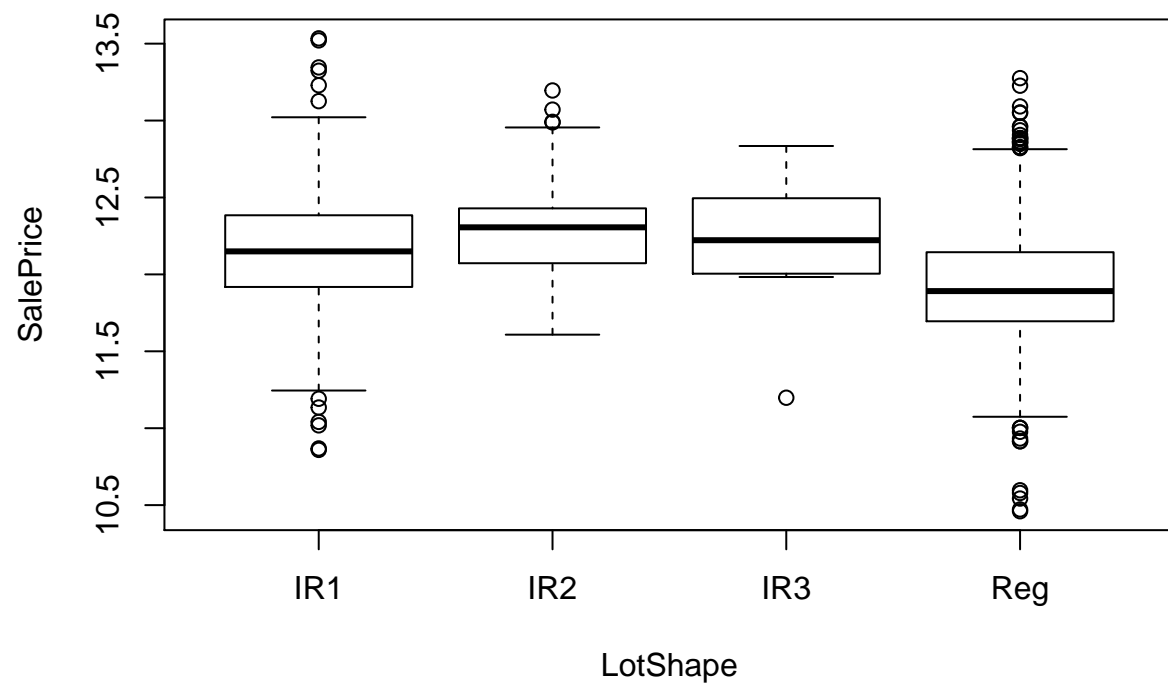


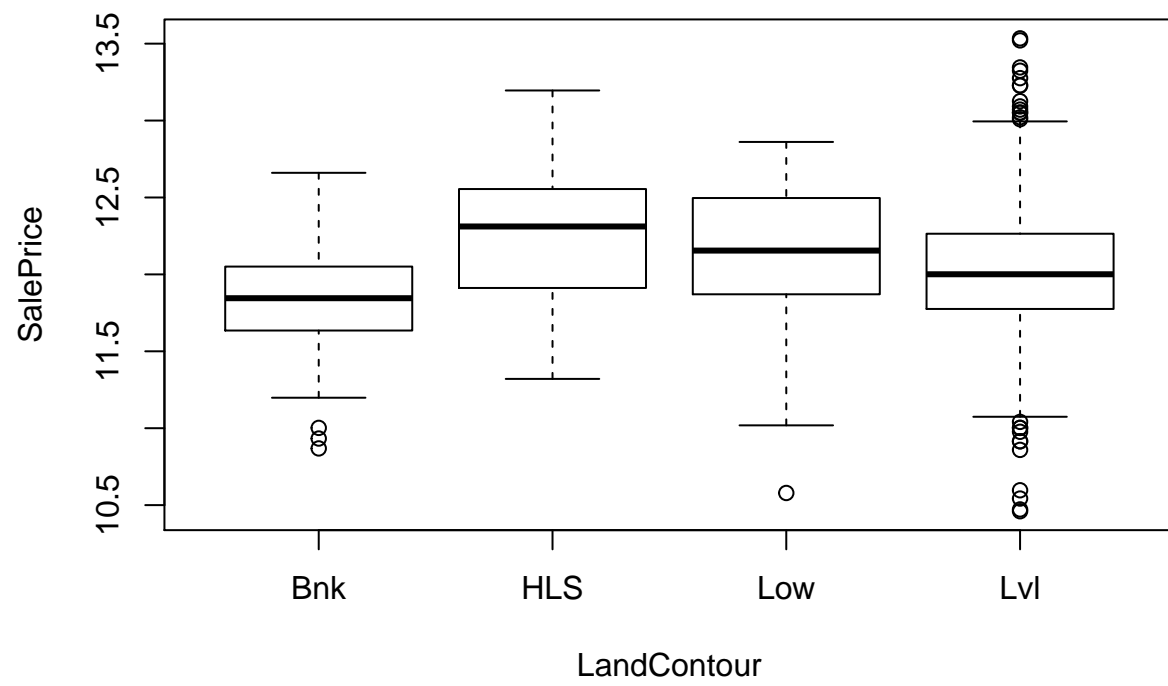


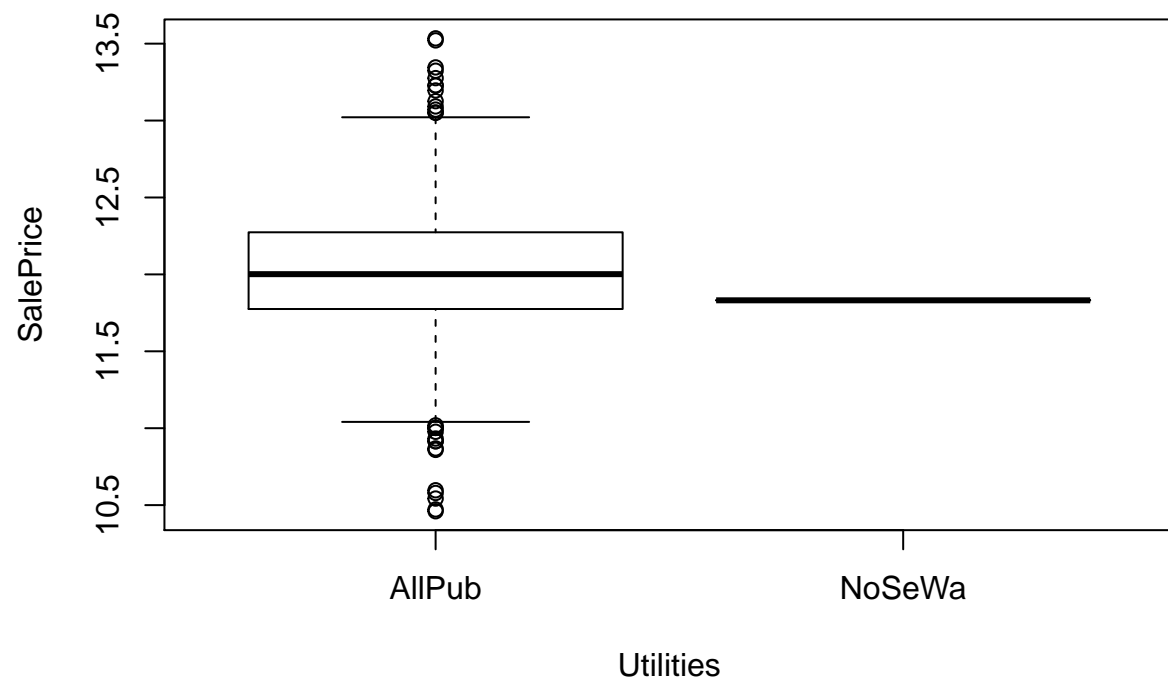


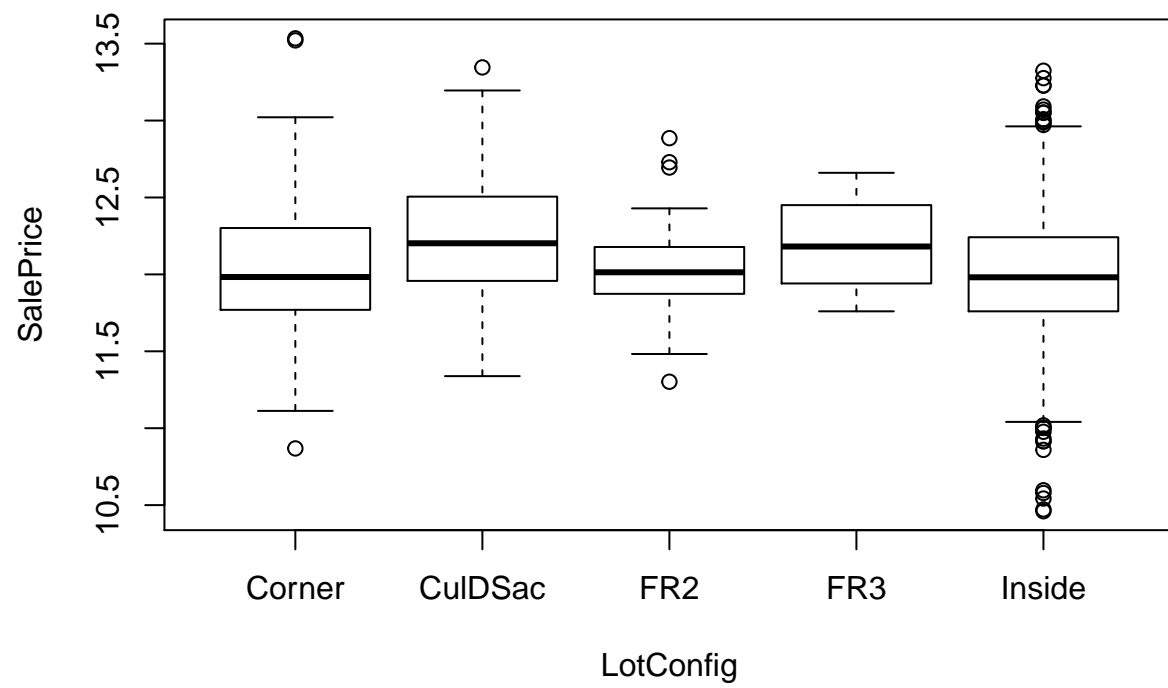


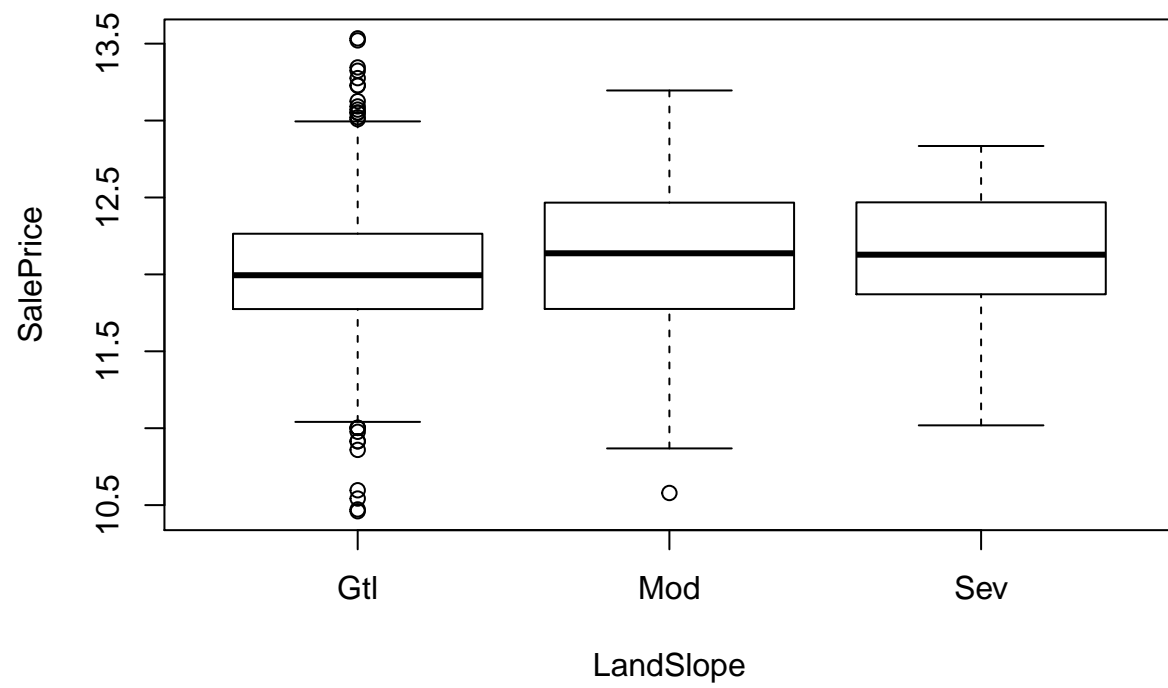


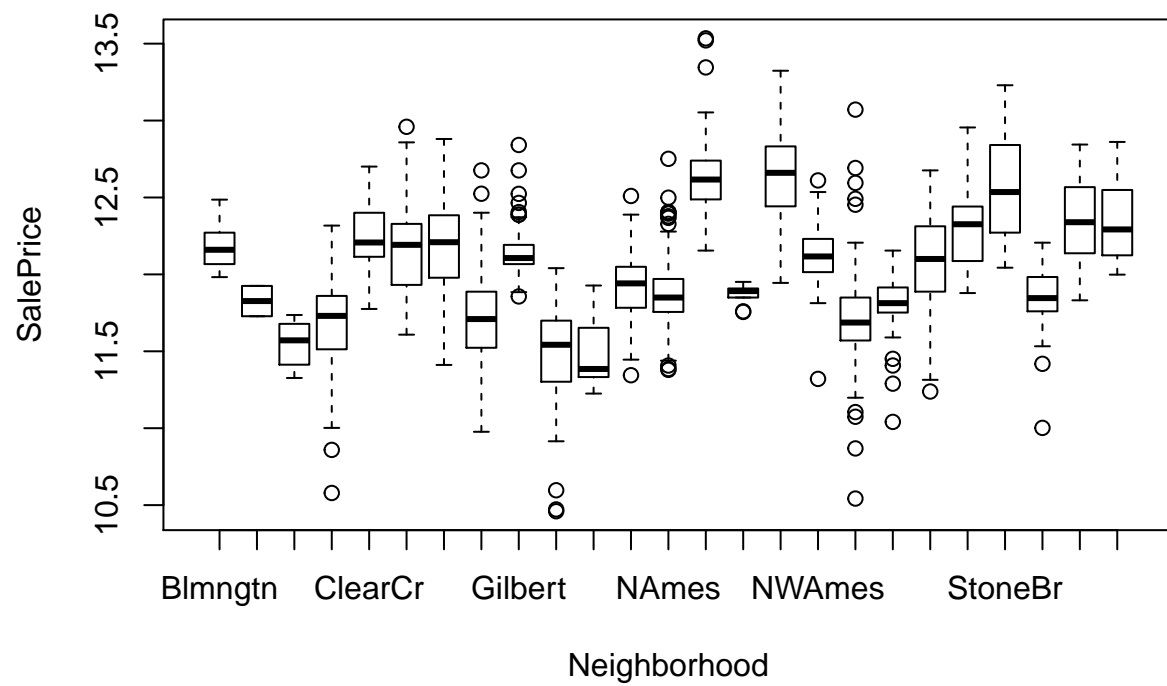


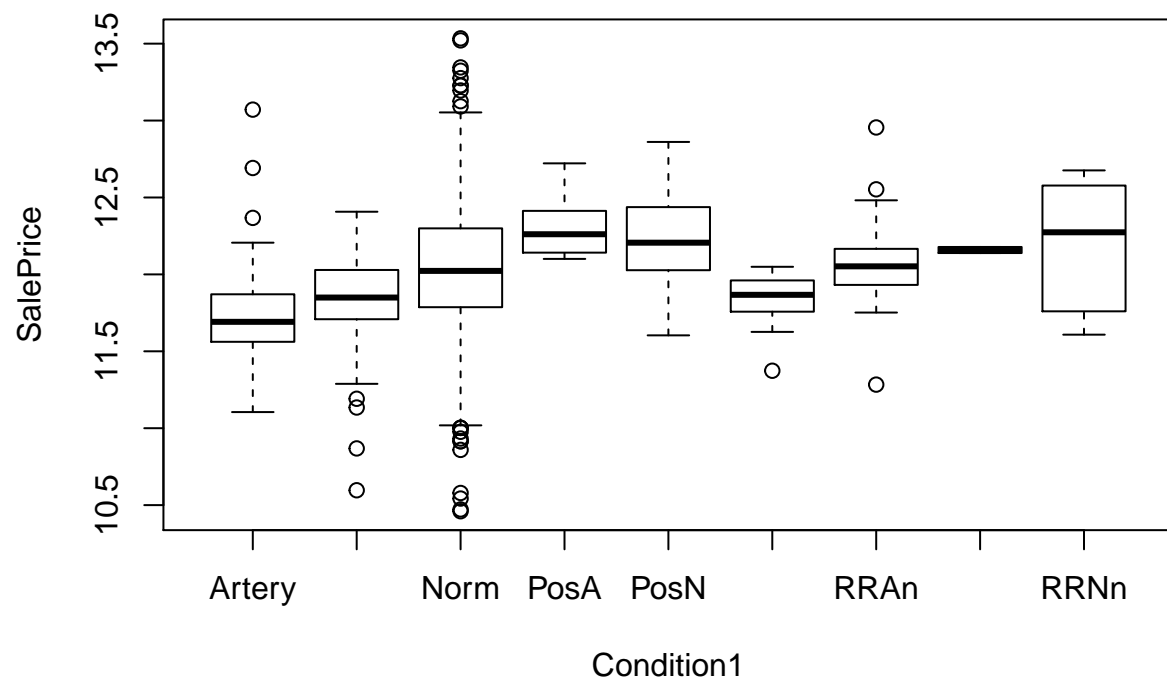


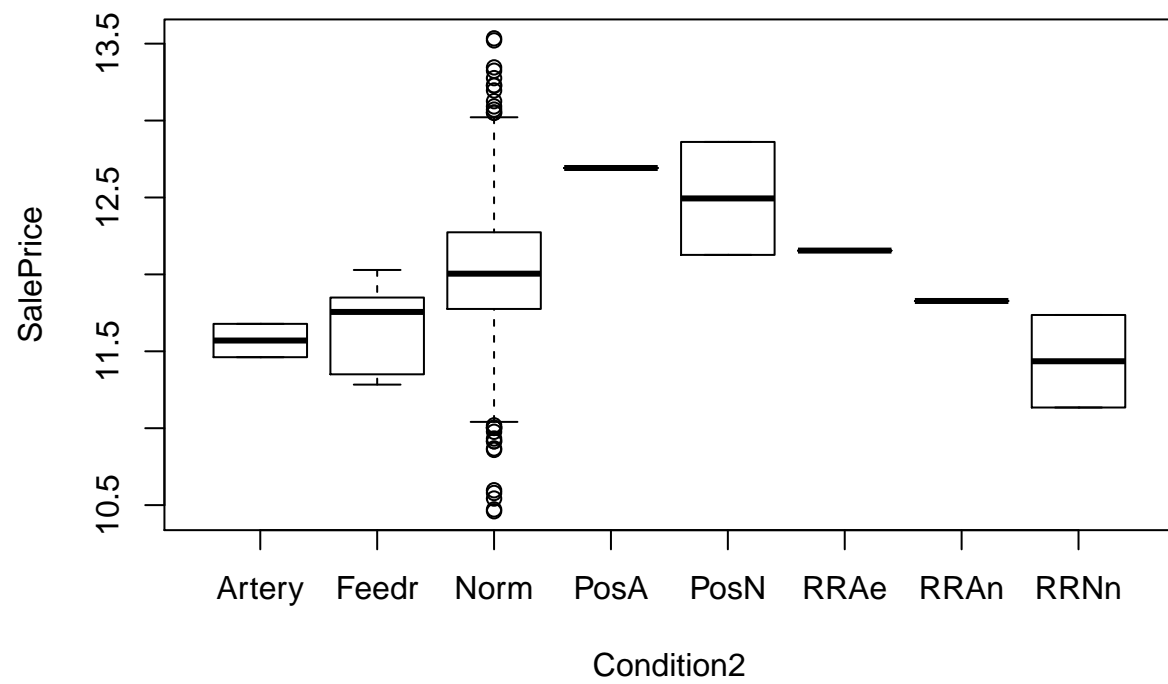


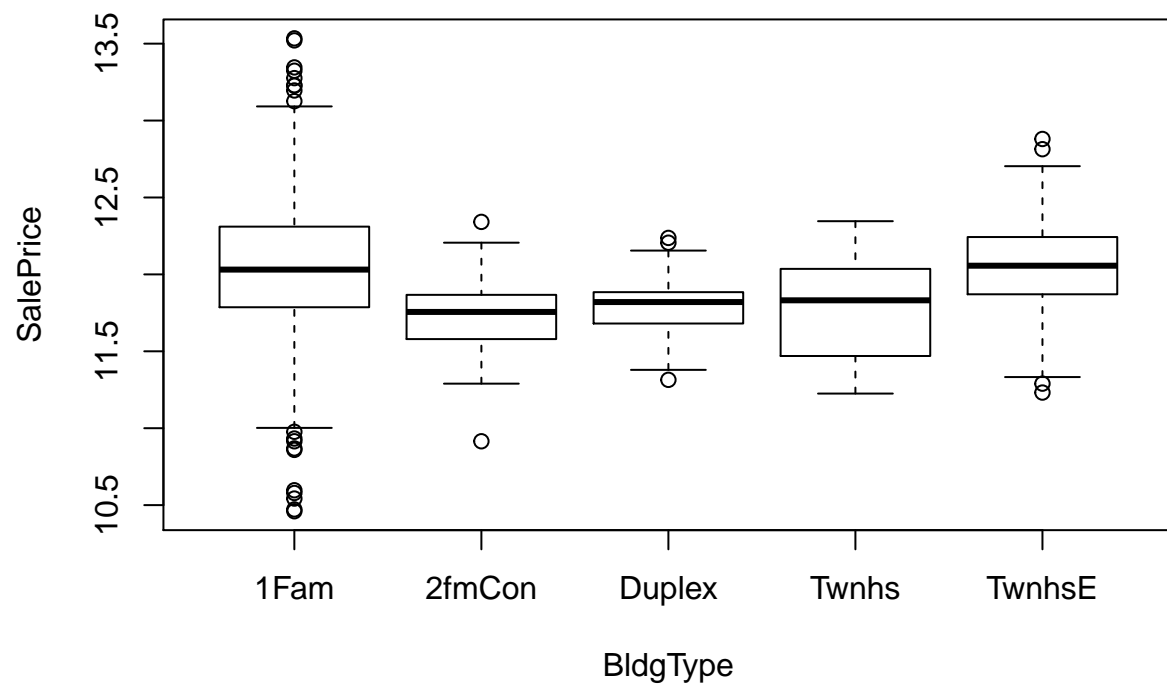


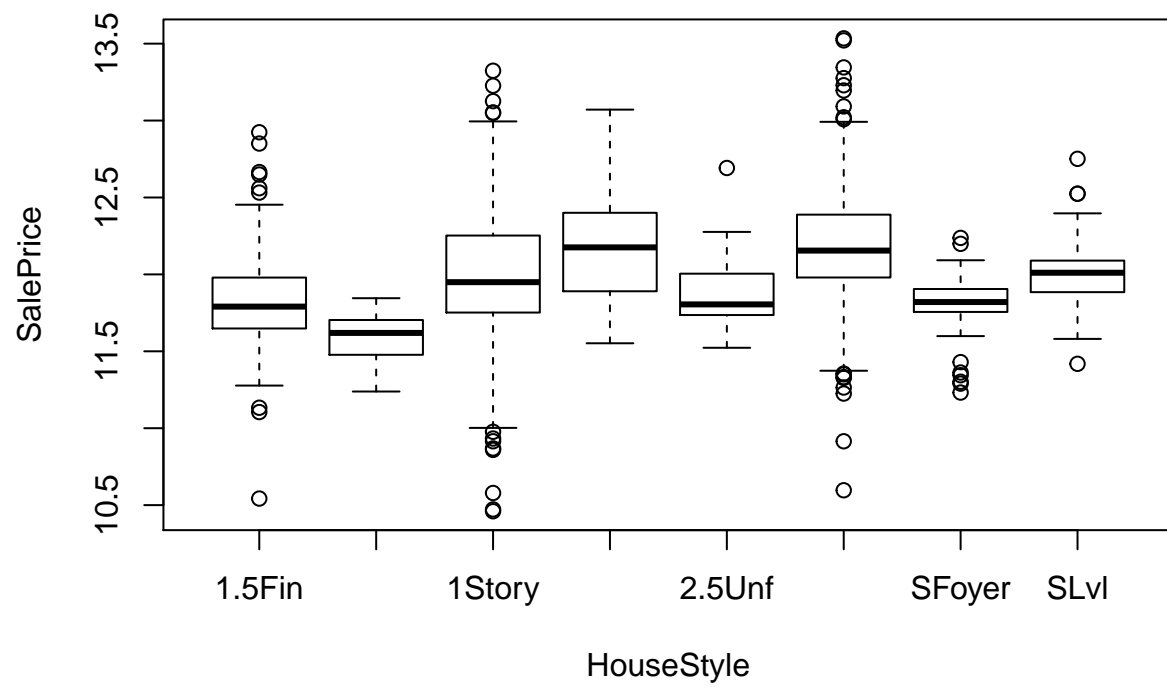


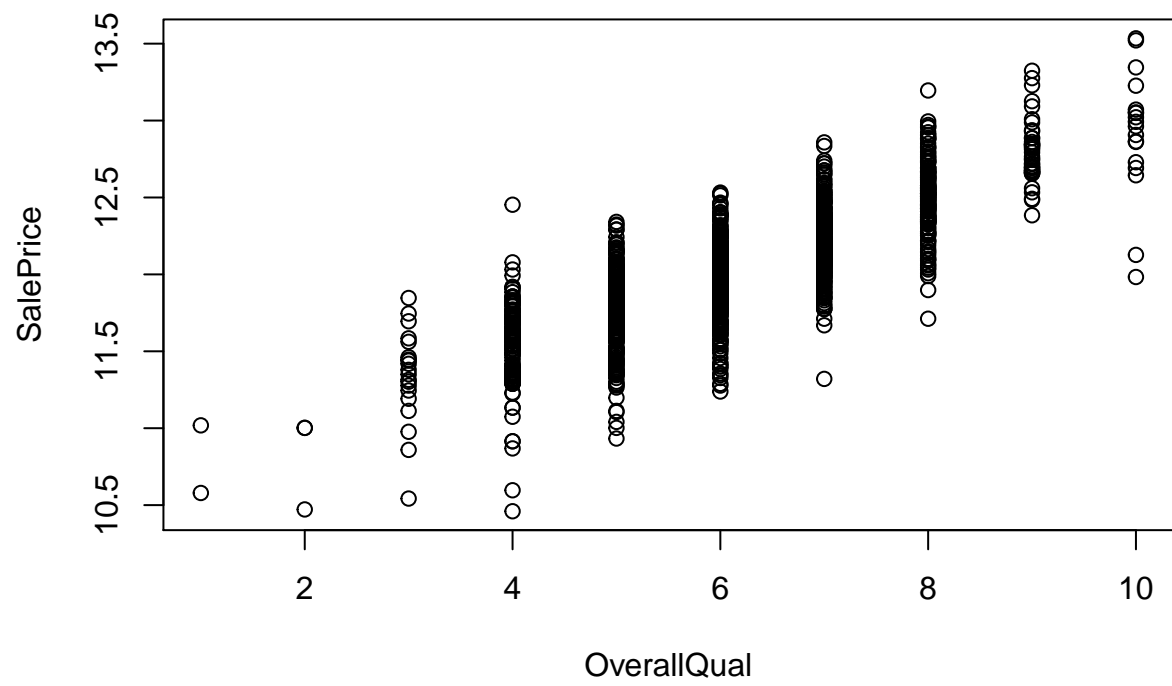


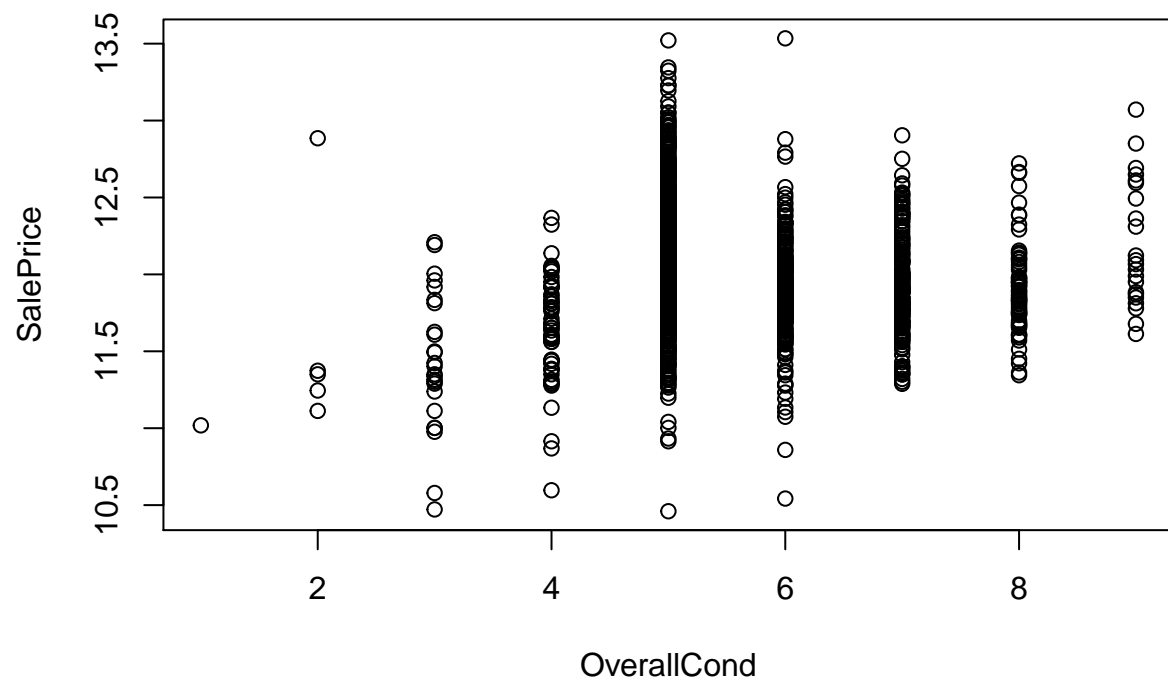


