

The Ames Iowa House Price Prediction

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Part I: Exploratory Data Analysis

Part I.A Check data - (1) Basic information about data

```
train <- read.csv("train.csv", header=TRUE)
test  <- read.csv("test_new.csv", header=TRUE)

print("Basic information for training dataset")
```

```
## [1] "Basic information for training dataset"
```

```
print(is.data.frame(train))
```

```
## [1] TRUE
```

```
print(dim(train))
```

```
## [1] 1460    81
```

```
print("Basic information for training dataset")
```

```
## [1] "Basic information for training dataset"
```

```
print(is.data.frame(test))
```

```
## [1] TRUE
```

```
print(dim(test))
```

```
## [1] 1447    81
```

```
str(train)
```

```

## 'data.frame':    1460 obs. of  81 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        : chr  "RL" "RL" "RL" "RL" ...
## $ 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          : chr  "Pave" "Pave" "Pave" "Pave" ...
## $ Alley           : chr  NA NA NA NA ...
## $ LotShape        : chr  "Reg" "Reg" "IR1" "IR1" ...
## $ LandContour     : chr  "Lvl" "Lvl" "Lvl" "Lvl" ...
## $ Utilities       : chr  "AllPub" "AllPub" "AllPub" "AllPub" ...
## $ LotConfig       : chr  "Inside" "FR2" "Inside" "Corner" ...
## $ LandSlope       : chr  "Gtl" "Gtl" "Gtl" "Gtl" ...
## $ Neighborhood    : chr  "CollgCr" "Veenker" "CollgCr" "Crawfor" ...
## $ Condition1      : chr  "Norm" "Feedr" "Norm" "Norm" ...
## $ Condition2      : chr  "Norm" "Norm" "Norm" "Norm" ...
## $ BldgType        : chr  "1Fam" "1Fam" "1Fam" "1Fam" ...
## $ HouseStyle      : chr  "2Story" "1Story" "2Story" "2Story" ...
## $ 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 ...
## $ RoofStyle       : chr  "Gable" "Gable" "Gable" "Gable" ...
## $ RoofMatl        : chr  "CompShg" "CompShg" "CompShg" "CompShg" ...
## $ Exterior1st     : chr  "VinylSd" "MetalSd" "VinylSd" "Wd Sdng" ...
## $ Exterior2nd     : chr  "VinylSd" "MetalSd" "VinylSd" "Wd Shng" ...
## $ MasVnrType      : chr  "BrkFace" "None" "BrkFace" "None" ...
## $ MasVnrArea      : int  196 0 162 0 350 0 186 240 0 0 ...
## $ ExterQual       : chr  "Gd" "TA" "Gd" "TA" ...
## $ ExterCond       : chr  "TA" "TA" "TA" "TA" ...
## $ Foundation      : chr  "PConc" "CBlock" "PConc" "BrkTil" ...
## $ BsmtQual        : chr  "Gd" "Gd" "Gd" "TA" ...
## $ BsmtCond        : chr  "TA" "TA" "TA" "Gd" ...
## $ BsmtExposure    : chr  "No" "Gd" "Mn" "No" ...
## $ BsmtFinType1    : chr  "GLQ" "ALQ" "GLQ" "ALQ" ...
## $ BsmtFinSF1      : int  706 978 486 216 655 732 1369 859 0 851 ...
## $ BsmtFinType2    : chr  "Unf" "Unf" "Unf" "Unf" ...
## $ 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         : chr  "GasA" "GasA" "GasA" "GasA" ...
## $ HeatingQC       : chr  "Ex" "Ex" "Ex" "Gd" ...
## $ CentralAir      : chr  "Y" "Y" "Y" "Y" ...
## $ Electrical      : chr  "SBrkr" "SBrkr" "SBrkr" "SBrkr" ...
## $ 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 : chr "Gd" "TA" "Gd" "Gd" ...
## $ TotRmsAbvGrd : int 8 6 6 7 9 5 7 7 8 5 ...
## $ Functional : chr "Typ" "Typ" "Typ" "Typ" ...
## $ Fireplaces : int 0 1 1 1 1 0 1 2 2 2 ...
## $ FireplaceQu : chr NA "TA" "TA" "Gd" ...
## $ GarageType : chr "Attchd" "Attchd" "Attchd" "Detchd" ...
## $ GarageYrBlt : int 2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
## $ GarageFinish : chr "RFn" "RFn" "RFn" "Unf" ...
## $ 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 : chr "TA" "TA" "TA" "TA" ...
## $ GarageCond : chr "TA" "TA" "TA" "TA" ...
## $ PavedDrive : chr "Y" "Y" "Y" "Y" ...
## $ 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 : chr NA NA NA NA ...
## $ Fence : chr NA NA NA NA ...
## $ MiscFeature : chr NA NA 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 : chr "WD" "WD" "WD" "WD" ...
## $ SaleCondition : chr "Normal" "Normal" "Normal" "Abnorml" ...
## $ SalePrice : int 208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...

```

Part I.A Check data - (2) Data type

After checking the data, we found that the data type in the dataset is not very accurate. Some categorical data is stored as numeric type. Thus, we manually listed out the categorical and numerical variables and correct the data type accordingly.

We have two types of variables: 52 Categorical variables, and 28 Numeric variables.

Categorical variables (52)

– Nominal (27)

– Ordinal (25)

Nominal (27): MSSubClass, MSZoning, Street, Alley, LotShape, LandContour, Utilities, LotConfig, Neighborhood, Condition1, Condition2, BldgType, HouseStyle, RoofStyle, CentralAir, RoofMatl, Exterior1st, Exterior2nd, MasVnrType, Foundation, Heating, Functional, GarageType, Fence, MiscFeature, SaleType, SaleCondition.

Ordinal (25): id, LandSlope, OverallQual, OverallCond, YearBuilt, YearRemodAdd, ExterQual, ExterCond, BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2, HeatingQC, Electrical, KitchenQual, FireplaceQu, GarageYrBlt, GarageFinish, GarageQual, GarageCond, PoolQC, MoSold, YrSold, PavedDrive.

Numeric variables (28): LotFrontage, LotArea, MasVnrArea, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath, BsmtHalfBath, FullBath, HalfBath, Bedroom, Kitchen, TotRmsAbvGrd, Fireplaces, GarageCars, GarageArea, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch, PoolArea, MiscVal.

```

# check data type
# find categorical and numerical variables
category_col = c("Id", "LandSlope", "OverallQual", "OverallCond", "YearBuilt",
                 "YearRemodAdd", "ExterQual", "ExterCond", "BsmtQual", "BsmtCond",
                 "BsmtExposure", "BsmtFinType1", "BsmtFinType2", "HeatingQC",
                 "Electrical", "KitchenQual", "FireplaceQu", "GarageFinish",
                 "GarageQual", "GarageCond", "PoolQC", "MoSold", "YrSold", "PavedDrive",
                 "MSSubClass", "MSZoning", "Street", "Alley", "LotShape", "LandContour",
                 "Utilities", "LotConfig", "Neighborhood", "Condition1", "Condition2",
                 "BldgType", "HouseStyle", "RoofStyle", "CentralAir", "RoofMatl",
                 "Exterior1st", "Exterior2nd", "MasVnrType", "Foundation", "Heating",
                 "Functional", "GarageType", "Fence", "MiscFeature", "SaleType",
                 "SaleCondition")

numeric_col = c("LotFrontage", "LotArea", "MasVnrArea", "BsmtFinSF1", "BsmtFinSF2",
               "BsmtUnfSF", "TotalBsmtSF", "X1stFlrSF", "X2ndFlrSF", "LowQualFinSF",
               "GrLivArea", "BsmtFullBath", "BsmtHalfBath", "FullBath", "HalfBath",
               "BedroomAbvGr", "KitchenAbvGr", "TotRmsAbvGrd", "Fireplaces",
               "GarageCars", "GarageArea", "WoodDeckSF", "OpenPorchSF", "EnclosedPorch",
               "X3SsnPorch", "ScreenPorch", "PoolArea", "MiscVal", "GarageYrBlt")

# change the type of variable
train = train %>% mutate_at(category_col, as.character)
train = train %>% mutate_at(numeric_col, as.integer)

# check whether the type is changed successfully
str(train)

```

```

## 'data.frame':   1460 obs. of  81 variables:
## $ Id           : chr  "1" "2" "3" "4" ...
## $ MSSubClass    : chr  "60" "20" "60" "70" ...
## $ MSZoning      : chr  "RL" "RL" "RL" "RL" ...
## $ 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        : chr   "Pave" "Pave" "Pave" "Pave" ...
## $ Alley         : chr    NA  NA  NA  NA ...
## $ LotShape      : chr   "Reg" "Reg" "IR1" "IR1" ...
## $ LandContour   : chr   "Lvl" "Lvl" "Lvl" "Lvl" ...
## $ Utilities     : chr  "AllPub" "AllPub" "AllPub" "AllPub" ...
## $ LotConfig     : chr   "Inside" "FR2" "Inside" "Corner" ...
## $ LandSlope     : chr   "Gtl" "Gtl" "Gtl" "Gtl" ...
## $ Neighborhood  : chr  "CollgCr" "Veenker" "CollgCr" "Crawfor" ...
## $ Condition1    : chr   "Norm" "Feedr" "Norm" "Norm" ...
## $ Condition2    : chr   "Norm" "Norm" "Norm" "Norm" ...
## $ BldgType      : chr   "1Fam" "1Fam" "1Fam" "1Fam" ...
## $ HouseStyle    : chr   "2Story" "1Story" "2Story" "2Story" ...
## $ OverallQual   : chr   "7" "6" "7" "7" ...
## $ OverallCond   : chr   "5" "8" "5" "5" ...
## $ YearBuilt     : chr  "2003" "1976" "2001" "1915" ...
## $ YearRemodAdd   : chr  "2003" "1976" "2002" "1970" ...
## $ RoofStyle     : chr   "Gable" "Gable" "Gable" "Gable" ...
## $ RoofMatl      : chr   "CompShg" "CompShg" "CompShg" "CompShg" ...
## $ Exterior1st   : chr   "VinylSd" "MetalSd" "VinylSd" "Wd Sdng" ...
## $ Exterior2nd   : chr   "VinylSd" "MetalSd" "VinylSd" "Wd Shng" ...
## $ MasVnrType    : chr   "BrkFace" "None" "BrkFace" "None" ...

```

```

## $ MasVnrArea : int 196 0 162 0 350 0 186 240 0 0 ...
## $ ExterQual : chr "Gd" "TA" "Gd" "TA" ...
## $ ExterCond : chr "TA" "TA" "TA" "TA" ...
## $ Foundation : chr "PConc" "CBlock" "PConc" "BrkTil" ...
## $ BsmtQual : chr "Gd" "Gd" "Gd" "TA" ...
## $ BsmtCond : chr "TA" "TA" "TA" "Gd" ...
## $ BsmtExposure : chr "No" "Gd" "Mn" "No" ...
## $ BsmtFinType1 : chr "GLQ" "ALQ" "GLQ" "ALQ" ...
## $ BsmtFinSF1 : int 706 978 486 216 655 732 1369 859 0 851 ...
## $ BsmtFinType2 : chr "Unf" "Unf" "Unf" "Unf" ...
## $ BsmtFinSF2 : int 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 : chr "GasA" "GasA" "GasA" "GasA" ...
## $ HeatingQC : chr "Ex" "Ex" "Ex" "Gd" ...
## $ CentralAir : chr "Y" "Y" "Y" "Y" ...
## $ Electrical : chr "SBrkr" "SBrkr" "SBrkr" "SBrkr" ...
## $ 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 ...
## $ GrLivArea : int 1710 1262 1786 1717 2198 1362 1694 2090 1774 1077 ...
## $ BsmtFullBath : int 1 0 1 1 1 1 1 0 1 ...
## $ BsmtHalfBath : int 0 1 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 : chr "Gd" "TA" "Gd" "Gd" ...
## $ TotRmsAbvGrd : int 8 6 6 7 9 5 7 7 8 5 ...
## $ Functional : chr "Typ" "Typ" "Typ" "Typ" ...
## $ Fireplaces : int 0 1 1 1 1 0 1 2 2 2 ...
## $ FireplaceQu : chr NA "TA" "TA" "Gd" ...
## $ GarageType : chr "Attchd" "Attchd" "Attchd" "Detchd" ...
## $ GarageYrBlt : int 2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
## $ GarageFinish : chr "RFn" "RFn" "RFn" "Unf" ...
## $ 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 : chr "TA" "TA" "TA" "TA" ...
## $ GarageCond : chr "TA" "TA" "TA" "TA" ...
## $ PavedDrive : chr "Y" "Y" "Y" "Y" ...
## $ 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 : chr NA NA NA NA ...
## $ Fence : chr NA NA NA NA ...
## $ MiscFeature : chr NA NA NA NA ...
## $ MiscVal : int 0 0 0 0 0 700 0 350 0 0 ...
## $ MoSold : chr "2" "5" "9" "2" ...
## $ YrSold : chr "2008" "2007" "2008" "2006" ...
## $ SaleType : chr "WD" "WD" "WD" "WD" ...
## $ SaleCondition : chr "Normal" "Normal" "Normal" "Abnorml" ...

