Housing data analysis - Women Who Code workshop

Darya Vanichkina

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Useful links Darya mentioned in the workshop:

- The link about assignment operators
- Subsetting data frames
- The apply family
- Useful reference for dplyr

```
load.libraries <- c('tidyverse', 'forcats', 'corrplot', 'caret', 'Metrics', 'randomForest', 'xgboost',
install.lib <- load.libraries[!load.libraries %in% installed.packages()]
for(libs in install.lib) install.packages(libs, dependences = TRUE)
sapply(load.libraries, library, character = TRUE)
knitr::opts_chunk$set(echo = TRUE)
```

Task 1

Load the data in from csv.

```
trainH <- read.csv("train.csv")
testH <- read.csv("test.csv")
```

Task 2

1. What features are there in the data?
2. What are the dimensions of the data?
3. What are the column headers?

Use the summary() and str() functions to explore…

```
dim(trainH)
```

```
## [1] 1459   69
```

```
names(trainH)
```

```
##  [1] "Id"            "MSSubClass"    "MSZoning"      "LotFrontage"
##  [5] "LotArea"       "Street"        "LotShape"      "LandContour"
##  [9] "LotConfig"     "LandSlope"     "Neighborhood"  "BldgType"
## [13] "HouseStyle"    "OverallQual"   "OverallCond"   "YearBuilt"
## [17] "YearRemodAdd"  "Foundation"    "BsmtQual"      "BsmtCond"
## [21] "BsmtExposure"  "BsmtFinType1"  "BsmtFinSF1"    "BsmtFinType2"
## [25] "BsmtFinSF2"    "BsmtUnfSF"     "TotalBsmtSF"   "Heating"
## [29] "HeatingQC"     "CentralAir"    "Electrical"    "X1stFlrSF"
## [33] "X2ndFlrSF"     "LowQualFinSF"  "GrLivArea"     "BsmtFullBath"
## [37] "BsmtHalfBath"  "FullBath"      "HalfBath"      "BedroomAbvGr"
## [41] "KitchenAbvGr"  "KitchenQual"   "TotRmsAbvGrd"  "Functional"
## [45] "Fireplaces"    "FireplaceQu"   "GarageType"    "GarageYrBlt"
## [49] "GarageFinish"  "GarageCars"    "GarageArea"    "GarageQual"
## [53] "GarageCond"    "PavedDrive"    "WoodDeckSF"    "OpenPorchSF"
## [57] "EnclosedPorch" "X3SsnPorch"    "ScreenPorch"   "PoolArea"
## [61] "PoolQC"        "Fence"         "MiscFeature"   "MiscVal"
```

```
## [65] "MoSold"        "YrSold"        "SaleType"      "SaleCondition"
## [69] "SalePrice"
```

```r
summary(trainH)
```

```
##        Id           MSSubClass        MSZoning     LotFrontage
##  Min.   :   1.0   Min.   : 20.00   C (all):  10   Min.   : 21.00
##  1st Qu.: 365.5   1st Qu.: 20.00   FV     :  65   1st Qu.: 59.00
##  Median : 730.0   Median : 50.00   RH     :  16   Median : 69.00
##  Mean   : 730.1   Mean   : 56.88   RL     :1150   Mean   : 70.05
##  3rd Qu.:1094.5   3rd Qu.: 70.00   RM     : 218   3rd Qu.: 80.00
##  Max.   :1460.0   Max.   :190.00                  Max.   :313.00
##                                                   NA's   :259
##     LotArea         Street     LotShape  LandContour   LotConfig
##  Min.   :  1300   Grvl:   6   IR1:484   Bnk:  63    Corner : 263
##  1st Qu.:  7549   Pave:1453   IR2: 41   HLS:  50    CulDSac:  94
##  Median :  9477               IR3: 10   Low:  36    FR2    :  47
##  Mean   : 10517               Reg:924   Lvl:1310    FR3    :   4
##  3rd Qu.: 11603                                     Inside :1051
##  Max.   :215245
##
##  LandSlope   Neighborhood   BldgType      HouseStyle   OverallQual
##  Gtl:1381   NAmes  :225   1Fam  :1219   1Story :726   Min.   : 1.0
##  Mod:  65   CollgCr:150   2fmCon:  31   2Story :445   1st Qu.: 5.0
##  Sev:  13   OldTown:113   Duplex:  52   1.5Fin :154   Median : 6.0
##             Edwards:100   Twnhs :  43   SLvl   : 64   Mean   : 6.1
##             Somerst: 86   TwnhsE: 114   SFoyer : 37   3rd Qu.: 7.0
##             Gilbert: 79                 1.5Unf : 14   Max.   :10.0
##             (Other):706                 (Other): 19
##   OverallCond      YearBuilt     YearRemodAdd   Foundation  BsmtQual
##  Min.   :1.000   Min.   :1872   Min.   :1950   BrkTil:146   Ex  :121
##  1st Qu.:5.000   1st Qu.:1954   1st Qu.:1967   CBlock:634   Fa  : 35
##  Median :5.000   Median :1973   Median :1994   PConc :646   Gd  :617
##  Mean   :5.576   Mean   :1971   Mean   :1985   Slab  : 24   TA  :649
##  3rd Qu.:6.000   3rd Qu.:2000   3rd Qu.:2004   Stone :  6   NA's: 37
##  Max.   :9.000   Max.   :2010   Max.   :2010   Wood  :  3
##
##  BsmtCond    BsmtExposure BsmtFinType1   BsmtFinSF1     BsmtFinType2
##  Fa  :  45   Av  :221     ALQ :220     Min.   :   0.0   ALQ :  19
##  Gd  :  65   Gd  :134     BLQ :148     1st Qu.:   0.0   BLQ :  33
##  Po  :   2   Mn  :114     GLQ :418     Median : 384.0   GLQ :  14
##  TA  :1310   No  :952     LwQ : 74     Mean   : 443.9   LwQ :  46
##  NA's:  37   NA's: 38     Rec :133     3rd Qu.: 712.5   Rec :  54
##                           Unf :429     Max.   :5644.0   Unf :1255
##                           NA's: 37                      NA's:  38
##    BsmtFinSF2        BsmtUnfSF       TotalBsmtSF    Heating     HeatingQC
##  Min.   :   0.00   Min.   :   0.0   Min.   :   0   Floor:   1   Ex:741
##  1st Qu.:   0.00   1st Qu.: 223.0   1st Qu.: 796   GasA :1427   Fa: 49
##  Median :   0.00   Median : 479.0   Median : 992   GasW :  18   Gd:240
##  Mean   :  46.58   Mean   : 567.4   Mean   :1058   Grav :   7   Po:  1
##  3rd Qu.:   0.00   3rd Qu.: 808.0   3rd Qu.:1298   OthW :   2   TA:428
##  Max.   :1474.00   Max.   :2336.0   Max.   :6110   Wall :   4
##
##  CentralAir Electrical     X1stFlrSF      X2ndFlrSF       LowQualFinSF
##  N:  95     FuseA:  94   Min.   : 334   Min.   :   0.0   Min.   :  0.000
```

```
##  Y:1364     FuseF:  27   1st Qu.: 882   1st Qu.:   0.0   1st Qu.:  0.000
##             FuseP:   3   Median :1088   Median :   0.0   Median :  0.000
##             Mix  :   1   Mean   :1163   Mean   : 346.8   Mean   :  5.848
##             SBrkr:1334   3rd Qu.:1392   3rd Qu.: 728.0   3rd Qu.:  0.000
##                          Max.   :4692   Max.   :2065.0   Max.   :572.000
##
##    GrLivArea     BsmtFullBath     BsmtHalfBath        FullBath
##  Min.   : 334   Min.   :0.0000   Min.   :0.00000   Min.   :0.000
##  1st Qu.:1129   1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:1.000
##  Median :1464   Median :0.0000   Median :0.00000   Median :2.000
##  Mean   :1516   Mean   :0.4256   Mean   :0.05757   Mean   :1.565
##  3rd Qu.:1778   3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:2.000
##  Max.   :5642   Max.   :3.0000   Max.   :2.00000   Max.   :3.000
##
##     HalfBath       BedroomAbvGr    KitchenAbvGr   KitchenQual
##  Min.   :0.0000   Min.   :0.000   Min.   :0.000   Ex:100
##  1st Qu.:0.0000   1st Qu.:2.000   1st Qu.:1.000   Fa: 39
##  Median :0.0000   Median :3.000   Median :1.000   Gd:585
##  Mean   :0.3825   Mean   :2.866   Mean   :1.047   TA:735
##  3rd Qu.:1.0000   3rd Qu.:3.000   3rd Qu.:1.000
##  Max.   :2.0000   Max.   :8.000   Max.   :3.000
##
##   TotRmsAbvGrd    Functional    Fireplaces     FireplaceQu   GarageType
##  Min.   : 2.000   Maj1:  14   Min.   :0.0000   Ex  : 24    2Types :  6
##  1st Qu.: 5.000   Maj2:   5   1st Qu.:0.0000   Fa  : 33    Attchd :870
##  Median : 6.000   Min1:  31   Median :1.0000   Gd  :380    Basment: 19
##  Mean   : 6.517   Min2:  34   Mean   :0.6134   Po  : 20    BuiltIn: 87
##  3rd Qu.: 7.000   Mod :  15   3rd Qu.:1.0000   TA  :313    CarPort:  9
##  Max.   :14.000   Sev :   1   Max.   :3.0000   NA's:689    Detchd :387
##                   Typ :1359                                NA's   : 81
##   GarageYrBlt   GarageFinish   GarageCars      GarageArea   GarageQual
##  Min.   :1900   Fin :351     Min.   :0.000   Min.   :   0   Ex  :   3
##  1st Qu.:1961   RFn :422     1st Qu.:1.000   1st Qu.: 333   Fa  :  48
##  Median :1980   Unf :605     Median :2.000   Median : 480   Gd  :  14
##  Mean   :1978   NA's: 81     Mean   :1.767   Mean   : 473   Po  :   3
##  3rd Qu.:2002                3rd Qu.:2.000   3rd Qu.: 576   TA  :1310
##  Max.   :2010                Max.   :4.000   Max.   :1418   NA's:  81
##  NA's   :81
##  GarageCond  PavedDrive   WoodDeckSF      OpenPorchSF     EnclosedPorch
##  Ex  :   2   N:  90     Min.   :  0.00   Min.   :  0.00   Min.   :  0.00
##  Fa  :  35   P:  30     1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.00
##  Gd  :   9   Y:1339     Median :  0.00   Median : 25.00   Median :  0.00
##  Po  :   7              Mean   : 94.24   Mean   : 46.69   Mean   : 21.97
##  TA  :1325              3rd Qu.:168.00   3rd Qu.: 68.00   3rd Qu.:  0.00
##  NA's:  81              Max.   :857.00   Max.   :547.00   Max.   :552.00
##
##    X3SsnPorch       ScreenPorch        PoolArea        PoolQC
##  Min.   :  0.000   Min.   :  0.00   Min.   :  0.000   Ex  :   2
##  1st Qu.:  0.000   1st Qu.:  0.00   1st Qu.:  0.000   Fa  :   2
##  Median :  0.000   Median :  0.00   Median :  0.000   Gd  :   3
##  Mean   :  3.412   Mean   : 15.07   Mean   :  2.761   NA's:1452
##  3rd Qu.:  0.000   3rd Qu.:  0.00   3rd Qu.:  0.000
##  Max.   :508.000   Max.   :480.00   Max.   :738.000
##
```

```
##    Fence      MiscFeature    MiscVal            MoSold
##  GdPrv:  59   Gar2:   2   Min.   :    0.00   Min.   : 1.000
##  GdWo :  54   Othr:   2   1st Qu.:    0.00   1st Qu.: 5.000
##  MnPrv: 157   Shed:  49   Median :    0.00   Median : 6.000
##  MnWw :  11   TenC:   1   Mean   :   43.52   Mean   : 6.323
##  NA's :1178   NA's:1405   3rd Qu.:    0.00   3rd Qu.: 8.000
##                           Max.   :15500.00   Max.   :12.000
##
##      YrSold        SaleType    SaleCondition    SalePrice
##  Min.   :2006   WD     :1266   Abnorml: 101   Min.   : 34900
##  1st Qu.:2007   New    : 122   AdjLand:   4   1st Qu.:129950
##  Median :2008   COD    :  43   Alloca :  12   Median :163000
##  Mean   :2008   ConLD  :   9   Family :  20   Mean   :180930
##  3rd Qu.:2009   ConLI  :   5   Normal :1197   3rd Qu.:214000
##  Max.   :2010   ConLw  :   5   Partial: 125   Max.   :755000
##                 (Other):   9
```

```r
str(trainH)
```

```
## 'data.frame':    1459 obs. of  69 variables:
##  $ Id           : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ MSSubClass   : int  60 20 60 70 60 50 20 60 50 190 ...
##  $ MSZoning     : Factor w/ 5 levels "C (all)","FV",..: 4 4 4 4 4 4 4 4 5 4 ...
##  $ LotFrontage  : int  65 80 68 60 84 85 75 NA 51 50 ...
##  $ LotArea      : int  8450 9600 11250 9550 14260 14115 10084 10382 6120 7420 ...
##  $ Street       : Factor w/ 2 levels "Grvl","Pave": 2 2 2 2 2 2 2 2 2 2 ...
##  $ LotShape     : Factor w/ 4 levels "IR1","IR2","IR3",..: 4 4 1 1 1 1 4 1 4 4 ...
##  $ LandContour  : Factor w/ 4 levels "Bnk","HLS","Low",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ LotConfig    : Factor w/ 5 levels "Corner","CulDSac",..: 5 3 5 1 3 5 5 1 5 1 ...
##  $ LandSlope    : Factor w/ 3 levels "Gtl","Mod","Sev": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Neighborhood : Factor w/ 25 levels "Blmngtn","Blueste",..: 6 25 6 7 14 12 21 17 18 4 ...
##  $ BldgType     : Factor w/ 5 levels "1Fam","2fmCon",..: 1 1 1 1 1 1 1 1 1 2 ...
##  $ HouseStyle   : Factor w/ 8 levels "1.5Fin","1.5Unf",..: 6 3 6 6 6 1 3 6 1 2 ...
##  $ OverallQual  : int  7 6 7 7 8 5 8 7 7 5 ...
##  $ OverallCond  : int  5 8 5 5 5 5 5 6 5 6 ...
##  $ YearBuilt    : int  2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 ...
##  $ YearRemodAdd : int  2003 1976 2002 1970 2000 1995 2005 1973 1950 1950 ...
##  $ Foundation   : Factor w/ 6 levels "BrkTil","CBlock",..: 3 2 3 1 3 6 3 2 1 1 ...
##  $ BsmtQual     : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 3 3 4 3 3 1 3 4 4 ...
##  $ BsmtCond     : Factor w/ 4 levels "Fa","Gd","Po",..: 4 4 4 2 4 4 4 4 4 4 ...
##  $ BsmtExposure : Factor w/ 4 levels "Av","Gd","Mn",..: 4 2 3 4 1 4 1 3 4 4 ...
##  $ BsmtFinType1 : Factor w/ 6 levels "ALQ","BLQ","GLQ",..: 3 1 3 1 3 3 3 1 6 3 ...
##  $ BsmtFinSF1   : int  706 978 486 216 655 732 1369 859 0 851 ...
##  $ BsmtFinType2 : Factor w/ 6 levels "ALQ","BLQ","GLQ",..: 6 6 6 6 6 6 6 2 6 6 ...
##  $ BsmtFinSF2   : int  0 0 0 0 0 0 0 32 0 0 ...
##  $ BsmtUnfSF    : int  150 284 434 540 490 64 317 216 952 140 ...
##  $ TotalBsmtSF  : int  856 1262 920 756 1145 796 1686 1107 952 991 ...
##  $ Heating      : Factor w/ 6 levels "Floor","GasA",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ HeatingQC    : Factor w/ 5 levels "Ex","Fa","Gd",..: 1 1 1 3 1 1 1 1 3 1 ...
##  $ CentralAir   : Factor w/ 2 levels "N","Y": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Electrical   : Factor w/ 5 levels "FuseA","FuseF",..: 5 5 5 5 5 5 5 5 2 5 ...
##  $ X1stFlrSF    : int  856 1262 920 961 1145 796 1694 1107 1022 1077 ...
##  $ X2ndFlrSF    : int  854 0 866 756 1053 566 0 983 752 0 ...
##  $ LowQualFinSF : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ GrLivArea    : int  1710 1262 1786 1717 2198 1362 1694 2090 1774 1077 ...
```