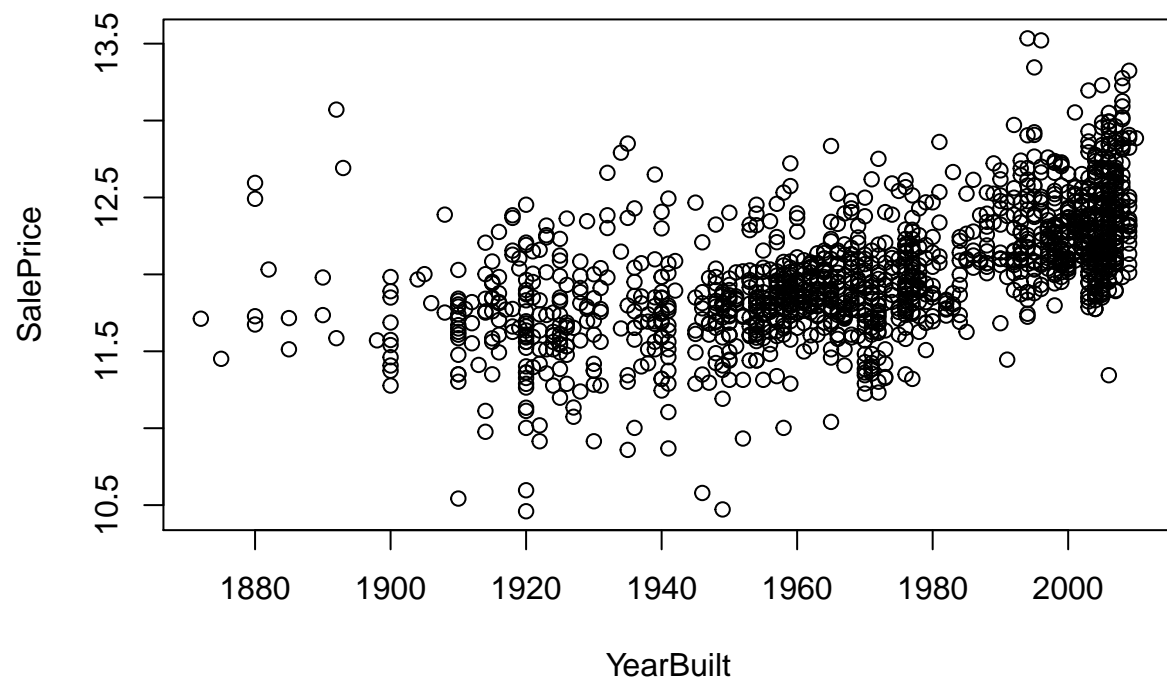


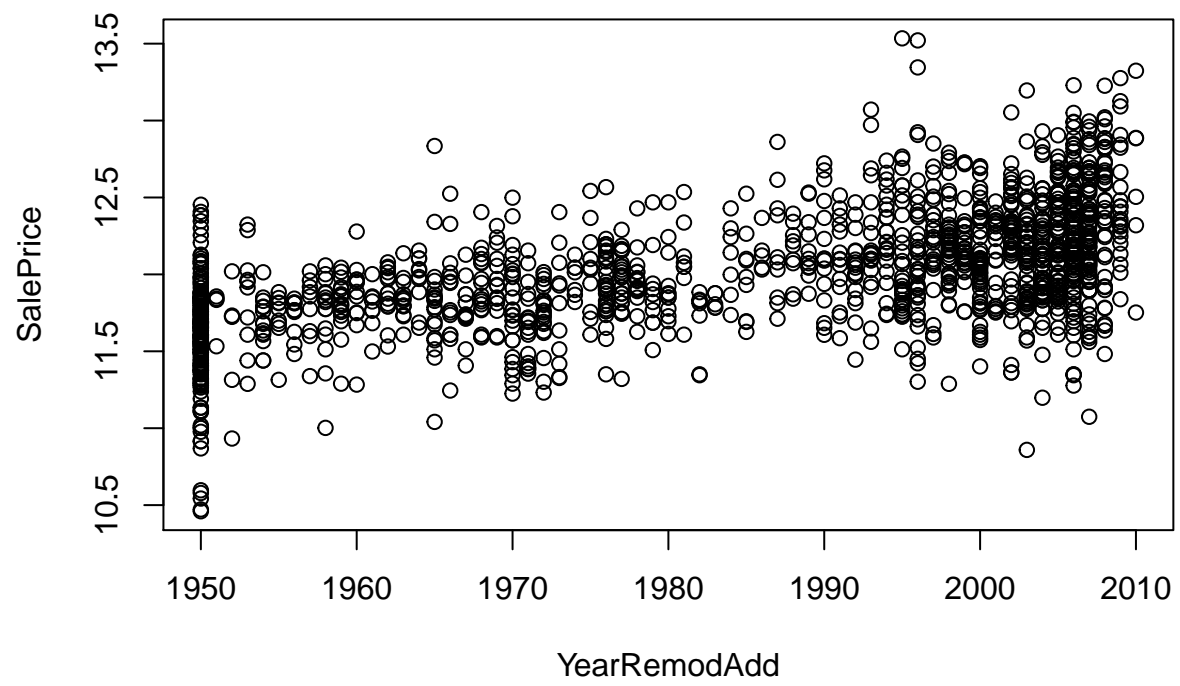


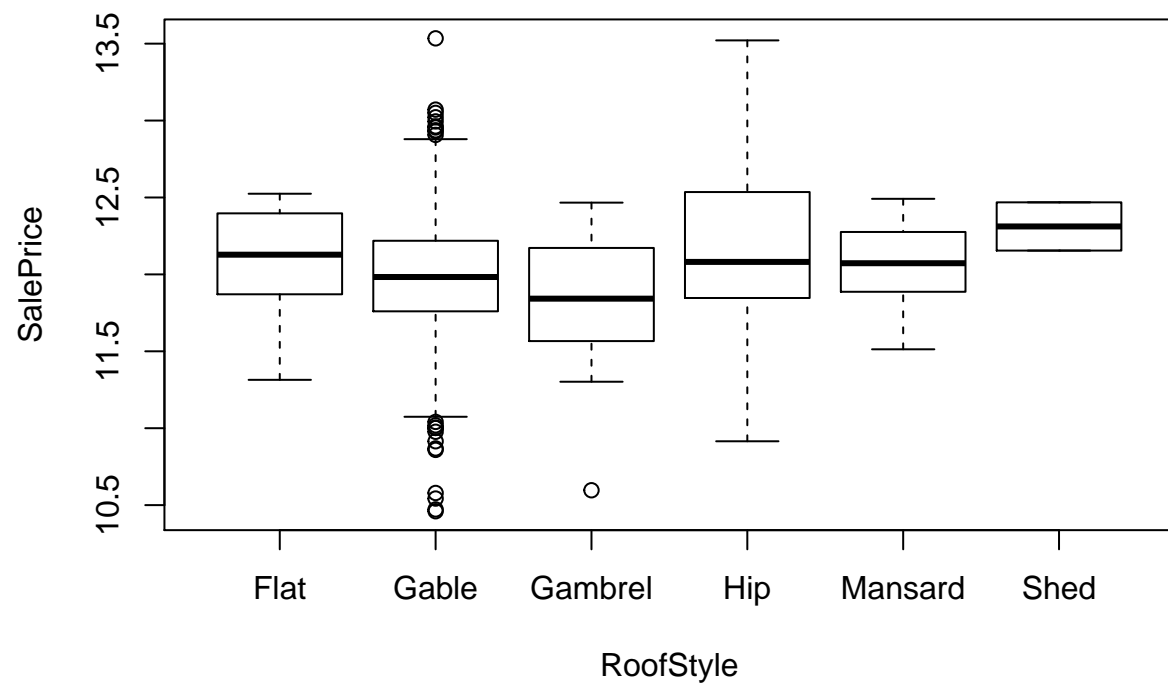


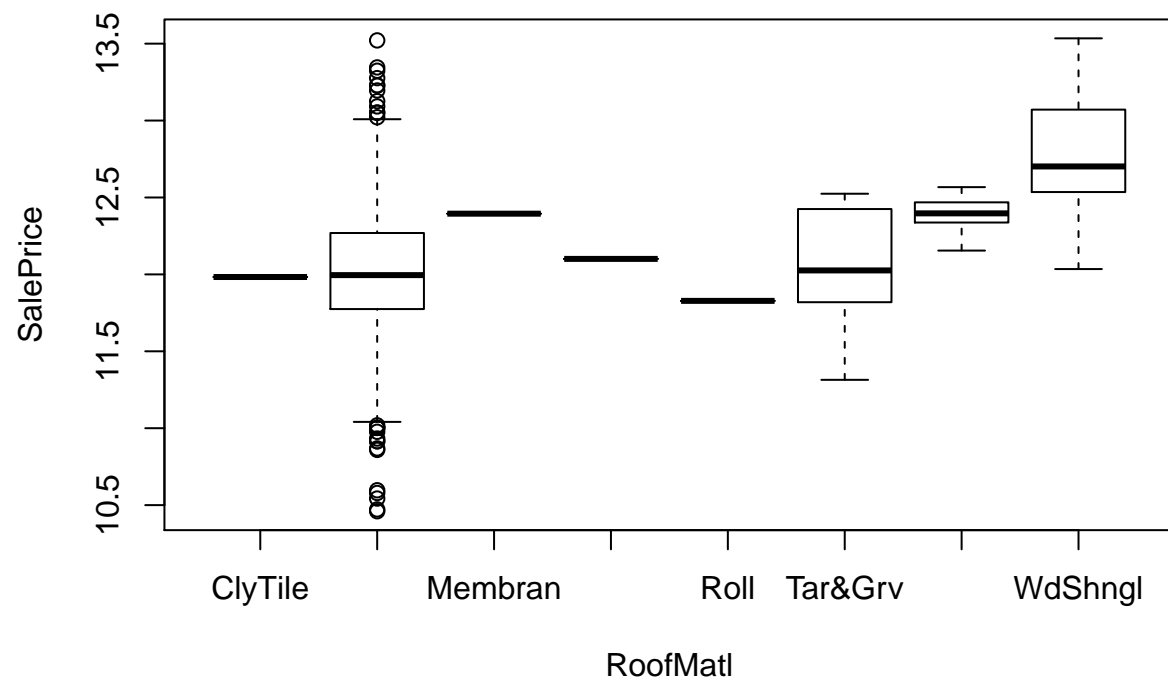


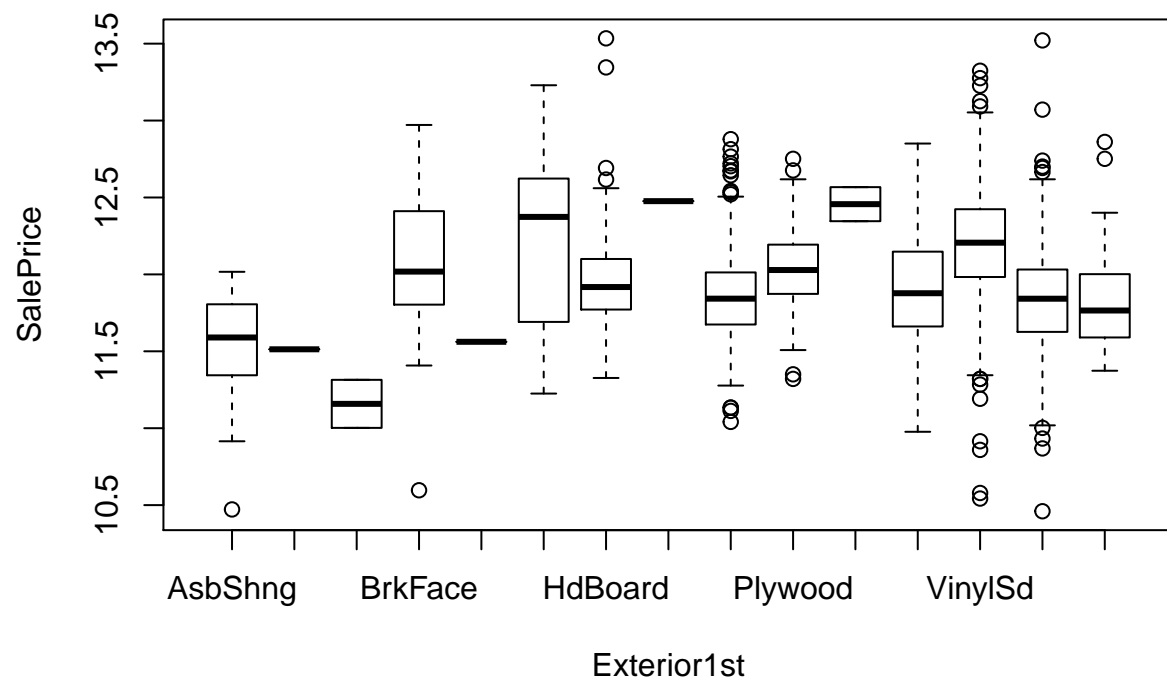


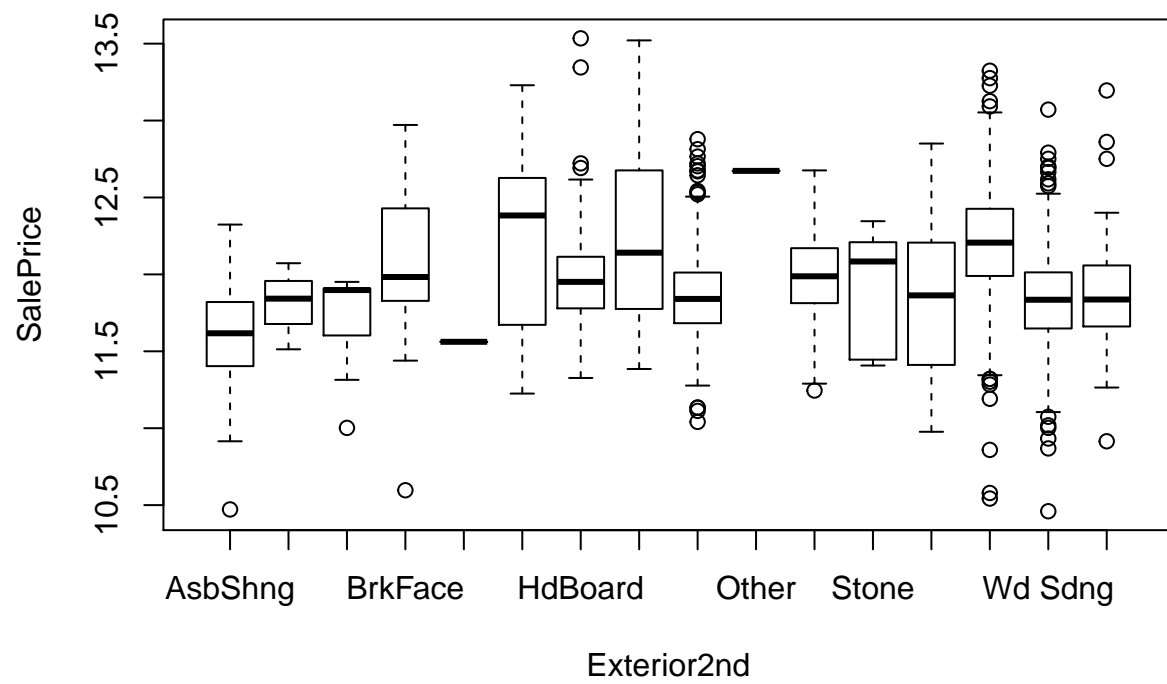


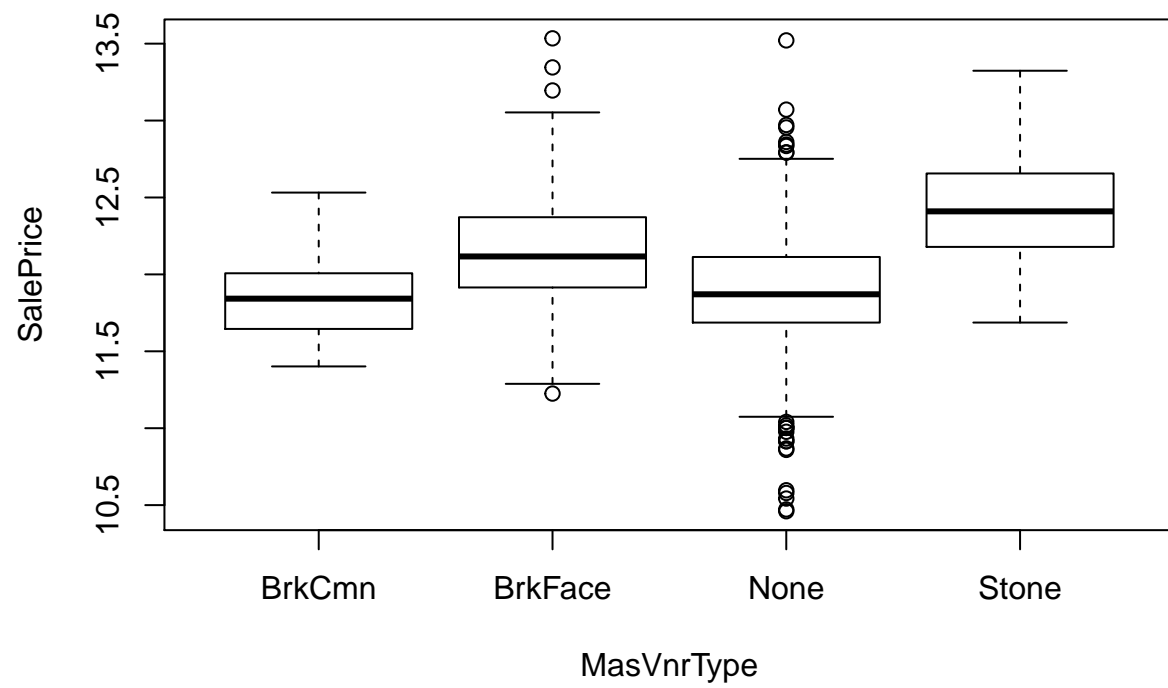


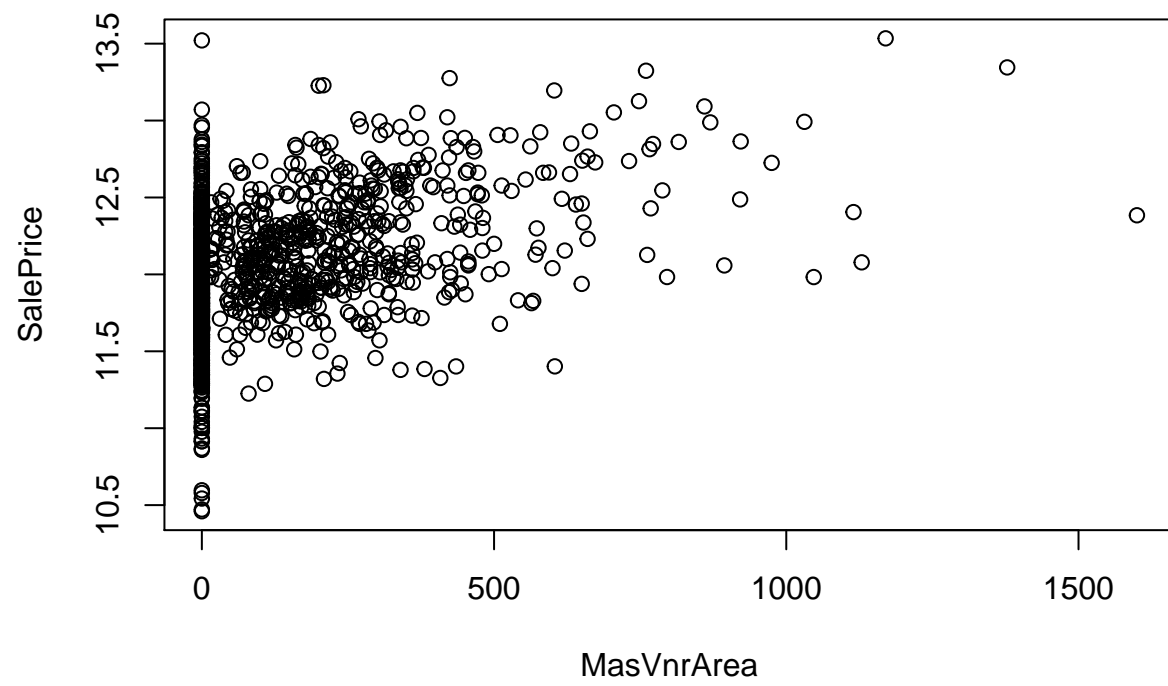


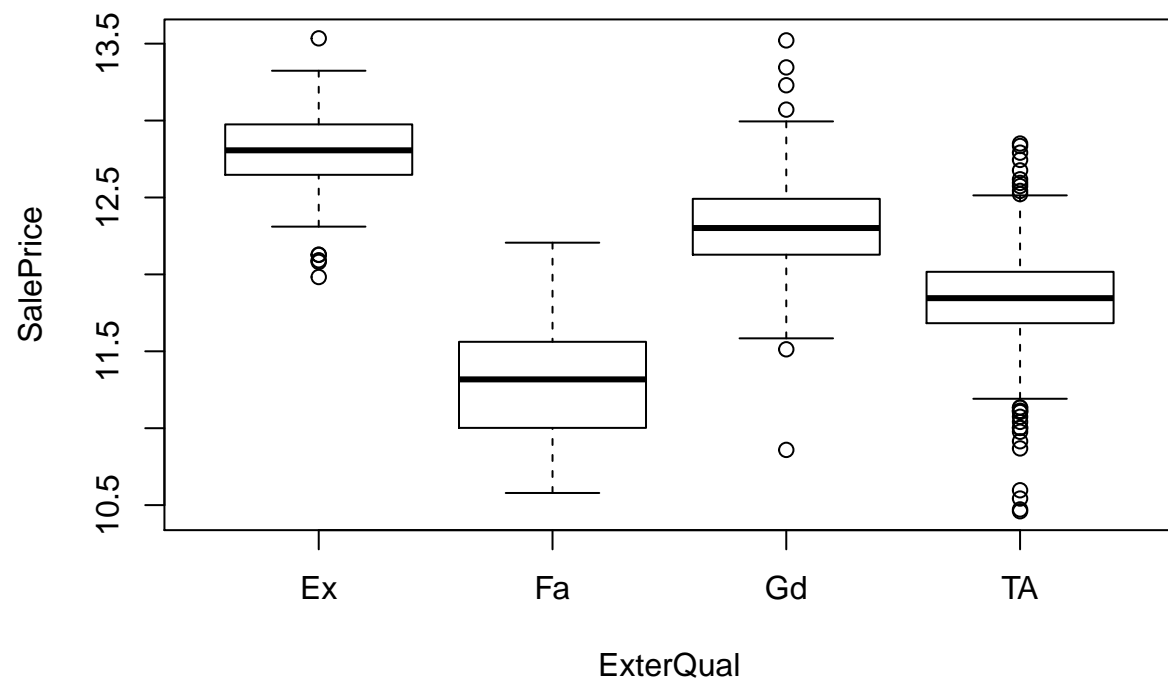


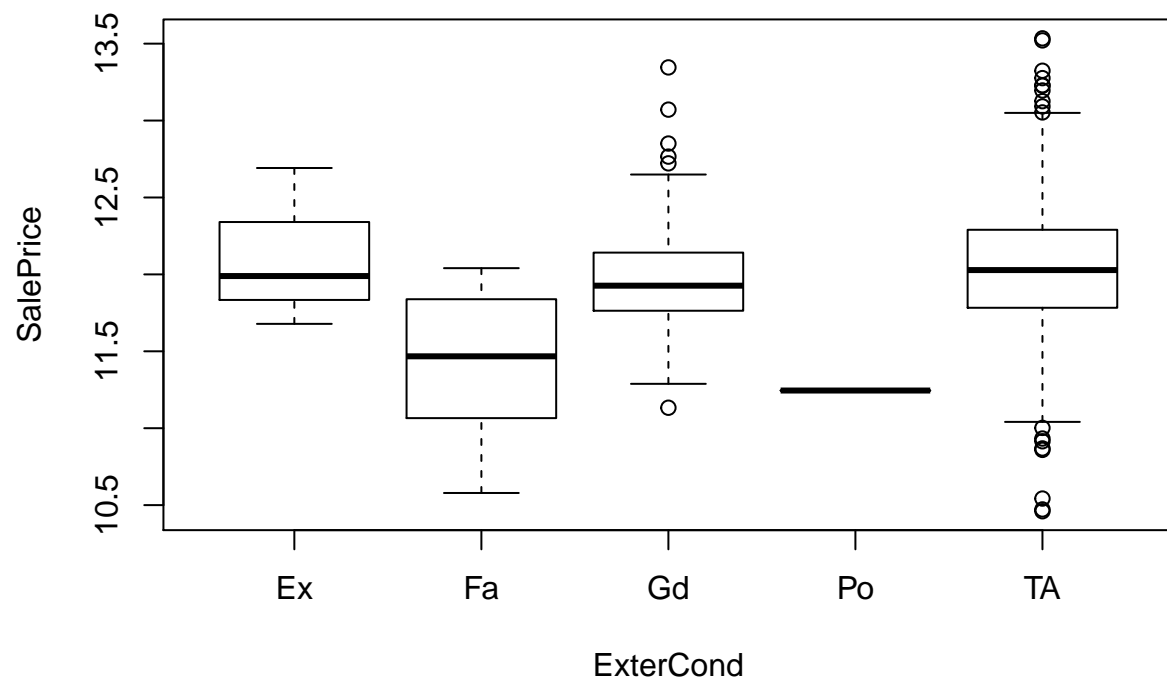


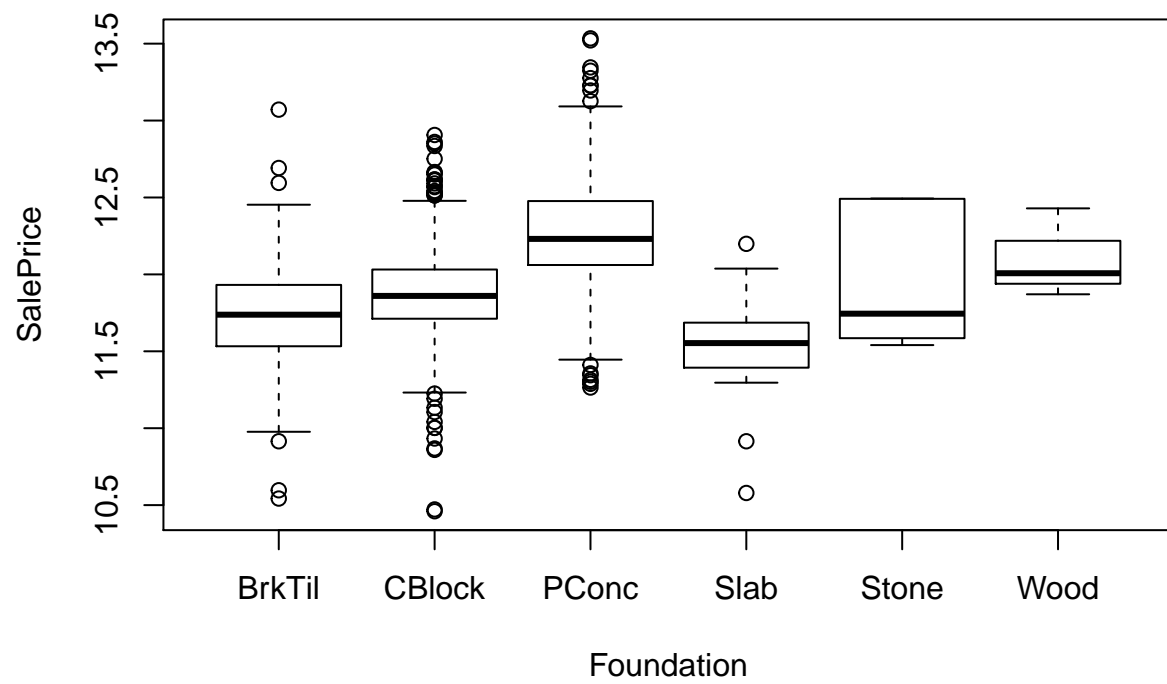


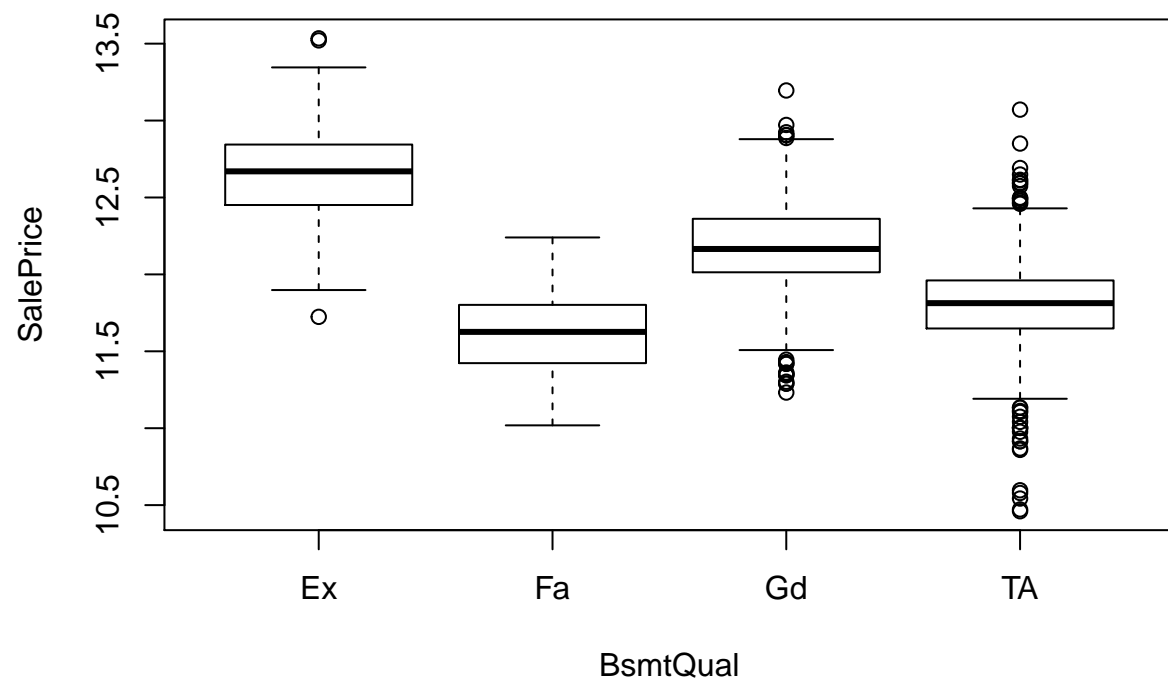