```

```
## $ SalePrice      : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

Here, we can see the data type are correct.

Part I.A Check data - (3) duplicate / null value

```
# check number of duplicated records
sum(duplicated(train))
```

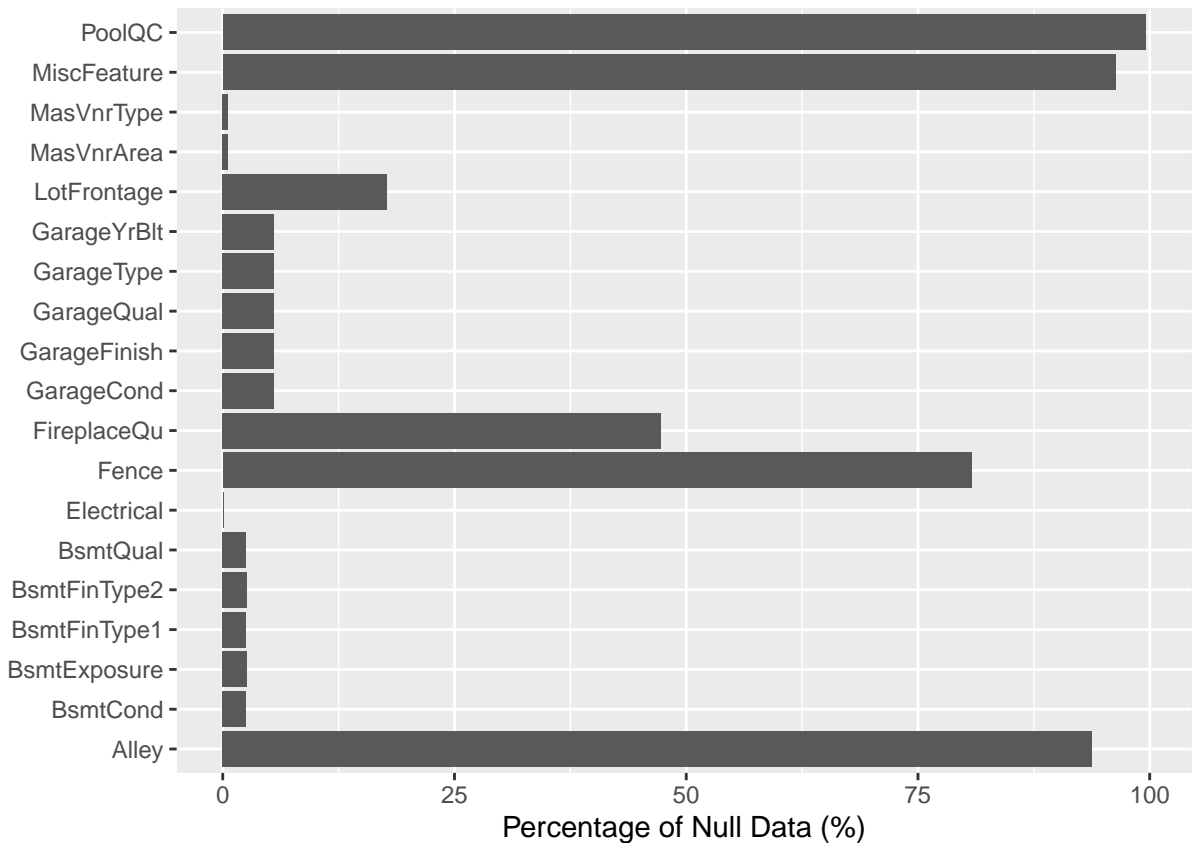
```
## [1] 0
```

```
# check number/percentage of NA data
na_per = c()
col_names = c()
for (i in 2: 80) {
  if (sum(is.na(train[,i]))/dim(train)[1]*100 > 0) {
    na_per = append(na_per, sum(is.na(train[,i]))/dim(train)[1]*100)
    col_names = append(col_names, colnames(train)[i])
  }
}
```

```
# draw the visualization to see percentage of NA
df = as.data.frame(col_names, na_per)
```

```
## Warning in as.data.frame.vector(x, ..., nm = nm): 'row.names' is not a character
## vector of length 19 -- omitting it. Will be an error!
```

```
pt = ggplot(data = df, aes(x = na_per, y = col_names)) +
  geom_bar(stat="identity") +
  labs(x = "Percentage of Null Data (%)", y = "")
pt
```



In the Data Processing section, we first checked the duplicated records and found there is no duplicated records. Then, we checked the number and percentage of null values for each variable. We built a visualization for the variables with null values. After checking the data, we found that NA does not only stands for the missing data. For the categorical data, we found that NA means “Not Accessible”. Thus, we replaced the “NA” in the categorical variables with “No”. For the numeric variables, NA can mean 0 or missing. Thus, we decide to use the medium value to replace “NA”.

```
# replace the null value
train <- train %>% mutate_if(is.numeric, function(x) ifelse(is.na(x), median(x, na.rm=T), x))
train <- train %>% mutate_if(is.character, ~replace_na(., "No"))
test <- test %>% mutate_if(is.numeric, function(x) ifelse(is.na(x), median(x, na.rm=T), x))
test <- test %>% mutate_if(is.character, ~replace_na(., "No"))
print(dim(train))
```

```
## [1] 1460 81
```

```
print(dim(test))
```

```
## [1] 1447 81
```

```
head(train)
```

```
##   Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape LandContour
## 1 1          60      RL          65    8450   Pave    No      Reg          Lvl
```

##	2	2	20	RL	80	9600	Pave	No	Reg	Lvl
##	3	3	60	RL	68	11250	Pave	No	IR1	Lvl
##	4	4	70	RL	60	9550	Pave	No	IR1	Lvl
##	5	5	60	RL	84	14260	Pave	No	IR1	Lvl
##	6	6	50	RL	85	14115	Pave	No	IR1	Lvl
##	Utilities LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType									
##	1	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam		
##	2	AllPub	FR2	Gtl	Veenker	Feedr	Norm	1Fam		
##	3	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam		
##	4	AllPub	Corner	Gtl	Crawfor	Norm	Norm	1Fam		
##	5	AllPub	FR2	Gtl	NoRidge	Norm	Norm	1Fam		
##	6	AllPub	Inside	Gtl	Mitchel	Norm	Norm	1Fam		
##	HouseStyle OverallQual OverallCond YearBuilt YearRemodAdd RoofStyle RoofMatl									
##	1	2Story		7	5	2003	2003	Gable	CompShg	
##	2	1Story		6	8	1976	1976	Gable	CompShg	
##	3	2Story		7	5	2001	2002	Gable	CompShg	
##	4	2Story		7	5	1915	1970	Gable	CompShg	
##	5	2Story		8	5	2000	2000	Gable	CompShg	
##	6	1.5Fin		5	5	1993	1995	Gable	CompShg	
##	Exterior1st Exterior2nd MasVnrType MasVnrArea ExterQual ExterCond Foundation									
##	1	VinylSd	VinylSd	BrkFace	196	Gd	TA	PConc		
##	2	MetalSd	MetalSd	None	0	TA	TA	CBlock		
##	3	VinylSd	VinylSd	BrkFace	162	Gd	TA	PConc		
##	4	Wd Sdng	Wd Shng	None	0	TA	TA	BrkTil		
##	5	VinylSd	VinylSd	BrkFace	350	Gd	TA	PConc		
##	6	VinylSd	VinylSd	None	0	TA	TA	Wood		
##	BsmtQual BsmtCond BsmtExposure BsmtFinType1 BsmtFinSF1 BsmtFinType2									
##	1	Gd	TA	No	GLQ	706	Unf			
##	2	Gd	TA	Gd	ALQ	978	Unf			
##	3	Gd	TA	Mn	GLQ	486	Unf			
##	4	TA	Gd	No	ALQ	216	Unf			
##	5	Gd	TA	Av	GLQ	655	Unf			
##	6	Gd	TA	No	GLQ	732	Unf			
##	BsmtFinSF2 BsmtUnfSF TotalBsmtSF Heating HeatingQC CentralAir Electrical									
##	1	0	150	856	GasA	Ex	Y	SBrkr		
##	2	0	284	1262	GasA	Ex	Y	SBrkr		
##	3	0	434	920	GasA	Ex	Y	SBrkr		
##	4	0	540	756	GasA	Gd	Y	SBrkr		
##	5	0	490	1145	GasA	Ex	Y	SBrkr		
##	6	0	64	796	GasA	Ex	Y	SBrkr		
##	X1stFlrSF X2ndFlrSF LowQualFinSF GrLivArea BsmtFullBath BsmtHalfBath FullBath									
##	1	856	854	0	1710	1	0	2		
##	2	1262	0	0	1262	0	1	2		
##	3	920	866	0	1786	1	0	2		
##	4	961	756	0	1717	1	0	1		
##	5	1145	1053	0	2198	1	0	2		
##	6	796	566	0	1362	1	0	1		
##	HalfBath BedroomAbvGr KitchenAbvGr KitchenQual TotRmsAbvGrd Functional									
##	1	1	3	1	Gd	8	Typ			
##	2	0	3	1	TA	6	Typ			
##	3	1	3	1	Gd	6	Typ			
##	4	0	3	1	Gd	7	Typ			
##	5	1	4	1	Gd	9	Typ			
##	6	1	1	1	TA	5	Typ			


```
##      Fireplaces FireplaceQu GarageType GarageYrBlt GarageFinish GarageCars
## 1           0           No    Attchd      2003         RFn          2
## 2           1           TA    Attchd      1976         RFn          2
## 3           1           TA    Attchd      2001         RFn          2
## 4           1           Gd    Detchd      1998         Unf          3
## 5           1           TA    Attchd      2000         RFn          3
## 6           0           No    Attchd      1993         Unf          2
##      GarageArea GarageQual GarageCond PavedDrive WoodDeckSF OpenPorchSF
## 1          548          TA          TA          Y          0          61
## 2          460          TA          TA          Y         298          0
## 3          608          TA          TA          Y          0          42
## 4          642          TA          TA          Y          0          35
## 5          836          TA          TA          Y         192          84
## 6          480          TA          TA          Y          40          30
##      EnclosedPorch X3SsnPorch ScreenPorch PoolArea PoolQC Fence MiscFeature
## 1              0              0              0          0      No      No      No
## 2              0              0              0          0      No      No      No
## 3              0              0              0          0      No      No      No
## 4             272              0              0          0      No      No      No
## 5              0              0              0          0      No      No      No
## 6              0             320              0          0      No MnPrv      Shed
##      MiscVal MoSold YrSold SaleType SaleCondition SalePrice
## 1          0         2   2008         WD         Normal   208500
## 2          0         5   2007         WD         Normal   181500
## 3          0         9   2008         WD         Normal   223500
## 4          0         2   2006         WD        Abnorml   140000
## 5          0        12   2008         WD         Normal   250000
## 6         700        10   2009         WD         Normal   143000
```

```
# check whether all the null values are solved
```

```
sum(is.na(train))
```

```
## [1] 0
```

```
sum(is.na(test))
```

```
## [1] 0
```

```
# We treated all the year as categorical value.
```

```
# Thus, here we change year back to categorical value after filling the null data
```

```
train$GarageYrBlt = as.character(train$GarageYrBlt)
```

```
test$GarageYrBlt = as.character(test$GarageYrBlt)
```

```
str(train)
```

```
## 'data.frame':   1460 obs. of  81 variables:
## $ Id          : chr  "1" "2" "3" "4" ...
## $ MSSubClass   : chr  "60" "20" "60" "70" ...
## $ MSZoning     : chr  "RL" "RL" "RL" "RL" ...
## $ LotFrontage  : int   65 80 68 60 84 85 75 69 51 50 ...
## $ LotArea      : int  8450 9600 11250 9550 14260 14115 10084 10382 6120 7420 ...
## $ Street       : chr  "Pave" "Pave" "Pave" "Pave" ...
## $ Alley        : chr  "No" "No" "No" "No" ...
```