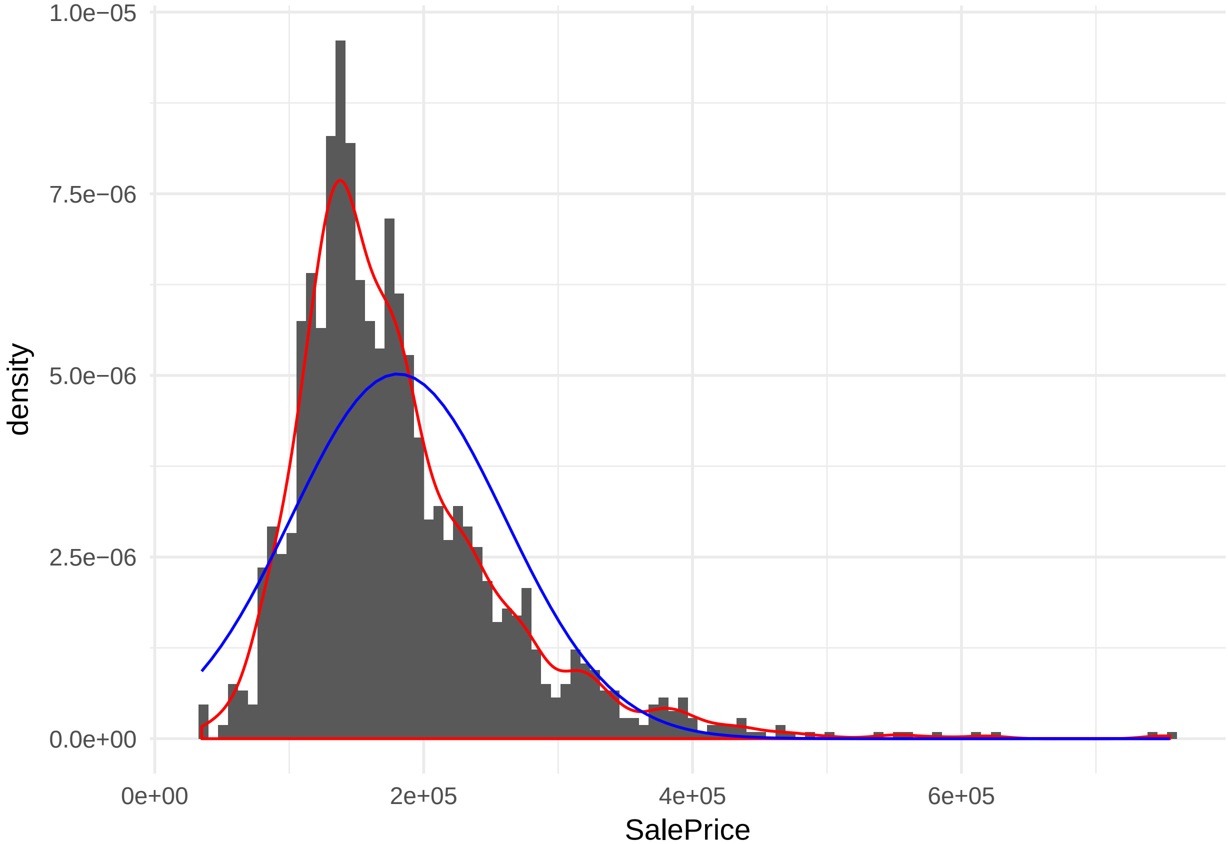
```
##  $ BsmtFullBath : int  1 0 1 1 1 1 1 1 0 1 ...
##  $ BsmtHalfBath : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ FullBath     : int  2 2 2 1 2 1 2 2 2 1 ...
##  $ HalfBath     : int  1 0 1 0 1 1 0 1 0 0 ...
##  $ BedroomAbvGr : int  3 3 3 3 4 1 3 3 2 2 ...
##  $ KitchenAbvGr : int  1 1 1 1 1 1 1 1 2 2 ...
##  $ KitchenQual  : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 4 3 3 3 4 3 4 4 4 ...
##  $ TotRmsAbvGrd : int  8 6 6 7 9 5 7 7 8 5 ...
##  $ Functional   : Factor w/ 7 levels "Maj1","Maj2",..: 7 7 7 7 7 7 7 7 3 7 ...
##  $ Fireplaces   : int  0 1 1 1 1 0 1 2 2 2 ...
##  $ FireplaceQu  : Factor w/ 5 levels "Ex","Fa","Gd",..: NA 5 5 3 5 NA 3 5 5 5 ...
##  $ GarageType   : Factor w/ 6 levels "2Types","Attchd",..: 2 2 2 6 2 2 2 2 6 2 ...
##  $ GarageYrBlt  : int  2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
##  $ GarageFinish : Factor w/ 3 levels "Fin","RFn","Unf": 2 2 2 3 2 3 2 2 3 2 ...
##  $ GarageCars   : int  2 2 2 3 3 2 2 2 2 1 ...
##  $ GarageArea   : int  548 460 608 642 836 480 636 484 468 205 ...
##  $ GarageQual   : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 2 3 ...
##  $ GarageCond   : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ PavedDrive   : Factor w/ 3 levels "N","P","Y": 3 3 3 3 3 3 3 3 3 3 ...
##  $ WoodDeckSF   : int  0 298 0 0 192 40 255 235 90 0 ...
##  $ OpenPorchSF  : int  61 0 42 35 84 30 57 204 0 4 ...
##  $ EnclosedPorch: int  0 0 0 272 0 0 0 228 205 0 ...
##  $ X3SsnPorch   : int  0 0 0 0 0 320 0 0 0 0 ...
##  $ ScreenPorch  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ PoolArea     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ PoolQC       : Factor w/ 3 levels "Ex","Fa","Gd": NA NA NA NA NA NA NA NA NA NA ...
##  $ Fence        : Factor w/ 4 levels "GdPrv","GdWo",..: NA NA NA NA NA 3 NA NA NA NA ...
##  $ MiscFeature  : Factor w/ 4 levels "Gar2","Othr",..: NA NA NA NA NA 3 NA 3 NA NA ...
##  $ MiscVal      : int  0 0 0 0 0 700 0 350 0 0 ...
##  $ MoSold       : int  2 5 9 2 12 10 8 11 4 1 ...
##  $ YrSold       : int  2008 2007 2008 2006 2008 2009 2007 2009 2008 2008 ...
##  $ SaleType     : Factor w/ 9 levels "COD","Con","ConLD",..: 9 9 9 9 9 9 9 9 9 9 ...
##  $ SaleCondition: Factor w/ 6 levels "Abnorml","AdjLand",..: 5 5 5 1 5 5 5 5 1 5 ...
##  $ SalePrice    : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

What does the distribution of sale price look like?

Task 3

1. Is the sale price (the variable we're interested in prediting) normally distributed?
2. Plot a histogram of the distribution using ggplot2.
3. Find its mean, standard deviation

```
trainH %>% ggplot(., aes(x = SalePrice)) +
  geom_histogram(bins = 100, aes(y =..density..)) +
  geom_density(col = "red") +  theme_minimal() +
  stat_function(fun=dnorm, color="blue", args=list(mean=mean(trainH$SalePrice),  sd=sd(trainH$SalePrice
```




```
# what is the mean?
mean(trainH$SalePrice)
```

```
## [1] 180930.4
```

```
# what is the standard deviation?
sd(trainH$SalePrice)
```

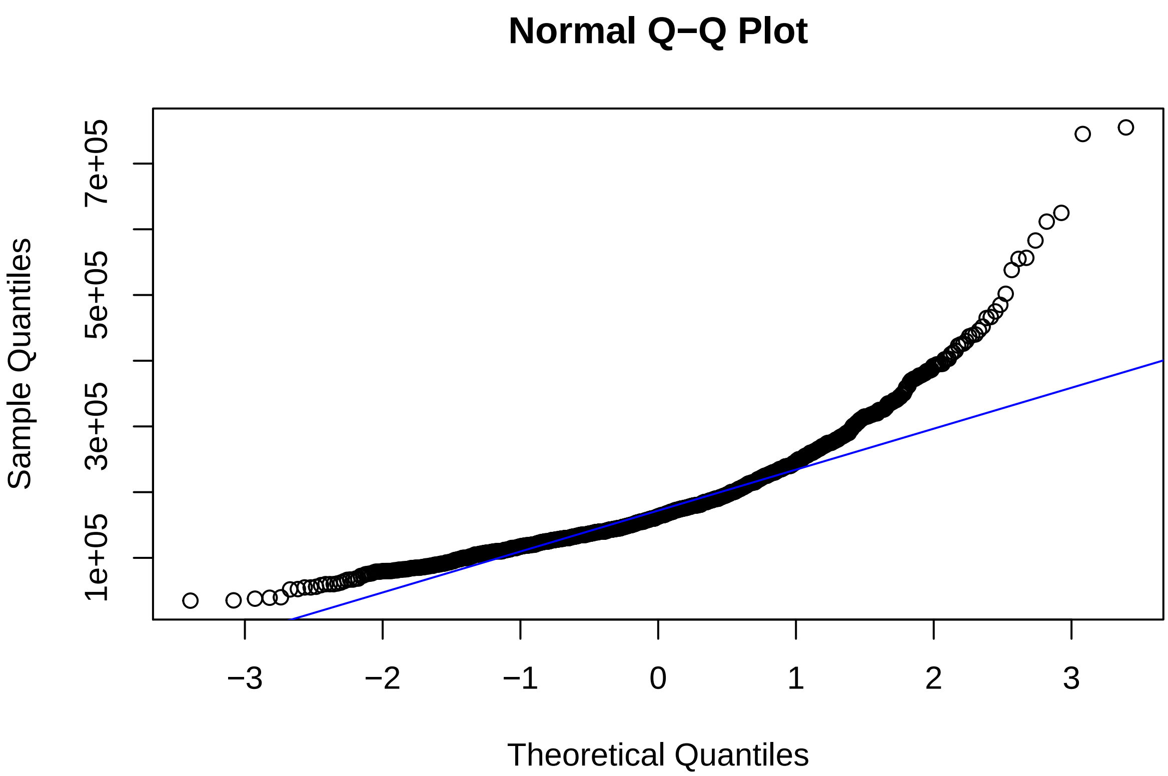
```
## [1] 79468.96
```

Task 4

1.Plot a quantile-quantile plot (QQ plot) to "assess" normality.