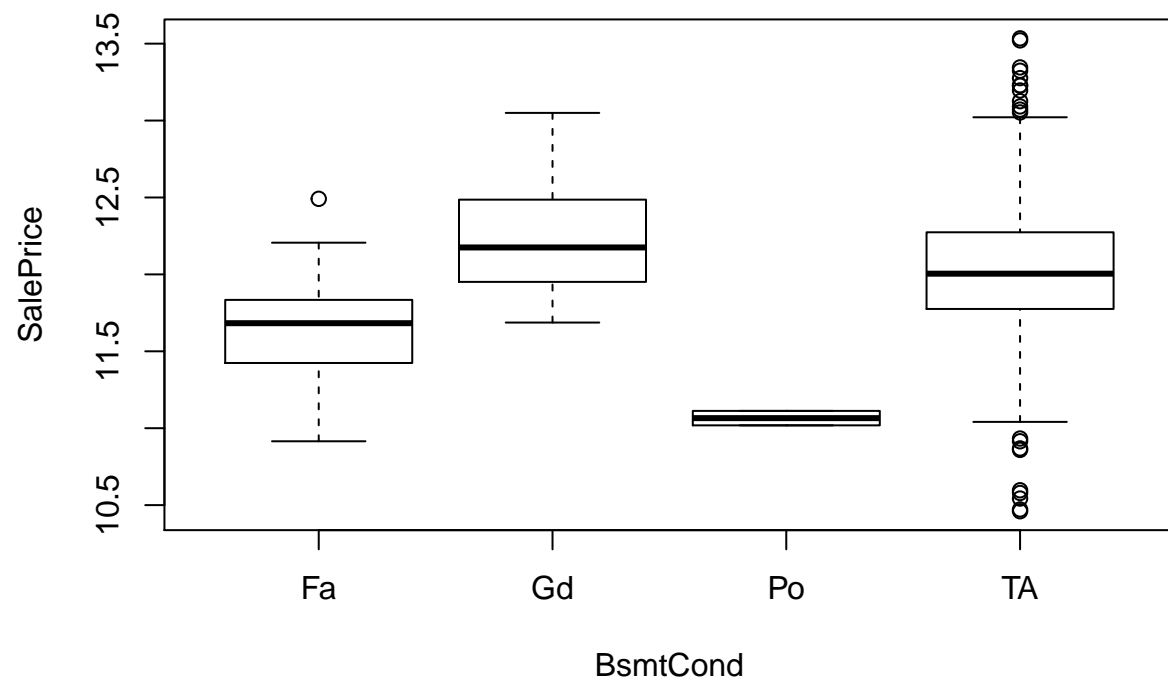


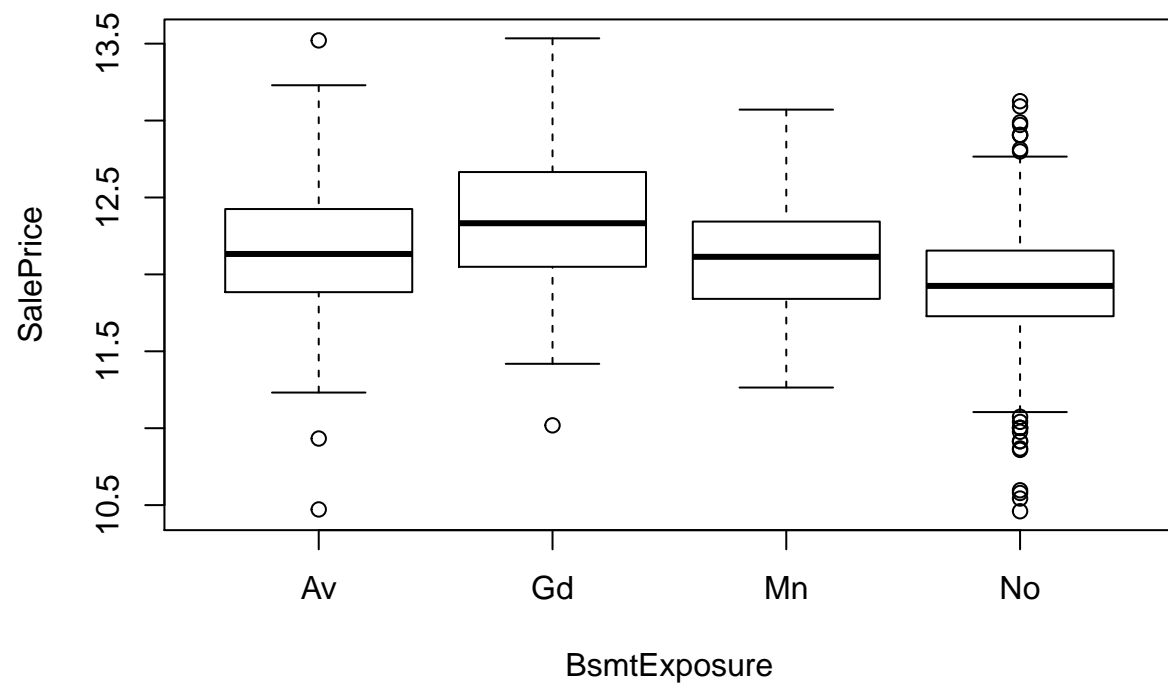


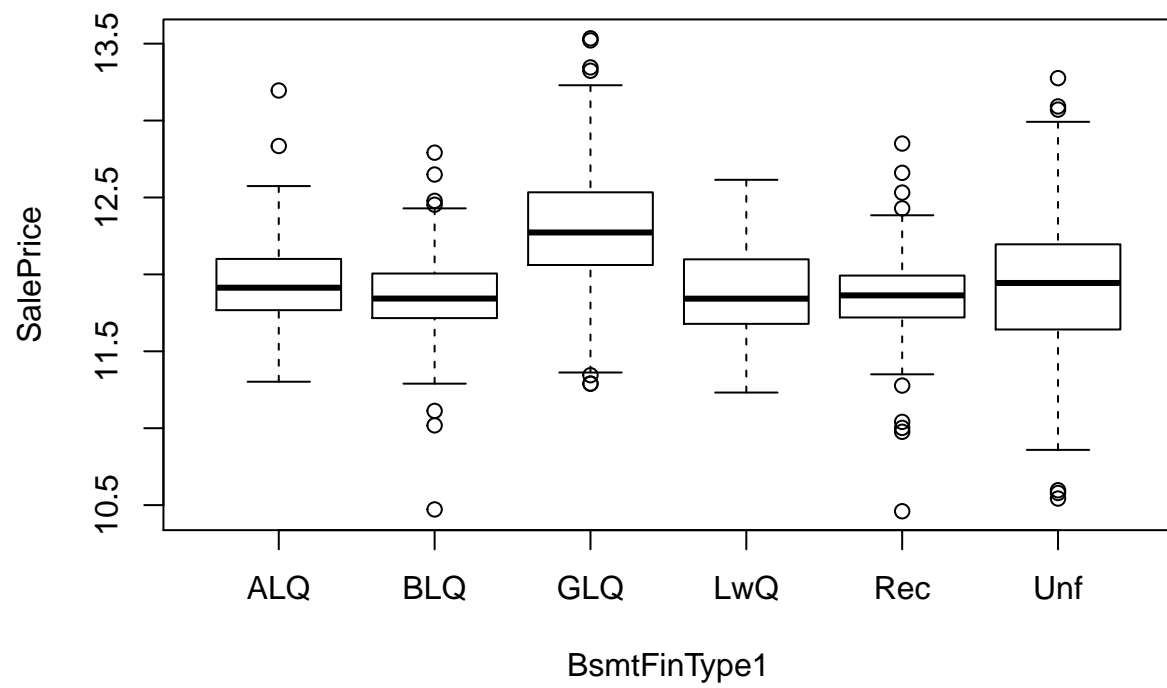


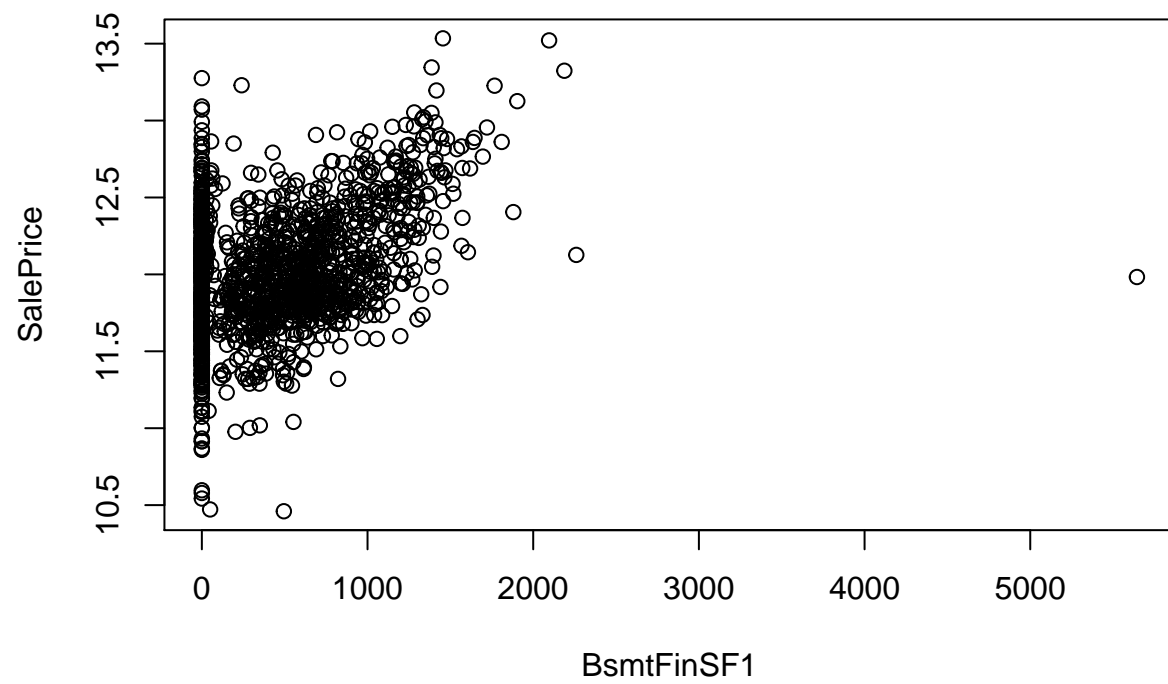


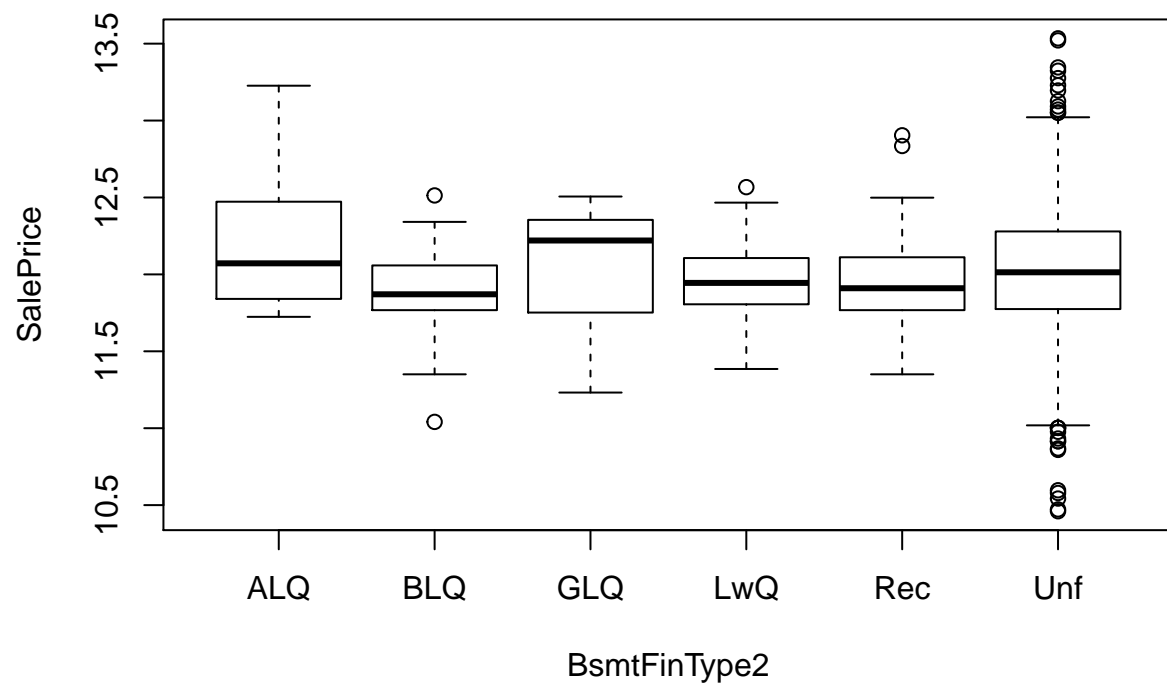


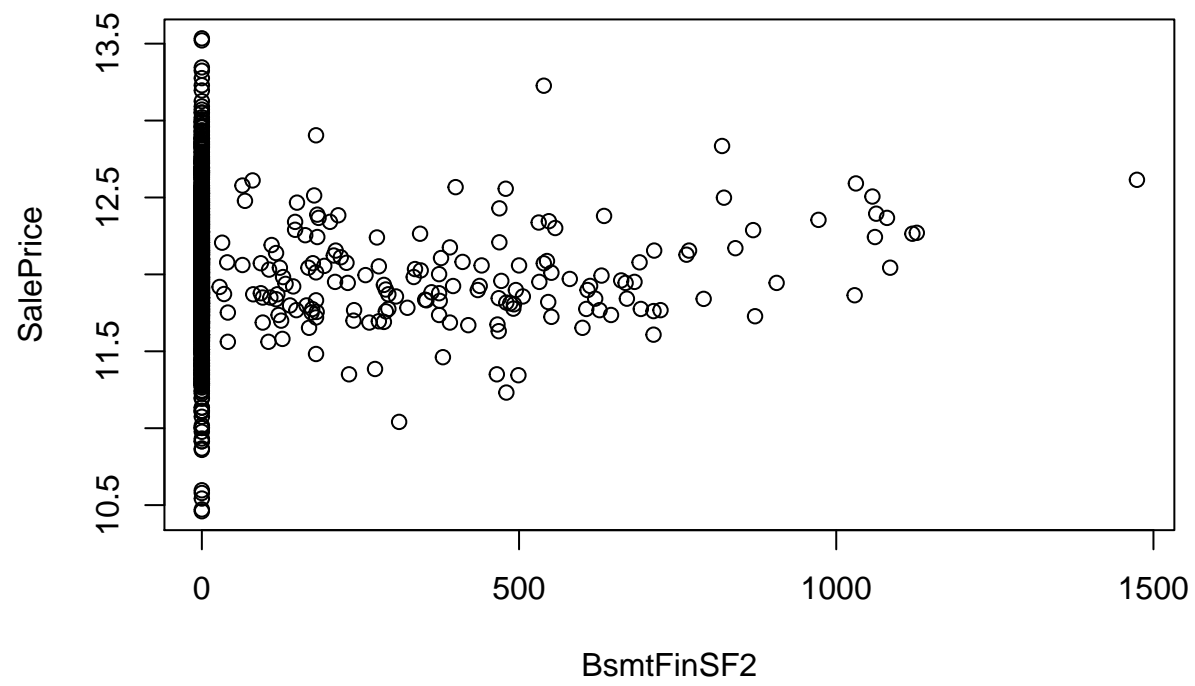


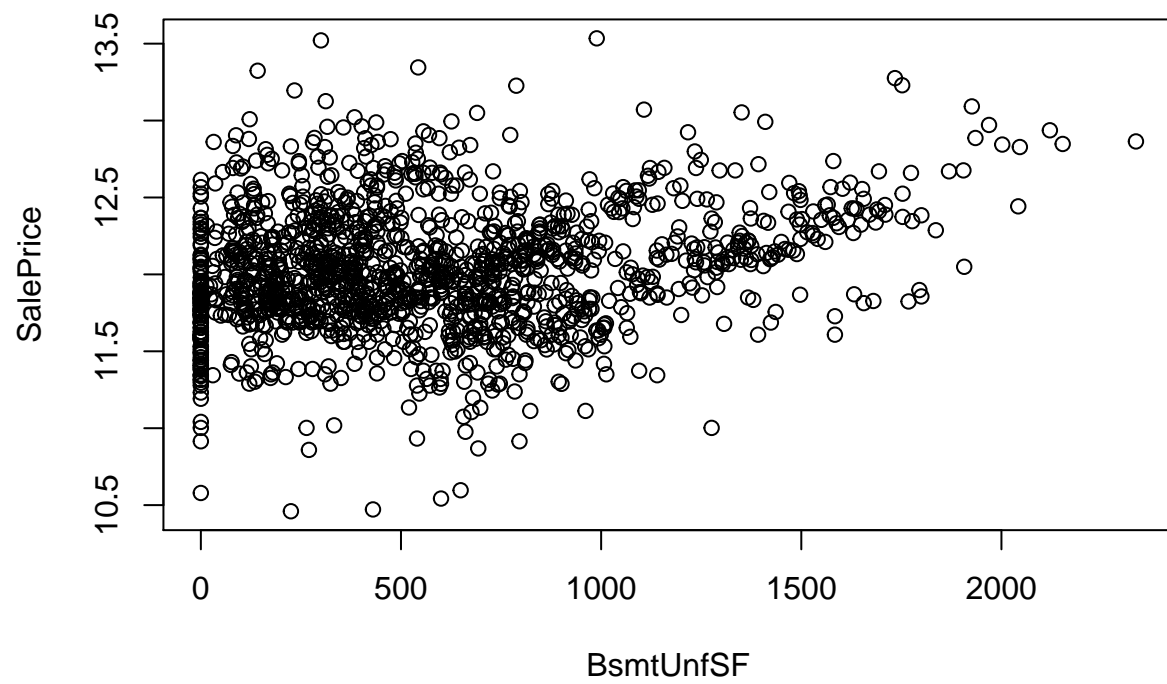


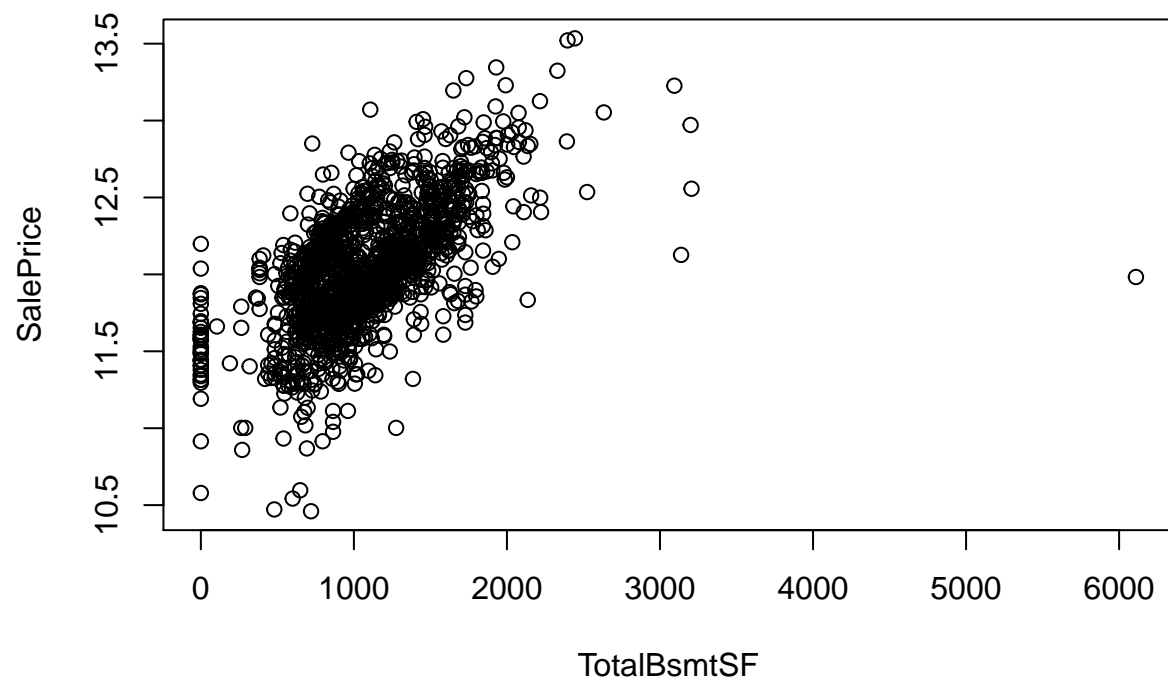


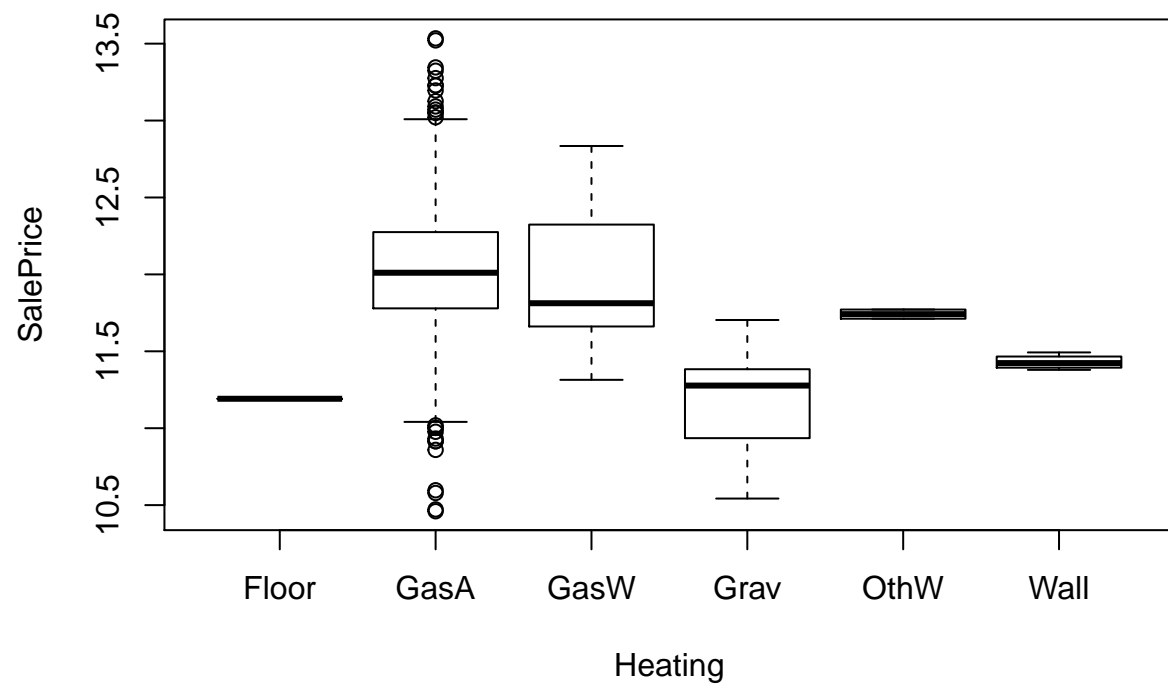


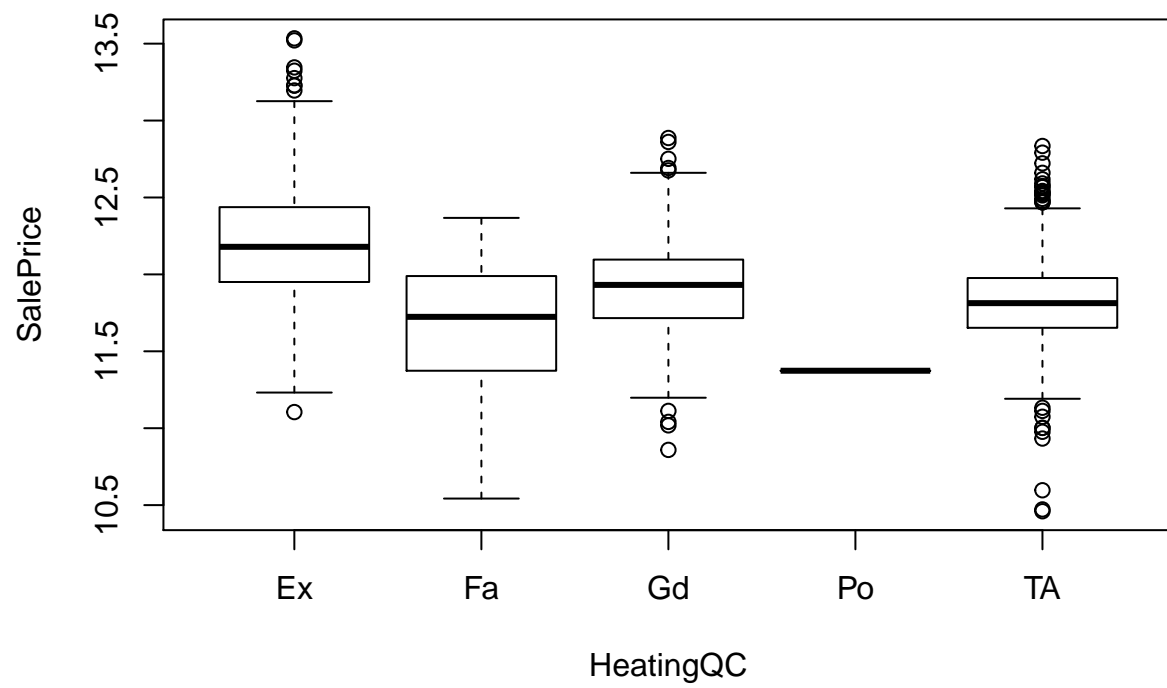


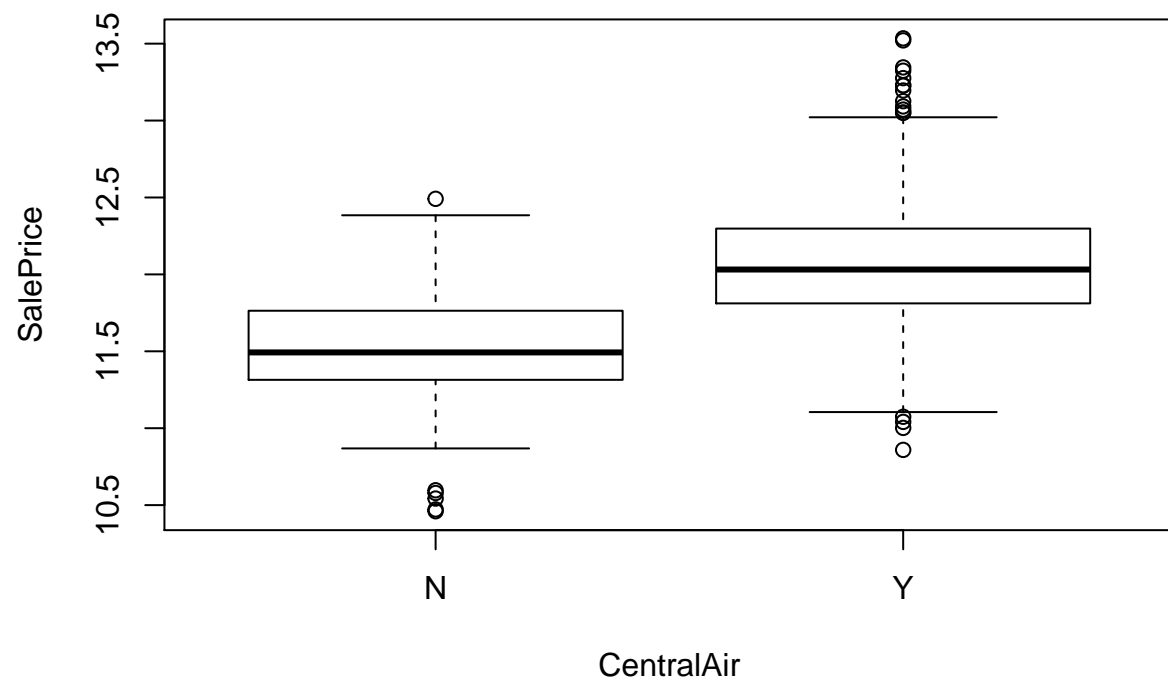


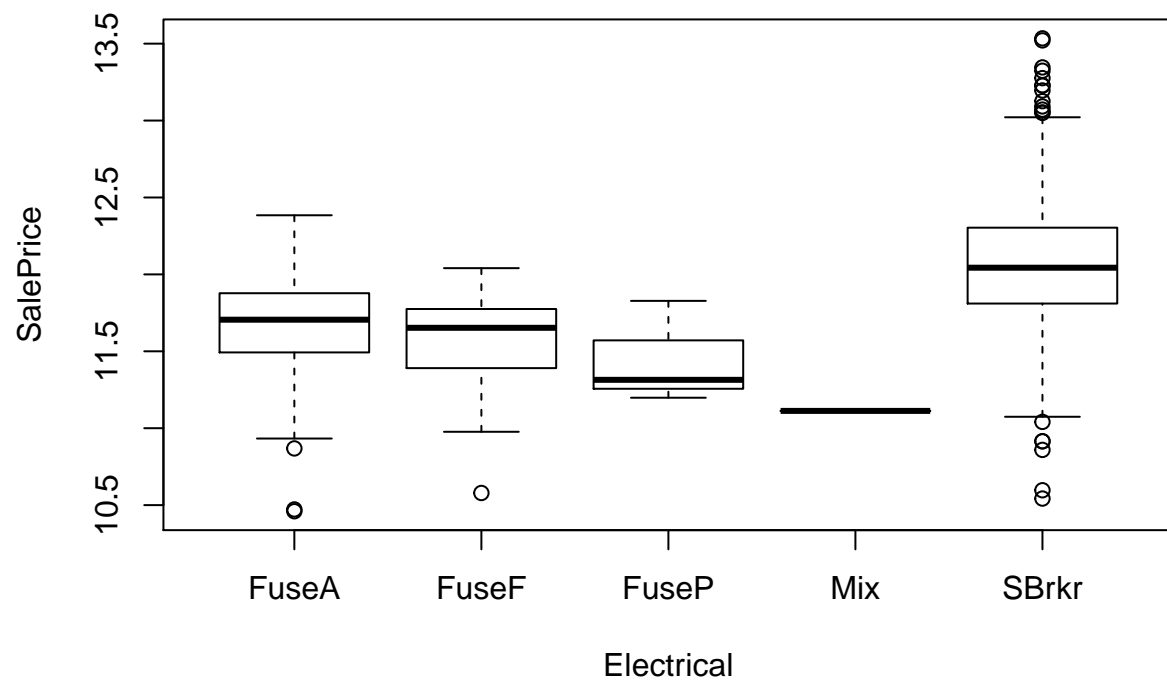