```

## $ LotShape      : chr "Reg" "Reg" "IR1" "IR1" ...
## $ LandContour   : chr "Lvl" "Lvl" "Lvl" "Lvl" ...
## $ Utilities     : chr "AllPub" "AllPub" "AllPub" "AllPub" ...
## $ LotConfig     : chr "Inside" "FR2" "Inside" "Corner" ...
## $ LandSlope     : chr "Gtl" "Gtl" "Gtl" "Gtl" ...
## $ Neighborhood  : chr "CollgCr" "Veenker" "CollgCr" "Crawfor" ...
## $ Condition1    : chr "Norm" "Feedr" "Norm" "Norm" ...
## $ Condition2    : chr "Norm" "Norm" "Norm" "Norm" ...
## $ BldgType       : chr "1Fam" "1Fam" "1Fam" "1Fam" ...
## $ HouseStyle     : chr "2Story" "1Story" "2Story" "2Story" ...
## $ OverallQual    : chr "7" "6" "7" "7" ...
## $ OverallCond    : chr "5" "8" "5" "5" ...
## $ YearBuilt      : chr "2003" "1976" "2001" "1915" ...
## $ YearRemodAdd   : chr "2003" "1976" "2002" "1970" ...
## $ RoofStyle      : chr "Gable" "Gable" "Gable" "Gable" ...
## $ RoofMatl       : chr "CompShg" "CompShg" "CompShg" "CompShg" ...
## $ Exterior1st    : chr "VinylSd" "MetalSd" "VinylSd" "Wd Sdng" ...
## $ Exterior2nd    : chr "VinylSd" "MetalSd" "VinylSd" "Wd Shng" ...
## $ MasVnrType     : chr "BrkFace" "None" "BrkFace" "None" ...
## $ MasVnrArea     : num 196 0 162 0 350 0 186 240 0 0 ...
## $ ExterQual       : chr "Gd" "TA" "Gd" "TA" ...
## $ ExterCond       : chr "TA" "TA" "TA" "TA" ...
## $ Foundation     : chr "PConc" "CBlock" "PConc" "BrkTil" ...
## $ BsmtQual        : chr "Gd" "Gd" "Gd" "TA" ...
## $ BsmtCond        : chr "TA" "TA" "TA" "Gd" ...
## $ BsmtExposure    : chr "No" "Gd" "Mn" "No" ...
## $ BsmtFinType1    : chr "GLQ" "ALQ" "GLQ" "ALQ" ...
## $ BsmtFinSF1      : int 706 978 486 216 655 732 1369 859 0 851 ...
## $ BsmtFinType2    : chr "Unf" "Unf" "Unf" "Unf" ...
## $ BsmtFinSF2      : int 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         : chr "GasA" "GasA" "GasA" "GasA" ...
## $ HeatingQC       : chr "Ex" "Ex" "Ex" "Gd" ...
## $ CentralAir      : chr "Y" "Y" "Y" "Y" ...
## $ Electrical      : chr "SBrkr" "SBrkr" "SBrkr" "SBrkr" ...
## $ 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 ...
## $ 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 ...
## $ 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      : chr "Gd" "TA" "Gd" "Gd" ...
## $ TotRmsAbvGrd    : int 8 6 6 7 9 5 7 7 8 5 ...
## $ Functional       : chr "Typ" "Typ" "Typ" "Typ" ...
## $ Fireplaces       : int 0 1 1 1 1 0 1 2 2 2 ...
## $ FireplaceQu      : chr "No" "TA" "TA" "Gd" ...
## $ GarageType       : chr "Attchd" "Attchd" "Attchd" "Detchd" ...
## $ GarageYrBlt      : chr "2003" "1976" "2001" "1998" ...
## $ GarageFinish     : chr "RFn" "RFn" "RFn" "Unf" ...

```

```
## $ 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 : chr "TA" "TA" "TA" "TA" ...
## $ GarageCond : chr "TA" "TA" "TA" "TA" ...
## $ PavedDrive : chr "Y" "Y" "Y" "Y" ...
## $ 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 : chr "No" "No" "No" "No" ...
## $ Fence : chr "No" "No" "No" "No" ...
## $ MiscFeature : chr "No" "No" "No" "No" ...
## $ MiscVal : int 0 0 0 0 0 700 0 350 0 0 ...
## $ MoSold : chr "2" "5" "9" "2" ...
## $ YrSold : chr "2008" "2007" "2008" "2006" ...
## $ SaleType : chr "WD" "WD" "WD" "WD" ...
## $ SaleCondition: chr "Normal" "Normal" "Normal" "Abnorml" ...
## $ SalePrice : int 208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

Part I.B EDA

```
dim(train)
```

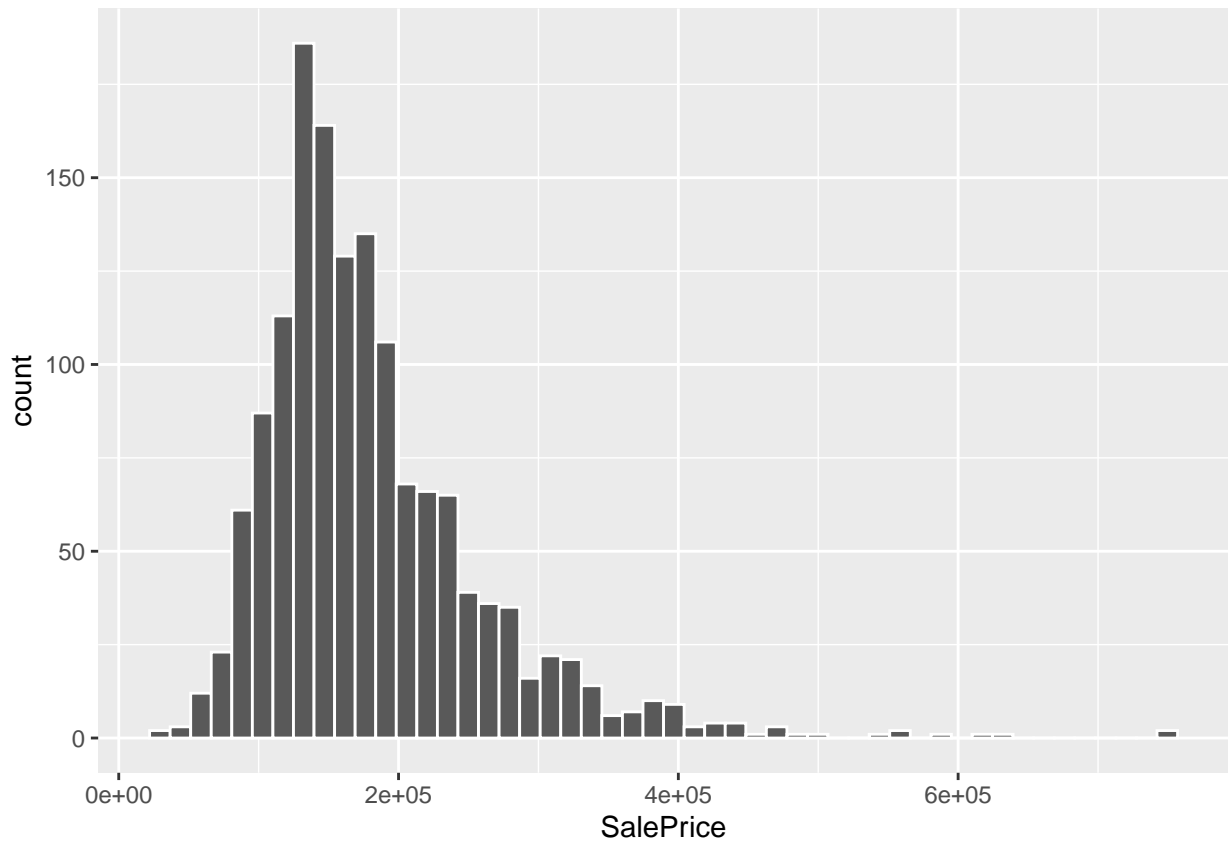
```
## [1] 1460 81
```

There are 1460 observations and 81 variables in the training data set. First, let's start to explore the response - Sale Price (in dollars).

Part I.B EDA - (1) Response: SalePrice

```
ggplot(train, aes(x = SalePrice)) +
  geom_histogram(bins = 50, col= "white")
```

Part I.B EDA - (1.1) Histogram of SalePrice



The plot is right-skewed, which means that there is less expensive house than inexpensive ones.

```
summary(train$SalePrice)
```

Part I.B EDA - (1.2) Histogram of SalePrice

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	34900	129975	163000	180921	214000	755000

The median of Sale Price of the houses is \$163000.

The mean of Sale Price of the houses is \$180921.

The least expensive house is \$34900.

The most expensive house is \$755000.

Part I.B EDA - (2) Correlation

Part I.B EDA - (2.1) Correlation between numeric predictor variables Next, to investigate if there are early signs of variables are likely to be significant in predicting response. First, let's look at those numeric variables.

```

num_data <- subset(train, select = c(LotFrontage, LotArea, MasVnrArea, BsmtFinSF1,
                                     BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, X1stFlrSF,
                                     X2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath,
                                     BsmtHalfBath, FullBath, HalfBath, BedroomAbvGr,
                                     KitchenAbvGr, TotRmsAbvGrd, Fireplaces, GarageCars,
                                     GarageArea, WoodDeckSF, OpenPorchSF, EnclosedPorch,
                                     X3SsnPorch, ScreenPorch, PoolArea, MiscVal))

# Correlation between numerical data
cor_matrix = cor(num_data)

# We set 0.6 as the threshold for strong correlation
strong_cor = cor_matrix

# we fill all the absolute correlation value less than 0.6 as NA and the value on the diagonal as NA
strong_cor[abs(strong_cor) < 0.6] = NA
strong_cor[upper.tri(strong_cor, diag = TRUE)] = NA

# Then we find the variables with high correlation (>=0.6)
index <- which(strong_cor >= 0.6 | strong_cor <= -0.6, arr.ind = T)
strong_cor_var = cbind.data.frame(var1 = rownames(strong_cor)[index[,1]], # get the row name
                                  var2 = colnames(strong_cor)[index[,2]]) # get the column name
strong_cor_var

```

```

##           var1           var2
## 1 BsmtFullBath BsmtFinSF1
## 2   X1stFlrSF TotalBsmtSF
## 3   GrLivArea  X2ndFlrSF
## 4     HalfBath  X2ndFlrSF
## 5 TotRmsAbvGrd  X2ndFlrSF
## 6     FullBath  GrLivArea
## 7 TotRmsAbvGrd  GrLivArea
## 8 TotRmsAbvGrd BedroomAbvGr
## 9   GarageArea  GarageCars

```

From the correlation table above, we can clearly find that [BsmtFinSF1, BsmtFullBath], [TotalBsmtSF, X1stFlrSF], [GrLivArea, X2ndFlrSF], [HalfBath, X2ndFlrSF], [TotRmsAbvGrd, X2ndFlrSF], [GrLivArea, TotRmsAbvGrd], [GrLivArea, FullBath], [BedroomAbvGr, TotRmsAbvGrd], [GarageArea, GarageCars] have appear to be potentially problematic collinearity amongst the predictor variables.

```

corr_xy = cor(train[,unlist(lapply(train, is.numeric))])
y_col = ncol(cor(train[,unlist(lapply(train, is.numeric))]))
corr_xy_df = cbind.data.frame(SalePrice=cor(train[,unlist(lapply(train, is.numeric))])[y_col])
strong_corr_xy = filter(corr_xy_df, corr_xy_df > 0.6)
strong_corr_xy