```
Note: This plot compares the data we have (Sample Quantiles) with a theoretical sample coming from a no
```

```
qqnorm(trainH$SalePrice)
qqline(trainH$SalePrice, col = "blue")
```

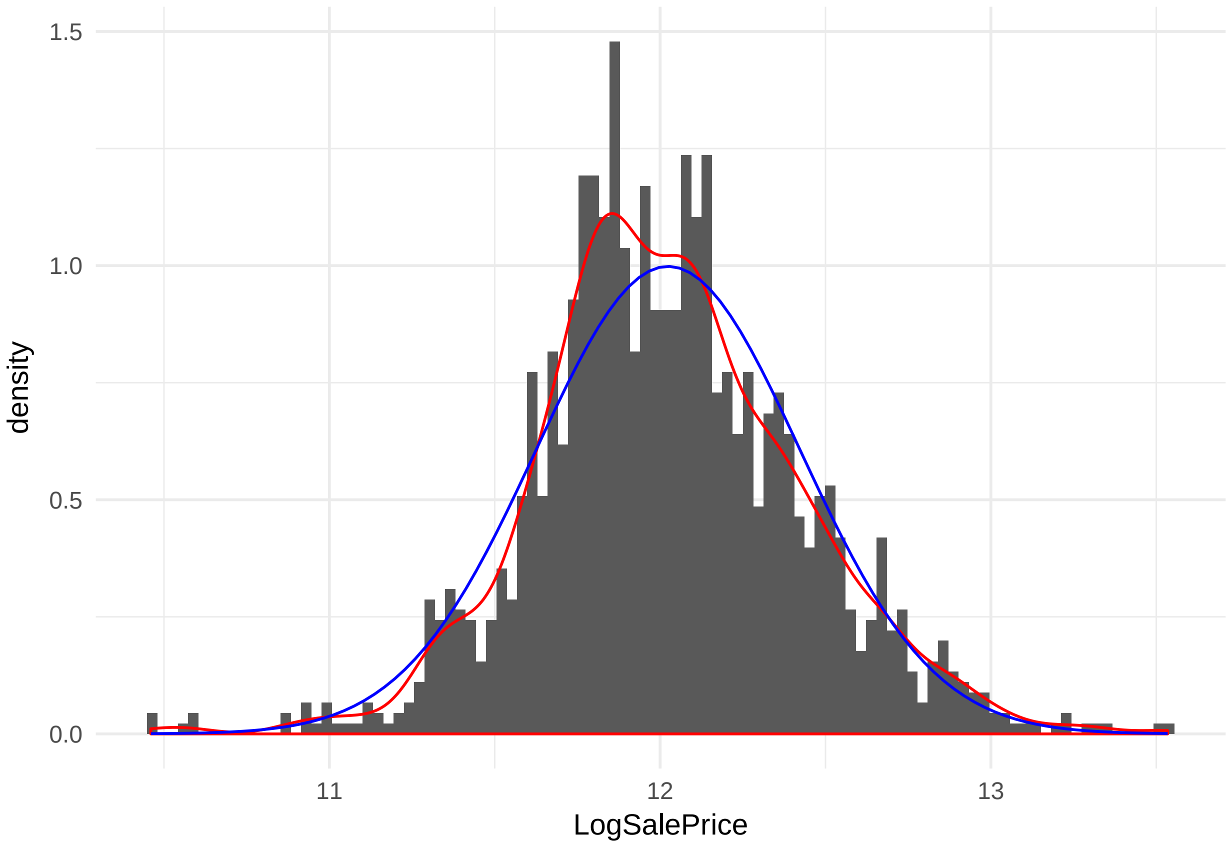


A standard way of transforming the data to be better approximated by a normal distribution is by using the log-transform?

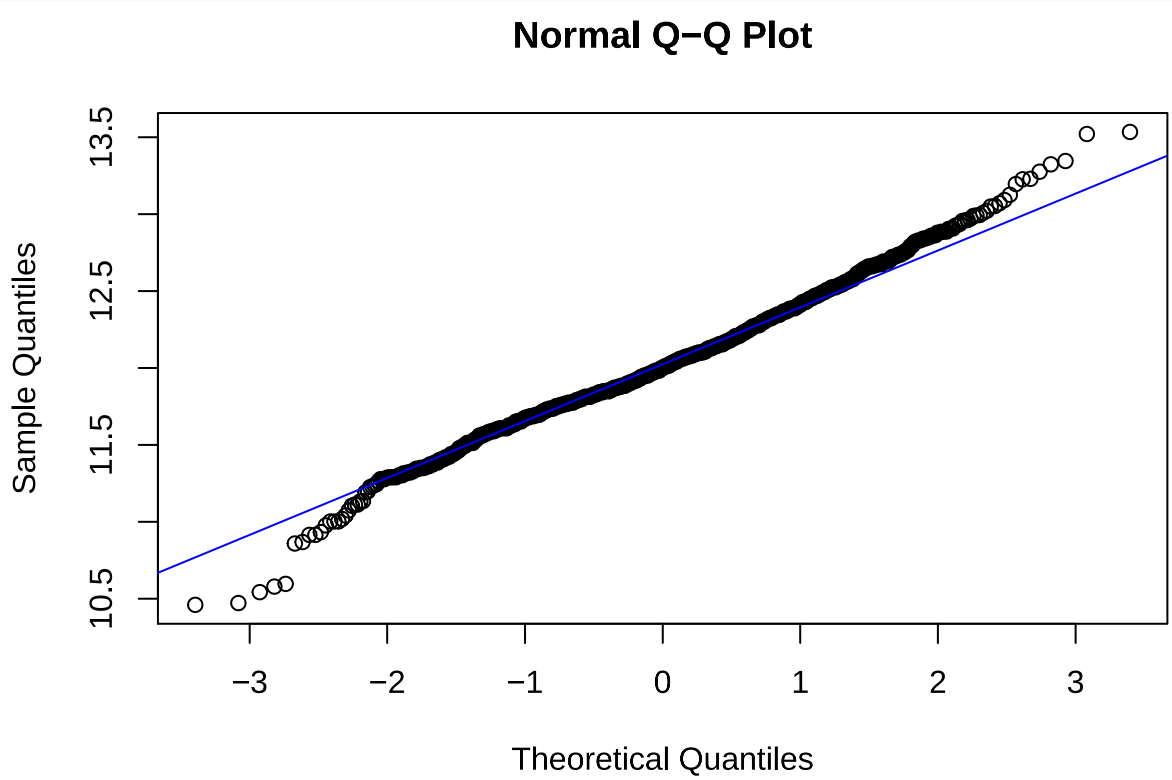
Task 5

1. Carry out this transformation
2. Use a histogram and QQ plot to see whether it works…

```
trainH <- trainH %>%
  mutate(LogSalePrice =  log(SalePrice + 1)) %>%
  mutate(SalePrice =  NULL)

# plot
trainH %>% ggplot(., aes(x = LogSalePrice)) + geom_histogram(bins = 100, aes(y =..density..)) +  geom_d
```




```
qqnorm(trainH$LogSalePrice)
qqline(trainH$LogSalePrice, col = "blue")
```



Missing data

Task 6

What happens if we only use complete data? How much data is missing?

Topics used here (but not explored): Subsetting data frames The apply family

```
trainHcomplete <- trainH[complete.cases(trainH), ]
colSums(sapply(trainH, is.na)) [colSums(sapply(trainH, is.na)) > 0]
```

```
##  LotFrontage     BsmtQual     BsmtCond BsmtExposure BsmtFinType1
##          259           37           37           38           37
## BsmtFinType2  FireplaceQu   GarageType  GarageYrBlt GarageFinish
##           38          689           81           81           81
##   GarageQual   GarageCond       PoolQC        Fence  MiscFeature
##           81           81         1452         1178         1405
```

```
colSums(sapply(testH, is.na)) [colSums(sapply(testH, is.na)) > 0]
```

```
##  LotFrontage     BsmtQual     BsmtCond BsmtExposure BsmtFinType1
##          226           39           40           39           37
## BsmtFinType2  FireplaceQu   GarageType  GarageYrBlt GarageFinish
##           37          721           76           77           77
##   GarageQual   GarageCond       PoolQC        Fence  MiscFeature
##           77           77         1445         1160         1397
```

We need to combine the datasets for imputation, so that we don't have NAs in the test data as well!

Task 7

Combine the testing and training data.

```
trainH$source <- "train"
testH$source <- "test"
testH$LogSalePrice <- NA
alldata <- rbind(trainH, testH)
colSums(sapply(alldata, is.na)) [colSums(sapply(alldata, is.na)) > 0]
```

```
##  LotFrontage     BsmtQual     BsmtCond BsmtExposure BsmtFinType1
##          485           76           77           77           74
## BsmtFinType2  FireplaceQu   GarageType  GarageYrBlt GarageFinish
##           75         1410          157          158          158
##   GarageQual   GarageCond       PoolQC        Fence  MiscFeature
##          158          158         2897         2338         2802
## LogSalePrice
##         1448
```

How do we impute the missing data?

Task 8

Explore the data using the table() function (variable by variable).

```
table(alldata$PoolQC)
```

```
##
## Ex Fa Gd
##  4  2  4
```

Read the metadata file and see that many of the NAs should be recoded as None since these features are lacking in the house.

Task 9

Recode the NA values that should be None using mutate() and fct_explicit_na().

```
alldata <- alldata %>%
  mutate(PoolQC = fct_explicit_na(PoolQC, na_level = "None")) %>%
  mutate(MiscFeature = fct_explicit_na(MiscFeature, na_level = "None")) %>%
  mutate(Fence = fct_explicit_na(Fence, na_level = "None")) %>%
  mutate(FireplaceQu = fct_explicit_na(FireplaceQu, na_level = "None")) %>%
  mutate(GarageType = fct_explicit_na(GarageType, na_level = "None")) %>%
  mutate(GarageFinish = fct_explicit_na(GarageFinish, na_level = "None")) %>%
  mutate(GarageQual = fct_explicit_na(GarageQual, na_level = "None")) %>%
  mutate(GarageCond = fct_explicit_na(GarageCond, na_level = "None")) %>%
  mutate(BsmtQual = fct_explicit_na(BsmtQual, na_level = "None")) %>%
  mutate(BsmtCond = fct_explicit_na(BsmtCond, na_level = "None")) %>%
  mutate(BsmtExposure = fct_explicit_na(BsmtExposure, na_level = "None")) %>%
  mutate(BsmtFinType1 = fct_explicit_na(BsmtFinType1, na_level = "None")) %>%
  mutate(BsmtFinType2 = fct_explicit_na(BsmtFinType2, na_level = "None"))

colSums(sapply(alldata, is.na)) [colSums(sapply(alldata, is.na)) > 0]
```

```
##  LotFrontage  GarageYrBlt LogSalePrice
##          485          158         1448
```

Task 10

For the GarageYrBlt - set NA values using replace_na() to zero.

```
alldata <- alldata %>% replace_na(list(BsmtFinSF1 = 0, BsmtFinSF2 = 0,  BsmtUnfSF = 0, TotalBsmtSF = 0,

colSums(sapply(alldata, is.na)) [colSums(sapply(alldata, is.na)) > 0]
```

```
##  LotFrontage LogSalePrice
##          485         1448
```

Task 11

For Lot frontage - set it to be the median for the neighborhood using group_by() and mutate().