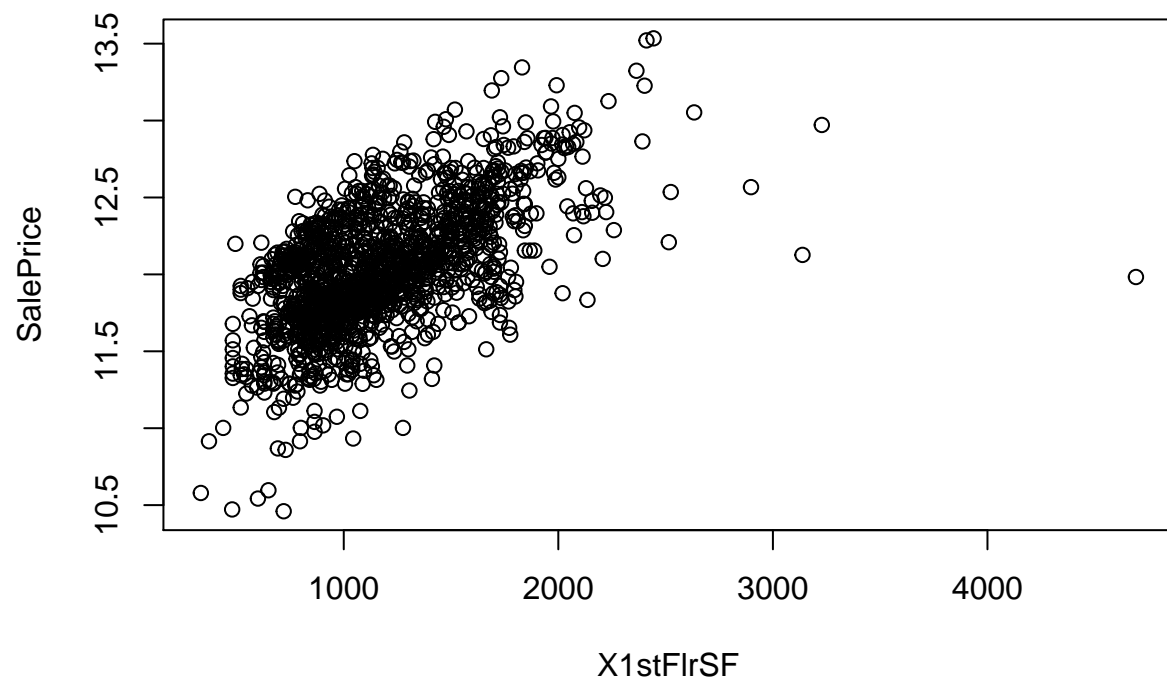


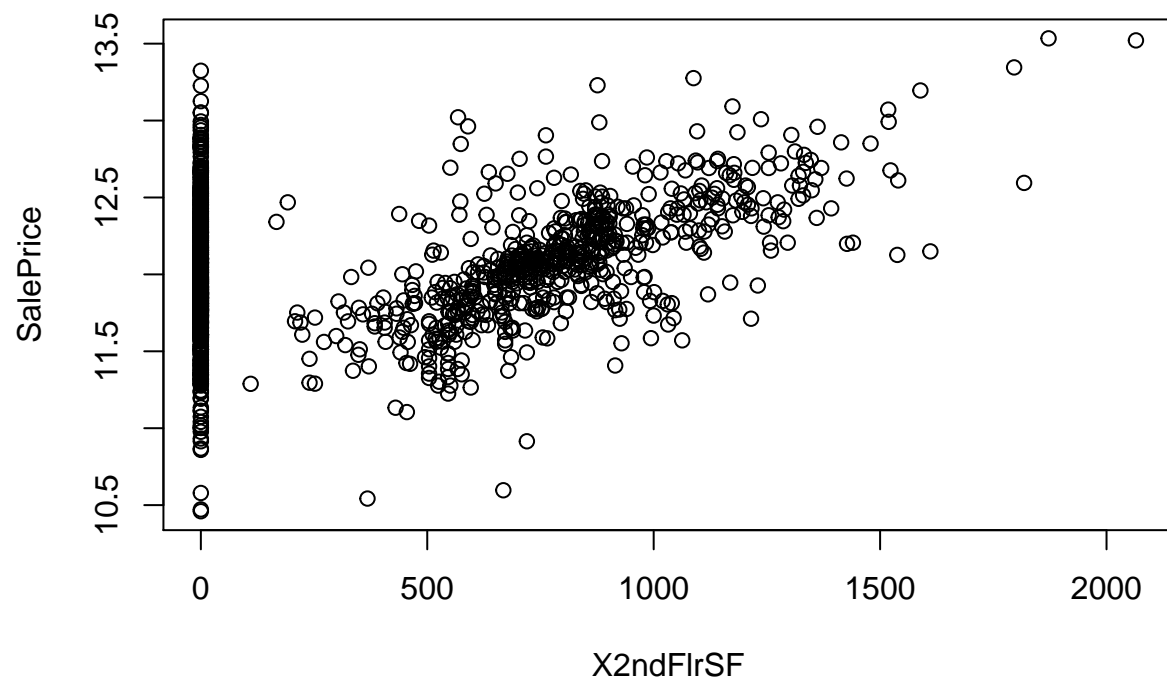


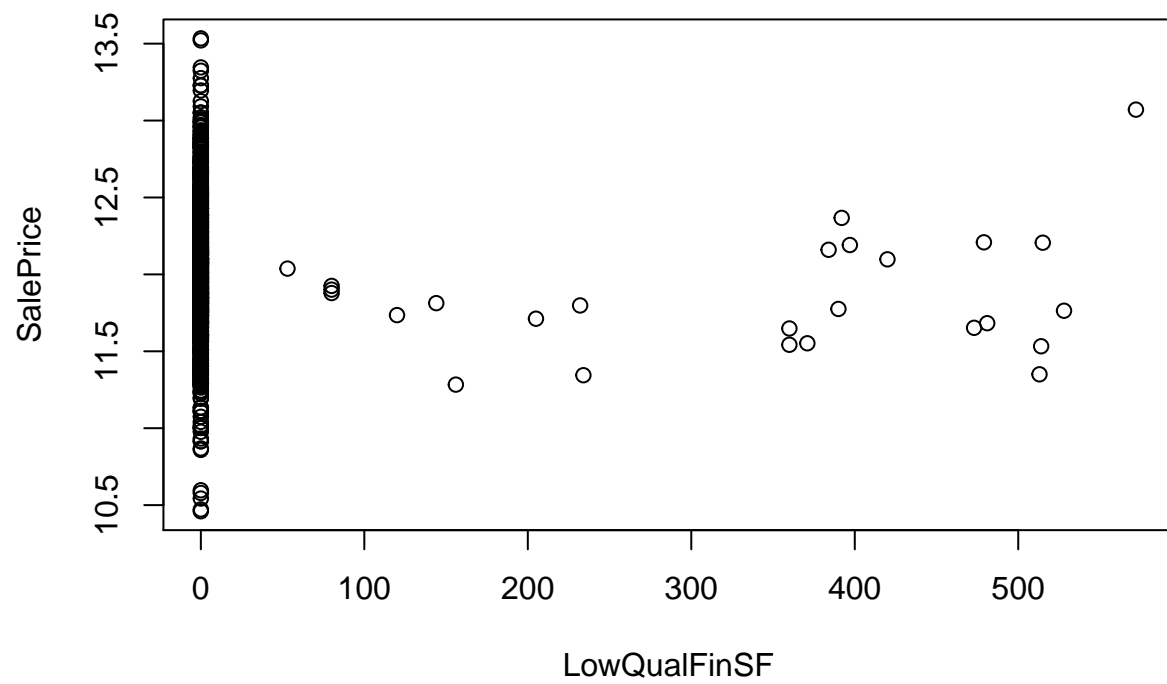


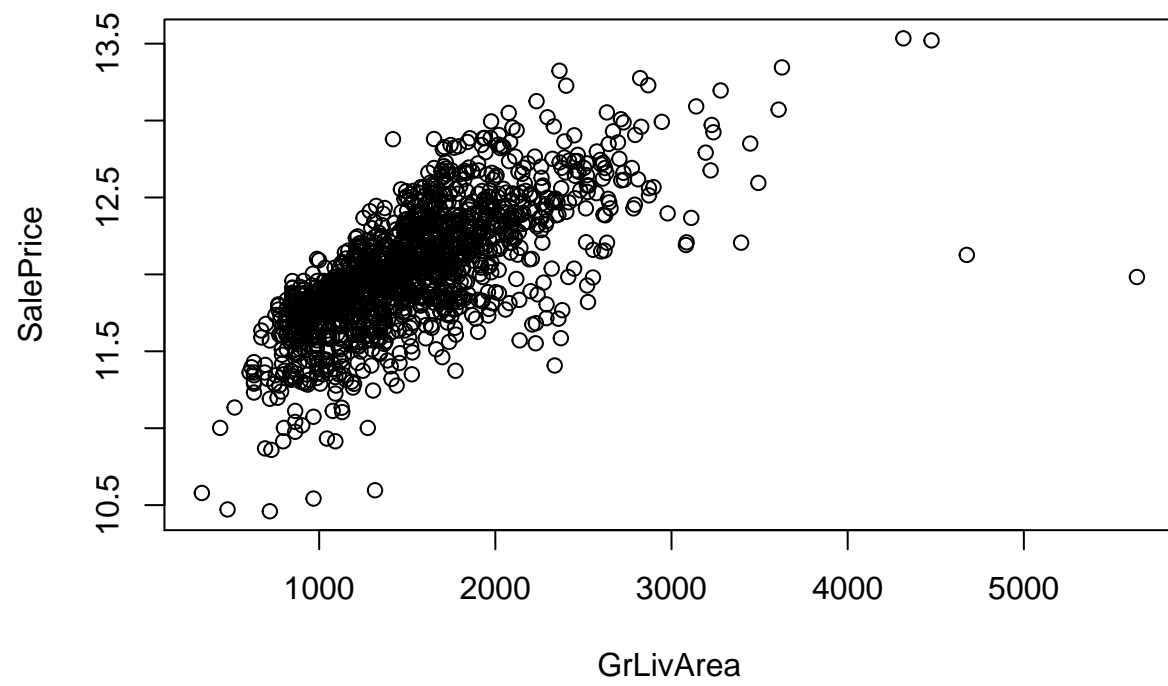


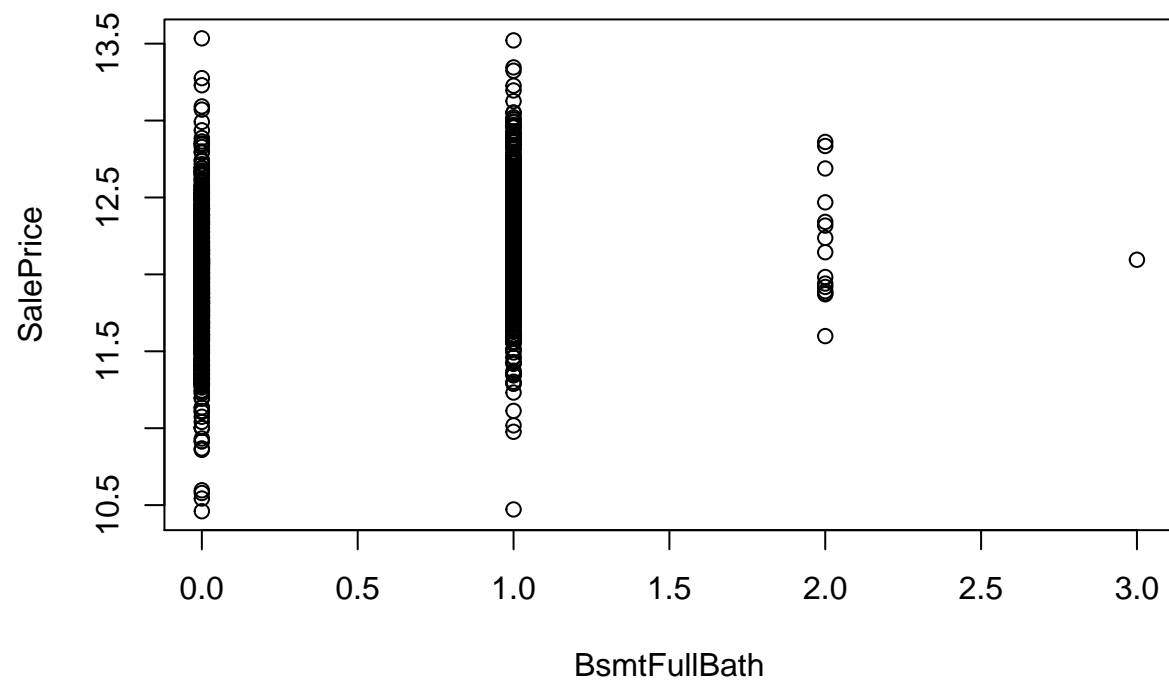


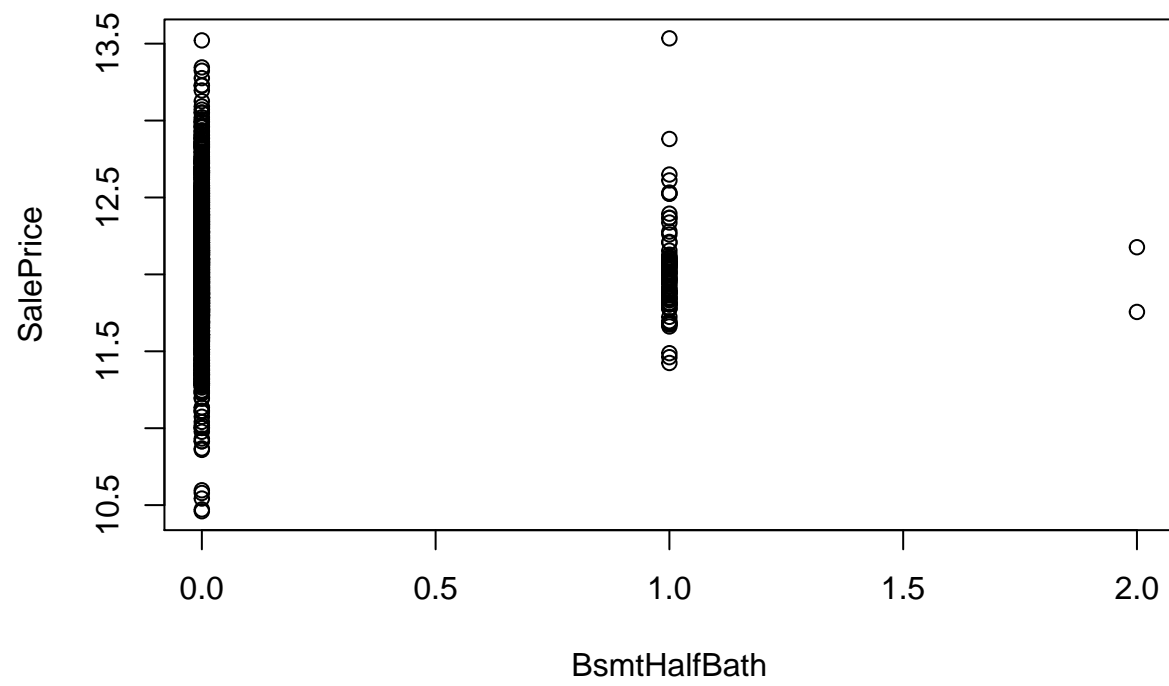


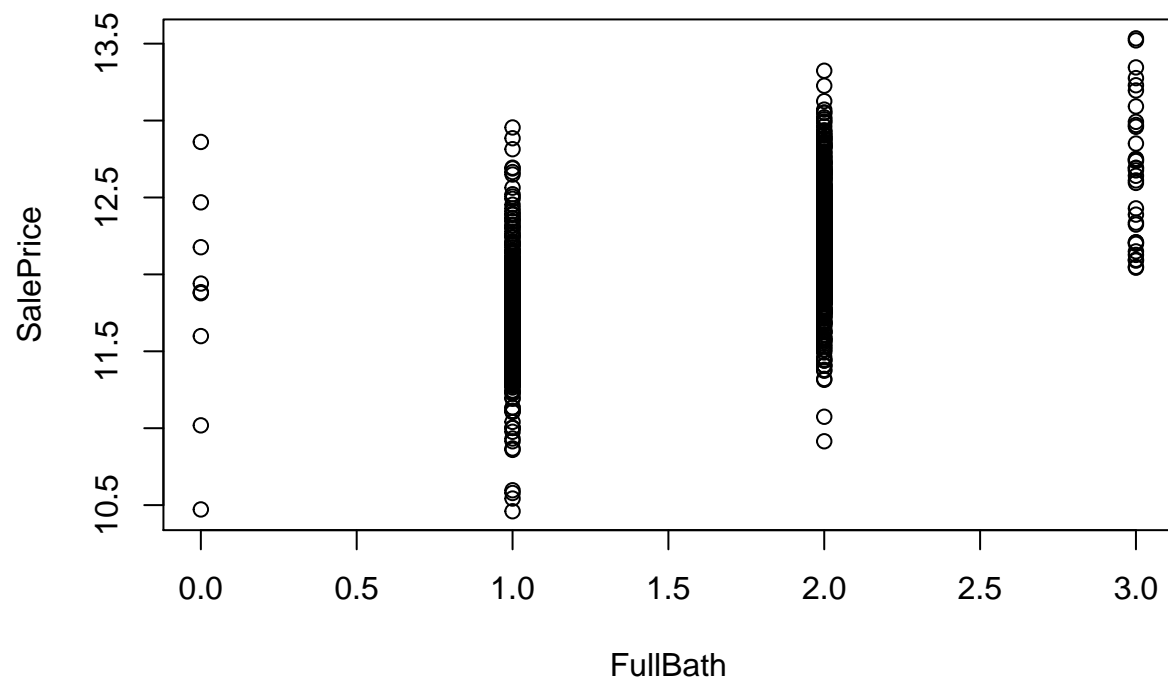


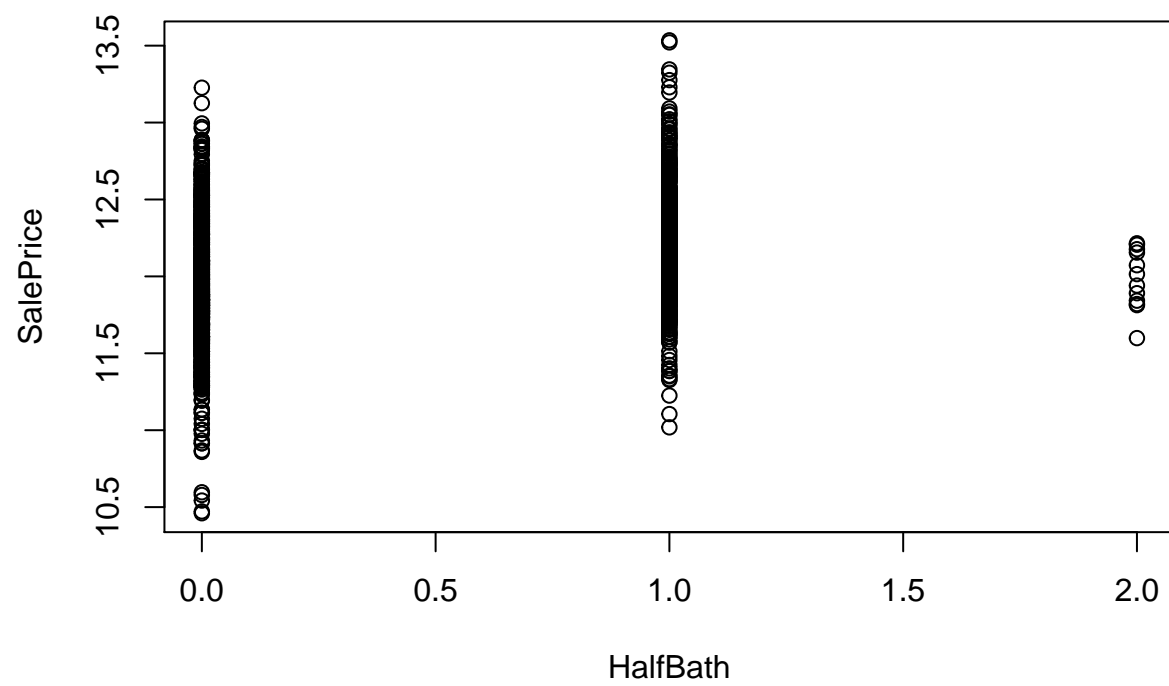


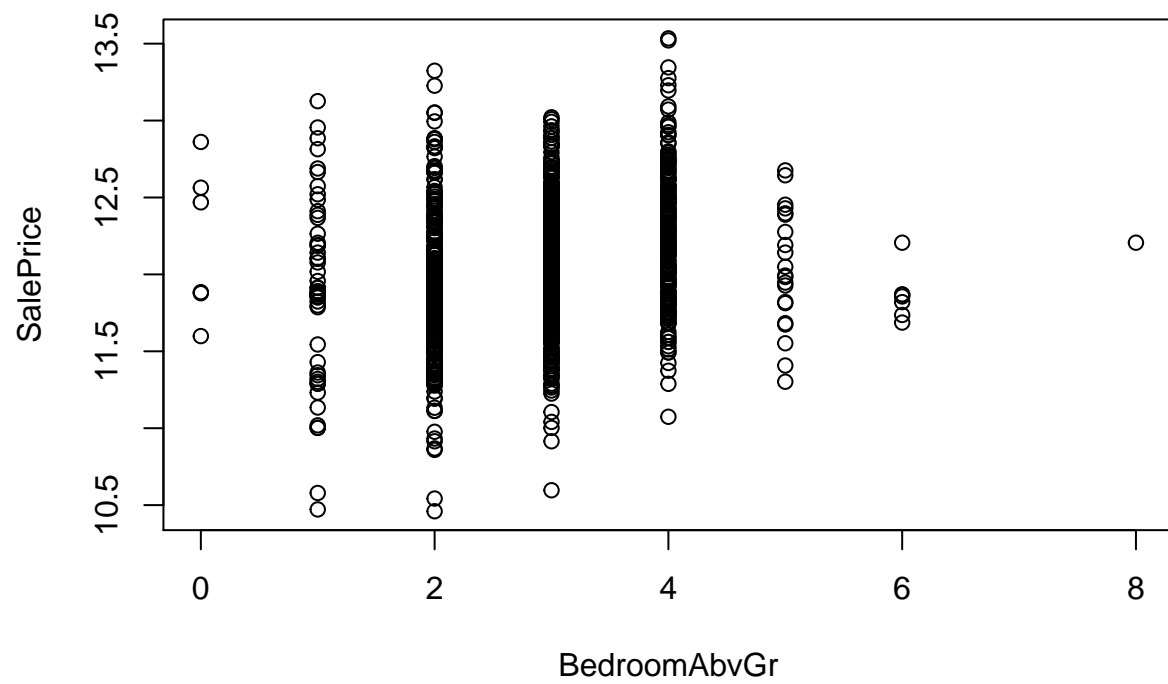


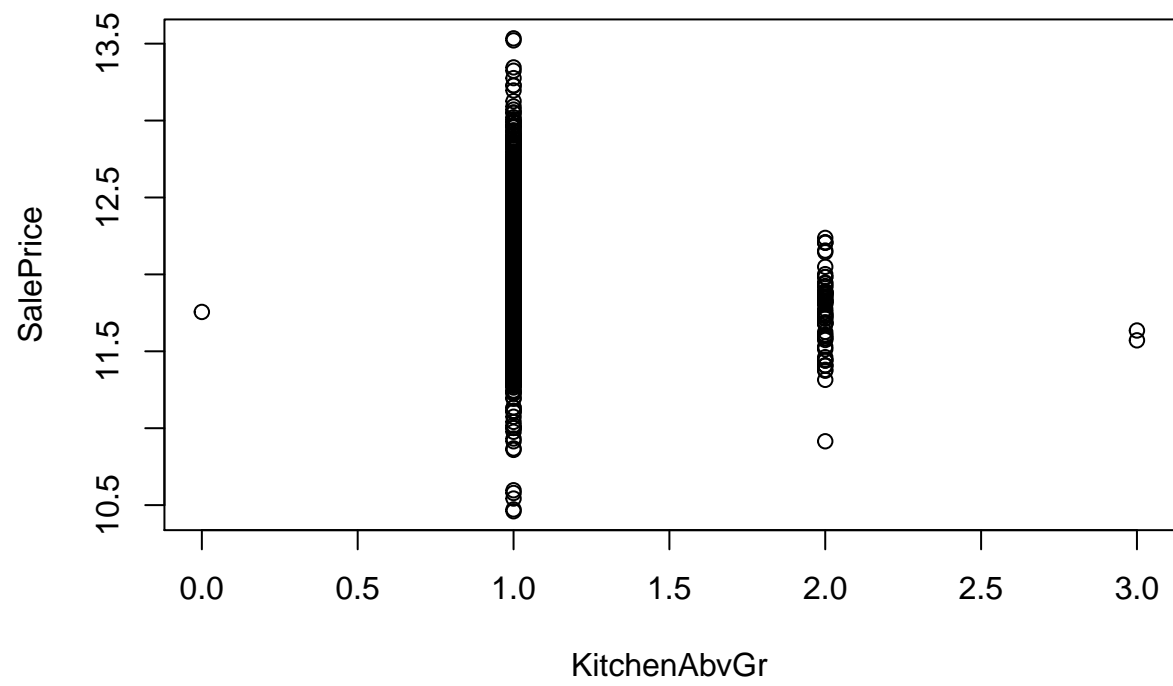


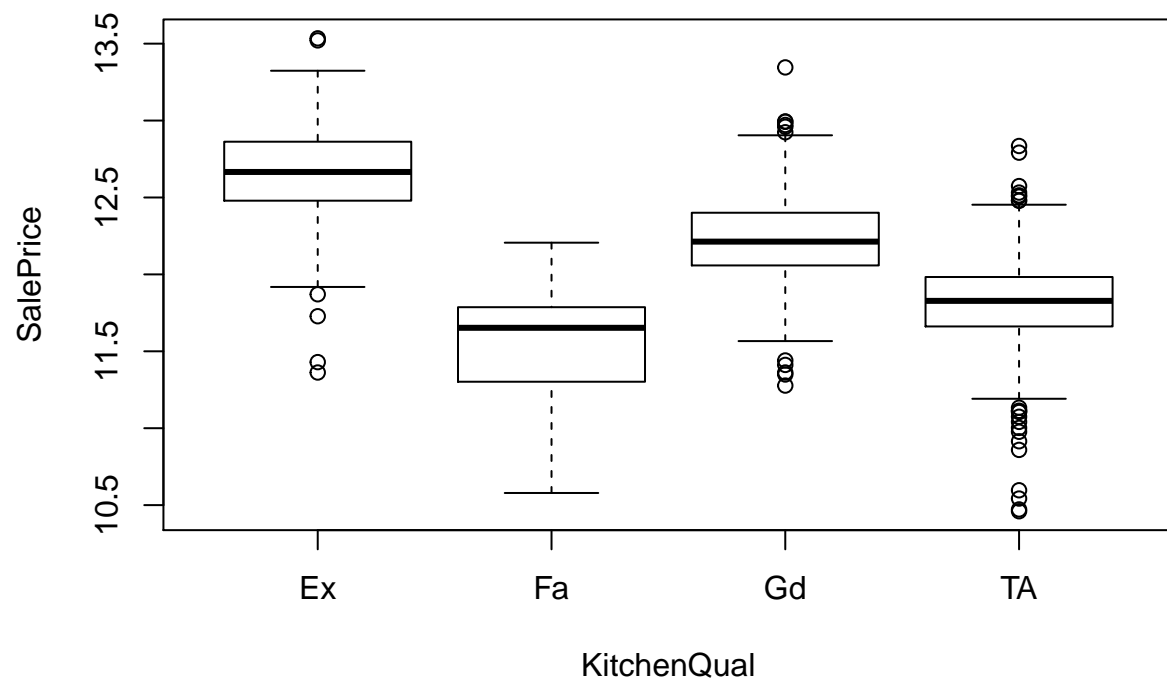


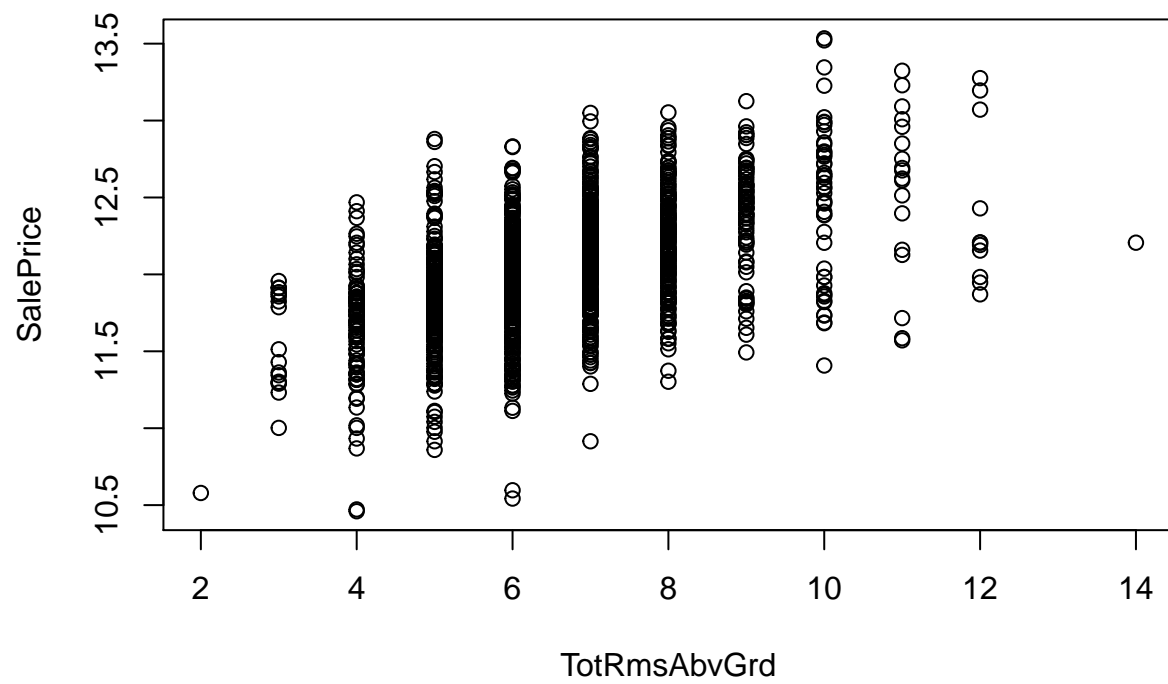


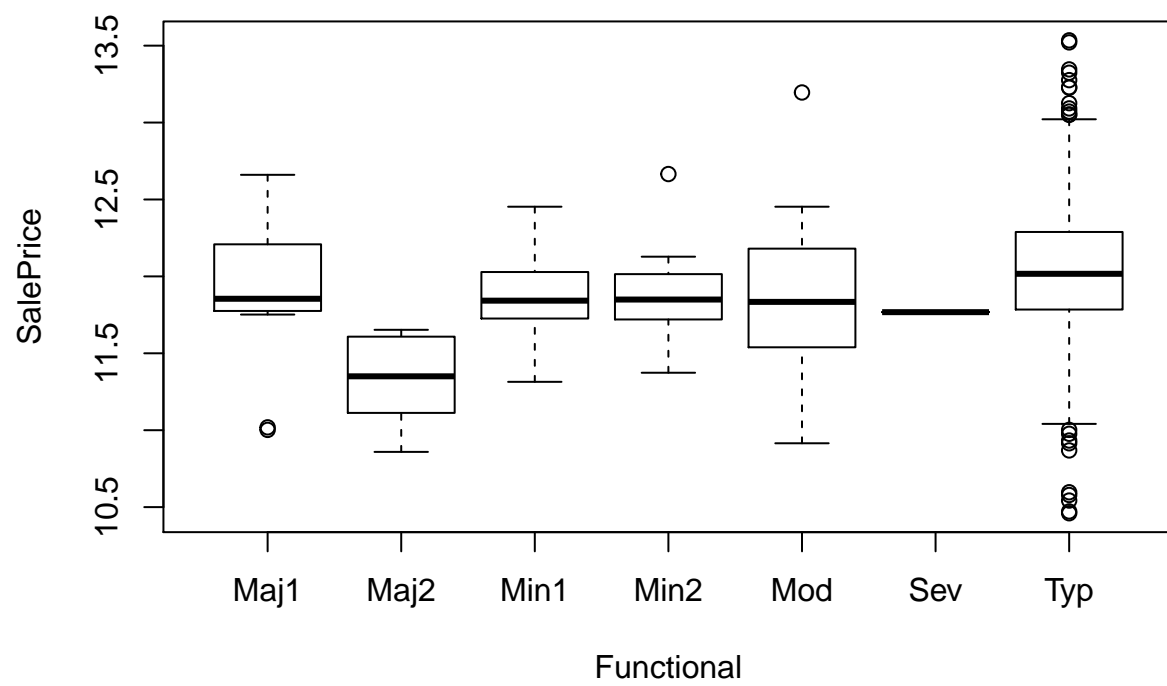