```

Part I.B EDA - (2.2) Correlation between numeric predictor variables and response variable

```

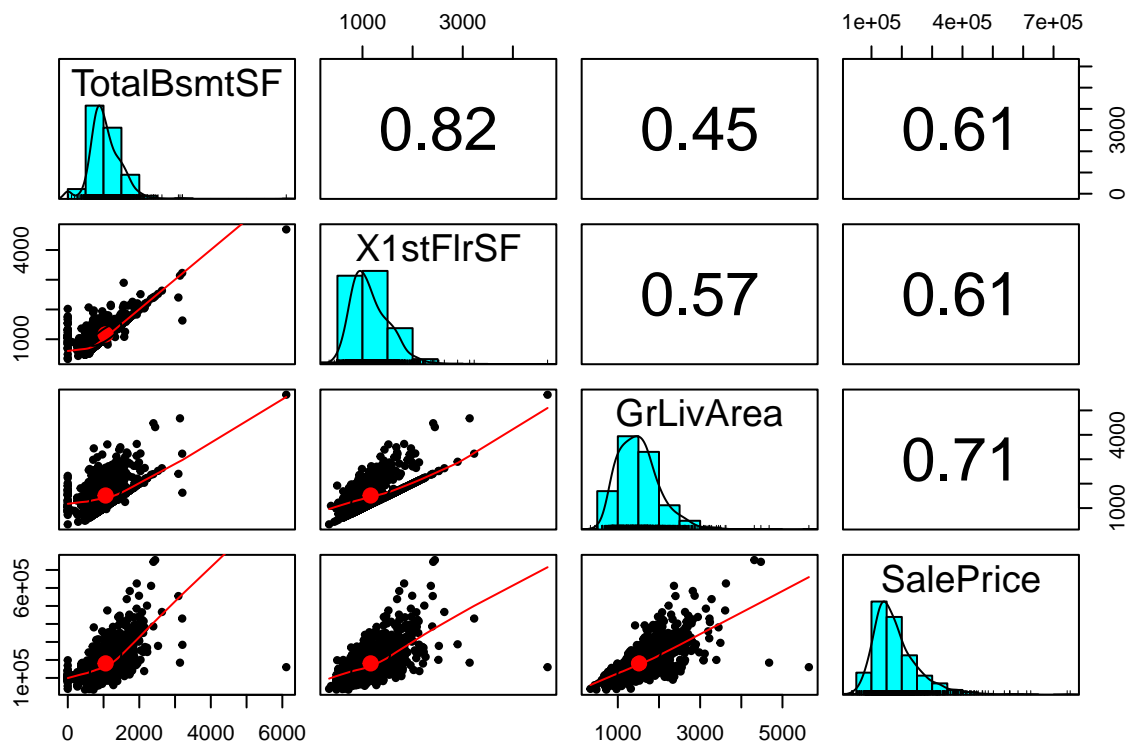
##           SalePrice

```

```
## TotalBsmntSF 0.6135806
## X1stFlrSF    0.6058522
## GrLivArea    0.7086245
## GarageCars   0.6404092
## GarageArea   0.6234314
## SalePrice    1.0000000
```

From the last part, we find that the variables *TotalBsmntSF*, *X1stFlrSF*, *GrLivArea*, *GarageCars*, *GarageArea* have strong correlation with the response *SalePrice*.

```
strong_collearity <- subset(train,
                             select = c(TotalBsmntSF, X1stFlrSF, GrLivArea, SalePrice))
pairs.panels(strong_collearity)
```



From the plot, we can verify that all of these three variables

- (1) *TotalBsmntSF* (Total square feet of basement area)
- (2) *X1stFlrSF* (First Floor square feet)
- (3) *GrLivArea* (Above grade (ground) living area square feet)

have strong positive correlation with the response *SalePrice*.

In other words, as each of these three factors increases, *SalePrice* will get increase.

In addition, we would also explore those categorical variables that might be useful for predicting the response.

Part I.B EDA - (2.3) Correlation between categorical predictor variables and response variable

Part I.B EDA - (2.3) Categorical Predictor 1: OverallQual

OverallQual:

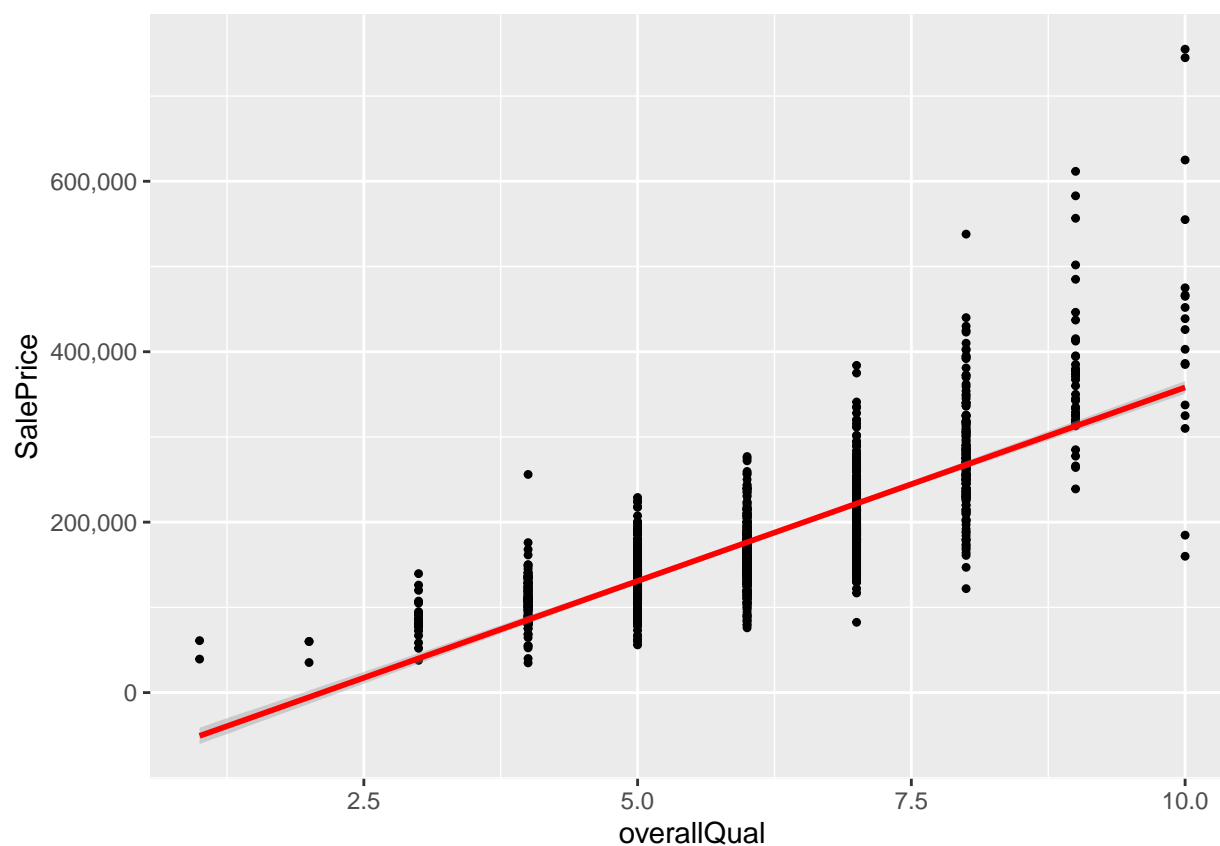
```
overallQual <- as.numeric(train$OverallQual)
cor(overallQual, train$SalePrice)
```

```
## [1] 0.7909816
```

Thus, *OverallQual* has a strong positive correlation with the *SalePrice*.

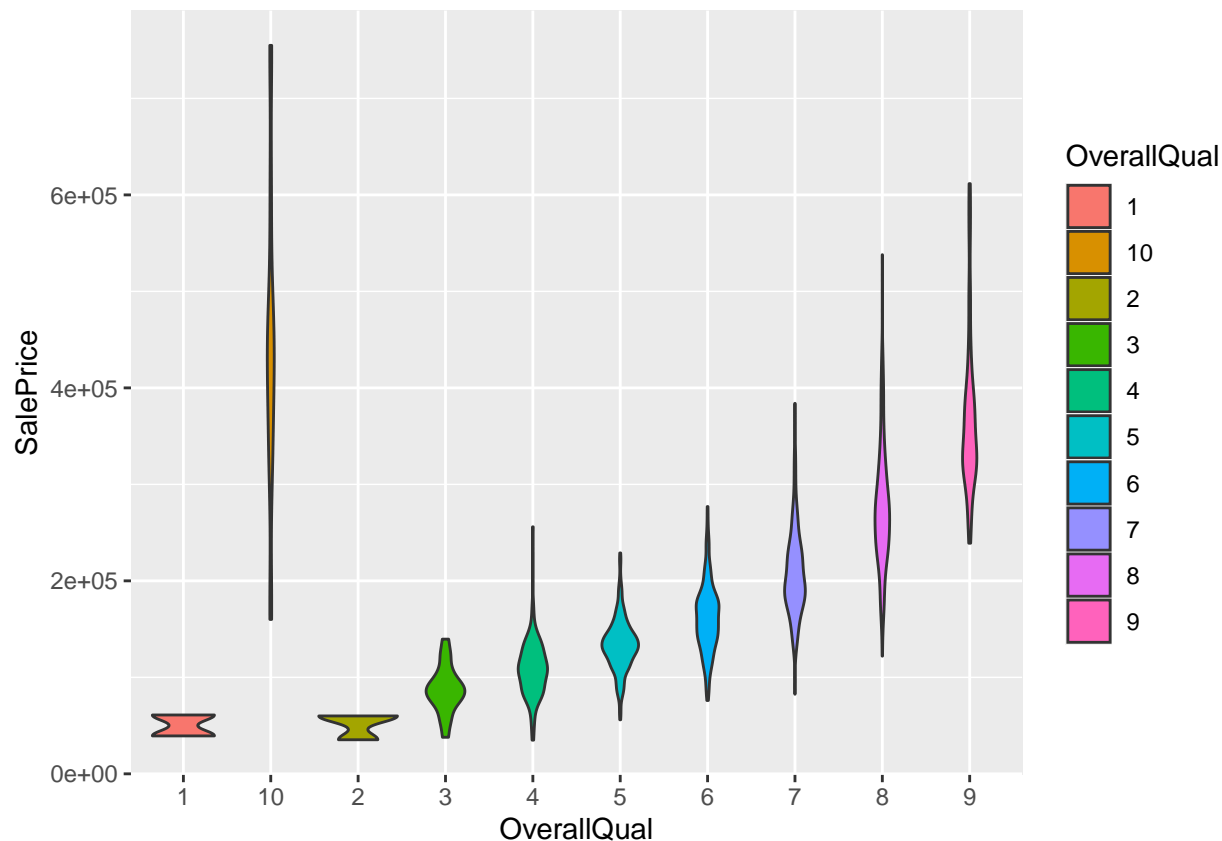
```
ggplot(train, aes(x=overallQual, y=SalePrice)) +
  geom_point(shape=20) +
  geom_smooth(method="lm", color = "red") +
  scale_y_continuous(labels=comma)
```

```
## 'geom_smooth()' using formula 'y ~ x'
```



This plot verifies that *OverallQual* has a strong positive correlation with the *SalePrice*.

```
train$OverallQual=as.factor(train$OverallQual)
train%>%ggplot(aes(x=OverallQual, y=SalePrice))+geom_violin(aes(fill=OverallQual))
```



10	Very Excellent
9	Excellent
8	Very Good
7	Good
6	Above Average
5	Average
4	Below Average
3	Fair
2	Poor
1	Very Poor

From the plot above, we can find that as Rates the overall material and finish of the house increases, the sale price of the house gets increased. Besides, if the rates the overall material and finish of the house is below average, the sale price varies for the largest range other than that of other rates. In addition, there is no big difference of the mean sale price of house at rate = 6 and rate = 7.