```
alldata <- alldata %>%
  group_by(Neighborhood) %>%
  mutate(LotFrontage=ifelse(is.na(LotFrontage), median(LotFrontage, na.rm=TRUE), LotFrontage))
```

Now split data again

Task 12

Split back into training (trainHC) and test (testHC) sets (because kaggle training set had prices, test didn't).

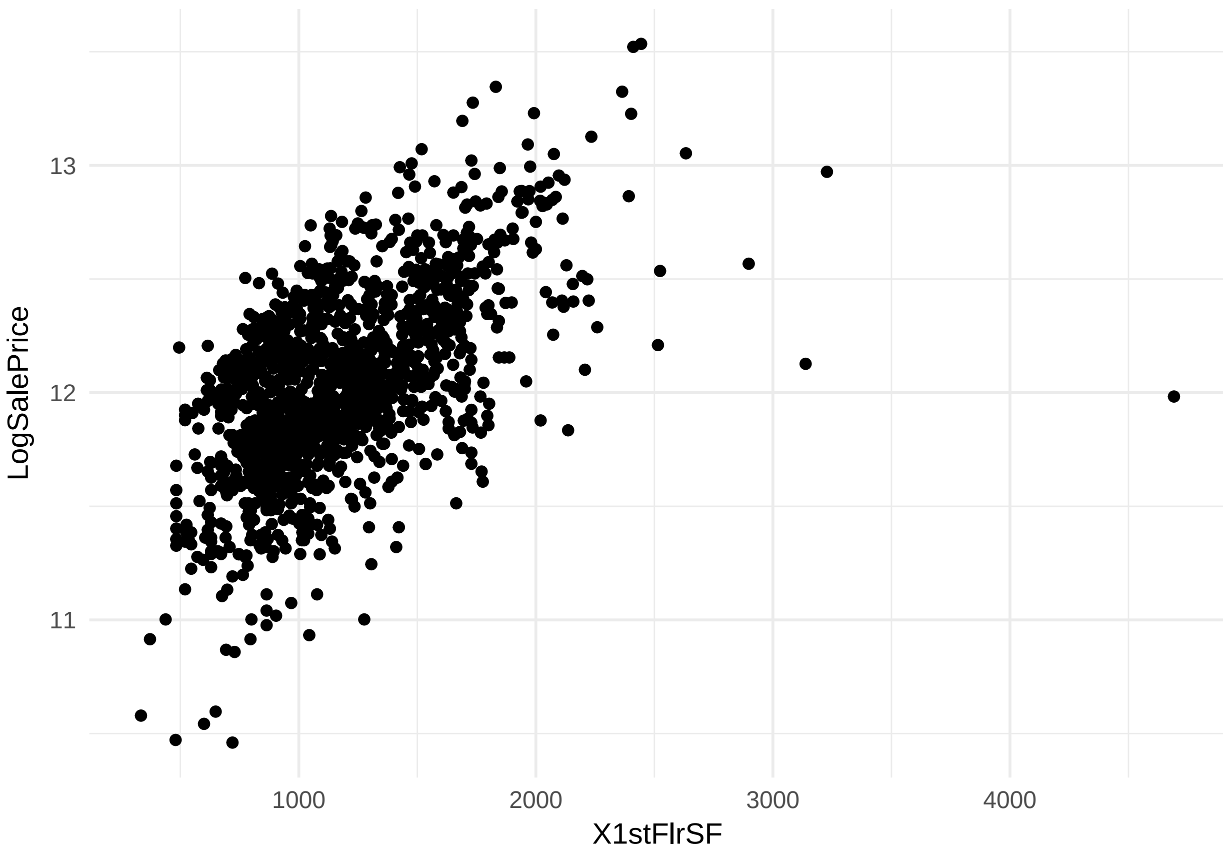
```
trainHC <-alldata %>% filter(source == "train")
testHC <-alldata %>% filter(source == "test")
```

Basic exploratory data analysis of training data

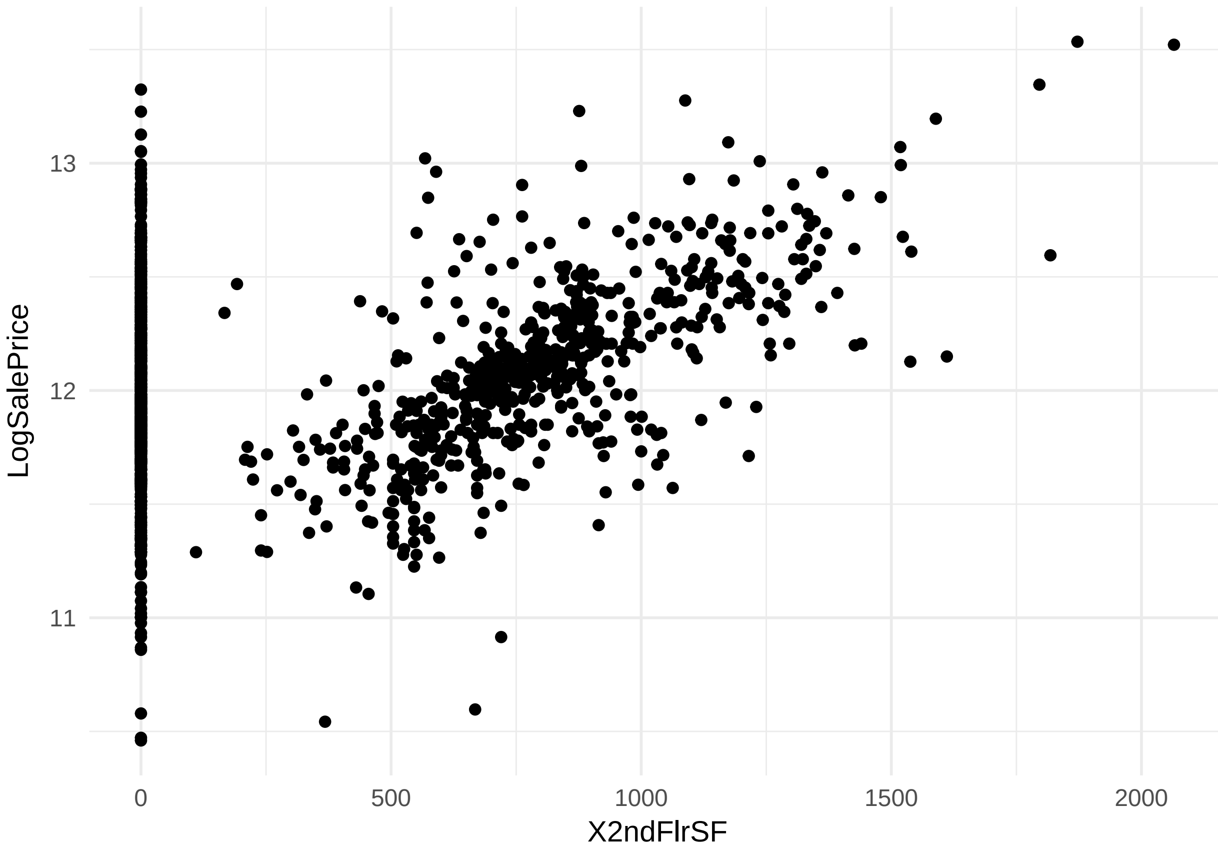
Task 13

1. How does the sale price depend on living area: X1stFlrSF, X2ndFlrSF, TotalBsmtSF? (use a scatterplot to visualise this)
2. Create a variable TotalSqFt which is a combination of these
3. Does it better predict the house price? (again, just using scatterplot at this point)

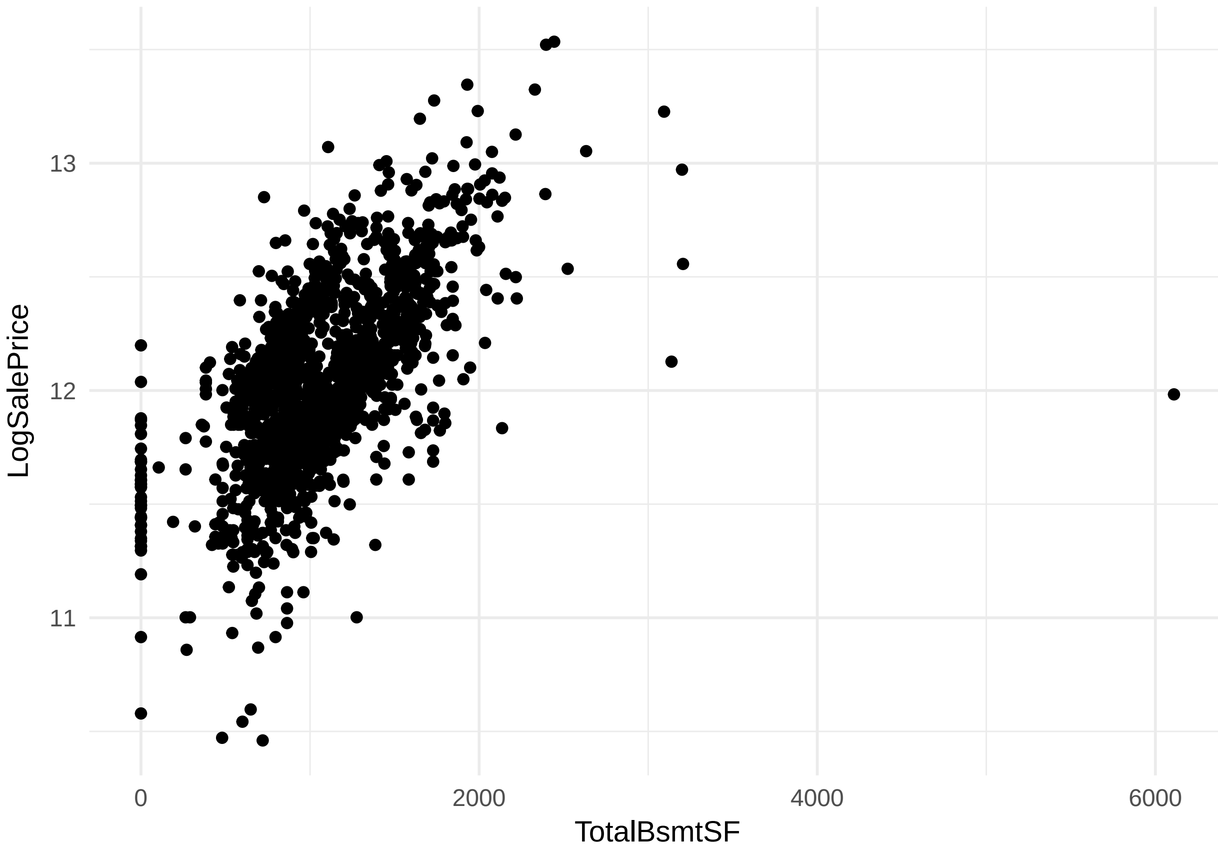
```
trainHC %>% ggplot(aes(x=X1stFlrSF, y = LogSalePrice)) + geom_point() + theme_minimal()
```



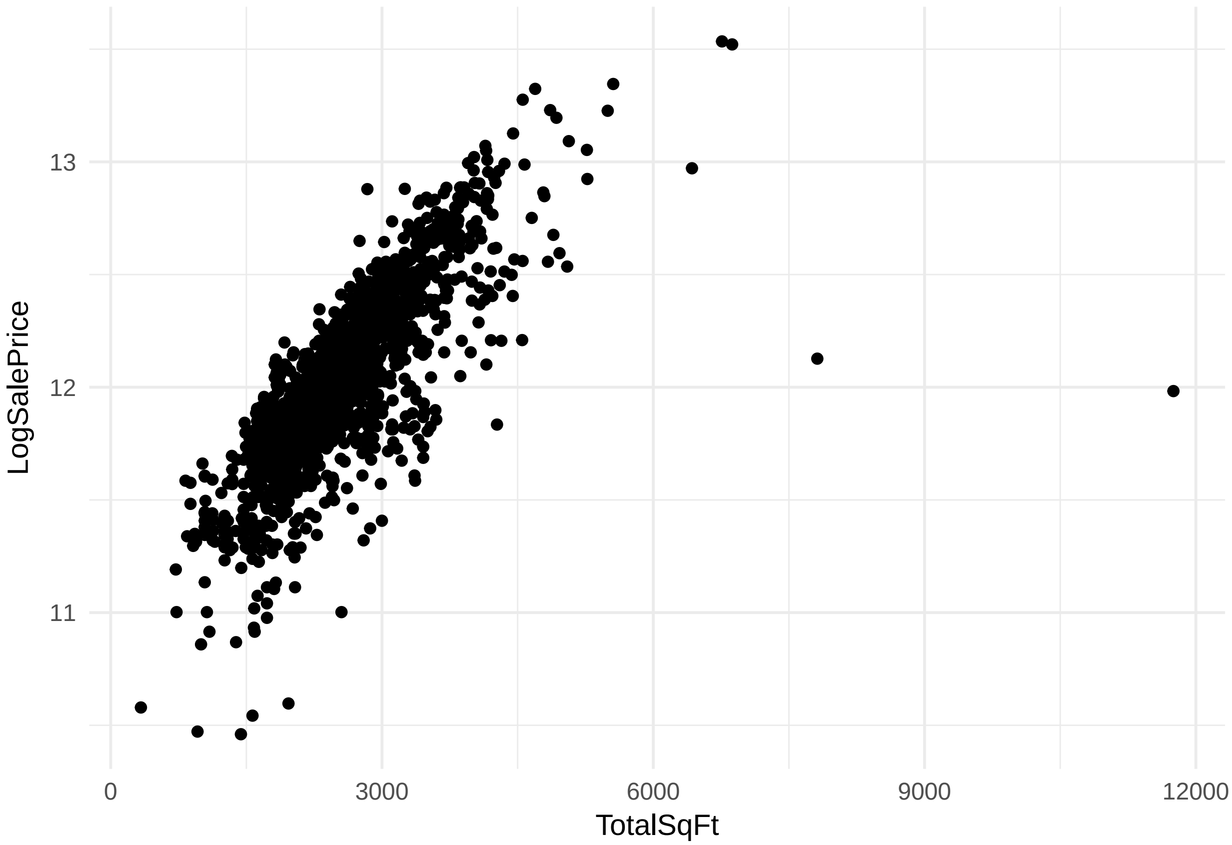

```
trainHC %>% ggplot(aes(x=X2ndFlrSF, y = LogSalePrice)) + geom_point() + theme_minimal()
```




```
trainHC %>% ggplot(aes(x=TotalBsmtSF, y = LogSalePrice)) + geom_point() + theme_minimal()
```