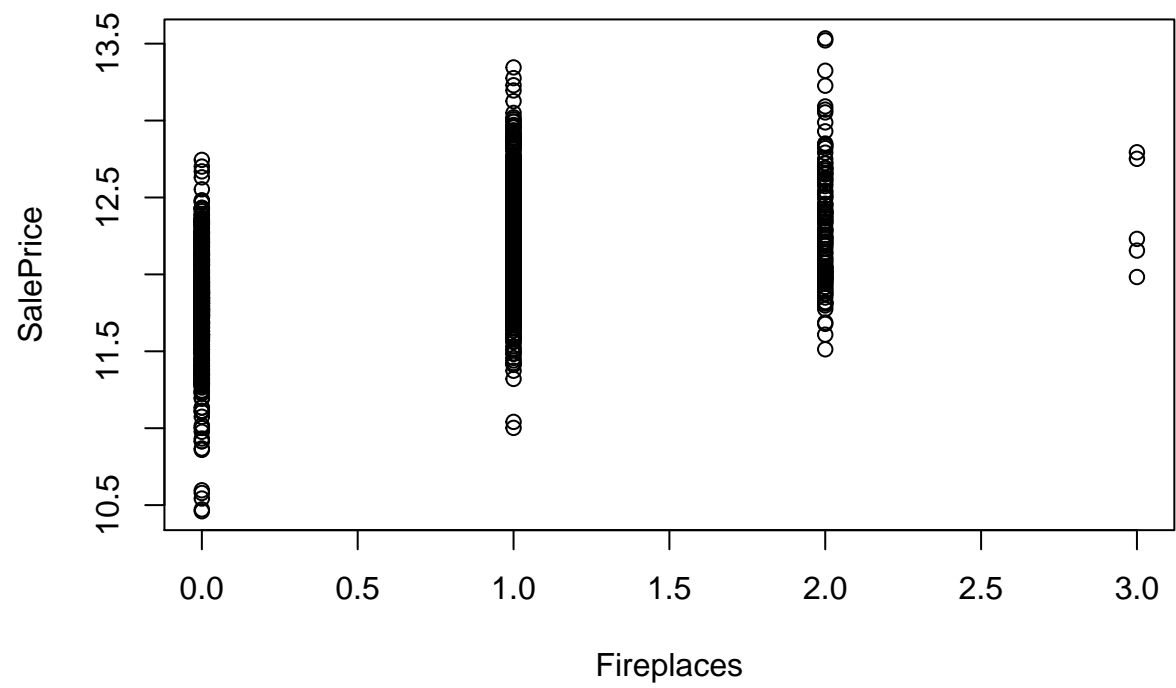


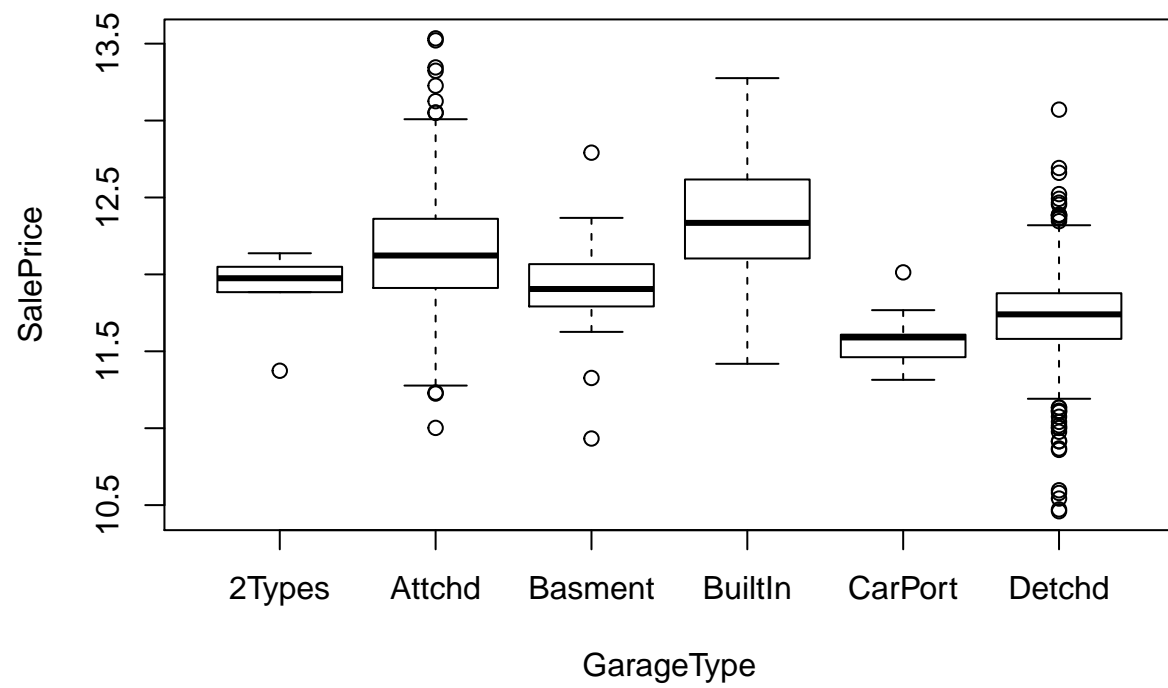


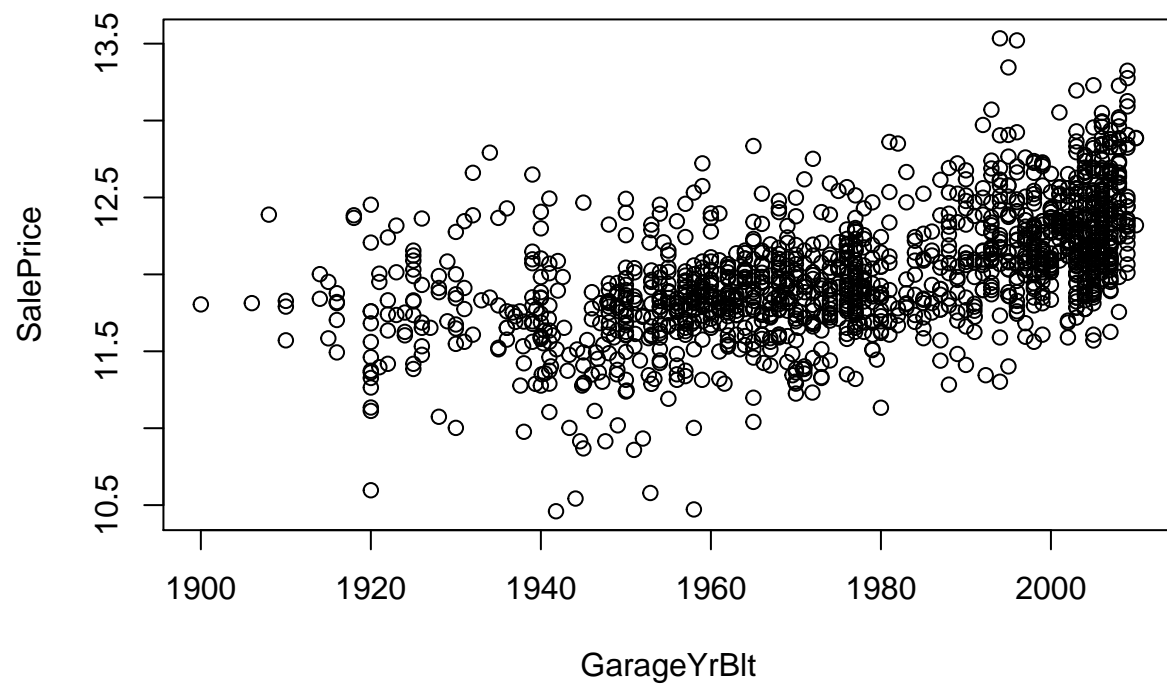


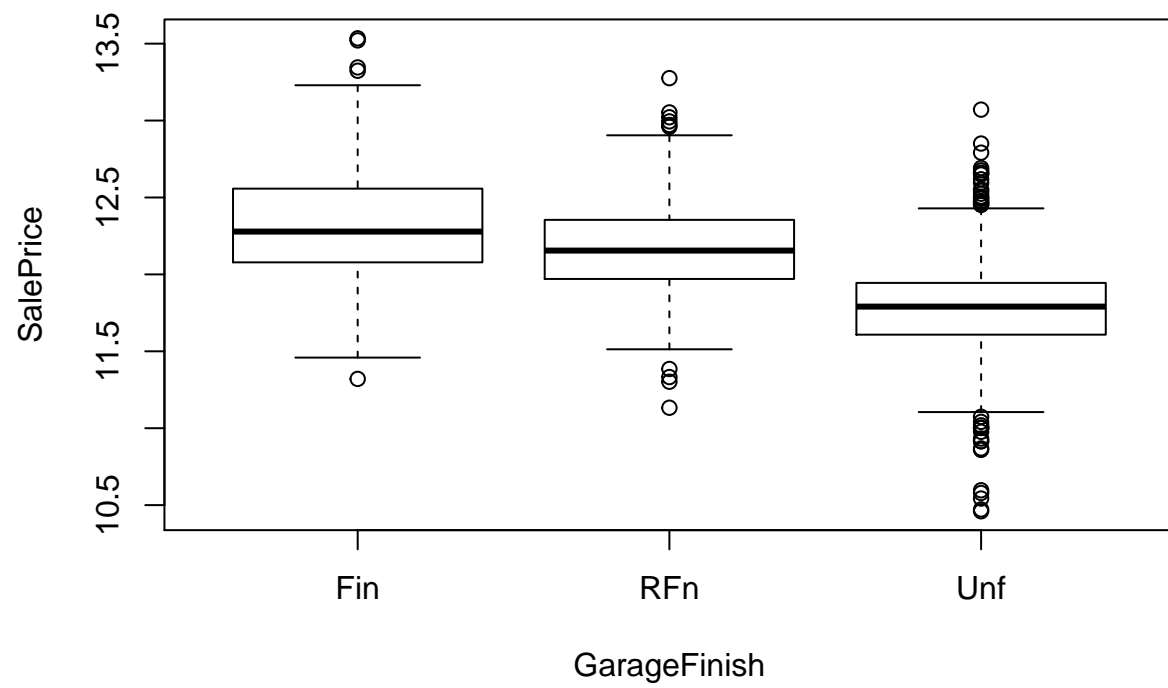


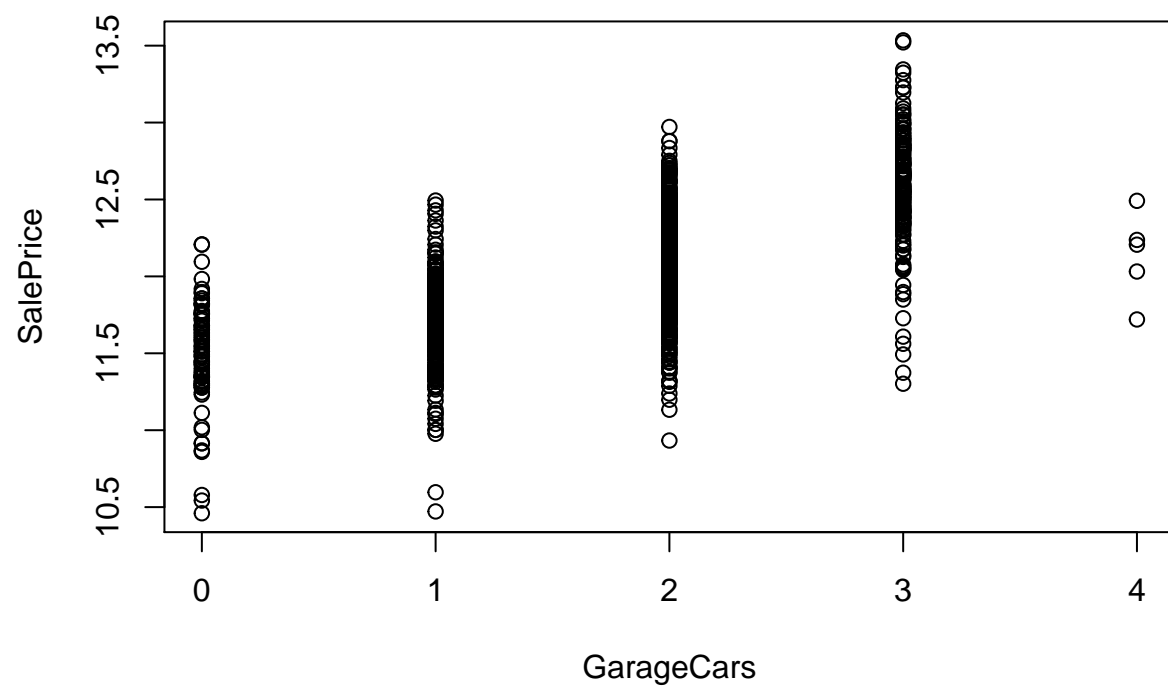


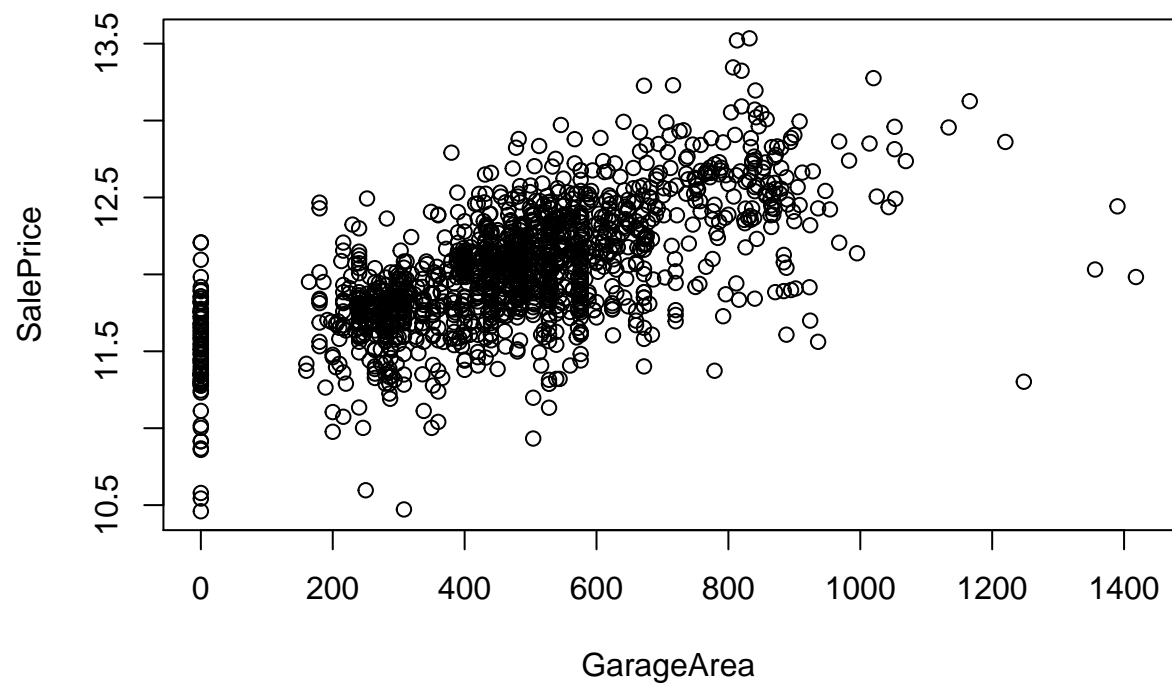


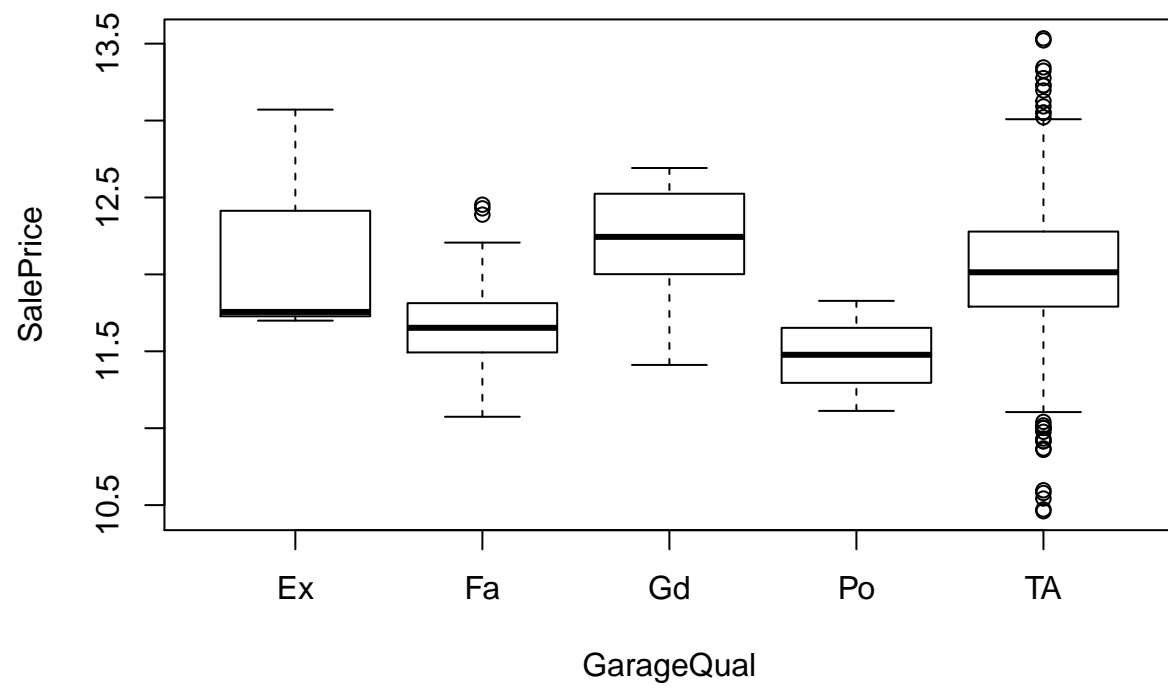


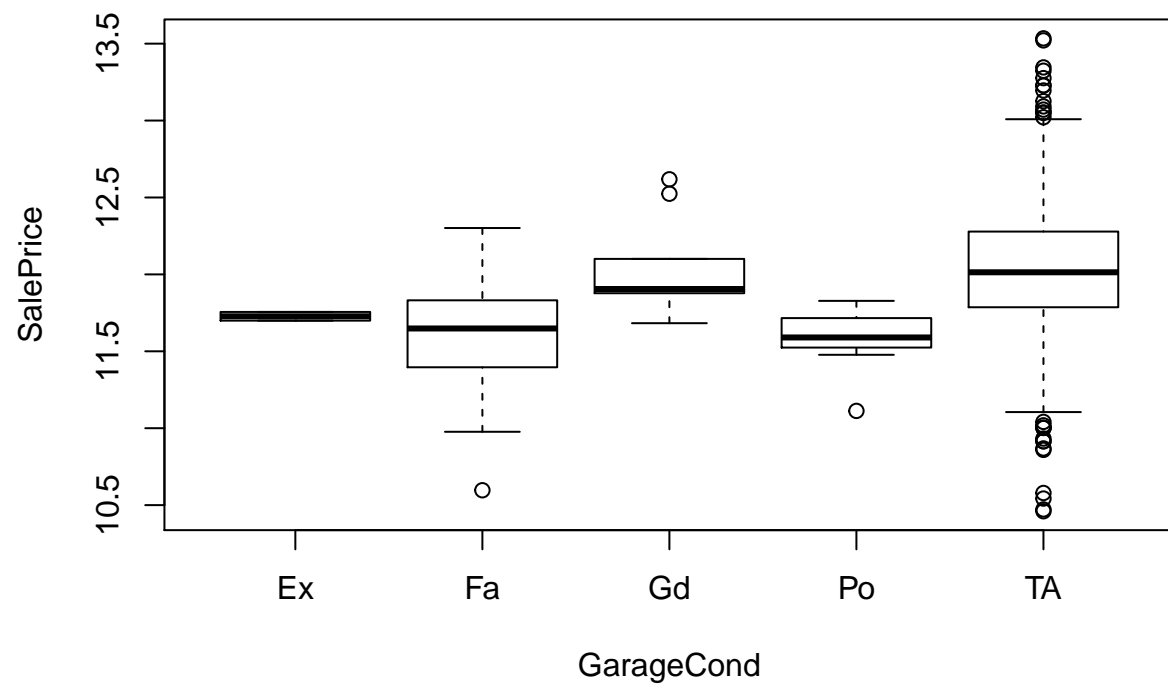


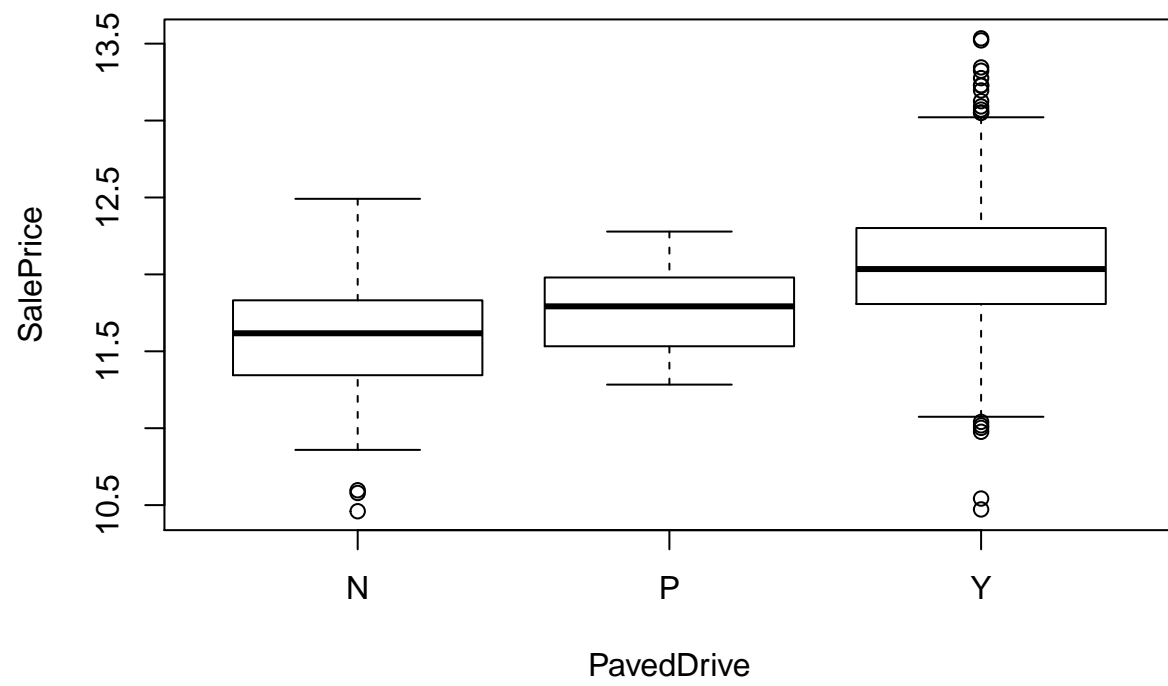


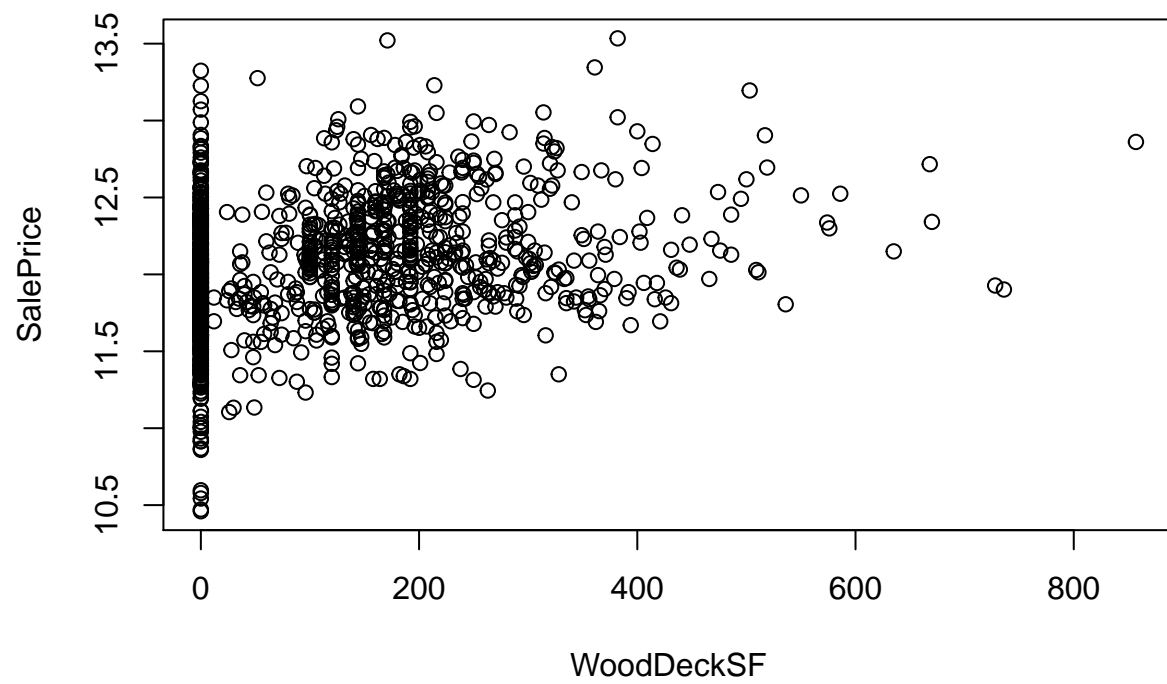


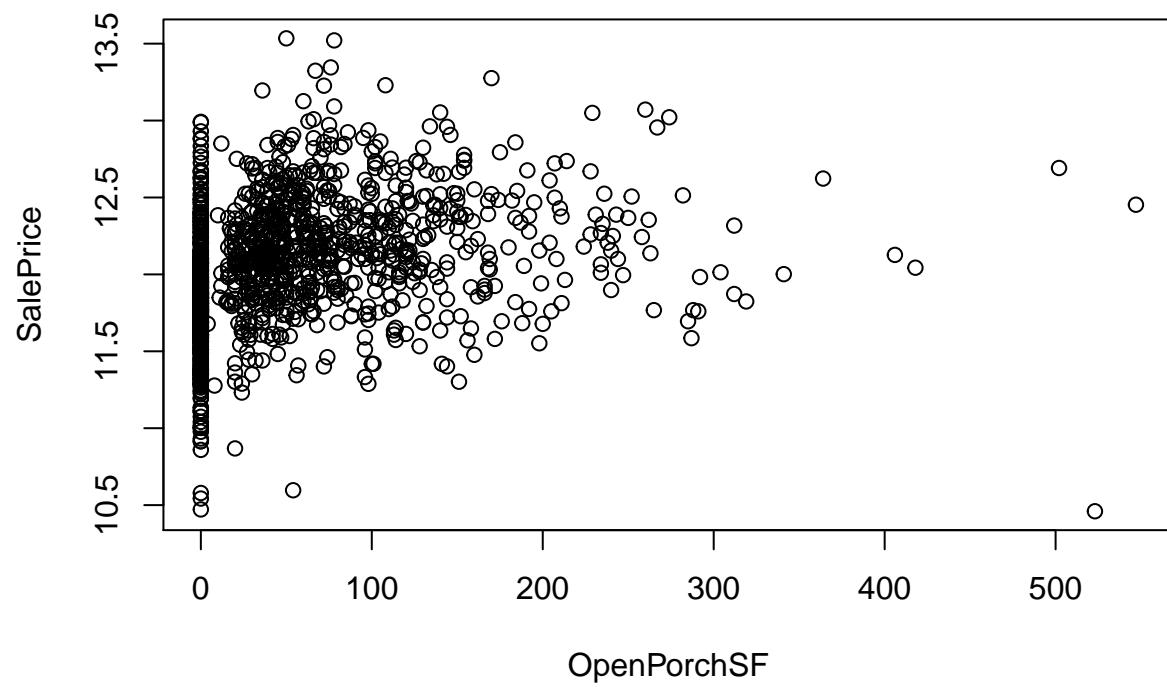


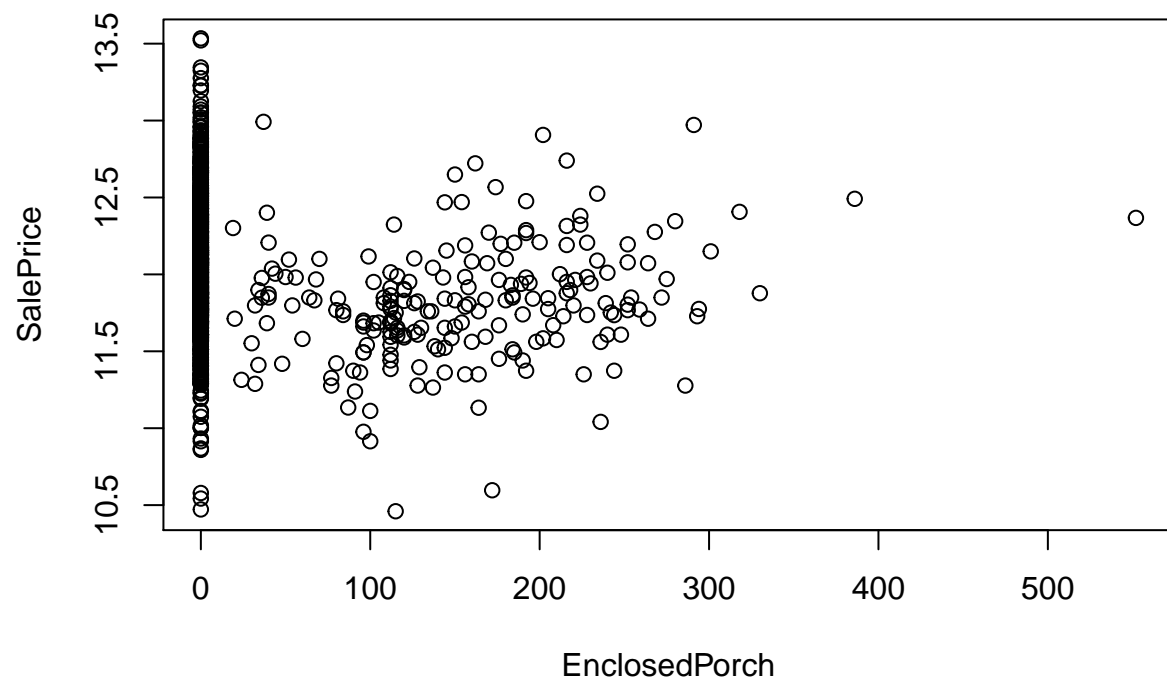