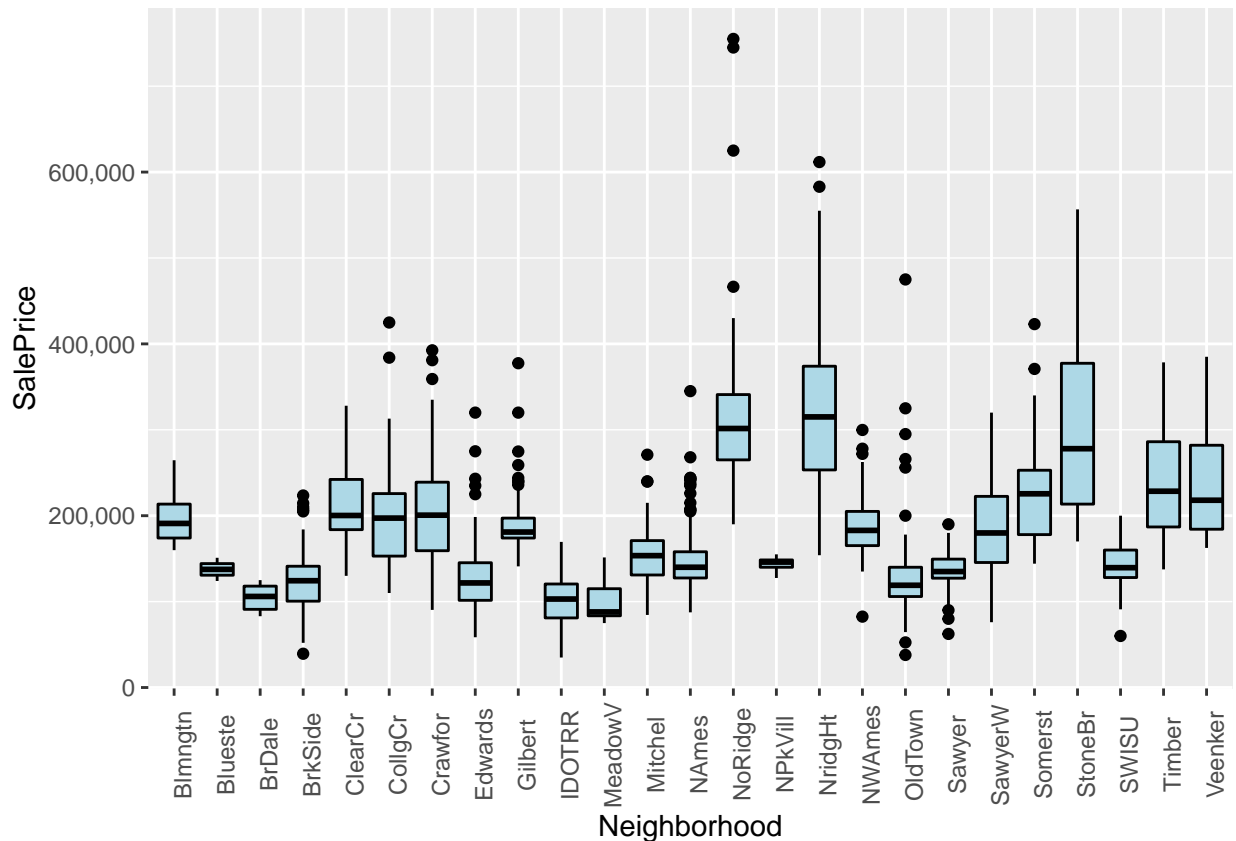
Part I.B EDA - (2.3) Categorical Predictor 2: Neighborhood

Also, we can find that *Neighborhood* is also a good predictor for its positive strong correlation with *SalePrice*.


```
cor(train$TotalBsmtSF , train$SalePrice)
```

```
## [1] 0.6135806
```

```
ggplot(train, aes(x=Neighborhood,y=SalePrice)) +  
  geom_boxplot(fill="light blue", color="black")+  
  theme(axis.text.x=element_text(angle = 90)) +  
  scale_y_continuous(labels=comma)
```



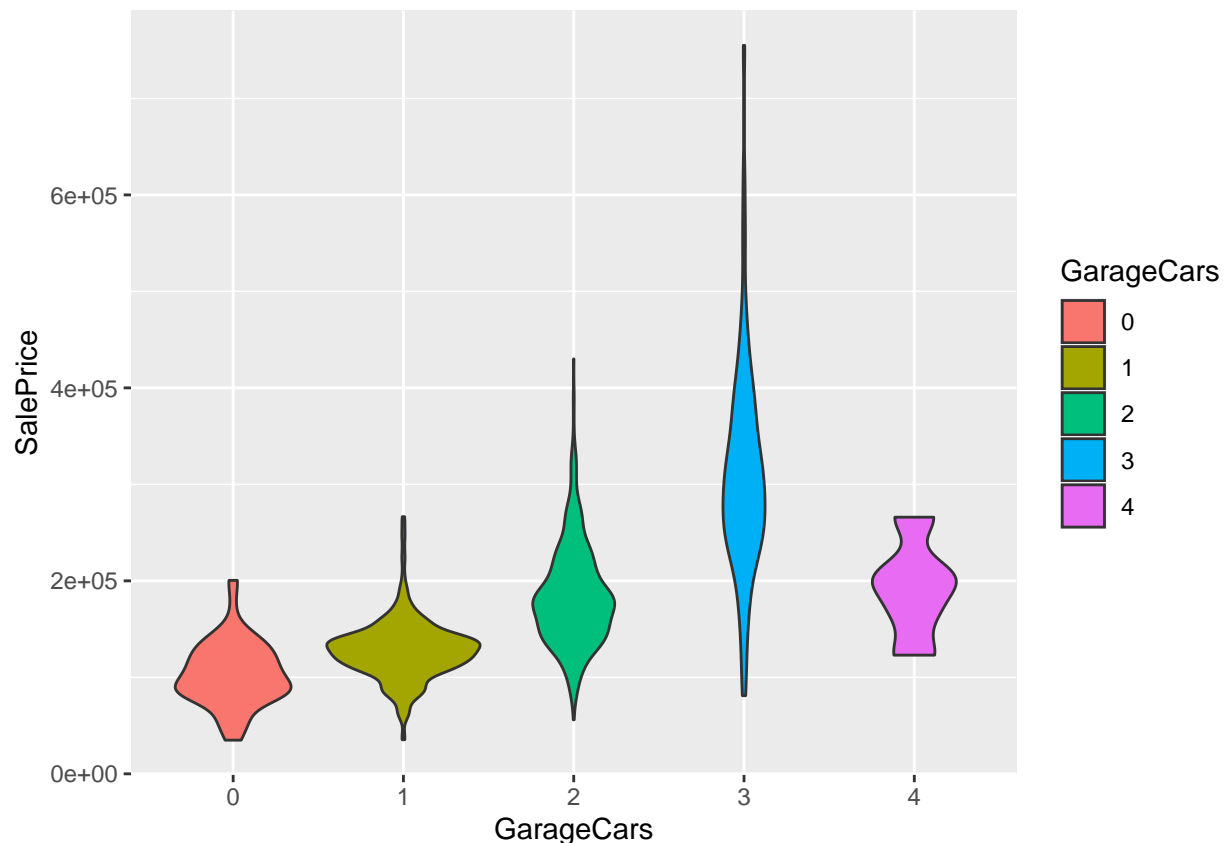
```
# change the scale from e-x type into real number
```

The neighborhoods of the house plays a significant role in the sale price. We can see that the houses around MeadowV were sold at the least expensive price, while those besides StoneBr were sold at the most expensive price. For houses' neighborhood is NoRidge, there are some of the most expensive price.

Part I.B EDA - (2.3) Categorical Predictor 3: GarageCars

Moreover, for the *GarageCars*, we would like to explore by plotting.

```
train$GarageCars=as.factor(train$GarageCars)  
train%>%ggplot(aes(x=GarageCars,y=SalePrice))+geom_violin(aes(fill=GarageCars))
```



We can see that for the house of size of garage in car capacity as 3, the sale price is the highest, while the houses with size of garage in car capacity as 0 have the most inexpensive sale price.

At last, we infer that the age of house might be an important predictor.

Part I.B EDA - (2.3) Categorical Predictor 4: YearBuilt

House's age since being built (2022-YearBuilt):

```
year <- as.numeric(train$YearBuilt)
AgeHouse <- 2022 - year
```

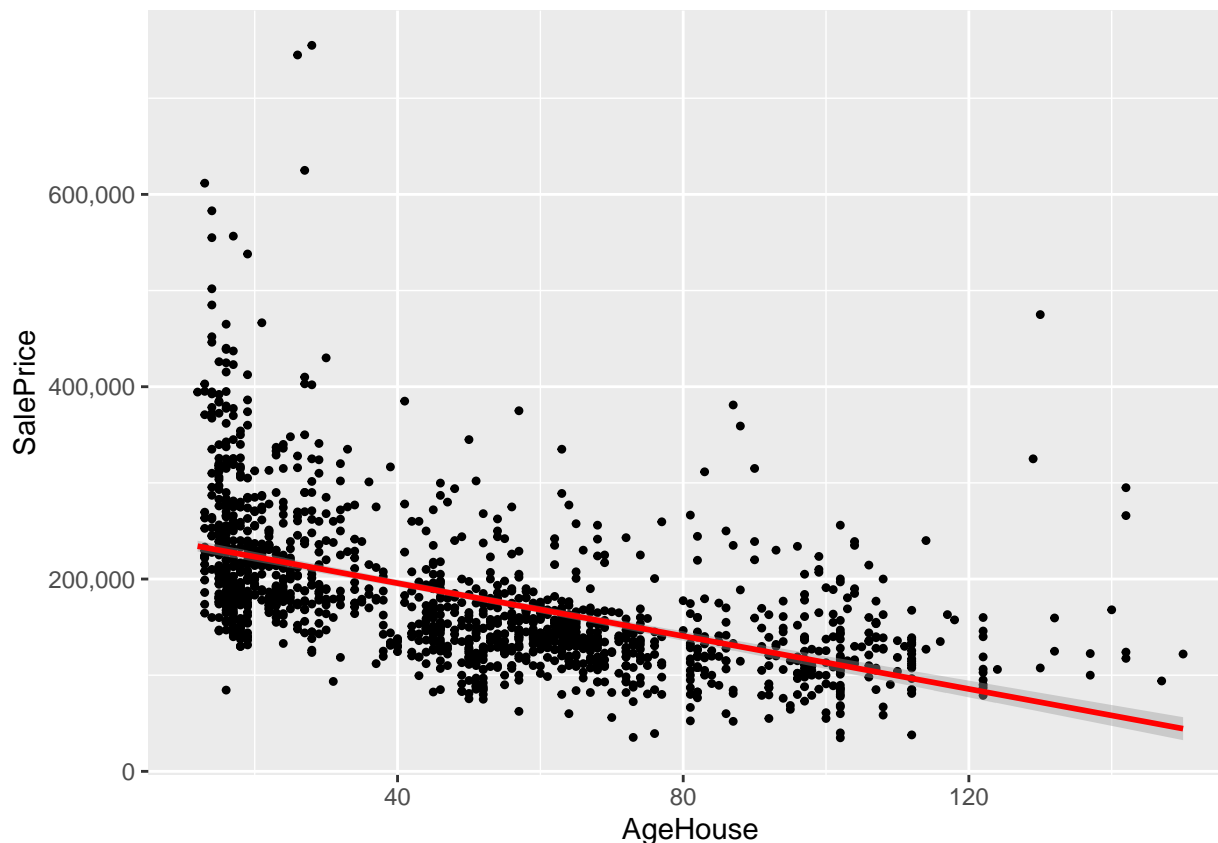
```
cor(AgeHouse, train$SalePrice)
```

```
## [1] -0.5228973
```

It shows that there is strong negative correlation between the age of house and the sale price.

```
ggplot(train, aes(x=AgeHouse, y=SalePrice)) + geom_point(shape=20) + geom_smooth(method="lm", color = "r")
```

```
## 'geom_smooth()' using formula 'y ~ x'
```



As the age of house increases, the sale price will get decreasing.

In brief, based on the EDA, there are lots of variables having weak correlation with the response. Thus, we would like to choose the LASSO and ridge regression for modeling.

Part II: Model Analysis

Part II.A - Motivation

Housing market is an important sector of the economy. Having an accurate prediction of housing price is of interest to the general public and the economic forecast. Conventional models for predictions include regression, decision trees, naive bayes, recurrent neural networks, etc. A good model should be able to generalize well to the test data, meaning that it should aim to capture the global minimum (in a strong convex optimization problem) without over-fitting or under-fitting, this means we need to take into account the bias-variance trade-off.

Motivated by these insights,

(1) we propose using Lasso (L1 regularization) for this particular task. Fitting a lasso-based regression model should ensure enough model capacity while minimizing the chance of over-fitting through regularization. It also has advantage over neural network given our limited amount of data samples. To find the best modeling strategy, we also test Ridge along with Lasso.

(2) Though the sample size here is larger than the number of variables, which means there is no high-dimensional problem, we find there are collinearity problems among the predictor variables through EDA. Thus, we choose to use PLS and PCA based model - PCR to overcome this problems.