```r
# create extra variable
trainHC$TotalSqFt <- trainHC$X1stFlrSF + trainHC$X2ndFlrSF + trainHC$TotalBsmtSF

trainHC %>% ggplot(aes(x=TotalSqFt, y = LogSalePrice)) + geom_point() + theme_minimal()
```



Task 14

Identify and remove outliers with a high total square foot, but low price.

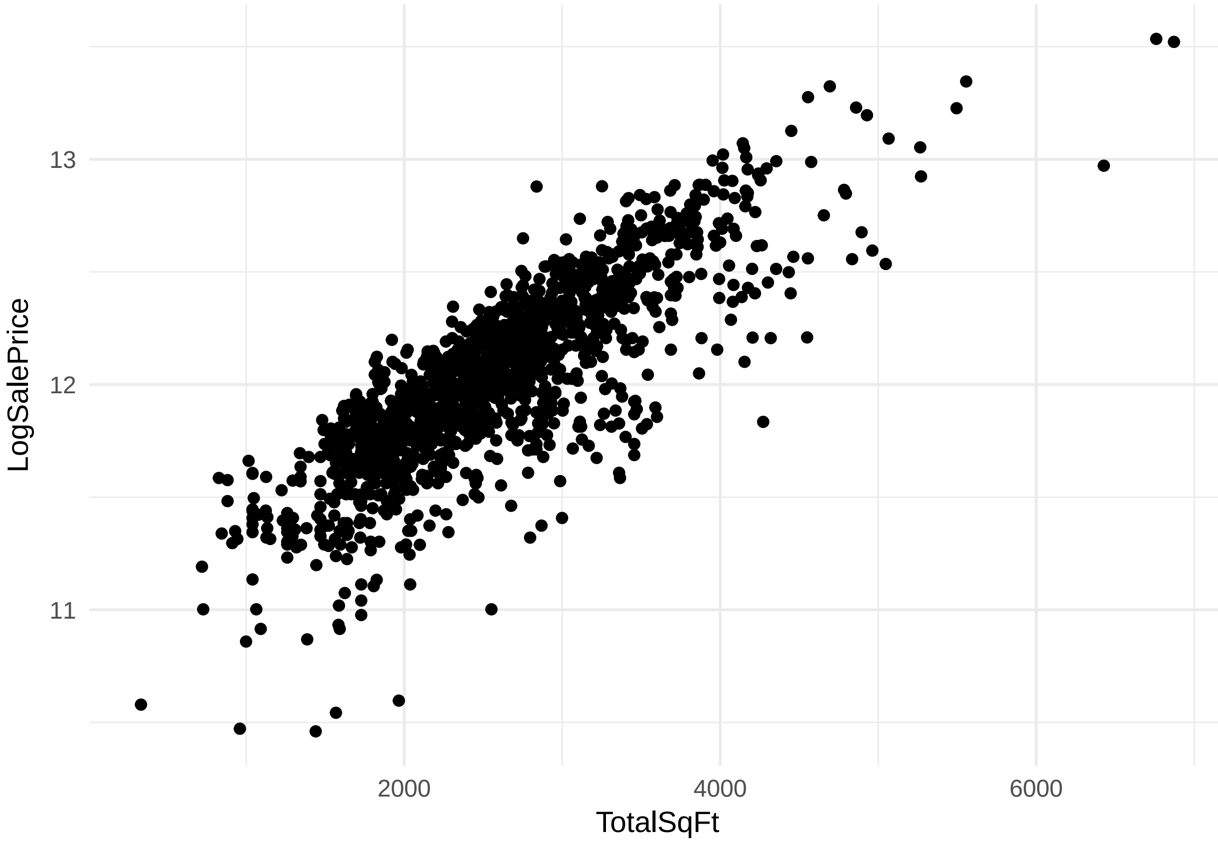
```
# identify largest houses by area
trainHC %>% arrange(desc(TotalSqFt)) %>% select(Id, TotalSqFt)
```

```
## Adding missing grouping variables: `Neighborhood`
```

```
## # A tibble: 1,459 x 3
## # Groups:   Neighborhood [25]
##    Neighborhood    Id TotalSqFt
##    <fct>        <int>     <dbl>
##  1 Edwards       1299    11752.
##  2 Edwards        524     7814.
##  3 NoRidge       1183     6872.
##  4 NoRidge        692     6760.
##  5 NoRidge        497     6428.
##  6 NoRidge       1170     5557.
##  7 NridgHt        441     5496.
##  8 NoRidge       1354     5271.
##  9 NoRidge       1374     5266.
## 10 NridgHt        799     5066.
## # ... with 1,449 more rows
```

```
# filter out based on size of top 2
trainHC <- trainHC %>% filter(TotalSqFt <= 7800)
# check that we've removed them
```

```r
trainHC %>% ggplot(aes(x=TotalSqFt, y = LogSalePrice)) + geom_point() + theme_minimal()
```



Does having more bedrooms increase sale price?

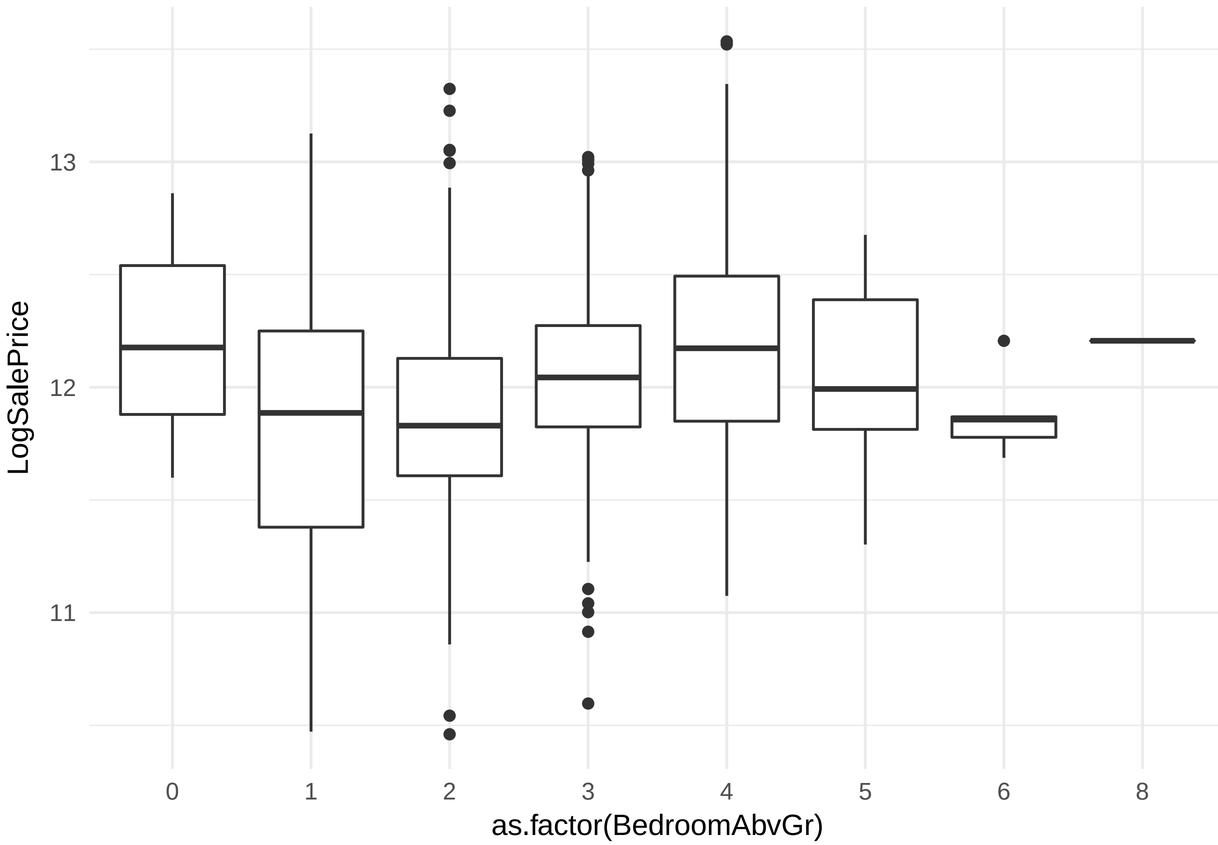
Task 15

Use a geom_boxplot() to explore this

```r
trainHC$BedroomAbvGr %>% summary()
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   0.000   2.000   3.000   2.866   3.000   8.000
```

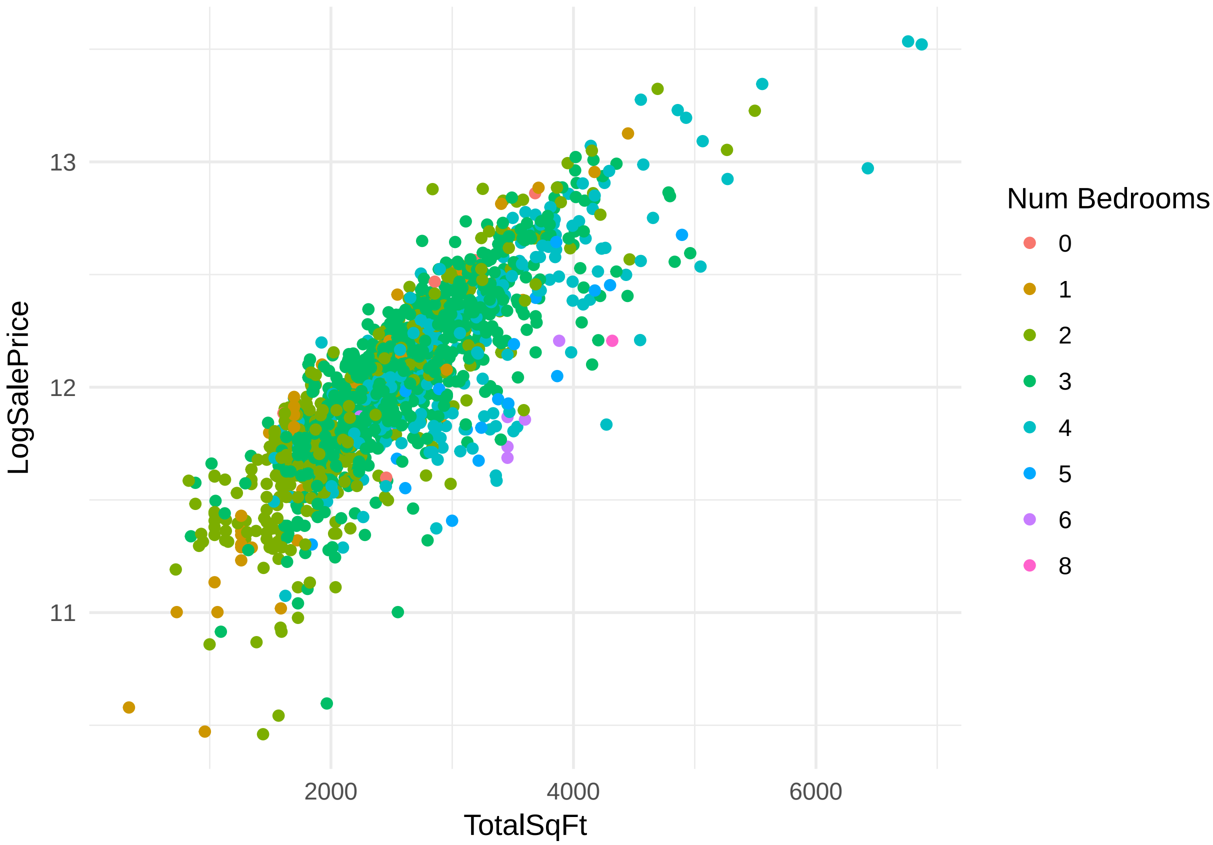
```r
trainHC %>% ggplot(aes(x=as.factor(BedroomAbvGr), y = LogSalePrice)) +
  geom_boxplot() + theme_minimal()
```



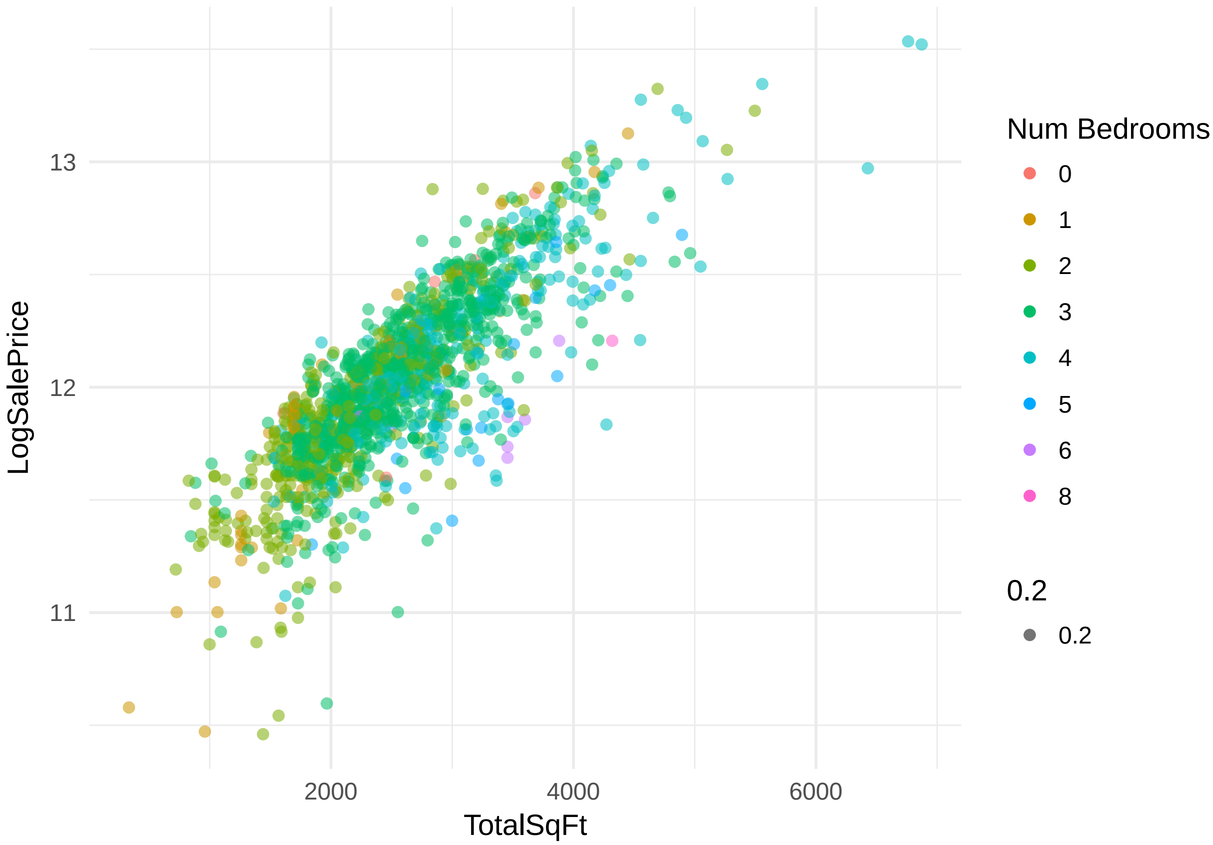
Task 16

Visualise both number of bedrooms (as a factor) and TotalSqFt as a scatterplot to see if a trend is visible.