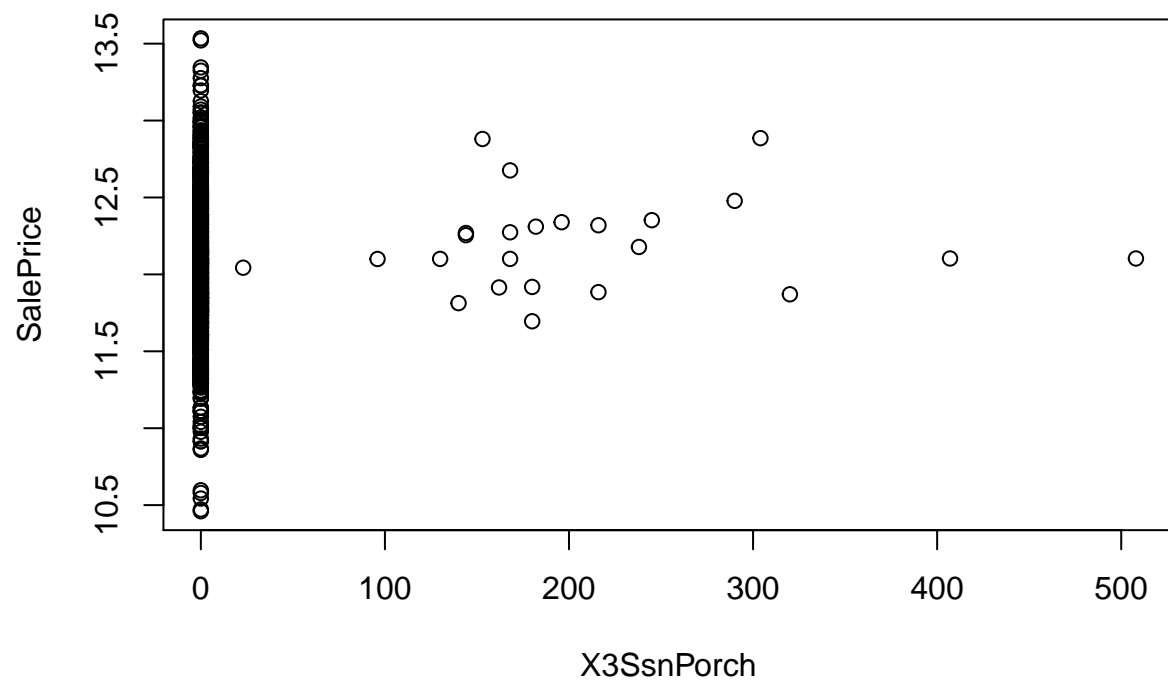


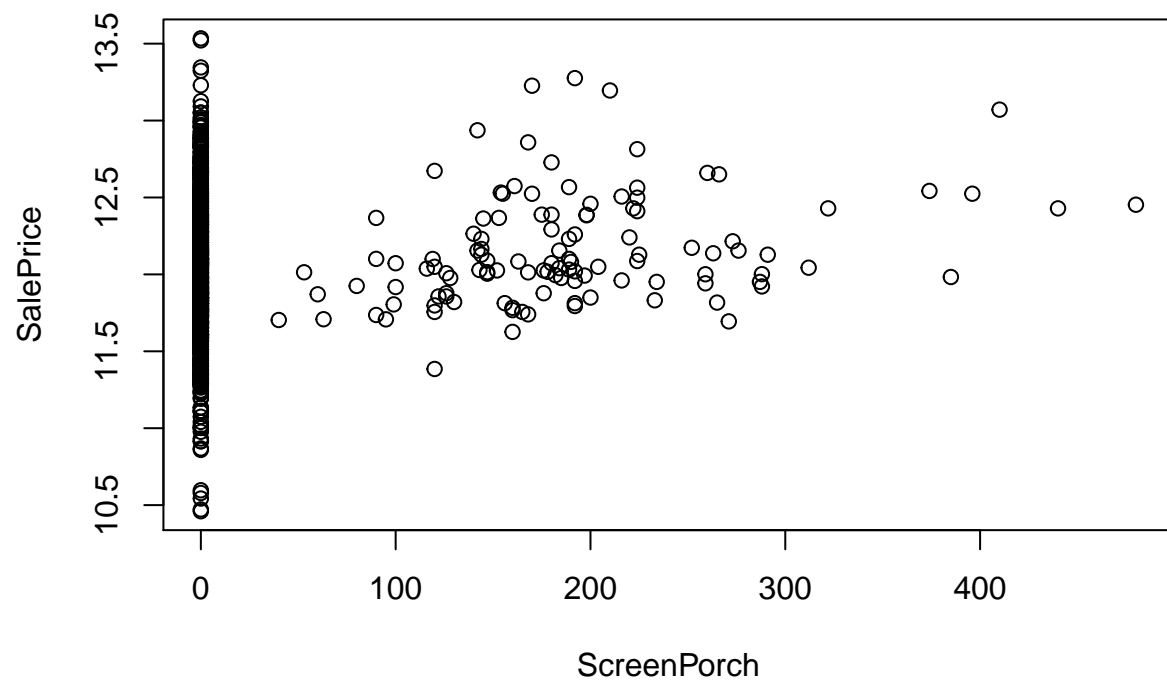


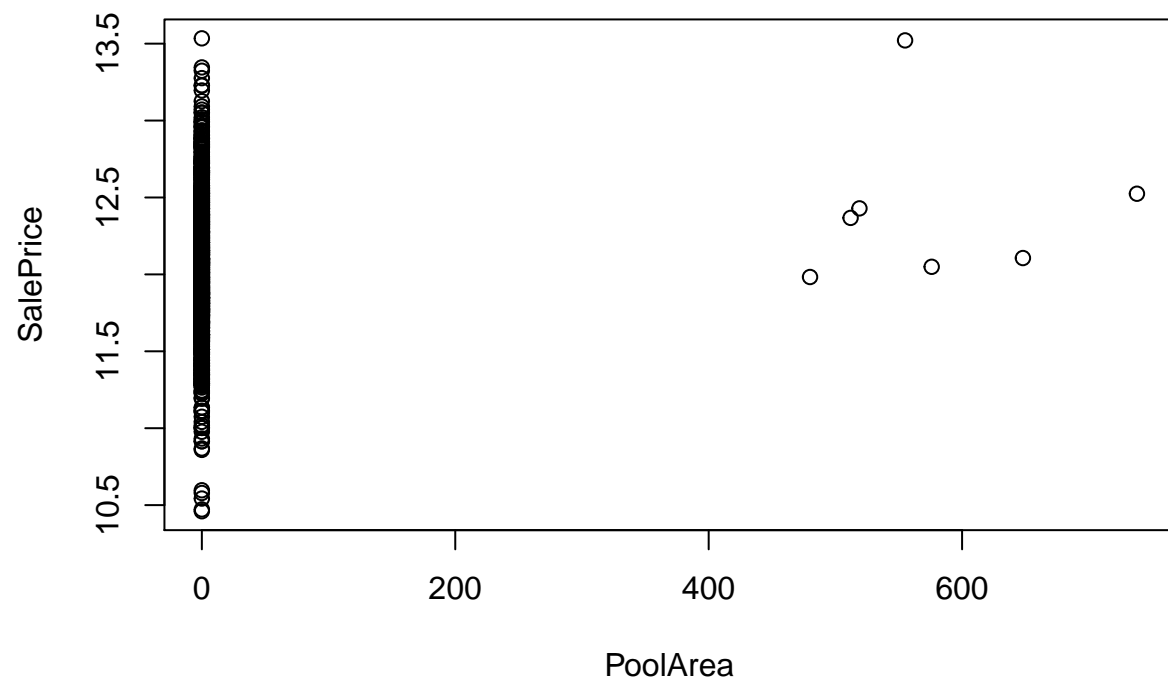


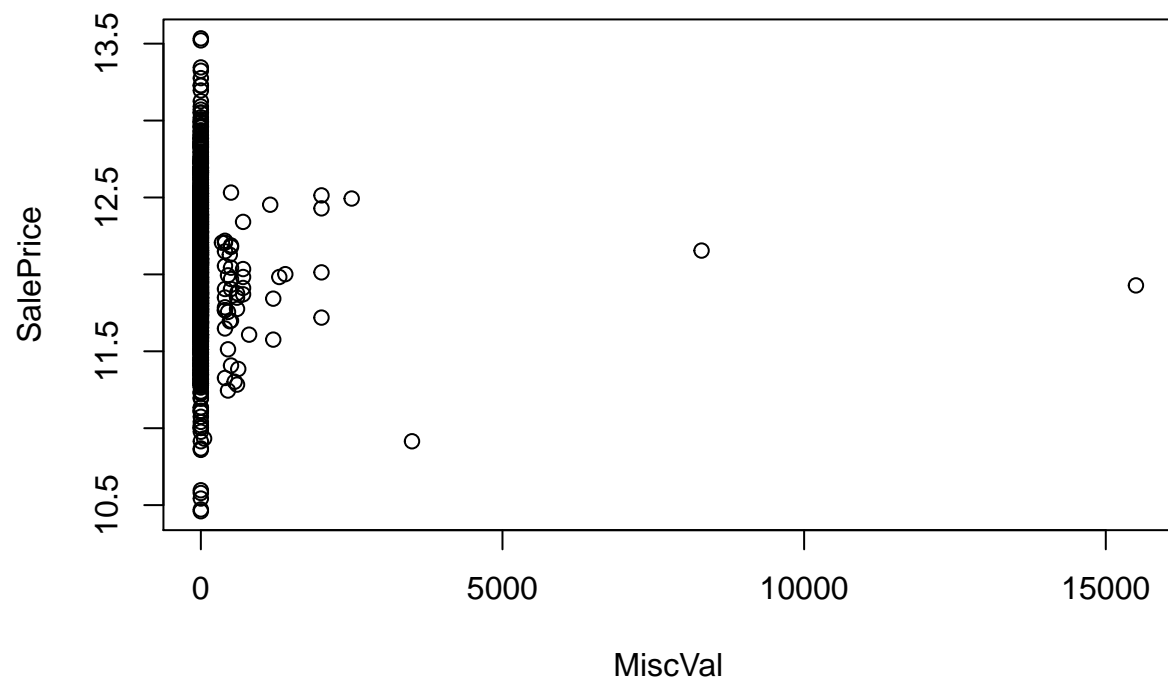


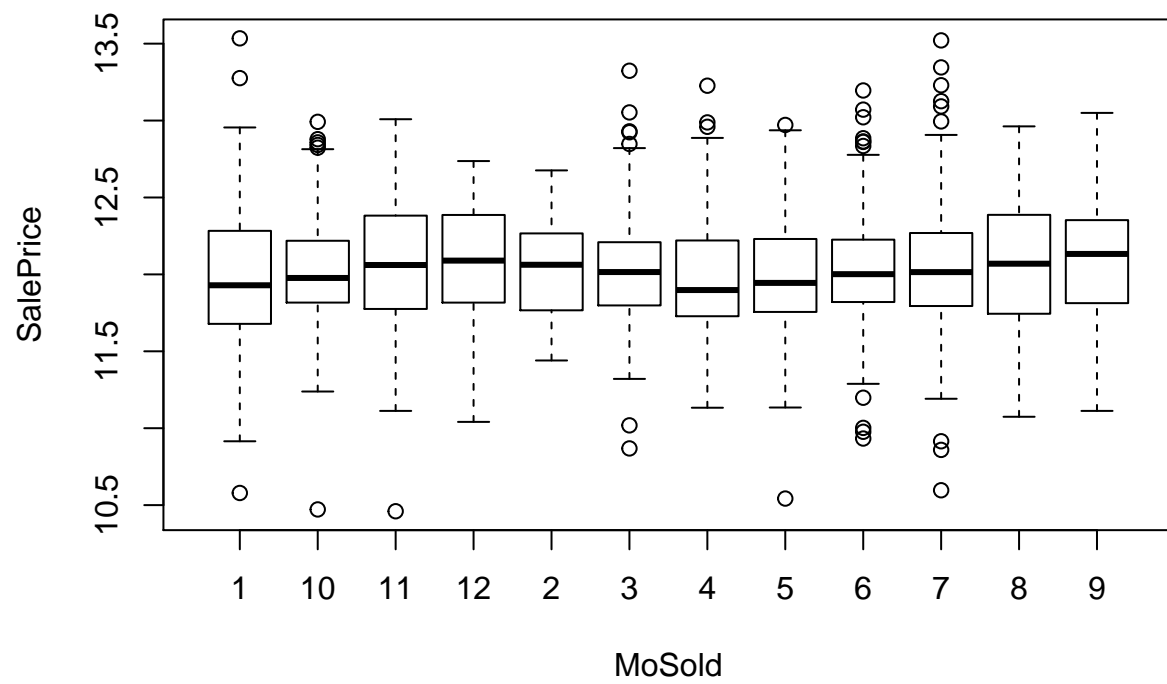


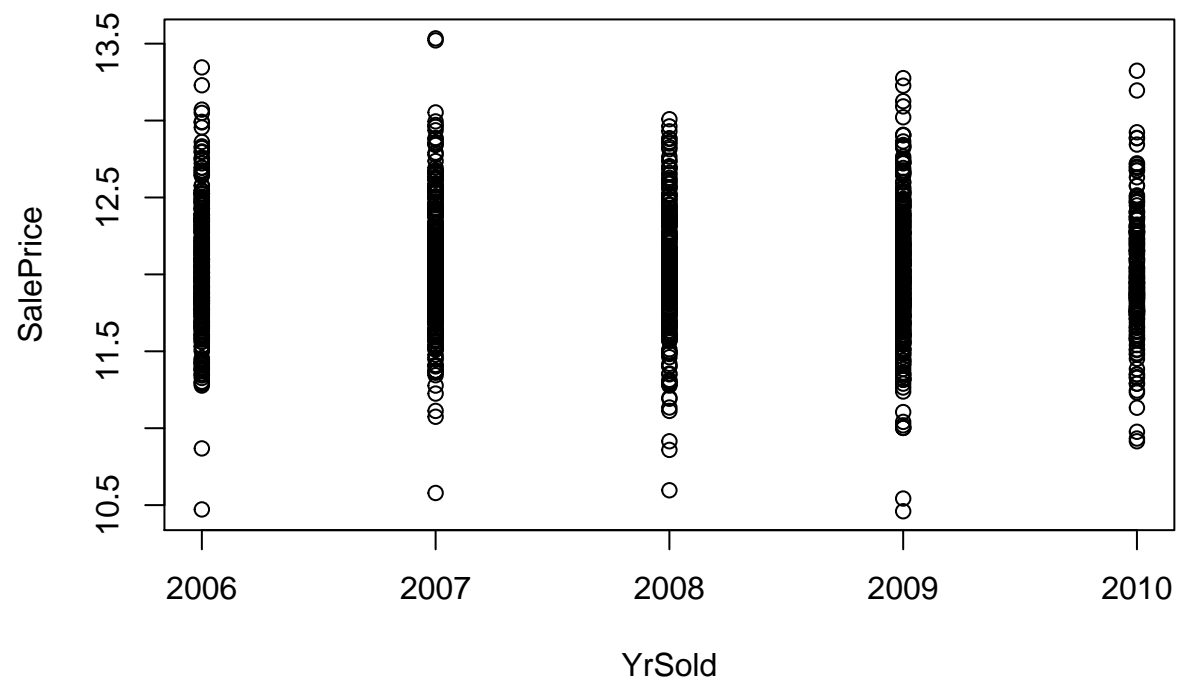


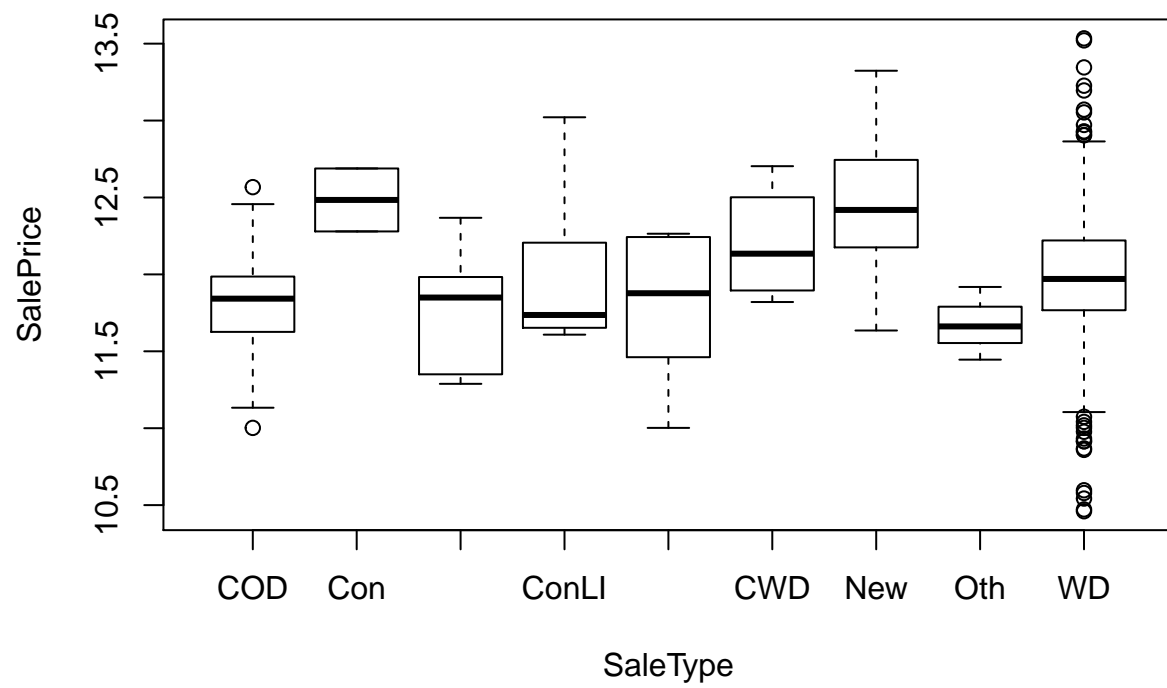


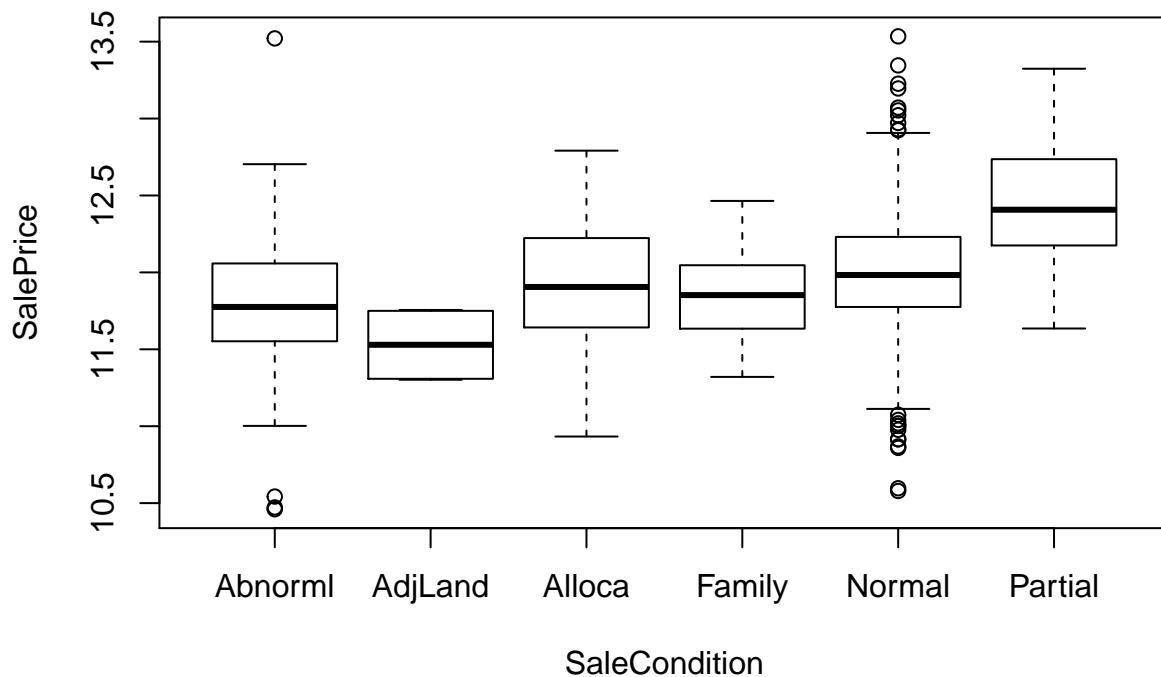












Visually observing the plots, the following variables seems like they might be correlated: OverallQual, TotalBsmtSF, X1stFlrSF, GrLivArea, TotRmsAbvGrd.