Part II.B - Math

(1) LASSO:

$$\min_{\beta_0, \beta} \left\{ \sum_{i=1}^N (y_i - \beta_0 - x_i^T \beta)^2 \right\} \text{ subject to } \sum_{j=1}^p |\beta_j| \leq t$$

where against $s = t(\lambda)$

(2) Ridge:

$$\min_{\beta_0, \beta} \left\{ \sum_{i=1}^N (y_i - \beta_0 - x_i^T \beta)^2 \right\} \text{ subject to } \sum_{j=1}^p \beta_j^2 \leq t$$

where against $s = t(\lambda)$

(3) PCR:

Let Z_1, Z_2, \dots, Z_m represent $M < p$ linear combinations of our original p predictors. That is

$$Z_m = \sum_{j=1}^p \phi_{jm} x_j$$

$$z_{im} = u_{mp} x_{ip}$$

for some constants $\phi_{1m}, \phi_{2m}, \dots, \phi_{pm}, m = 1, \dots, M$. We can then fit the linear regression model.

$$y_i = \theta_0 + \sum_{m=1}^M \theta_m z_{im} + \epsilon_i$$

$i = 1, \dots, n$ using least square. Note that in the upper equation, the regression coefficients are given by $\theta_0, \theta_1, \dots, \theta_M$

(4) PLS:

Set

$$U_{mp} = \hat{\alpha}_p$$

from the regression model

$$y_i = \alpha_0 + \alpha_p X_{ip}^{(m)} + \epsilon_i$$

and calculate

$$z_{im} = \sum_{p=1}^P U_{mp} x_{ip}$$

for each $p = 1, \dots, P$

$$y_i = \theta_0 + \sum_{m=1}^M \theta_m z_{im} + \epsilon_i$$

$i = 1, \dots, n$ using least square.

Part II.C - Preprocess before applying model

We find that the predictions in train and test data set are not the same. Thus, we choose to remove the mismatch to ensure the same distribution between the train and test data set.

```
x_train <- model.matrix(SalePrice~ . -1 , data = train)
y_train <- train$SalePrice
x_test  <- model.matrix(SalePrice~ . -1 , data = test)
y_test  <- test$SalePrice
print(dim(x_train))
```

```
## [1] 1460 2028
```

```
print(dim(x_test))
```

```
## [1] 1447 341
```

```
#x_train-x_test
missing_cols = c()
for (var in colnames(x_train)){
  if (!(var %in% colnames(x_test))){
    missing_cols <- c(missing_cols, var)
  }
}

#x_test-x_train
missing_cols_2 = c()
for (var in colnames(x_test)){
  if (!(var %in% colnames(x_train))){
    missing_cols_2 <- c(missing_cols_2, var)
  }
}

#we simply remove the mismatch to ensure the same distribution between train and test dataset
x_train <- x_train[, !colnames(x_train) %in% missing_cols]
x_test  <- x_test[, !colnames(x_test) %in% missing_cols_2]

train = train[, !colnames(train) %in% missing_cols]
train = train[, !colnames(train) %in% missing_cols_2]

test = test[, !colnames(test) %in% missing_cols]
test = train[, !colnames(train) %in% missing_cols]
```

Part II.D - Assumptions

Since Ridge Regression and Lasso Regression are special cases of the General Linear Model. They add penalty terms but otherwise all of the same conditions apply.

The normal linear regression model assumes:

$$Y_i = \beta_o + \sum_{k=1}^p \beta_k X_k + e_i$$

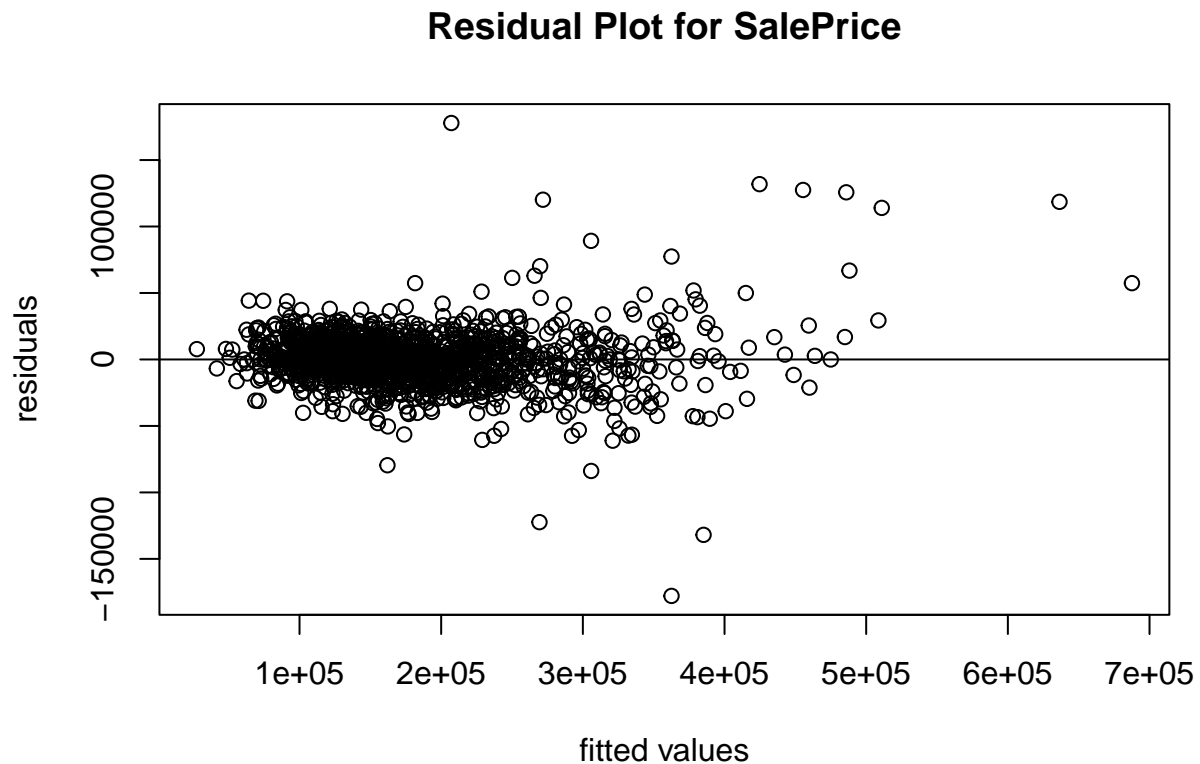
$$e_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

The final set of model assumptions for linear regression models are:

- (1) Mean Function: $E(e_i|X) = 0$.
- (2) Variance Function: $Var(e_i|X) = \sigma^2$.
- (3) Normality of the errors
- (4) Independence of the errors.
- (5) Little/No Multicollinearity in data.

(4.1) Check the Mean Function: $E(e_i|X) = 0$.

```
model.lm = lm(SalePrice ~., data = train)
plot(fitted(model.lm), resid(model.lm), xlab = "fitted values",
     ylab = "residuals", main = "Residual Plot for SalePrice")
abline(h = 0)
```

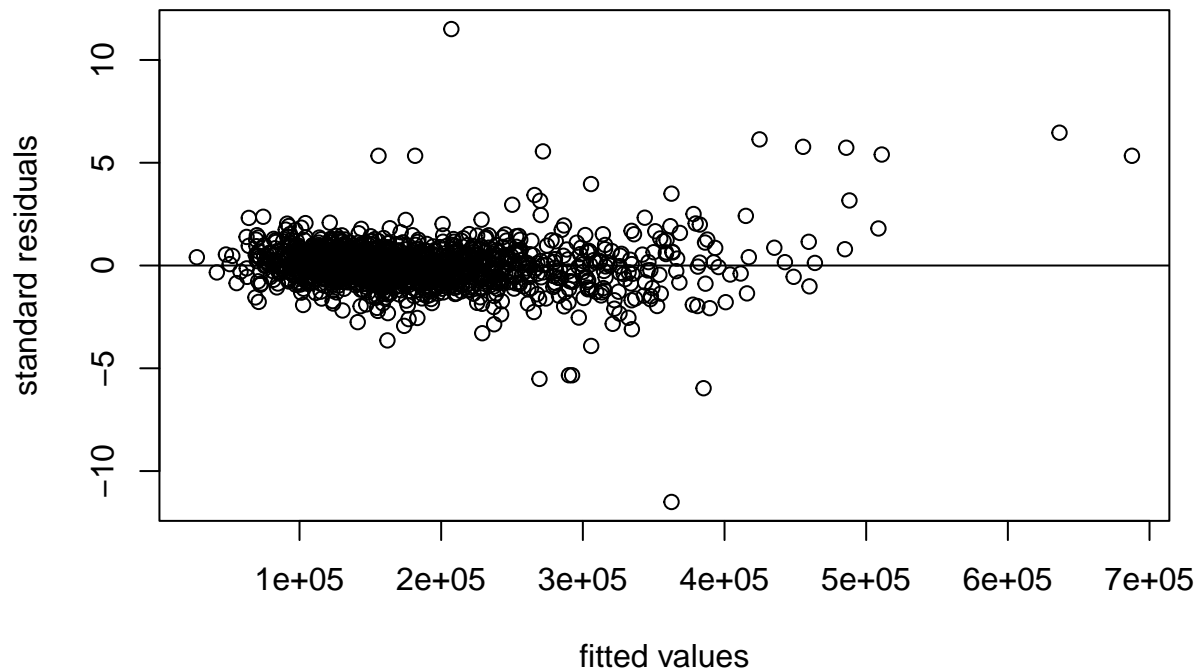


Based on the graph, it is noted that though there are few outliers, most dots are around 0, which means that the mean of the error is approximately 0, which meet the assumption(1) of the model.

Thus, the fitted mean function is appropriate.

(4.2) Check Variance Function: $Var(e_i|X) = \sigma^2$.

```
model.lm = lm(SalePrice ~., data = train)
plot(fitted(model.lm), rstandard(model.lm), xlab = "fitted values",
     ylab = "standard residuals", main = "")
abline(h = 0)
```



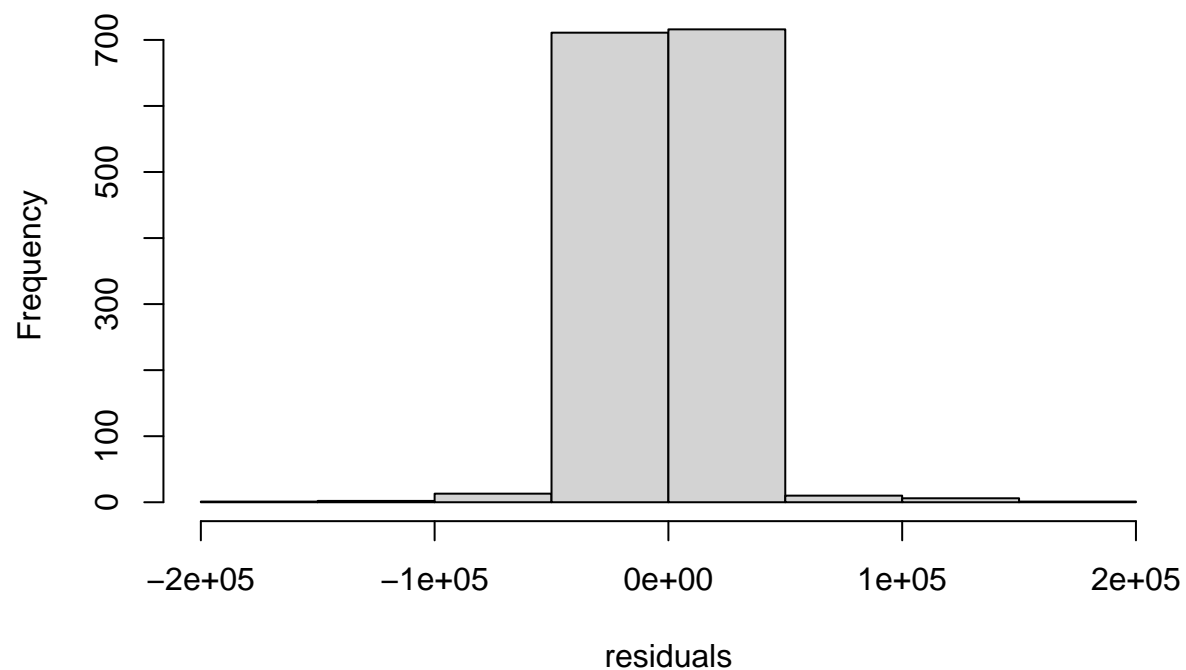
Based on the graph, it is noted that though there are few outliers, most dots are around 0 (a constant), which means that the variance of the error is approximately constant, which meet the assumption(2) of the model.

Thus, the fitted variance function is appropriate.