```
trainHC %>% ggplot(aes(x=TotalSqFt, y = LogSalePrice, colour = as.factor(BedroomAbvGr))) + geom_point()
```




```
trainHC %>% ggplot(aes(x=TotalSqFt, y = LogSalePrice, colour = as.factor(BedroomAbvGr), alpha = 0.2)) +
```

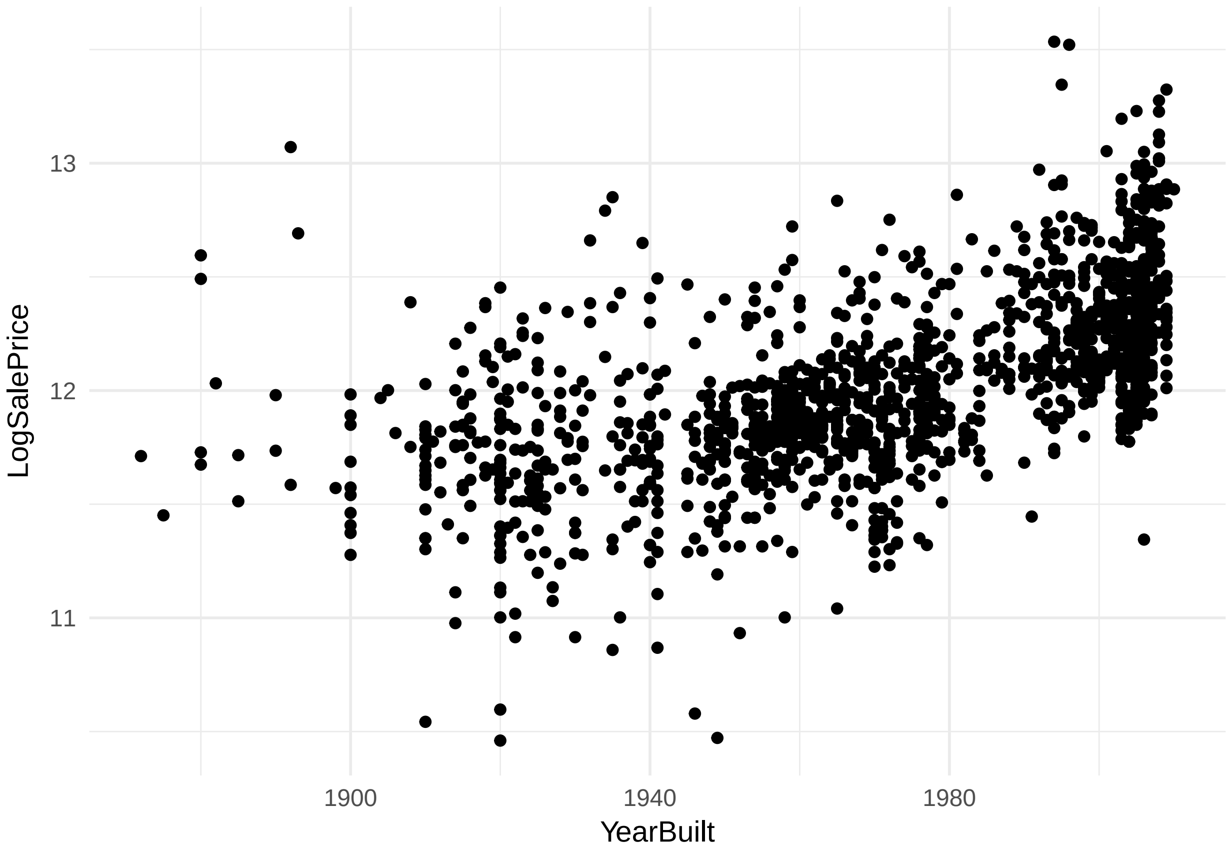


Are newer or more recently renovated properties more expensive?

Task 17

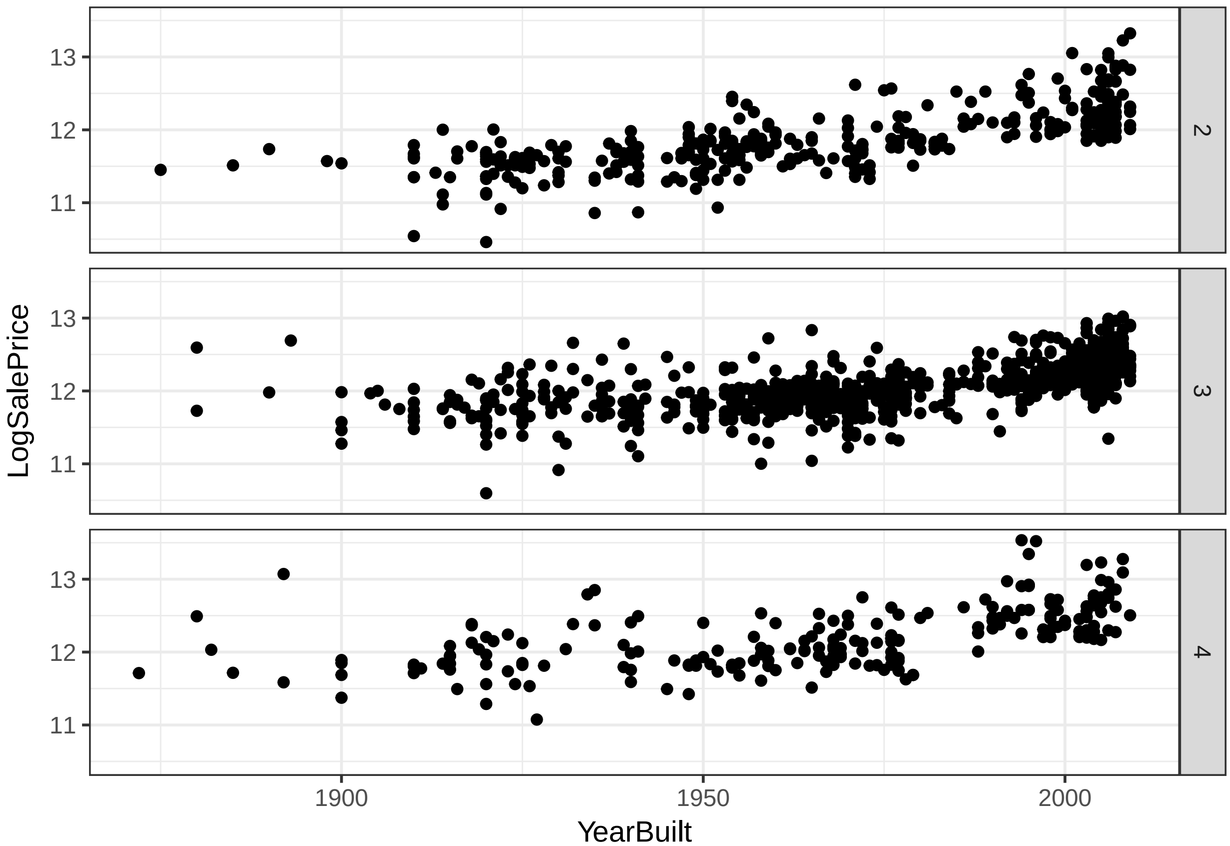
1. Investigate this generally and then
2. … specifically for 2 - 4 bedroom properties.

```
trainHC %>% ggplot(aes(x=YearBuilt, y = LogSalePrice)) + geom_point() + theme_minimal()
```




```
trainHC %>% ggplot(aes(x=YearRemodAdd, y = LogSalePrice)) + geom_point() + theme_minimal()
```


```
trainHC %>% filter(BedroomAbvGr >= 2) %>% filter(BedroomAbvGr <= 4) %>% ggplot(aes(x=YearBuilt, y = LogS
```



Lets convert kitchen quality to numeric (we'll see why we need this later):

From the metadata we know it can be:

- Ex Excellent
- Gd Good
- TA Typical/Average
- Fa Fair
- Po Poor

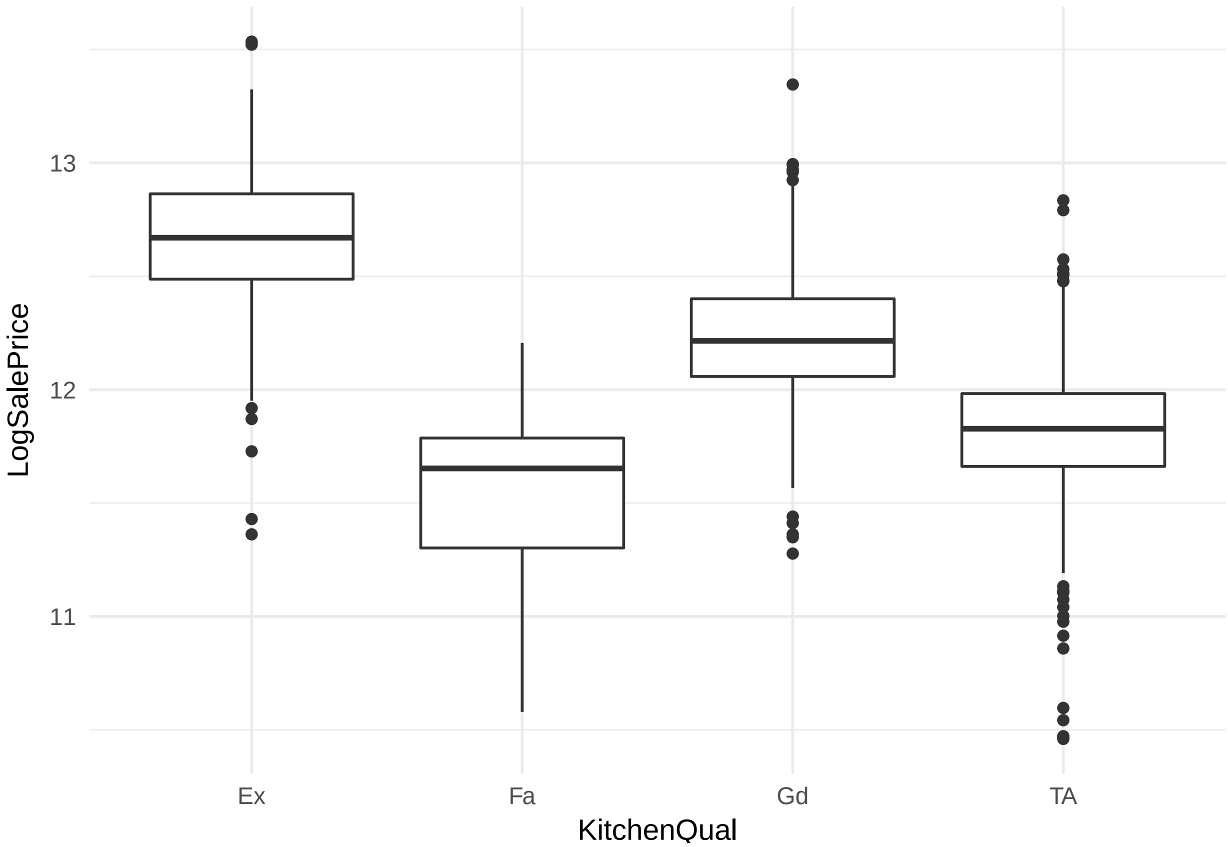
Task 18

Recode this to numeric values using mutate() and recode().

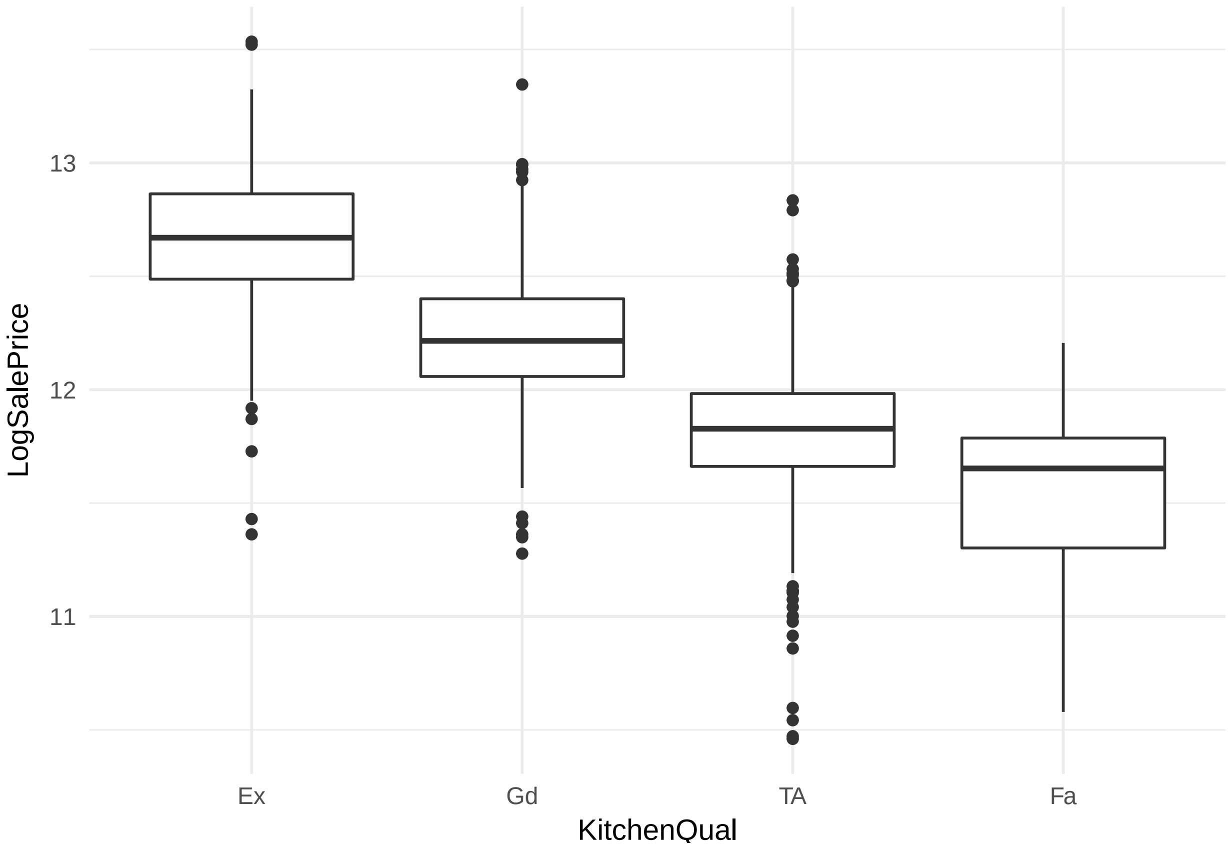
```
class(trainHC$KitchenQual)
```