Section 3 - Creating Predictive Models

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.6.3
```

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

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

```
## Warning: package 'ggplot2' was built under R version 3.6.3
```

```
##
```

```
## Attaching package: 'ggplot2'
```

```
## The following object is masked from 'package:randomForest':
```

```
##
```

```
## margin
```



```
# Train test split
train.index <- createDataPartition(dataHouse$SalePrice, p = 0.8, list = FALSE)
data_train <- dataHouse[train.index, ]
data_test <- dataHouse[-train.index, ]
```

Lasso Linear Regression Model

```
set.seed(1)

lasso <- train(
  SalePrice ~., data = data_train, method = "glmnet",
  trControl = trainControl("cv", number = 10),
  tuneGrid = expand.grid(alpha = 1, lambda = 10^seq(-3, 3, length = 100)))
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

Best tuned coefficients:

```
coeffs <- as.matrix(coef(lasso$finalModel, lasso$bestTune$lambda))
coeffs
```

```
##                                1
## (Intercept)                   7.276627e+00
## MSSubClass160                 -9.153581e-02
## MSSubClass180                  0.000000e+00
## MSSubClass190                  0.000000e+00
## MSSubClass20                   2.841034e-02
## MSSubClass30                  -4.184269e-02
## MSSubClass40                   0.000000e+00
## MSSubClass45                   0.000000e+00
## MSSubClass50                   0.000000e+00
## MSSubClass60                   0.000000e+00
## MSSubClass70                   0.000000e+00
## MSSubClass75                   0.000000e+00
## MSSubClass80                   0.000000e+00
## MSSubClass85                   0.000000e+00
## MSSubClass90                   0.000000e+00
## MSZoningFV                    3.904708e-02
## MSZoningRH                    0.000000e+00
## MSZoningRL                    4.004596e-02
## MSZoningRM                    0.000000e+00
## LotFrontage                   0.000000e+00
## LotArea                      1.352954e-06
## StreetPave                    5.237496e-02
## LotShapeIR2                   0.000000e+00
## LotShapeIR3                  -9.447559e-02
## LotShapeReg                   0.000000e+00
## LandContourHLS                0.000000e+00
## LandContourLow                0.000000e+00
## LandContourLvl                0.000000e+00
## UtilitiesNoSeWa              -3.322919e-02
```

## LotConfigCulDSac	3.811951e-02
## LotConfigFR2	0.000000e+00
## LotConfigFR3	0.000000e+00
## LotConfigInside	0.000000e+00
## LandSlopeMod	0.000000e+00
## LandSlopeSev	0.000000e+00
## NeighborhoodBlueste	0.000000e+00
## NeighborhoodBrDale	0.000000e+00
## NeighborhoodBrkSide	4.369358e-04
## NeighborhoodClearCr	2.440725e-02
## NeighborhoodCollgCr	0.000000e+00
## NeighborhoodCrawfor	1.176998e-01
## NeighborhoodEdwards	-3.605538e-02
## NeighborhoodGilbert	0.000000e+00
## NeighborhoodIDOTRR	-8.028385e-02
## NeighborhoodMeadowV	-6.511095e-02
## NeighborhoodMitchel	0.000000e+00
## NeighborhoodNames	0.000000e+00
## NeighborhoodNoRidge	5.332634e-02
## NeighborhoodNPkVill	0.000000e+00
## NeighborhoodNridgHt	1.140510e-01
## NeighborhoodNWAmes	0.000000e+00
## NeighborhoodOldTown	-3.192463e-02
## NeighborhoodSawyer	0.000000e+00
## NeighborhoodSawyerW	0.000000e+00
## NeighborhoodSomerst	4.725641e-02
## NeighborhoodStoneBr	1.330543e-01
## NeighborhoodSWISU	0.000000e+00
## NeighborhoodTimber	0.000000e+00
## NeighborhoodVeenker	3.015219e-02
## Condition1Feedr	-1.228277e-02
## Condition1Norm	2.783237e-02
## Condition1PosA	0.000000e+00
## Condition1PosN	0.000000e+00
## Condition1RR Ae	0.000000e+00
## Condition1RRAn	0.000000e+00
## Condition1RRNe	0.000000e+00
## Condition1RRNn	0.000000e+00
## Condition2Feedr	0.000000e+00
## Condition2Norm	0.000000e+00
## Condition2PosA	0.000000e+00
## Condition2PosN	-4.758618e-01
## Condition2RR Ae	0.000000e+00
## Condition2RRAn	0.000000e+00
## Condition2RRNn	0.000000e+00
## BldgType2fmCon	0.000000e+00
## BldgTypeDuplex	0.000000e+00
## BldgTypeTwnhs	-2.758086e-02
## BldgTypeTwnhsE	-1.867469e-02
## HouseStyle1.5Unf	0.000000e+00
## HouseStyle1Story	0.000000e+00
## HouseStyle2.5Fin	0.000000e+00
## HouseStyle2.5Unf	0.000000e+00
## HouseStyle2Story	0.000000e+00

## HouseStyleSFoyer	0.000000e+00
## HouseStyleSLvl	0.000000e+00
## OverallQual	7.049432e-02
## OverallCond	2.831610e-02
## YearBuilt	7.839586e-04
## YearRemodAdd	9.272254e-04
## RoofStyleGable	-2.644506e-03
## RoofStyleGambrel	0.000000e+00
## RoofStyleHip	0.000000e+00
## RoofStyleMansard	0.000000e+00
## RoofStyleShed	0.000000e+00
## RoofMatlCompShg	0.000000e+00
## RoofMatlMembran	0.000000e+00
## RoofMatlMetal	0.000000e+00
## RoofMatlRoll	0.000000e+00
## RoofMatlTar&Grv	0.000000e+00
## RoofMatlWdShake	0.000000e+00
## RoofMatlWdShngl	5.974352e-02
## Exterior1stAsphShn	0.000000e+00
## Exterior1stBrkComm	0.000000e+00
## Exterior1stBrkFace	3.886782e-02
## Exterior1stCBlock	0.000000e+00
## Exterior1stCemntBd	0.000000e+00
## Exterior1stHdBoard	-5.692639e-03
## Exterior1stImStucc	0.000000e+00
## Exterior1stMetalSd	0.000000e+00
## Exterior1stPlywood	0.000000e+00
## Exterior1stStone	0.000000e+00
## Exterior1stStucco	0.000000e+00
## Exterior1stVinylSd	0.000000e+00
## Exterior1stWd Sdng	-1.033213e-02
## Exterior1stWdShing	0.000000e+00
## Exterior2ndAsphShn	0.000000e+00
## Exterior2ndBrk Cmn	0.000000e+00
## Exterior2ndBrkFace	0.000000e+00
## Exterior2ndCBlock	0.000000e+00
## Exterior2ndCmentBd	0.000000e+00
## Exterior2ndHdBoard	0.000000e+00
## Exterior2ndImStucc	0.000000e+00
## Exterior2ndMetalSd	0.000000e+00
## Exterior2ndOther	0.000000e+00
## Exterior2ndPlywood	0.000000e+00
## Exterior2ndStone	0.000000e+00
## Exterior2ndStucco	-4.102236e-02
## Exterior2ndVinylSd	0.000000e+00
## Exterior2ndWd Sdng	0.000000e+00
## Exterior2ndWd Shng	0.000000e+00
## MasVnrTypeBrkFace	0.000000e+00
## MasVnrTypeNone	0.000000e+00
## MasVnrTypeStone	3.420891e-03
## MasVnrArea	1.505733e-05
## ExterQualFa	-6.924633e-03
## ExterQualGd	0.000000e+00
## ExterQualTA	-6.947233e-03

## ExterCondFa	-2.405911e-02
## ExterCondGd	0.000000e+00
## ExterCondPo	0.000000e+00
## ExterCondTA	0.000000e+00
## FoundationCBlock	0.000000e+00
## FoundationPConc	1.422058e-02
## FoundationSlab	-3.276404e-02
## FoundationStone	0.000000e+00
## FoundationWood	0.000000e+00
## BsmtQualFa	0.000000e+00
## BsmtQualGd	0.000000e+00
## BsmtQualTA	-1.399450e-02
## BsmtCondGd	0.000000e+00
## BsmtCondPo	0.000000e+00
## BsmtCondTA	0.000000e+00
## BsmtExposureGd	4.772708e-02
## BsmtExposureMn	0.000000e+00
## BsmtExposureNo	-4.829930e-03
## BsmtFinType1BLQ	0.000000e+00
## BsmtFinType1GLQ	1.047856e-02
## BsmtFinType1LwQ	0.000000e+00
## BsmtFinType1Rec	0.000000e+00
## BsmtFinType1Unf	-2.868208e-02
## BsmtFinSF1	0.000000e+00
## BsmtFinType2BLQ	-2.790412e-02
## BsmtFinType2GLQ	0.000000e+00
## BsmtFinType2LwQ	0.000000e+00
## BsmtFinType2Rec	0.000000e+00
## BsmtFinType2Unf	0.000000e+00
## BsmtFinSF2	0.000000e+00
## BsmtUnfSF	0.000000e+00
## TotalBsmtSF	2.773587e-05
## HeatingGasA	0.000000e+00
## HeatingGasW	3.210388e-02
## HeatingGrav	-9.300081e-02
## HeatingOthW	0.000000e+00
## HeatingWall	0.000000e+00
## HeatingQCFa	0.000000e+00
## HeatingQCGd	0.000000e+00
## HeatingQCPo	0.000000e+00
## HeatingQCTA	-1.484642e-02
## CentralAirY	7.121859e-02
## ElectricalFuseF	0.000000e+00
## ElectricalFuseP	0.000000e+00
## ElectricalMix	0.000000e+00
## ElectricalSBrkr	0.000000e+00
## X1stFlrSF	3.309808e-07
## X2ndFlrSF	0.000000e+00
## LowQualFinSF	0.000000e+00
## GrLivArea	1.969026e-04
## BsmtFullBath	4.148992e-02
## BsmtHalfBath	0.000000e+00
## FullBath	2.378506e-02
## HalfBath	1.509926e-02

## BedroomAbvGr	0.000000e+00
## KitchenAbvGr	-3.777305e-02
## KitchenQualFa	0.000000e+00
## KitchenQualGd	0.000000e+00
## KitchenQualTA	-1.885371e-02
## TotRmsAbvGrd	5.294280e-03
## FunctionalMaj2	-1.052601e-01
## FunctionalMin1	0.000000e+00
## FunctionalMin2	0.000000e+00
## FunctionalMod	-6.941289e-03
## FunctionalSev	-1.711373e-01
## FunctionalTyp	2.555149e-02
## Fireplaces	2.758108e-02
## GarageTypeAttchd	0.000000e+00
## GarageTypeBasment	0.000000e+00
## GarageTypeBuiltIn	0.000000e+00
## GarageTypeCarPort	0.000000e+00
## GarageTypeDetchd	-4.766737e-03
## GarageYrBlt	0.000000e+00
## GarageFinishRFn	0.000000e+00
## GarageFinishUnf	-1.346648e-02
## GarageCars	6.953160e-02
## GarageArea	0.000000e+00
## GarageQualFa	0.000000e+00
## GarageQualGd	1.742896e-02
## GarageQualPo	0.000000e+00
## GarageQualTA	0.000000e+00
## GarageCondFa	-3.960323e-02
## GarageCondGd	0.000000e+00
## GarageCondPo	0.000000e+00
## GarageCondTA	0.000000e+00
## PavedDriveP	0.000000e+00
## PavedDriveY	1.910285e-02
## WoodDeckSF	7.947326e-05
## OpenPorchSF	1.083448e-06
## EnclosedPorch	0.000000e+00
## X3SsnPorch	0.000000e+00
## ScreenPorch	1.837631e-04
## PoolArea	-2.301343e-04
## MiscVal	0.000000e+00
## MoSold10	0.000000e+00
## MoSold11	0.000000e+00
## MoSold12	0.000000e+00
## MoSold2	0.000000e+00
## MoSold3	0.000000e+00
## MoSold4	0.000000e+00
## MoSold5	0.000000e+00
## MoSold6	0.000000e+00
## MoSold7	0.000000e+00
## MoSold8	0.000000e+00
## MoSold9	0.000000e+00
## YrSold	0.000000e+00
## SaleTypeCon	0.000000e+00
## SaleTypeConLD	0.000000e+00

```
## SaleTypeConLI      0.000000e+00
## SaleTypeConLw      0.000000e+00
## SaleTypeCWD        0.000000e+00
## SaleTypeNew        7.025603e-02
## SaleTypeOth        0.000000e+00
## SaleTypeWD         0.000000e+00
## SaleConditionAdjLand 0.000000e+00
## SaleConditionAlloca 0.000000e+00
## SaleConditionFamily 0.000000e+00
## SaleConditionNormal 3.169134e-02
## SaleConditionPartial 0.000000e+00
```

```
coeffs[coeffs[,1] ==0, ]
```

```
##      MSSubClass180      MSSubClass190      MSSubClass40
##      0              0              0
##      MSSubClass45      MSSubClass50      MSSubClass60
##      0              0              0
##      MSSubClass70      MSSubClass75      MSSubClass80
##      0              0              0
##      MSSubClass85      MSSubClass90      MSZoningRH
##      0              0              0
##      MSZoningRM        LotFrontage      LotShapeIR2
##      0              0              0
##      LotShapeReg      LandContourHLS      LandContourLow
##      0              0              0
##      LandContourLvl      LotConfigFR2      LotConfigFR3
##      0              0              0
##      LotConfigInside      LandSlopeMod      LandSlopeSev
##      0              0              0
##      NeighborhoodBlueste  NeighborhoodBrDale  NeighborhoodCollgCr
##      0              0              0
##      NeighborhoodGilbert  NeighborhoodMitchel  NeighborhoodNames
##      0              0              0
##      NeighborhoodNPkVill  NeighborhoodNWAmes  NeighborhoodSawyer
##      0              0              0
##      NeighborhoodSawyerW  NeighborhoodSWISU  NeighborhoodTimber
##      0              0              0
##      Condition1PosA      Condition1PosN      Condition1RR Ae
##      0              0              0
##      Condition1RRAn      Condition1RRNe      Condition1RRNn
##      0              0              0
##      Condition2Feedr      Condition2Norm      Condition2PosA
##      0              0              0
##      Condition2RR Ae      Condition2RRAn      Condition2RRNn
##      0              0              0
##      BldgType2fmCon      BldgTypeDuplex      HouseStyle1.5Unf
##      0              0              0
##      HouseStyle1Story      HouseStyle2.5Fin      HouseStyle2.5Unf
##      0              0              0
##      HouseStyle2Story      HouseStyleSFoyer      HouseStyleSLvl
##      0              0              0
##      RoofStyleGambrel      RoofStyleHip      RoofStyleMansard
##      0              0              0
```

##	RoofStyleShed	RoofMatlCompShg	RoofMatlMembran
##	0	0	0
##	RoofMatlMetal	RoofMatlRoll	RoofMatlTar&Grv
##	0	0	0
##	RoofMatlWdShake	Exterior1stAsphShn	Exterior1stBrkComm
##	0	0	0
##	Exterior1stCBlock	Exterior1stCemntBd	Exterior1stImStucc
##	0	0	0
##	Exterior1stMetalSd	Exterior1stPlywood	Exterior1stStone
##	0	0	0
##	Exterior1stStucco	Exterior1stVinylSd	Exterior1stWdShing
##	0	0	0
##	Exterior2ndAsphShn	Exterior2ndBrk Cmn	Exterior2ndBrkFace
##	0	0	0
##	Exterior2ndCBlock	Exterior2ndCmentBd	Exterior2ndHdBoard
##	0	0	0
##	Exterior2ndImStucc	Exterior2ndMetalSd	Exterior2ndOther
##	0	0	0
##	Exterior2ndPlywood	Exterior2ndStone	Exterior2ndVinylSd
##	0	0	0
##	Exterior2ndWd Sdng	Exterior2ndWd Shng	MasVnrTypeBrkFace
##	0	0	0
##	MasVnrTypeNone	ExterQualGd	ExterCondGd
##	0	0	0
##	ExterCondPo	ExterCondTA	FoundationCBlock
##	0	0	0
##	FoundationStone	FoundationWood	BsmtQualFa
##	0	0	0
##	BsmtQualGd	BsmtCondGd	BsmtCondPo
##	0	0	0
##	BsmtCondTA	BsmtExposureMn	BsmtFinType1BLQ
##	0	0	0
##	BsmtFinType1LwQ	BsmtFinType1Rec	BsmtFinSF1
##	0	0	0
##	BsmtFinType2GLQ	BsmtFinType2LwQ	BsmtFinType2Rec
##	0	0	0
##	BsmtFinType2Unf	BsmtFinSF2	BsmtUnfSF
##	0	0	0
##	HeatingGasA	HeatingOthW	HeatingWall
##	0	0	0
##	HeatingQCFa	HeatingQCGd	HeatingQCPo
##	0	0	0
##	ElectricalFuseF	ElectricalFuseP	ElectricalMix
##	0	0	0
##	ElectricalSBrkr	X2ndFlrSF	LowQualFinSF
##	0	0	0
##	BsmtHalfBath	BedroomAbvGr	KitchenQualFa
##	0	0	0
##	KitchenQualGd	FunctionalMin1	FunctionalMin2
##	0	0	0
##	GarageTypeAttchd	GarageTypeBasment	GarageTypeBuiltIn
##	0	0	0
##	GarageTypeCarPort	GarageYrBlt	GarageFinishRFn
##	0	0	0

```
##      GarageArea      GarageQualFa      GarageQualPo
##           0           0           0
##      GarageQualTA      GarageCondGd      GarageCondPo
##           0           0           0
##      GarageCondTA      PavedDriveP      EnclosedPorch
##           0           0           0
##      X3SsnPorch      MiscVal      MoSold10
##           0           0           0
##      MoSold11      MoSold12      MoSold2
##           0           0           0
##      MoSold3      MoSold4      MoSold5
##           0           0           0
##      MoSold6      MoSold7      MoSold8
##           0           0           0
##      MoSold9      YrSold      SaleTypeCon
##           0           0           0
##      SaleTypeConLD      SaleTypeConLI      SaleTypeConLw
##           0           0           0
##      SaleTypeCWD      SaleTypeOth      SaleTypeWD
##           0           0           0
## SaleConditionAdjLand SaleConditionAlloca SaleConditionFamily
##           0           0           0
## SaleConditionPartial
##           0
```

Some variables lambda values were reduced to zero, which means they weren't used in the model for prediction. The lasso models automatically carry out variable selection. Variables shown above were the ones which were reduced to 0.

```
predictions <- predict(lasso,data_test)
RMSE(predictions, data_test$SalePrice)
```

```
## [1] 0.1167734
```

Ridge Linear Regression Model

```
set.seed(1)

ridge <- train(
  SalePrice ~., data = data_train, method = "glmnet",
  trControl = trainControl("cv", number = 10),
  tuneGrid = expand.grid(alpha = 0, lambda = 10^seq(-3, 3, length = 100)))
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

```
predictions <- predict(ridge,data_test)
RMSE(predictions, data_test$SalePrice)
```

```
## [1] 0.1237117
```


Elastic Net Linear Regression Model

```
set.seed(1)

enet <- train(
  SalePrice ~., data = data_train, method = "glmnet",
  trControl = trainControl("cv", number = 10),
  tuneGrid = expand.grid(alpha = seq(0,1, length=10), lambda = 10^seq(-3, 3, length = 100)))
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

```
predictions <- predict(enet,data_test)
RMSE(predictions, data_test$SalePrice)
```

```
## [1] 0.1179759
```

Random Forest Models

```
set.seed(1)

m_rf <- train(SalePrice ~ ., data = data_train, method = "rf", importance = TRUE,
  trControl = trainControl(method = "cv", number = 10), tuneGrid = expand.grid(mtry = c(2, 4, 6, 8, 10, 12, 14, 16, 18, 20)))
```

```
predictions <- predict(m_rf,data_test)
RMSE(predictions, data_test$SalePrice)
```

```
## [1] 0.1331681
```

```
varImp(m_rf)
```

```
## rf variable importance
##
##   only 20 most important variables shown (out of 255)
##
##               Overall
## GrLivArea      100.00
## X1stFlrSF       90.38
## OverallQual     86.70
## TotalBsmtSF     85.92
## LotArea        83.21
## BsmtFinSF1      79.45
## GarageArea      78.14
## X2ndFlrSF       76.74
## Fireplaces      70.22
## GarageCars      69.94
## LotFrontage     66.37
## OverallCond     65.92
## ExterQualTA     63.80
## TotRmsAbvGrd    63.62
```

```
## YearBuilt      62.88
## BsmtQualGd    60.58
## HalfBath      58.87
## GarageYrBlt   58.66
## GarageFinishUnf 58.38
## YearRemodAdd  58.05
```

```
listRFImp <- varImp(m_rf)$importance
listRFImp$Var <- row.names(listRFImp)
row.names(listRFImp) <- NULL
listRFImp <- listRFImp[order(listRFImp$Overall, decreasing = TRUE),][1:20,2]
```

```
#as.data.frame(coeffs[coeffs[,1] !=0,])
```

```
coeffsDF <- as.data.frame(coeffs)
coeffsDF$Var <- row.names(coeffsDF)
row.names(coeffsDF) <- NULL

coeffsDF <- coeffsDF[coeffsDF$Var %in% listRFImp,]
coeffsDF
```

```
##          1          Var
## 20  0.000000e+00 LotFrontage
## 21  1.352954e-06 LotArea
## 86  7.049432e-02 OverallQual
## 87  2.831610e-02 OverallCond
## 88  7.839586e-04 YearBuilt
## 89  9.272254e-04 YearRemodAdd
## 137 -6.947233e-03 ExterQualTA
## 148  0.000000e+00 BsmtQualGd
## 161  0.000000e+00 BsmtFinSF1
## 169  2.773587e-05 TotalBsmtSF
## 184  3.309808e-07 X1stFlrSF
## 185  0.000000e+00 X2ndFlrSF
## 187  1.969026e-04 GrLivArea
## 191  1.509926e-02 HalfBath
## 197  5.294280e-03 TotRmsAbvGrd
## 204  2.758108e-02 Fireplaces
## 210  0.000000e+00 GarageYrBlt
## 212 -1.346648e-02 GarageFinishUnf
## 213  6.953160e-02 GarageCars
## 214  0.000000e+00 GarageArea
```

By examining the filtered DF, we can see what the Lasso Regression model determined for the top 20 variables that the Random Forest model deemed important. Of the 20 that were identified important by RF, 5 were totally ignored by Lasso, and the one that most important in RF ‘GrLivArea’, was one of the important in Lasso but not the most important.

Gradient Boosted Trees Model

```
set.seed(1)
```

```
gbm <- train(
  SalePrice ~., data = data_train, method = "gbm",
  trControl = trainControl("cv", number = 10), preProc = "nzv")
```

## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	0.1483	nan	0.1000	0.0145
## 2	0.1372	nan	0.1000	0.0119
## 3	0.1276	nan	0.1000	0.0094
## 4	0.1190	nan	0.1000	0.0083
## 5	0.1115	nan	0.1000	0.0079
## 6	0.1056	nan	0.1000	0.0060
## 7	0.0995	nan	0.1000	0.0057
## 8	0.0943	nan	0.1000	0.0051
## 9	0.0895	nan	0.1000	0.0042
## 10	0.0852	nan	0.1000	0.0039
## 20	0.0560	nan	0.1000	0.0018
## 40	0.0325	nan	0.1000	0.0002
## 60	0.0240	nan	0.1000	0.0002
## 80	0.0200	nan	0.1000	0.0000
## 100	0.0181	nan	0.1000	-0.0000
## 120	0.0170	nan	0.1000	-0.0000
## 140	0.0161	nan	0.1000	-0.0000
## 150	0.0157	nan	0.1000	-0.0000
##				
## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	0.1466	nan	0.1000	0.0162
## 2	0.1321	nan	0.1000	0.0131
## 3	0.1203	nan	0.1000	0.0108
## 4	0.1085	nan	0.1000	0.0106
## 5	0.0991	nan	0.1000	0.0099
## 6	0.0926	nan	0.1000	0.0057
## 7	0.0858	nan	0.1000	0.0058
## 8	0.0789	nan	0.1000	0.0064
## 9	0.0738	nan	0.1000	0.0052
## 10	0.0687	nan	0.1000	0.0049
## 20	0.0388	nan	0.1000	0.0019
## 40	0.0212	nan	0.1000	0.0002
## 60	0.0169	nan	0.1000	-0.0002
## 80	0.0148	nan	0.1000	-0.0000
## 100	0.0135	nan	0.1000	-0.0001
## 120	0.0127	nan	0.1000	-0.0000
## 140	0.0120	nan	0.1000	-0.0000
## 150	0.0117	nan	0.1000	-0.0001
##				
## Iter	TrainDeviance	ValidDeviance	StepSize	Improve
## 1	0.1449	nan	0.1000	0.0186
## 2	0.1291	nan	0.1000	0.0155
## 3	0.1154	nan	0.1000	0.0136
## 4	0.1040	nan	0.1000	0.0114
## 5	0.0938	nan	0.1000	0.0093
## 6	0.0856	nan	0.1000	0.0080
## 7	0.0780	nan	0.1000	0.0076
## 8	0.0719	nan	0.1000	0.0053

##	9	0.0655	nan	0.1000	0.0063
##	10	0.0602	nan	0.1000	0.0044
##	20	0.0320	nan	0.1000	0.0011
##	40	0.0175	nan	0.1000	0.0001
##	60	0.0140	nan	0.1000	0.0000
##	80	0.0124	nan	0.1000	0.0000
##	100	0.0112	nan	0.1000	0.0000
##	120	0.0101	nan	0.1000	0.0000
##	140	0.0094	nan	0.1000	-0.0000
##	150	0.0091	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1482	nan	0.1000	0.0139
##	2	0.1373	nan	0.1000	0.0114
##	3	0.1272	nan	0.1000	0.0093
##	4	0.1195	nan	0.1000	0.0068
##	5	0.1125	nan	0.1000	0.0073
##	6	0.1058	nan	0.1000	0.0065
##	7	0.1001	nan	0.1000	0.0060
##	8	0.0947	nan	0.1000	0.0048
##	9	0.0901	nan	0.1000	0.0044
##	10	0.0854	nan	0.1000	0.0040
##	20	0.0567	nan	0.1000	0.0015
##	40	0.0335	nan	0.1000	0.0005
##	60	0.0245	nan	0.1000	0.0002
##	80	0.0203	nan	0.1000	0.0001
##	100	0.0180	nan	0.1000	0.0000
##	120	0.0167	nan	0.1000	-0.0000
##	140	0.0158	nan	0.1000	0.0000
##	150	0.0155	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1472	nan	0.1000	0.0166
##	2	0.1326	nan	0.1000	0.0136
##	3	0.1205	nan	0.1000	0.0114
##	4	0.1096	nan	0.1000	0.0105
##	5	0.1006	nan	0.1000	0.0079
##	6	0.0926	nan	0.1000	0.0079
##	7	0.0866	nan	0.1000	0.0047
##	8	0.0800	nan	0.1000	0.0057
##	9	0.0740	nan	0.1000	0.0058
##	10	0.0691	nan	0.1000	0.0043
##	20	0.0406	nan	0.1000	0.0015
##	40	0.0230	nan	0.1000	0.0002
##	60	0.0182	nan	0.1000	0.0001
##	80	0.0161	nan	0.1000	-0.0001
##	100	0.0148	nan	0.1000	-0.0001
##	120	0.0140	nan	0.1000	-0.0001
##	140	0.0133	nan	0.1000	-0.0000
##	150	0.0129	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1438	nan	0.1000	0.0176
##	2	0.1284	nan	0.1000	0.0163

##	3	0.1149	nan	0.1000	0.0135
##	4	0.1034	nan	0.1000	0.0106
##	5	0.0937	nan	0.1000	0.0076
##	6	0.0844	nan	0.1000	0.0092
##	7	0.0770	nan	0.1000	0.0064
##	8	0.0705	nan	0.1000	0.0060
##	9	0.0647	nan	0.1000	0.0053
##	10	0.0596	nan	0.1000	0.0044
##	20	0.0322	nan	0.1000	0.0011
##	40	0.0178	nan	0.1000	0.0001
##	60	0.0143	nan	0.1000	-0.0001
##	80	0.0128	nan	0.1000	-0.0000
##	100	0.0118	nan	0.1000	-0.0000
##	120	0.0110	nan	0.1000	-0.0000
##	140	0.0103	nan	0.1000	-0.0001
##	150	0.0101	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1466	nan	0.1000	0.0140
##	2	0.1356	nan	0.1000	0.0115
##	3	0.1262	nan	0.1000	0.0095
##	4	0.1183	nan	0.1000	0.0082
##	5	0.1117	nan	0.1000	0.0067
##	6	0.1051	nan	0.1000	0.0068
##	7	0.0992	nan	0.1000	0.0056
##	8	0.0936	nan	0.1000	0.0054
##	9	0.0887	nan	0.1000	0.0042
##	10	0.0842	nan	0.1000	0.0043
##	20	0.0565	nan	0.1000	0.0018
##	40	0.0338	nan	0.1000	0.0005
##	60	0.0254	nan	0.1000	0.0002
##	80	0.0217	nan	0.1000	0.0000
##	100	0.0197	nan	0.1000	-0.0000
##	120	0.0183	nan	0.1000	0.0000
##	140	0.0175	nan	0.1000	-0.0000
##	150	0.0171	nan	0.1000	0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1440	nan	0.1000	0.0162
##	2	0.1287	nan	0.1000	0.0140
##	3	0.1164	nan	0.1000	0.0118
##	4	0.1069	nan	0.1000	0.0098
##	5	0.0985	nan	0.1000	0.0068
##	6	0.0909	nan	0.1000	0.0075
##	7	0.0841	nan	0.1000	0.0063
##	8	0.0783	nan	0.1000	0.0054
##	9	0.0727	nan	0.1000	0.0056
##	10	0.0679	nan	0.1000	0.0045
##	20	0.0401	nan	0.1000	0.0017
##	40	0.0230	nan	0.1000	0.0001
##	60	0.0180	nan	0.1000	0.0000
##	80	0.0157	nan	0.1000	-0.0000
##	100	0.0147	nan	0.1000	-0.0001
##	120	0.0137	nan	0.1000	-0.0001