(4.3) Check Normality of the errors

Our two main graphical approaches will be: Histogram and Normal probability plot:

```
hist(resid(model.lm), xlab="residuals",main="")
```

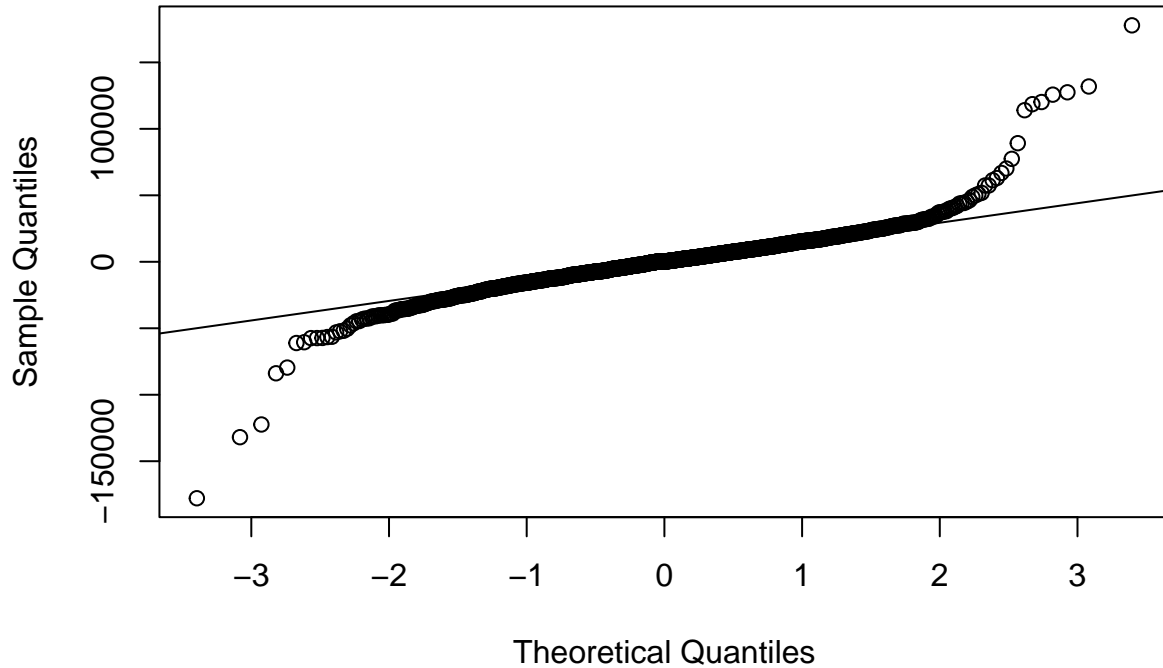


Based on the histogram of residuals, it is noted that the graph is approximately symmetry and cut in half, each side is the mirror of the other.

Thus, the residuals are normally distributed, which means that the assumption(3) in the model is correct.

```
qqnorm(resid(model.lm)); qqline(resid(model.lm))
```


Normal Q-Q Plot



Based on the plot above, though we can see that points on the lower-end have lower measurement than the Normal model predicts and the points on the upper-end have higher measurement than the Normal model predicts, most points are approximately on the line. It might be due to the outliers.

Thus, the residuals are normally distributed, which means that the assumption(3) in the model is correct.

(4.4) Check independence of the errors.

Common violation of independence in regression models are often related to structure in the mechanism that generated the sample: error for data collected sequentially/spatially/clusters. The error for data collected spatially might cause the dependence of the error issue in this dataset, but it is hard to check with the available dataset.

Thus, we assume there is no such problem.

(4.5) Check the independence of the variables.

Based on the EDA in Part I, we can see that there are multicollinearity among the variables.

Thus, it fails to meet the assumption(5).

Overall:

The final set of model assumptions are:

- (1) Mean Function: $E(e_i|X) = 0$.
- (2) Variance Function: $Var(e_i|X) = \sigma^2$.
- (3) Normality of the errors
- (4) Independence of the errors.
- (5) Little/no Multicollinearity in data.

After checking, we see that the assumptions 1-3 are met. It is hard to check whether assumption 4 is met. Here, we assume the independence of the error.

Through the EDA in Part I, we see that there are collinearity issue in our dataset. In consideration of some useless variables exist in our data set, we still want to use Lasso to zero out them and see how many variables can help us to predict the price of the house.

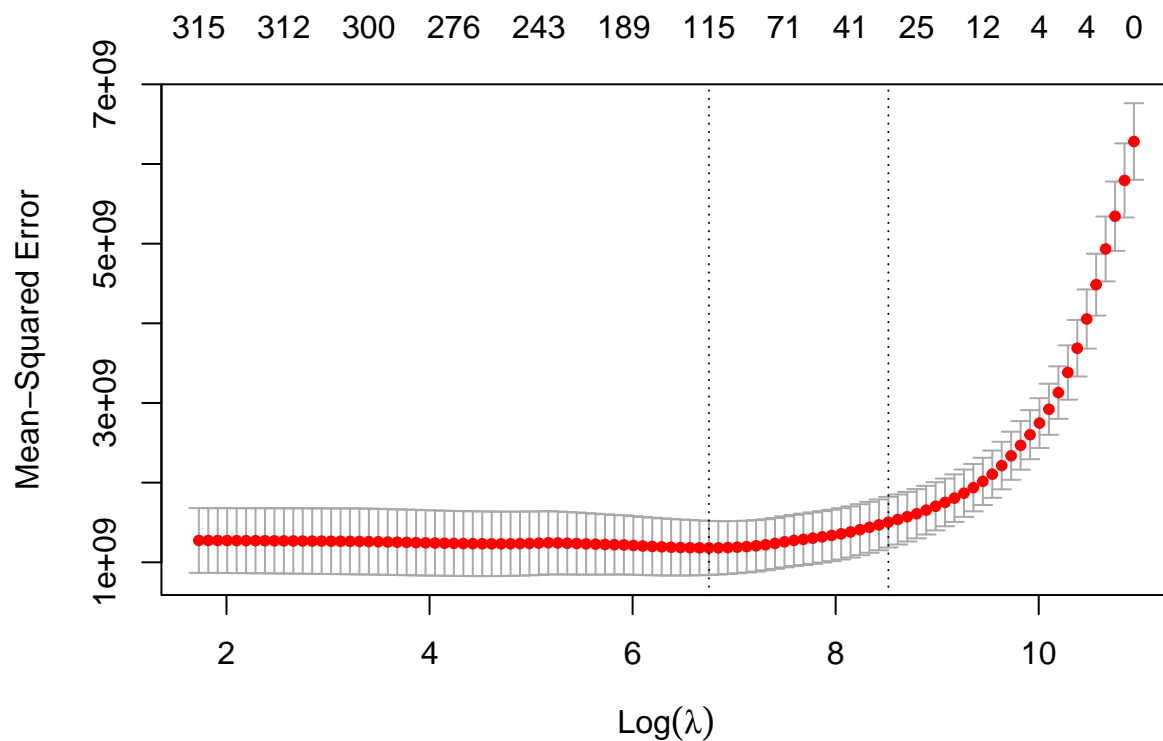
Part II.E - Validation

Here we explain one important step to the data augmentation. For fairness purposes, we need to ensure that our train and test distributions are the same (e.g. predictors existing in test data must also exist in train data). For this reason, we first compute the confusion matrix of both the train and test data, we then drop the features that are in the disjoint set of train and test sets.

Part II.F - Models

Part II.F - Models - (1) Lasso

```
set.seed(4620)
cv.lasso <- cv.glmnet(x_train, y_train, type.measure = "mse", alpha = 1)
plot(cv.lasso)
```



```

model.lasso =glmnet(x_train,y_train,lambda=cv.lasso$lambda.min, alpha=1)
pred <- predict(model.lasso,x_test)
mse_lasso = mean((pred-y_test)^2)
mse_lasso

```

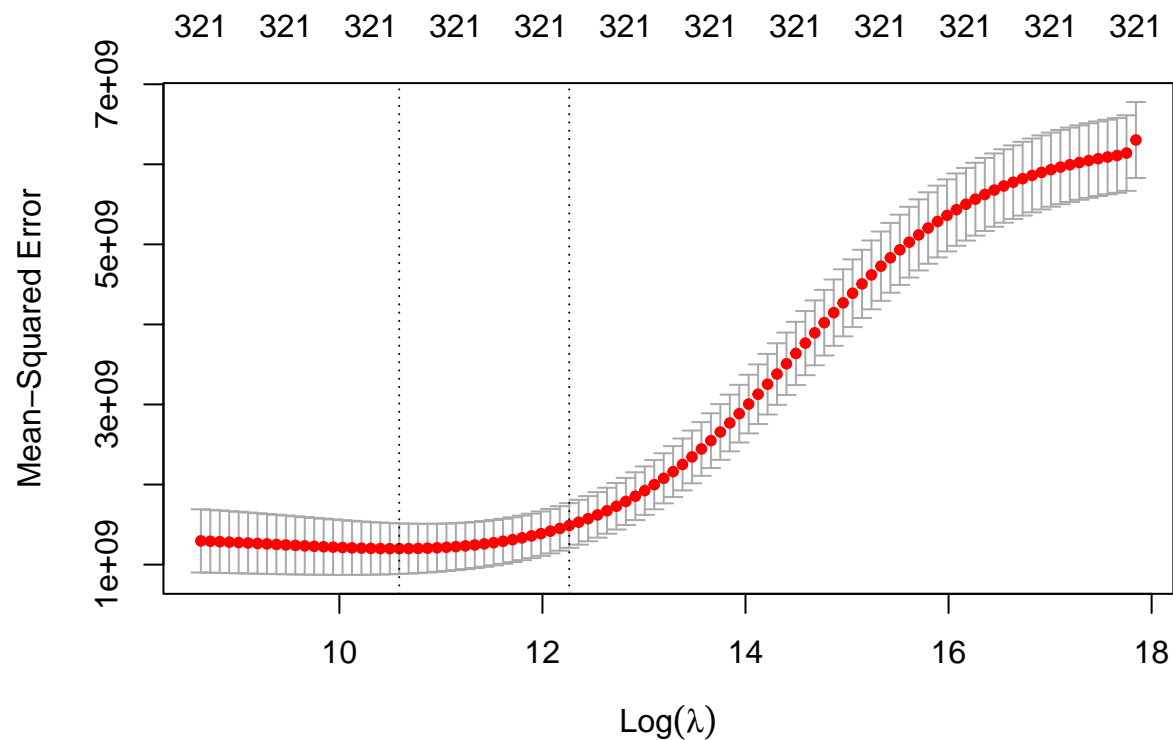
```
## [1] 794699318
```

Part II.F - Models - (2) Ridge

```

set.seed(4620)
cv.ridge <- cv.glmnet(x_train, y_train, type.measure = "mse", alpha = 0)
plot(cv.ridge)

```



```

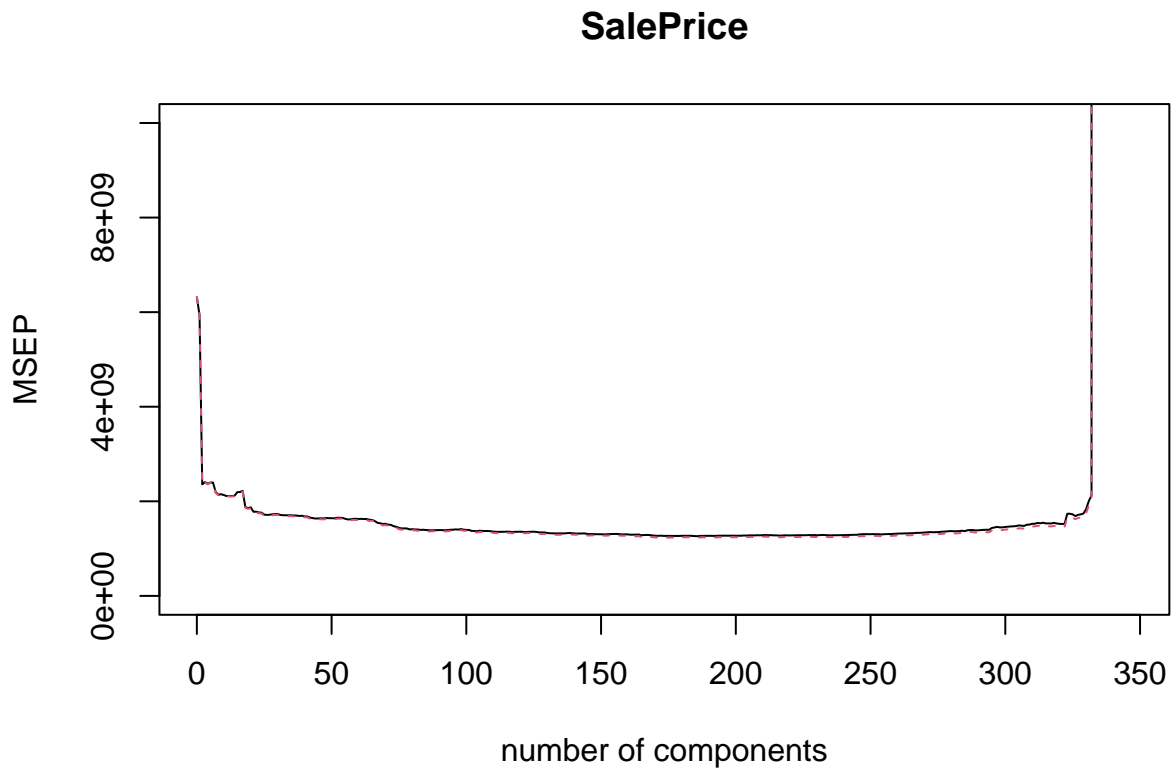
model.ridge = glmnet(x_train,y_train,lambda=cv.ridge$lambda.min, alpha=0)
pred <- predict(model.ridge,x_test)
mse_ridge = mean((pred-y_test)^2)
mse_ridge