```
## [1] "factor"
```

```
trainHC %>% ggplot(aes(x = KitchenQual, y = LogSalePrice)) + geom_boxplot() + theme_minimal()
```




```
trainHC %>% mutate( KitchenQual = fct_relevel(KitchenQual, "Ex", "Gd", "TA", "Fa", "Po")) %>% ggplot(aes
```




```
trainHC <- trainHC %>% mutate( KitchenQual = dplyr::recode(KitchenQual, `Ex` = 5L, `Gd` = 4L, `TA` = 3L
testHC <- testHC %>% mutate( KitchenQual = dplyr::recode(KitchenQual, `Ex` = 5L, `Gd` = 4L, `TA` = 3L,

# %>% ggplot(aes(x = as.factor(KitchenQual), y = LogSalePrice)) + geom_boxplot() + theme_minimal()
```

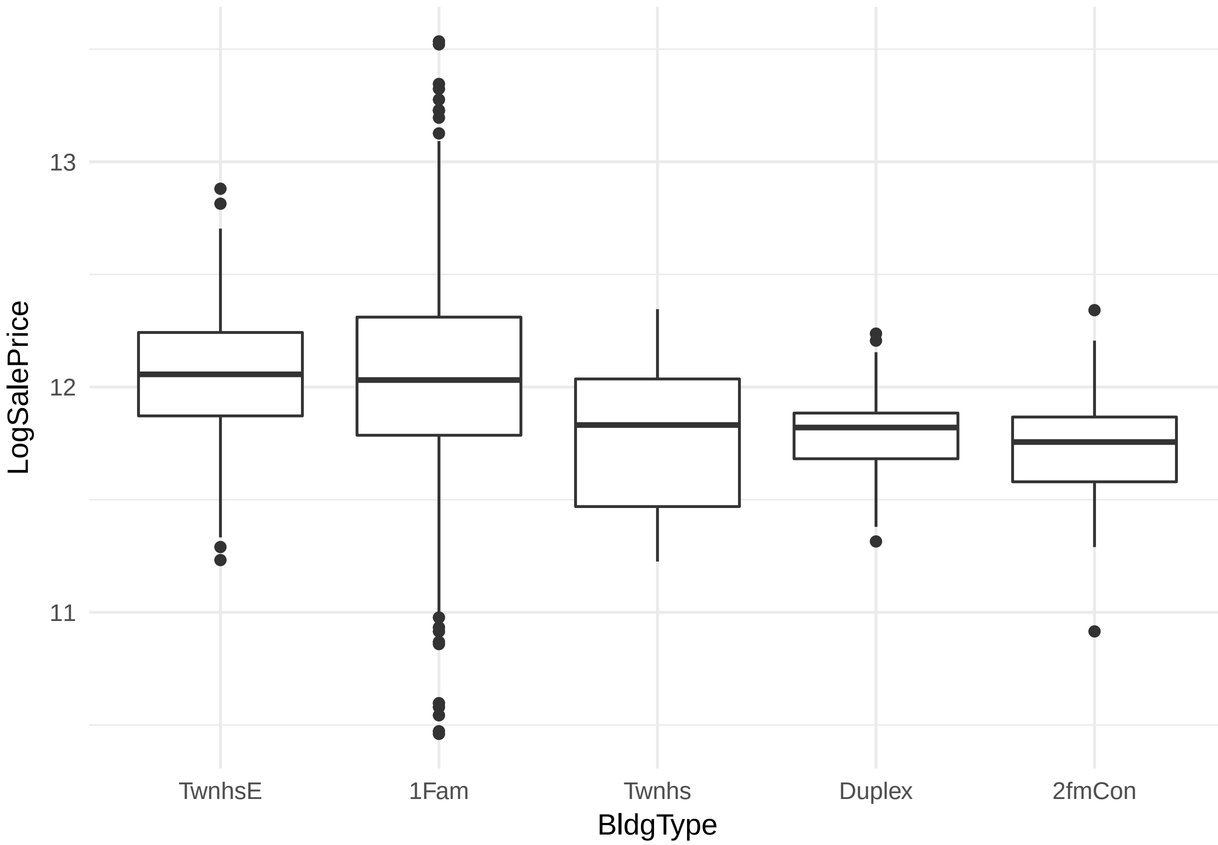
Task 19

Convert Bldgtype to numeric

```
trainHC %>% group_by(BldgType) %>%
  summarise( med = median(LogSalePrice)) %>%
  arrange(desc(med))
```

```
## # A tibble: 5 x 2
##   BldgType   med
##   <fct>    <dbl>
## 1 TwnhsE    12.1
## 2 1Fam      12.0
## 3 Twnhs     11.8
## 4 Duplex    11.8
## 5 2fmCon    11.8
```

```
trainHC %>% mutate( BldgType = fct_relevel(BldgType, "TwnhsE", "1Fam","Twnhs","Duplex", "2fmCon")) %>%
```



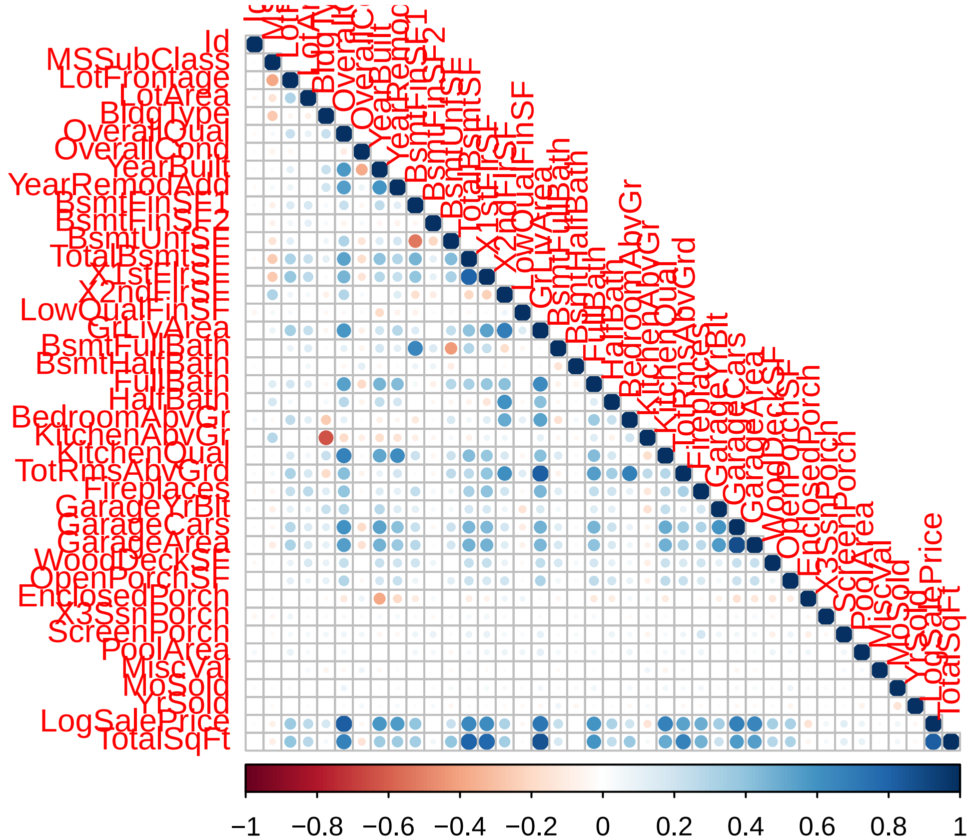

```
trainHC <- trainHC %>% mutate( BldgType = dplyr::recode(BldgType, `TwnhsE` = 5L, `1Fam` = 4L, `Twnhs` =
testHC <- testHC %>% mutate( BldgType = dplyr::recode(BldgType, `TwnhsE` = 5L, `1Fam` = 4L, `Twnhs` = 3L
```

What variables are correlated with each other and with price?

Task 20

1. Plot a correlation plot using corrplot() for all numeric variables and
2. … those that show the top correlation with LogSalePrice.

```
trainHCnumeric <- trainHC[ , sapply(trainHC, is.numeric)]
corrplot(cor(trainHCnumeric, use="everything"), method="circle", type="lower",  sig.level = 0.01, insig
```

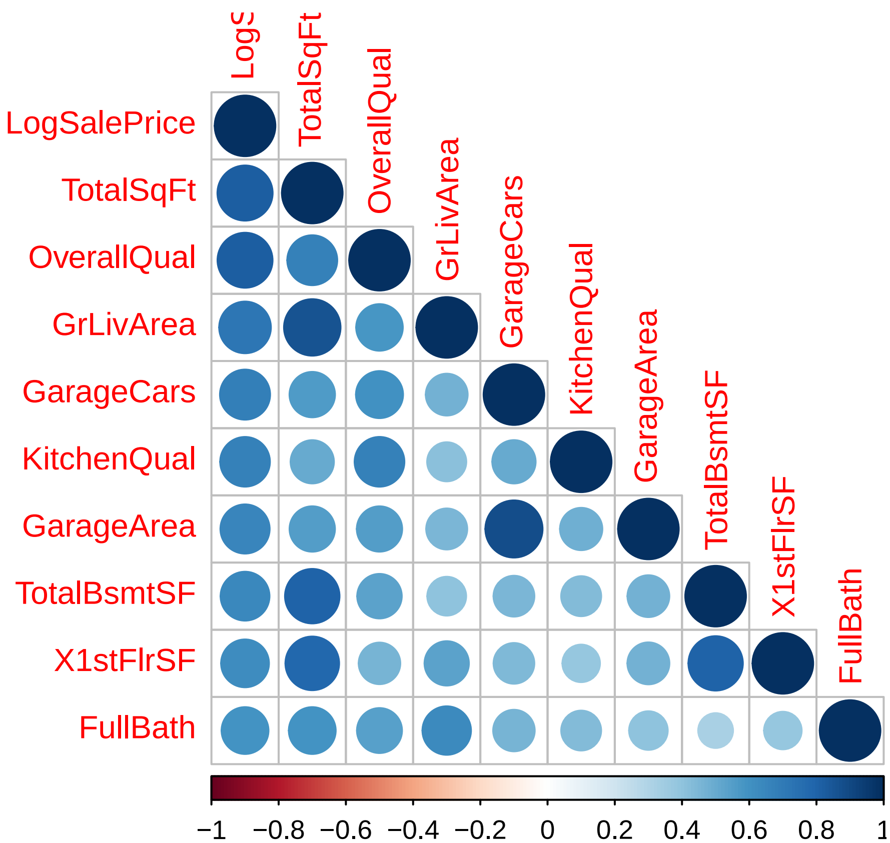