##	140	0.0130	nan	0.1000	-0.0000
##	150	0.0127	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1417	nan	0.1000	0.0175
##	2	0.1259	nan	0.1000	0.0163
##	3	0.1123	nan	0.1000	0.0124
##	4	0.1016	nan	0.1000	0.0112
##	5	0.0921	nan	0.1000	0.0091
##	6	0.0844	nan	0.1000	0.0070
##	7	0.0771	nan	0.1000	0.0066
##	8	0.0704	nan	0.1000	0.0062
##	9	0.0646	nan	0.1000	0.0050
##	10	0.0597	nan	0.1000	0.0043
##	20	0.0327	nan	0.1000	0.0014
##	40	0.0189	nan	0.1000	0.0002
##	60	0.0150	nan	0.1000	-0.0000
##	80	0.0132	nan	0.1000	0.0000
##	100	0.0121	nan	0.1000	-0.0000
##	120	0.0113	nan	0.1000	-0.0000
##	140	0.0105	nan	0.1000	-0.0000
##	150	0.0102	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1449	nan	0.1000	0.0140
##	2	0.1341	nan	0.1000	0.0113
##	3	0.1254	nan	0.1000	0.0087
##	4	0.1170	nan	0.1000	0.0081
##	5	0.1102	nan	0.1000	0.0074
##	6	0.1038	nan	0.1000	0.0063
##	7	0.0977	nan	0.1000	0.0054
##	8	0.0923	nan	0.1000	0.0046
##	9	0.0874	nan	0.1000	0.0046
##	10	0.0831	nan	0.1000	0.0035
##	20	0.0555	nan	0.1000	0.0017
##	40	0.0330	nan	0.1000	0.0004
##	60	0.0248	nan	0.1000	0.0002
##	80	0.0214	nan	0.1000	0.0000
##	100	0.0195	nan	0.1000	0.0000
##	120	0.0183	nan	0.1000	-0.0000
##	140	0.0175	nan	0.1000	-0.0001
##	150	0.0171	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1430	nan	0.1000	0.0155
##	2	0.1298	nan	0.1000	0.0135
##	3	0.1185	nan	0.1000	0.0113
##	4	0.1091	nan	0.1000	0.0083
##	5	0.1002	nan	0.1000	0.0096
##	6	0.0919	nan	0.1000	0.0081
##	7	0.0853	nan	0.1000	0.0056
##	8	0.0794	nan	0.1000	0.0053
##	9	0.0737	nan	0.1000	0.0058
##	10	0.0690	nan	0.1000	0.0043

##	20	0.0399	nan	0.1000	0.0019
##	40	0.0226	nan	0.1000	0.0002
##	60	0.0183	nan	0.1000	0.0001
##	80	0.0162	nan	0.1000	-0.0001
##	100	0.0149	nan	0.1000	-0.0000
##	120	0.0140	nan	0.1000	-0.0001
##	140	0.0134	nan	0.1000	-0.0000
##	150	0.0131	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1399	nan	0.1000	0.0170
##	2	0.1248	nan	0.1000	0.0145
##	3	0.1124	nan	0.1000	0.0127
##	4	0.1011	nan	0.1000	0.0114
##	5	0.0919	nan	0.1000	0.0079
##	6	0.0838	nan	0.1000	0.0076
##	7	0.0762	nan	0.1000	0.0074
##	8	0.0698	nan	0.1000	0.0064
##	9	0.0648	nan	0.1000	0.0048
##	10	0.0598	nan	0.1000	0.0045
##	20	0.0324	nan	0.1000	0.0012
##	40	0.0186	nan	0.1000	0.0001
##	60	0.0148	nan	0.1000	0.0001
##	80	0.0132	nan	0.1000	-0.0001
##	100	0.0120	nan	0.1000	-0.0000
##	120	0.0111	nan	0.1000	-0.0000
##	140	0.0103	nan	0.1000	-0.0000
##	150	0.0100	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1470	nan	0.1000	0.0143
##	2	0.1351	nan	0.1000	0.0108
##	3	0.1252	nan	0.1000	0.0089
##	4	0.1172	nan	0.1000	0.0079
##	5	0.1099	nan	0.1000	0.0073
##	6	0.1034	nan	0.1000	0.0060
##	7	0.0979	nan	0.1000	0.0049
##	8	0.0927	nan	0.1000	0.0049
##	9	0.0886	nan	0.1000	0.0037
##	10	0.0838	nan	0.1000	0.0046
##	20	0.0562	nan	0.1000	0.0020
##	40	0.0335	nan	0.1000	0.0007
##	60	0.0253	nan	0.1000	0.0002
##	80	0.0218	nan	0.1000	0.0001
##	100	0.0200	nan	0.1000	0.0000
##	120	0.0187	nan	0.1000	0.0000
##	140	0.0178	nan	0.1000	-0.0000
##	150	0.0174	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1445	nan	0.1000	0.0162
##	2	0.1315	nan	0.1000	0.0132
##	3	0.1206	nan	0.1000	0.0109
##	4	0.1097	nan	0.1000	0.0105

##	5	0.1012	nan	0.1000	0.0080
##	6	0.0938	nan	0.1000	0.0066
##	7	0.0865	nan	0.1000	0.0068
##	8	0.0799	nan	0.1000	0.0066
##	9	0.0741	nan	0.1000	0.0053
##	10	0.0690	nan	0.1000	0.0049
##	20	0.0409	nan	0.1000	0.0013
##	40	0.0240	nan	0.1000	0.0004
##	60	0.0190	nan	0.1000	0.0000
##	80	0.0168	nan	0.1000	-0.0001
##	100	0.0153	nan	0.1000	0.0000
##	120	0.0141	nan	0.1000	-0.0001
##	140	0.0133	nan	0.1000	-0.0000
##	150	0.0130	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1426	nan	0.1000	0.0173
##	2	0.1279	nan	0.1000	0.0148
##	3	0.1148	nan	0.1000	0.0130
##	4	0.1041	nan	0.1000	0.0096
##	5	0.0948	nan	0.1000	0.0079
##	6	0.0854	nan	0.1000	0.0086
##	7	0.0783	nan	0.1000	0.0071
##	8	0.0720	nan	0.1000	0.0059
##	9	0.0659	nan	0.1000	0.0055
##	10	0.0607	nan	0.1000	0.0047
##	20	0.0337	nan	0.1000	0.0011
##	40	0.0195	nan	0.1000	0.0002
##	60	0.0156	nan	0.1000	0.0000
##	80	0.0137	nan	0.1000	-0.0000
##	100	0.0124	nan	0.1000	-0.0001
##	120	0.0114	nan	0.1000	-0.0001
##	140	0.0106	nan	0.1000	-0.0000
##	150	0.0103	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1516	nan	0.1000	0.0149
##	2	0.1396	nan	0.1000	0.0123
##	3	0.1303	nan	0.1000	0.0093
##	4	0.1218	nan	0.1000	0.0083
##	5	0.1140	nan	0.1000	0.0080
##	6	0.1066	nan	0.1000	0.0069
##	7	0.1008	nan	0.1000	0.0055
##	8	0.0951	nan	0.1000	0.0051
##	9	0.0900	nan	0.1000	0.0050
##	10	0.0852	nan	0.1000	0.0044
##	20	0.0571	nan	0.1000	0.0019
##	40	0.0337	nan	0.1000	0.0006
##	60	0.0247	nan	0.1000	0.0001
##	80	0.0208	nan	0.1000	0.0001
##	100	0.0187	nan	0.1000	0.0000
##	120	0.0174	nan	0.1000	0.0000
##	140	0.0167	nan	0.1000	-0.0000
##	150	0.0164	nan	0.1000	0.0000


```

##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1497           nan        0.1000     0.0165
##      2         0.1351           nan        0.1000     0.0148
##      3         0.1224           nan        0.1000     0.0118
##      4         0.1112           nan        0.1000     0.0112
##      5         0.1021           nan        0.1000     0.0080
##      6         0.0940           nan        0.1000     0.0078
##      7         0.0864           nan        0.1000     0.0068
##      8         0.0805           nan        0.1000     0.0058
##      9         0.0748           nan        0.1000     0.0057
##     10         0.0703           nan        0.1000     0.0047
##     20         0.0410           nan        0.1000     0.0016
##     40         0.0226           nan        0.1000     0.0002
##     60         0.0178           nan        0.1000     0.0000
##     80         0.0161           nan        0.1000     0.0000
##    100         0.0148           nan        0.1000    -0.0000
##    120         0.0139           nan        0.1000    -0.0001
##    140         0.0133           nan        0.1000    -0.0000
##    150         0.0130           nan        0.1000     0.0000
##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1468           nan        0.1000     0.0206
##      2         0.1300           nan        0.1000     0.0145
##      3         0.1163           nan        0.1000     0.0129
##      4         0.1043           nan        0.1000     0.0115
##      5         0.0942           nan        0.1000     0.0097
##      6         0.0854           nan        0.1000     0.0080
##      7         0.0774           nan        0.1000     0.0065
##      8         0.0715           nan        0.1000     0.0056
##      9         0.0660           nan        0.1000     0.0044
##     10         0.0608           nan        0.1000     0.0051
##     20         0.0324           nan        0.1000     0.0014
##     40         0.0178           nan        0.1000     0.0002
##     60         0.0144           nan        0.1000    -0.0000
##     80         0.0131           nan        0.1000    -0.0000
##    100         0.0119           nan        0.1000    -0.0000
##    120         0.0110           nan        0.1000    -0.0001
##    140         0.0105           nan        0.1000    -0.0001
##    150         0.0101           nan        0.1000    -0.0001
##
## Iter    TrainDeviance    ValidDeviance    StepSize    Improve
##      1         0.1459           nan        0.1000     0.0140
##      2         0.1347           nan        0.1000     0.0116
##      3         0.1249           nan        0.1000     0.0089
##      4         0.1162           nan        0.1000     0.0084
##      5         0.1095           nan        0.1000     0.0063
##      6         0.1028           nan        0.1000     0.0062
##      7         0.0964           nan        0.1000     0.0061
##      8         0.0915           nan        0.1000     0.0050
##      9         0.0872           nan        0.1000     0.0046
##     10         0.0828           nan        0.1000     0.0042
##     20         0.0558           nan        0.1000     0.0019
##     40         0.0331           nan        0.1000     0.0006

```

##	60	0.0247	nan	0.1000	0.0001
##	80	0.0207	nan	0.1000	0.0000
##	100	0.0186	nan	0.1000	-0.0000
##	120	0.0176	nan	0.1000	-0.0001
##	140	0.0166	nan	0.1000	0.0000
##	150	0.0162	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1437	nan	0.1000	0.0157
##	2	0.1297	nan	0.1000	0.0138
##	3	0.1177	nan	0.1000	0.0121
##	4	0.1083	nan	0.1000	0.0088
##	5	0.0985	nan	0.1000	0.0092
##	6	0.0901	nan	0.1000	0.0076
##	7	0.0837	nan	0.1000	0.0061
##	8	0.0774	nan	0.1000	0.0058
##	9	0.0720	nan	0.1000	0.0048
##	10	0.0677	nan	0.1000	0.0041
##	20	0.0402	nan	0.1000	0.0014
##	40	0.0223	nan	0.1000	0.0002
##	60	0.0175	nan	0.1000	0.0001
##	80	0.0154	nan	0.1000	-0.0001
##	100	0.0140	nan	0.1000	0.0000
##	120	0.0131	nan	0.1000	-0.0000
##	140	0.0124	nan	0.1000	-0.0000
##	150	0.0121	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1405	nan	0.1000	0.0181
##	2	0.1245	nan	0.1000	0.0149
##	3	0.1113	nan	0.1000	0.0125
##	4	0.1007	nan	0.1000	0.0092
##	5	0.0906	nan	0.1000	0.0097
##	6	0.0822	nan	0.1000	0.0076
##	7	0.0758	nan	0.1000	0.0055
##	8	0.0698	nan	0.1000	0.0052
##	9	0.0643	nan	0.1000	0.0052
##	10	0.0595	nan	0.1000	0.0041
##	20	0.0325	nan	0.1000	0.0010
##	40	0.0183	nan	0.1000	0.0002
##	60	0.0146	nan	0.1000	-0.0001
##	80	0.0130	nan	0.1000	0.0000
##	100	0.0118	nan	0.1000	-0.0000
##	120	0.0109	nan	0.1000	-0.0001
##	140	0.0101	nan	0.1000	-0.0001
##	150	0.0098	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1433	nan	0.1000	0.0140
##	2	0.1325	nan	0.1000	0.0113
##	3	0.1229	nan	0.1000	0.0090
##	4	0.1148	nan	0.1000	0.0073
##	5	0.1071	nan	0.1000	0.0073
##	6	0.1012	nan	0.1000	0.0053

##	7	0.0957	nan	0.1000	0.0053
##	8	0.0900	nan	0.1000	0.0052
##	9	0.0851	nan	0.1000	0.0045
##	10	0.0810	nan	0.1000	0.0040
##	20	0.0540	nan	0.1000	0.0012
##	40	0.0320	nan	0.1000	0.0005
##	60	0.0239	nan	0.1000	0.0003
##	80	0.0203	nan	0.1000	-0.0001
##	100	0.0187	nan	0.1000	-0.0000
##	120	0.0174	nan	0.1000	0.0000
##	140	0.0166	nan	0.1000	-0.0001
##	150	0.0163	nan	0.1000	-0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1414	nan	0.1000	0.0163
##	2	0.1284	nan	0.1000	0.0134
##	3	0.1167	nan	0.1000	0.0112
##	4	0.1065	nan	0.1000	0.0107
##	5	0.0986	nan	0.1000	0.0071
##	6	0.0901	nan	0.1000	0.0084
##	7	0.0835	nan	0.1000	0.0067
##	8	0.0779	nan	0.1000	0.0053
##	9	0.0729	nan	0.1000	0.0048
##	10	0.0674	nan	0.1000	0.0054
##	20	0.0385	nan	0.1000	0.0016
##	40	0.0219	nan	0.1000	0.0003
##	60	0.0176	nan	0.1000	0.0000
##	80	0.0154	nan	0.1000	-0.0000
##	100	0.0142	nan	0.1000	-0.0000
##	120	0.0133	nan	0.1000	-0.0000
##	140	0.0125	nan	0.1000	-0.0000
##	150	0.0122	nan	0.1000	-0.0001

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1394	nan	0.1000	0.0193
##	2	0.1239	nan	0.1000	0.0151
##	3	0.1110	nan	0.1000	0.0127
##	4	0.0997	nan	0.1000	0.0117
##	5	0.0905	nan	0.1000	0.0082
##	6	0.0820	nan	0.1000	0.0083
##	7	0.0742	nan	0.1000	0.0074
##	8	0.0681	nan	0.1000	0.0058
##	9	0.0624	nan	0.1000	0.0060
##	10	0.0582	nan	0.1000	0.0038
##	20	0.0314	nan	0.1000	0.0013
##	40	0.0185	nan	0.1000	0.0001
##	60	0.0146	nan	0.1000	0.0000
##	80	0.0130	nan	0.1000	-0.0000
##	100	0.0118	nan	0.1000	-0.0000
##	120	0.0110	nan	0.1000	-0.0000
##	140	0.0103	nan	0.1000	-0.0000
##	150	0.0100	nan	0.1000	-0.0000

##

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
----	------	---------------	---------------	----------	---------

##	1	0.1495	nan	0.1000	0.0143
##	2	0.1376	nan	0.1000	0.0118
##	3	0.1283	nan	0.1000	0.0090
##	4	0.1202	nan	0.1000	0.0084
##	5	0.1127	nan	0.1000	0.0072
##	6	0.1057	nan	0.1000	0.0066
##	7	0.0994	nan	0.1000	0.0057
##	8	0.0941	nan	0.1000	0.0046
##	9	0.0894	nan	0.1000	0.0046
##	10	0.0851	nan	0.1000	0.0041
##	20	0.0581	nan	0.1000	0.0008
##	40	0.0341	nan	0.1000	0.0006
##	60	0.0255	nan	0.1000	0.0002
##	80	0.0215	nan	0.1000	0.0001
##	100	0.0195	nan	0.1000	-0.0000
##	120	0.0182	nan	0.1000	0.0001
##	140	0.0173	nan	0.1000	-0.0001
##	150	0.0170	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1464	nan	0.1000	0.0168
##	2	0.1325	nan	0.1000	0.0129
##	3	0.1202	nan	0.1000	0.0103
##	4	0.1106	nan	0.1000	0.0094
##	5	0.1009	nan	0.1000	0.0097
##	6	0.0926	nan	0.1000	0.0077
##	7	0.0855	nan	0.1000	0.0074
##	8	0.0798	nan	0.1000	0.0053
##	9	0.0746	nan	0.1000	0.0047
##	10	0.0696	nan	0.1000	0.0049
##	20	0.0403	nan	0.1000	0.0014
##	40	0.0226	nan	0.1000	0.0003
##	60	0.0179	nan	0.1000	0.0001
##	80	0.0158	nan	0.1000	-0.0001
##	100	0.0148	nan	0.1000	-0.0000
##	120	0.0138	nan	0.1000	-0.0000
##	140	0.0130	nan	0.1000	-0.0000
##	150	0.0128	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1453	nan	0.1000	0.0184
##	2	0.1297	nan	0.1000	0.0155
##	3	0.1155	nan	0.1000	0.0130
##	4	0.1041	nan	0.1000	0.0108
##	5	0.0940	nan	0.1000	0.0092
##	6	0.0851	nan	0.1000	0.0079
##	7	0.0778	nan	0.1000	0.0064
##	8	0.0708	nan	0.1000	0.0071
##	9	0.0652	nan	0.1000	0.0054
##	10	0.0603	nan	0.1000	0.0049
##	20	0.0325	nan	0.1000	0.0014
##	40	0.0184	nan	0.1000	0.0001
##	60	0.0151	nan	0.1000	0.0000
##	80	0.0131	nan	0.1000	-0.0000

##	100	0.0121	nan	0.1000	-0.0001
##	120	0.0113	nan	0.1000	-0.0001
##	140	0.0106	nan	0.1000	-0.0000
##	150	0.0103	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1444	nan	0.1000	0.0134
##	2	0.1332	nan	0.1000	0.0115
##	3	0.1237	nan	0.1000	0.0089
##	4	0.1158	nan	0.1000	0.0076
##	5	0.1086	nan	0.1000	0.0073
##	6	0.1024	nan	0.1000	0.0056
##	7	0.0965	nan	0.1000	0.0052
##	8	0.0914	nan	0.1000	0.0051
##	9	0.0865	nan	0.1000	0.0044
##	10	0.0822	nan	0.1000	0.0036
##	20	0.0552	nan	0.1000	0.0019
##	40	0.0329	nan	0.1000	0.0003
##	60	0.0246	nan	0.1000	0.0001
##	80	0.0209	nan	0.1000	0.0001
##	100	0.0189	nan	0.1000	0.0000
##	120	0.0176	nan	0.1000	0.0001
##	140	0.0168	nan	0.1000	-0.0000
##	150	0.0165	nan	0.1000	-0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1419	nan	0.1000	0.0163
##	2	0.1286	nan	0.1000	0.0136
##	3	0.1166	nan	0.1000	0.0105
##	4	0.1062	nan	0.1000	0.0113
##	5	0.0982	nan	0.1000	0.0090
##	6	0.0901	nan	0.1000	0.0079
##	7	0.0837	nan	0.1000	0.0058
##	8	0.0780	nan	0.1000	0.0051
##	9	0.0721	nan	0.1000	0.0056
##	10	0.0675	nan	0.1000	0.0039
##	20	0.0397	nan	0.1000	0.0013
##	40	0.0228	nan	0.1000	0.0002
##	60	0.0182	nan	0.1000	0.0001
##	80	0.0161	nan	0.1000	0.0000
##	100	0.0149	nan	0.1000	-0.0000
##	120	0.0138	nan	0.1000	-0.0000
##	140	0.0131	nan	0.1000	-0.0000
##	150	0.0127	nan	0.1000	0.0000
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.1395	nan	0.1000	0.0185
##	2	0.1243	nan	0.1000	0.0160
##	3	0.1113	nan	0.1000	0.0129
##	4	0.0995	nan	0.1000	0.0107
##	5	0.0901	nan	0.1000	0.0083
##	6	0.0824	nan	0.1000	0.0073
##	7	0.0755	nan	0.1000	0.0066
##	8	0.0692	nan	0.1000	0.0060

```
##      9      0.0639      nan      0.1000      0.0053
##     10      0.0593      nan      0.1000      0.0043
##     20      0.0322      nan      0.1000      0.0014
##     40      0.0186      nan      0.1000      0.0000
##     60      0.0149      nan      0.1000     -0.0001
##     80      0.0133      nan      0.1000     -0.0001
##    100      0.0122      nan      0.1000     -0.0000
##    120      0.0114      nan      0.1000     -0.0001
##    140      0.0107      nan      0.1000     -0.0000
##    150      0.0103      nan      0.1000     -0.0000
##
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1         0.1430           nan      0.1000     0.0185
##      2         0.1269           nan      0.1000     0.0145
##      3         0.1141           nan      0.1000     0.0124
##      4         0.1016           nan      0.1000     0.0119
##      5         0.0917           nan      0.1000     0.0102
##      6         0.0835           nan      0.1000     0.0073
##      7         0.0765           nan      0.1000     0.0071
##      8         0.0704           nan      0.1000     0.0050
##      9         0.0647           nan      0.1000     0.0052
##     10         0.0600           nan      0.1000     0.0044
##     20         0.0326           nan      0.1000     0.0014
##     40         0.0189           nan      0.1000    -0.0001
##     60         0.0148           nan      0.1000     0.0001
##     80         0.0132           nan      0.1000    -0.0000
##    100         0.0121           nan      0.1000    -0.0001
##    120         0.0112           nan      0.1000    -0.0000
##    140         0.0106           nan      0.1000    -0.0000
##    150         0.0103           nan      0.1000    -0.0000
```

```
predictions <- predict(gbm,data_test)
RMSE(predictions, data_test$SalePrice)
```

```
## [1] 0.1209606
```

Comparison of Models

```
compare=resamples(list(L=lasso, R=ridge, E=enet, RF = m_rf, G = gbm))
```

```
summary(compare)
```

```
##
## Call:
## summary.resamples(object = compare)
##
## Models: L, R, E, RF, G
## Number of resamples: 10
##
## MAE
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max. NA's
## L 0.07816799 0.08674583 0.09519405 0.09323783 0.09970306 0.1044491    0
```

```
## R 0.07670146 0.08862596 0.09988095 0.09506917 0.10156409 0.1050569 0
## E 0.07775151 0.08623393 0.09583900 0.09346221 0.10033290 0.1035560 0
## RF 0.07920558 0.09219023 0.09596471 0.09733000 0.10128513 0.1146040 0
## G 0.08507741 0.08999805 0.09521986 0.09332114 0.09617522 0.1026588 0
##
## RMSE
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max. NA's
## L 0.09778152 0.1217666 0.1452775 0.1518799 0.1575893 0.2695698 0
## R 0.09841857 0.1292656 0.1474946 0.1518827 0.1600506 0.2393770 0
## E 0.09687368 0.1229803 0.1459079 0.1492083 0.1521539 0.2525771 0
## RF 0.10259145 0.1415651 0.1510390 0.1487340 0.1570593 0.1860757 0
## G 0.10774435 0.1236806 0.1367302 0.1358157 0.1487888 0.1598050 0
##
## Rsquared
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max. NA's
## L 0.6420894 0.8496630 0.8959360 0.8551290 0.9138795 0.9399385 0
## R 0.6854652 0.8461922 0.8879079 0.8569824 0.8995269 0.9405751 0
## E 0.6622618 0.8557042 0.8957389 0.8610559 0.9161265 0.9415999 0
## RF 0.7961990 0.8514791 0.8764924 0.8746620 0.9014009 0.9420880 0
## G 0.8360557 0.8629792 0.8821800 0.8849289 0.9137745 0.9309447 0
```

Of the 5 models ran over the same dataset, the Gradient Boosted Trees model performed well producing the minimum RMSE compared to other models. The Ridge regression model performed the worst of them all.

Neural Networks with Dropout

```
# Convert Year columns to numeric
```

```
cols <- c("YearBuilt", "YearRemodAdd", "GarageYrBlt", "YrSold")
data_train[cols] <- sapply(data_train[cols], as.numeric)
data_test[cols] <- sapply(data_test[cols], as.numeric)
```

```
# Train validation split
```

```
train.index <- createDataPartition(data_train$SalePrice, p = 0.9, list = FALSE)
data_nn_train <- data_train[train.index, ]
data_nn_validation <- data_train[-train.index, ]
```

```
# Test set
```

```
data_nn_test <- data_test
```

```
# Separating and log transforming the target variable
```

```
data_nn_train_y <- data_nn_train$SalePrice
data_nn_train$SalePrice <- NULL
```

```
data_nn_test_y <- data_nn_test$SalePrice
data_nn_test$SalePrice <- NULL
```

```
data_nn_validation_y <- data_nn_validation$SalePrice
data_nn_validation$SalePrice <- NULL
```

```
# Scaling the data
```

```
ind <- sapply(data_nn_train, is.numeric) # Only for numeric
```

```
col_means_train <- lapply(data_nn_train[ind], mean)
col_stddevs_train <- lapply(data_nn_train[ind], sd)

data_nn_train[ind] <- lapply(data_nn_train[ind], scale)

# Scaling validation and testing data using mean and sd

data_nn_validation[ind] <- scale(data_nn_validation[ind], center = col_means_train, scale = col_stddevs_train)
data_nn_test[ind] <- scale(data_nn_test[ind], center = col_means_train, scale = col_stddevs_train)

# One Hot Encoding

library("mltools")
```

```
## Warning: package 'mltools' was built under R version 3.6.3
```

```
library("data.table")
```

```
## Warning: package 'data.table' was built under R version 3.6.3
```

```
data_nn_train = as.data.frame(one_hot(as.data.table(data_nn_train)))
data_nn_validation = as.data.frame(one_hot(as.data.table(data_nn_validation)))
data_nn_test = as.data.frame(one_hot(as.data.table(data_nn_test)))
```

```
library("tfruns")

runs <- tuning_run("house_train.R",
  flags = list(
    nodes_hlayer1 = c(600, 500, 400),
    nodes_hlayer2 = c(500, 250, 100),
    learning_rate = c(0.01, 0.05, 0.001, 0.0001),
    batch_size=c(10,20,50,75),
    epochs=c(30,50,100),
    activation=c("relu","sigmoid","tanh"),
    dropout1=c(0.3, 0.4, 0.5),
    dropout2=c(0.2, 0.3, 0.4)),
  sample = 0.01
)
```

```
#runs
#view_run(runs$run_dir[9])

runsHouse <- runs[order(runs$metric_val_loss, decreasing = FALSE),][1,]
```

Best performing with params: nodes_hlayer1 = 400, nodes_hlayer2 = 500, batch_size = 10, activation = sigmoid, learning_rate = 10^{-4} , epochs = 50 dropout1 = 0.4, dropout2 = 0.4.

The model doesn't overfit since the difference between error is little with the training error = 0.4511 and validation error = 0.0249.

Model Testing


```

# Combine validation and training data
data_nn_train_all <- rbind(data_nn_train, data_nn_validation)
data_nn_train_all_y <- c(data_nn_train_y, data_nn_validation_y)

set.seed(1)

model <- keras_model_sequential()
model %>%
  layer_dense(units = 900, activation = runsHouse$flag_activation, input_shape = dim(data_nn_train)[2])
  layer_dense(units = runsHouse$flag_nodes_hlayer1, activation = runsHouse$flag_activation) %>%
  layer_dropout(runsHouse$flag_dropout1) %>%
  layer_dense(units = runsHouse$flag_nodes_hlayer2, activation = runsHouse$flag_activation) %>%
  layer_dropout(runsHouse$flag_dropout2) %>%
  layer_dense(units = 1)

model %>%
  compile(optimizer = optimizer_adam(lr = runsHouse$flag_learning_rate), loss = 'mse')

set.seed(123)

model %>%
  fit(as.matrix(data_nn_train_all), as.matrix(data_nn_train_all_y), batch_size = runsHouse$flag_batch_size,
      validation_data = list(as.matrix(data_nn_test), as.matrix(data_nn_test_y)))

predictions <- model %>% predict(as.matrix(data_nn_test))

cat('RMSE:', RMSE(predictions, as.matrix(data_nn_test_y)))

## RMSE: 0.130623

```

Compared with the Gradient Boosted Trees model which had the $RMSE = 0.136$, this neural network was not able outperform the GBM by having a slightly worse RMSE.