```
correllationmatrix <- as.data.frame(cor(trainHCnumeric, use="everything"))
correllationmatrix$name <- row.names(correllationmatrix)
correllationmatrix %>% select(LogSalePrice, name) %>% arrange(desc(LogSalePrice))
```

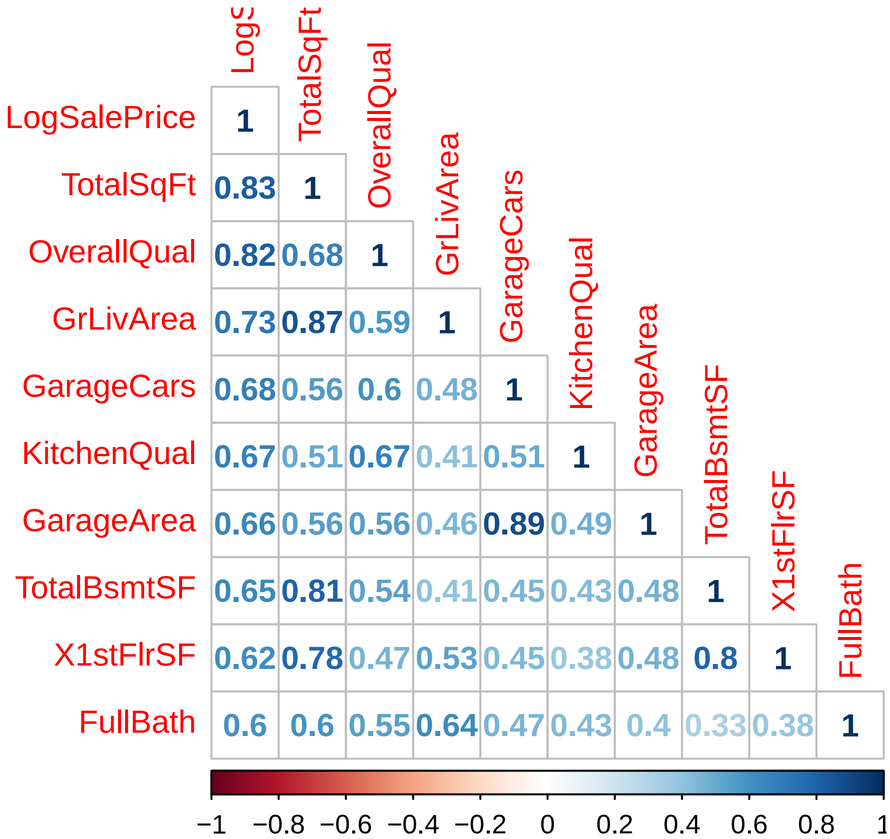
```
##    LogSalePrice          name
## 1   1.000000000  LogSalePrice
## 2   0.825621563     TotalSqFt
## 3   0.821589445   OverallQual
## 4   0.725226325     GrLivArea
## 5   0.681053086    GarageCars
## 6   0.670110020   KitchenQual
## 7   0.656157276    GarageArea
## 8   0.648154025   TotalBsmtSF
## 9   0.620761376     X1stFlrSF
## 10  0.596021367      FullBath
## 11  0.587301350     YearBuilt
## 12  0.566207618  YearRemodAdd
## 13  0.537716260   TotRmsAbvGrd
## 14  0.492158735    Fireplaces
## 15  0.392429541    BsmtFinSF1
## 16  0.367707716   LotFrontage
## 17  0.349021245   GarageYrBlt
## 18  0.334250438    WoodDeckSF
## 19  0.325277237   OpenPorchSF
## 20  0.319997950     X2ndFlrSF
## 21  0.314338716      HalfBath
## 22  0.260545186       LotArea
```

```
## 23  0.237160715  BsmtFullBath
## 24  0.221908923    BsmtUnfSF
## 25  0.209036056  BedroomAbvGr
## 26  0.176740414     BldgType
## 27  0.121250676   ScreenPorch
## 28  0.074338323     PoolArea
## 29  0.057073178       MoSold
## 30  0.054915665    X3SsnPorch
## 31  0.004865712    BsmtFinSF2
## 32 -0.005122225  BsmtHalfBath
## 33 -0.017801106            Id
## 34 -0.020011515      MiscVal
## 35 -0.036820651   OverallCond
## 36 -0.037152238       YrSold
## 37 -0.037950654  LowQualFinSF
## 38 -0.073981156    MSSubClass
## 39 -0.147534749  KitchenAbvGr
## 40 -0.149033033 EnclosedPorch
```

```r
# take out the top 10 names
varscare <- correllationmatrix %>%
  select(LogSalePrice, name) %>%
  arrange(desc(LogSalePrice)) %>%
  head(n = 10L) %>%
  select(name)

corrplot(cor(trainHC[,varscare$name ], use="everything"), method="circle", type="lower",  sig.level = 0
```



```
corrplot(cor(trainHC[,varscare$name ], use="everything"), method="number", type="lower",  sig.level = 0
```



Task 21

Use the createDataPartition() function to separate the training data into a training and testing subset. Allocate 50% of the data to each class. Run set.seed(12) before this.

```
set.seed(12)
partition <- createDataPartition(y = trainHC$LogSalePrice, p = 0.5, list=FALSE)
trainHC$source <- NULL
trainHCtrain <- trainHC[partition,]
trainHCtest <- trainHC[-partition,]
```

Task 22

Fit a linear model considering the “top 10”" correlated (top 9, ignore LogSalePrice for obvious reasons). Code the variables (column names) manually.

```
lm_model_top10 <- lm(LogSalePrice ~  TotalSqFt + OverallQual + GrLivArea + GarageCars + KitchenQual + Ga
summary(lm_model_top10)
```

```
##
## Call:
## lm(formula = LogSalePrice ~ TotalSqFt + OverallQual + GrLivArea +
##     GarageCars + KitchenQual + GarageArea + TotalBsmtSF + X1stFlrSF +
##     FullBath, data = trainHCtrain)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.81658 -0.07012  0.01089  0.09591  0.48633
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.044e+01  3.425e-02 304.673  < 2e-16 ***
## TotalSqFt    2.049e-04  1.265e-04   1.620   0.1056
## OverallQual  1.030e-01  7.003e-03  14.704  < 2e-16 ***
## GrLivArea    2.571e-05  1.243e-04   0.207   0.8362
## GarageCars   4.530e-02  1.765e-02   2.566   0.0105 *
## KitchenQual  7.292e-02  1.214e-02   6.009 2.97e-09 ***
## GarageArea   1.115e-04  5.909e-05   1.887   0.0595 .
## TotalBsmtSF -1.091e-05  1.302e-04  -0.084   0.9333
## X1stFlrSF    1.643e-05  3.096e-05   0.531   0.5958
## FullBath     1.508e-03  1.493e-02   0.101   0.9196
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1557 on 719 degrees of freedom
## Multiple R-squared:  0.8415, Adjusted R-squared:  0.8396
## F-statistic: 424.3 on 9 and 719 DF,  p-value: < 2.2e-16
```

Task 23

1. Use predict() to predict house prices using our top10 model on the "test" portion of the training dataset.
2. Use rmse to assess the root mean square error (our metric of accuracy).

```r
prediction_lm10 <- predict(lm_model_top10, trainHCtest, type="response")
trainHCtest$lm10 <- prediction_lm10
rm(prediction_lm10)
# rmse?
rmse(trainHCtest$LogSalePrice, trainHCtest$lm10)
```

```
## [1] 0.1642187
```

Task 24

1. Use randomForest() to train a random forest model on all of the variables.
2. Use predict() and rmse() to make the prediction and assess the accuracy respectively.
3. Was a linear (on 9 features) or random forest model more accurate?

```r
randFor <- randomForest(LogSalePrice ~ ., data=trainHCtrain)
# Predict using the test set
prediction_rf <- predict(randFor, trainHCtest)
trainHCtest$randFor <- prediction_rf
# rmse?
rmse(trainHCtest$LogSalePrice, trainHCtest$randFor)
```

```
## [1] 0.1426522
```

Task 25

1. Use xgboost to predict house prices from numeric features of training dataset.
2. Use xgb.plot.importance() to assess which variables are most important for predicting house prices.

```r
trainHCtrainNum <- as(as.matrix(trainHCtrain[ , sapply(trainHCtrain, is.numeric)]), "sparseMatrix")
trainHCtestNum <-  as(as.matrix(trainHCtest[ , sapply(trainHCtest, is.numeric)]), "sparseMatrix")

trainD <- xgb.DMatrix(data = trainHCtrainNum, label = trainHCtrainNum[,"LogSalePrice"])

#Cross validate the model
cv.sparse <- xgb.cv(data = trainD,
                    nrounds = 600,
                    min_child_weight = 0,
                    max_depth = 10,
                    eta = 0.02,
                    subsample = .7,
                    colsample_bytree = .7,
                    booster = "gbtree",
                    eval_metric = "rmse",
                    verbose = TRUE,
                    print_every_n = 50,
                    nfold = 4,
                    nthread = 2,
                    objective="reg:linear")
```

```
## [1]  train-rmse:11.298711+0.006494   test-rmse:11.298717+0.020349
## [51] train-rmse:4.141027+0.002037    test-rmse:4.140857+0.020967
## [101]    train-rmse:1.532924+0.000511    test-rmse:1.533403+0.010594
## [151]    train-rmse:0.582279+0.000587    test-rmse:0.590278+0.006681
## [201]    train-rmse:0.236154+0.001185    test-rmse:0.262242+0.001627
## [251]    train-rmse:0.108163+0.001541    test-rmse:0.165055+0.007037
## [301]    train-rmse:0.057875+0.001270    test-rmse:0.141474+0.011346
## [351]    train-rmse:0.035724+0.001017    test-rmse:0.135852+0.013019
## [401]    train-rmse:0.024493+0.000872    test-rmse:0.134516+0.013661
## [451]    train-rmse:0.017517+0.000861    test-rmse:0.134138+0.014040
## [501]    train-rmse:0.012909+0.000822    test-rmse:0.133998+0.014113
## [551]    train-rmse:0.009612+0.000696    test-rmse:0.134057+0.014240
## [600]    train-rmse:0.007242+0.000589    test-rmse:0.134118+0.014283
```

```r
#Train the model
#Choose the parameters for the model
param <- list(colsample_bytree = .7,
             subsample = .7,
             booster = "gbtree",
             max_depth = 10,
             eta = 0.02,
             eval_metric = "rmse",
             objective="reg:linear")


#Train the model using those parameters
bstSparse <-
  xgb.train(params = param,
            data = trainD,
            nrounds = 600,
            watchlist = list(train = trainD),
            verbose = TRUE,
            print_every_n = 50,
```

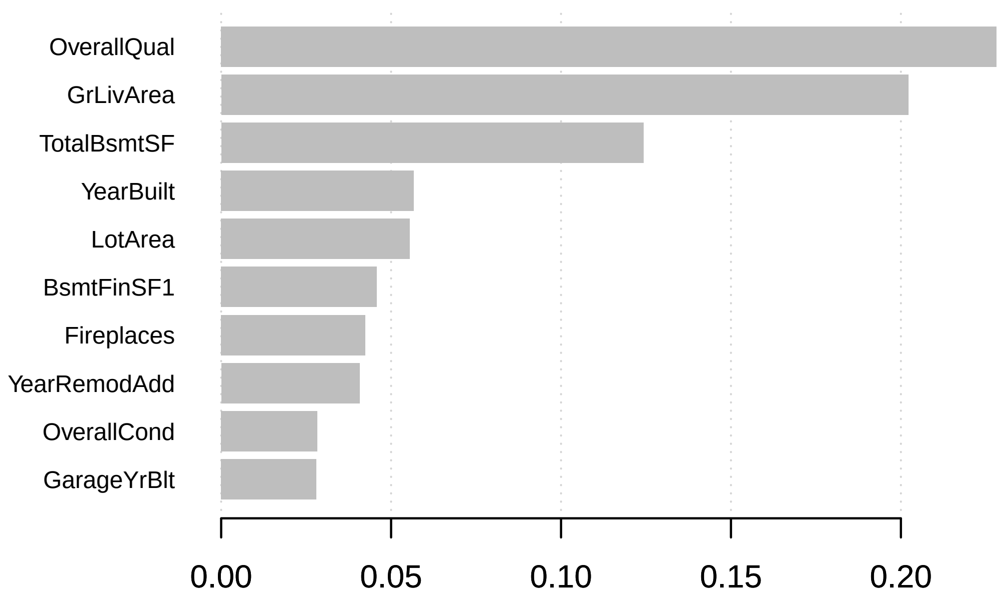
```r
            nthread = 2)
```

```
## [1]  train-rmse:11.298201
## [51] train-rmse:4.136751
## [101]    train-rmse:1.527979
## [151]    train-rmse:0.577598
## [201]    train-rmse:0.233840
## [251]    train-rmse:0.107654
## [301]    train-rmse:0.059118
## [351]    train-rmse:0.038267
## [401]    train-rmse:0.027442
## [451]    train-rmse:0.020410
## [501]    train-rmse:0.015795
## [551]    train-rmse:0.012201
## [600]    train-rmse:0.009644
```

```r
testD <- xgb.DMatrix(data = trainHCtestNum)

prediction <- predict(bstSparse, testD) #Make the prediction based on the half of the training data set

#Put testing prediction and test dataset all together

prediction <- as.data.frame(as.matrix(prediction))
colnames(prediction) <- "xgboost"
trainHCtest$xgboost <- prediction$xgboost


#Test with RMSE
rmse(trainHCtest$LogSalePrice, trainHCtest$xgboost)
```

```
## [1] 0.1382971
```

```r
# Feature importance
importance_matrix <- xgb.importance(dimnames(trainD)[[2]], model = bstSparse)
xgb.plot.importance(importance_matrix[1:10])
```



Task 26

1.Use the glmnet library to train a ridge regression model. 2. Is it more or less accurate than XGBoost?

```
trainHCtrainNumMatrix <- as.matrix(trainHCtrain[ , sapply(trainHCtrain, is.numeric)])
trainHCtestNumMatrix  <-  as.matrix(trainHCtest[ , sapply(trainHCtest, is.numeric)])
# cross validation for glmnet
glm.cv.ridge <- cv.glmnet(trainHCtrainNum[,c(1:38,40)], trainHCtrainNum[,"LogSalePrice"], alpha = 0)
penalty.ridge <- glm.cv.ridge$lambda.min
glm.ridge <- glmnet(x = trainHCtrainNum[,c(1:38,40)], y = trainHCtrainNum[,"LogSalePrice"], alpha = 0, l
y_pred.ridge <- as.numeric(predict(glm.ridge, trainHCtestNum[,c(1:38,40)] ))
rmse(trainHCtest$LogSalePrice, y_pred.ridge)
```

```
## [1] 0.1373092
```