```

```
## [1] 882528822
```

Part II.F - Models - (3) PCR

```
set.seed(4620)
model.pcr = pcr(SalePrice~.,data=train, validation="CV")
# summary(model.pcr)
validationplot(model.pcr, val.type="MSEP", ylim=c(0,999999999))
```



```
model.pcr2 = pcr(SalePrice~.,data=train,scale=TRUE,ncomp=170)
pcr.pred=predict(model.pcr2,ncomp=170)
mse_pcr = mean((as.vector(pcr.pred)-y_test)^2)
```

```
## Warning in as.vector(pcr.pred) - y_test: longer object length is not a multiple
## of shorter object length
```

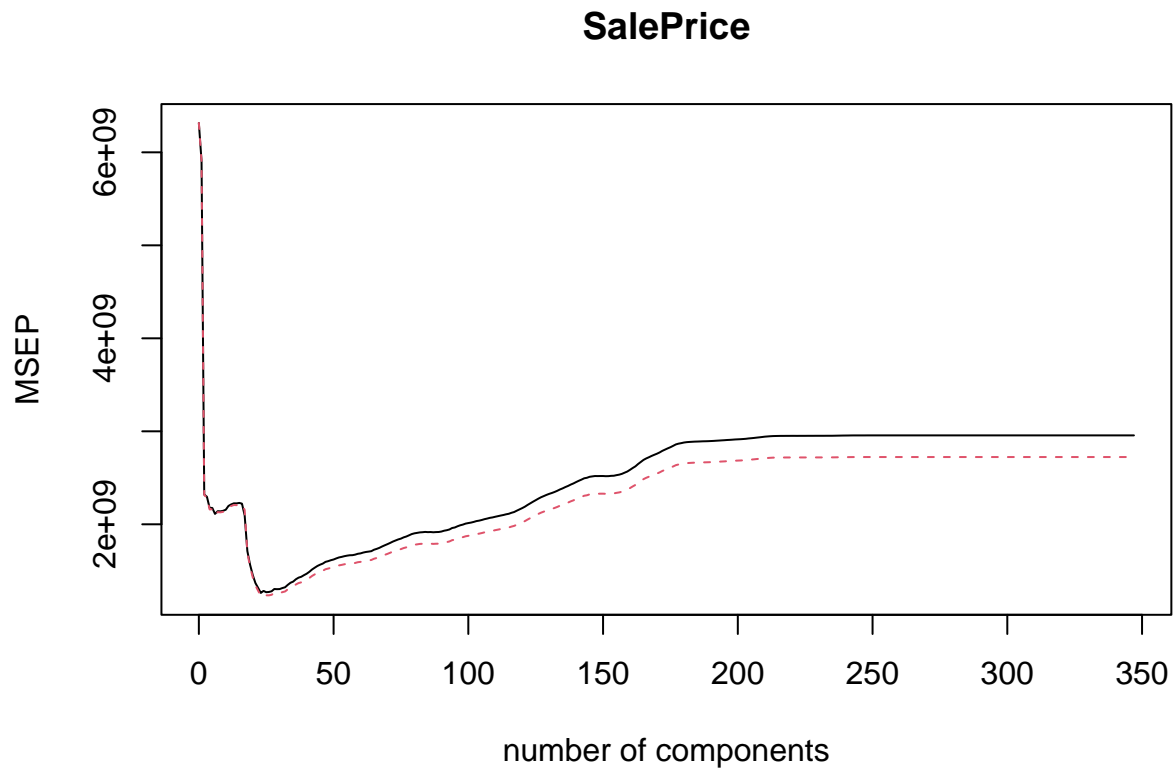
```
mse_pcr
```

```
## [1] 11747770871
```

For the dataset, it looks like the smallest CV error occurs when we use 170 principal components in the regression for SalePrice. This is fewer than the total number of predictors in the dataset (347), so it seems like the dimension-reduction in PCR is gaining us much.

Part II.F - Models - (4) PLS

```
set.seed(4620)
model.plsr = plsr(SalePrice~.,data=train,validation="CV")
# summary(model.plsr)
validationplot(model.plsr, val.type="MSEP")
```



```
model.plsr2 = plsr(SalePrice~.,data=train,scale=TRUE,ncomp=23)
pls.pred=predict(model.plsr2,ncomp=23)
mse_pls = mean((as.vector(pls.pred)-y_test)^2)
```

```
## Warning in as.vector(pls.pred) - y_test: longer object length is not a multiple
## of shorter object length
```

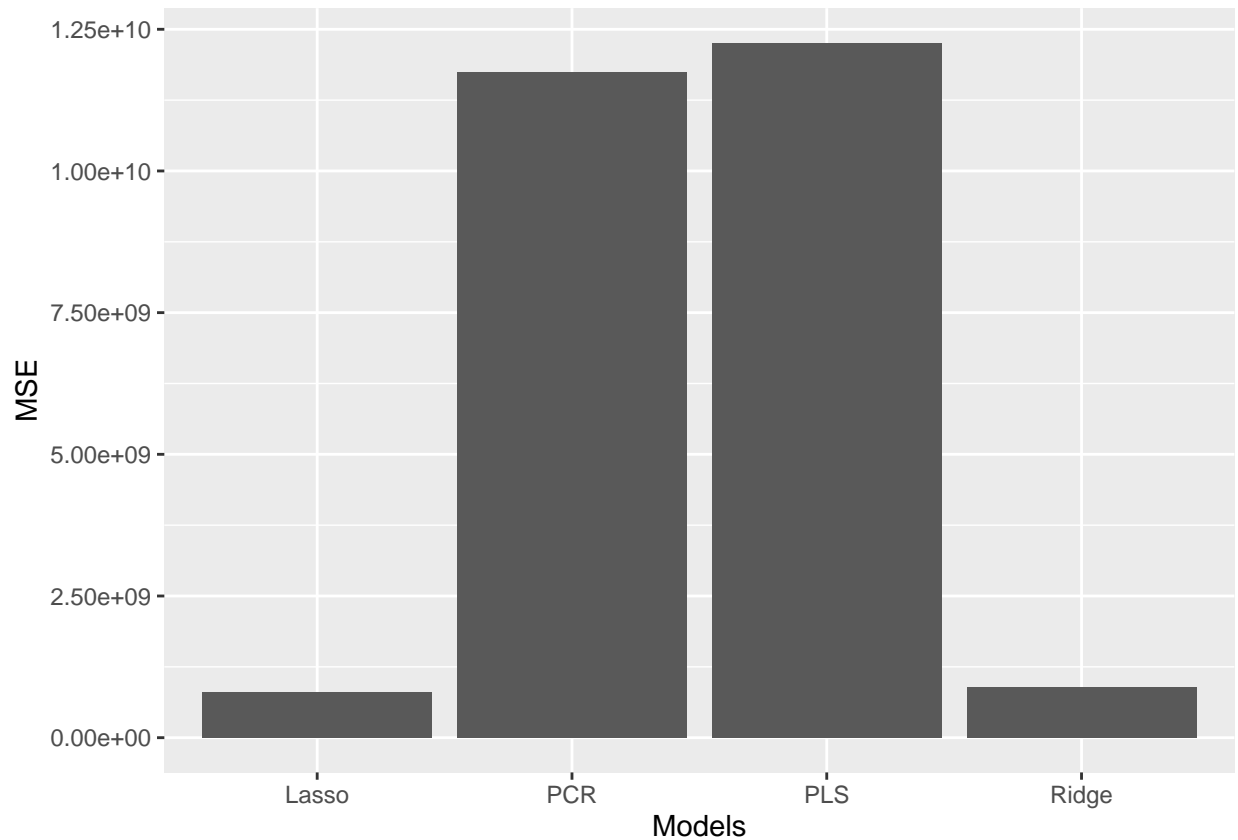
```
mse_pls
```

```
## [1] 12260383255
```

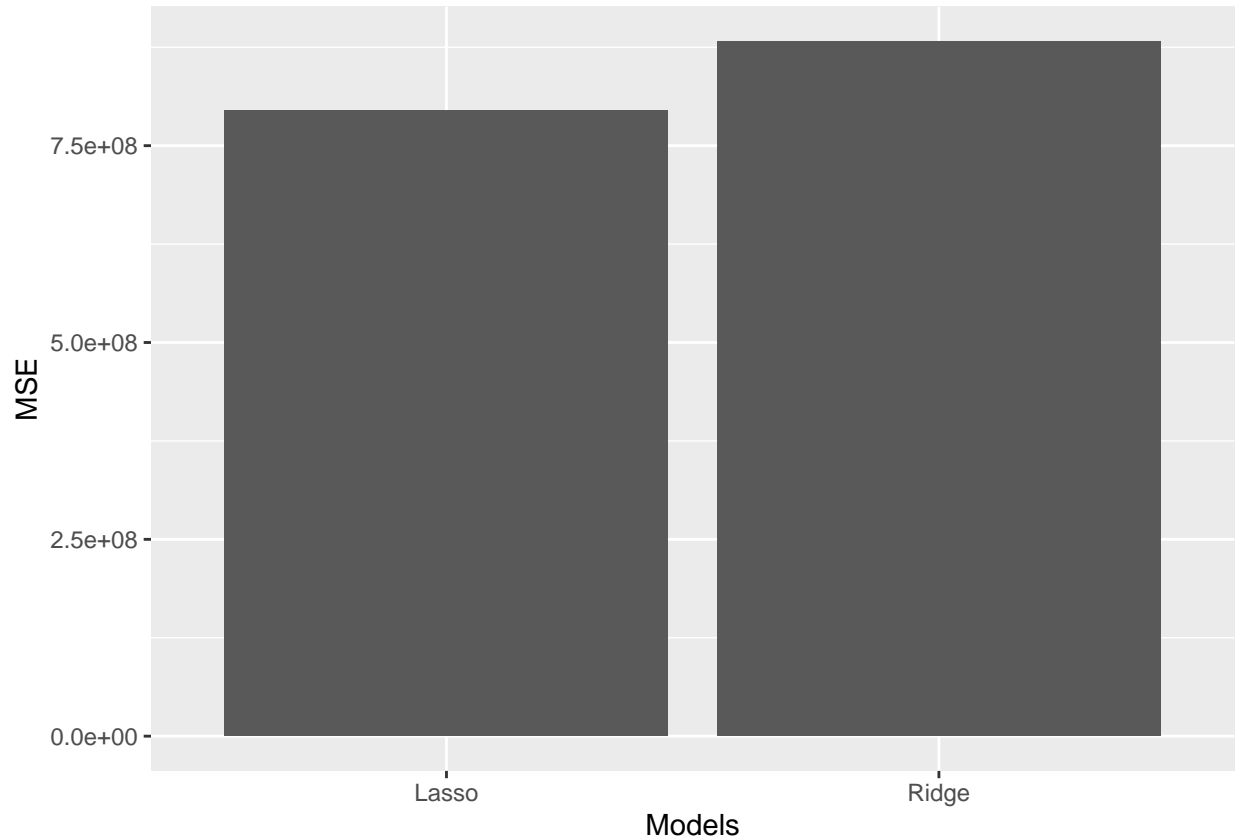
For the dataset, it looks like the smallest CV error occurs when we use 23 principal components in the regression for SalePrice. This is fewer than the total number of predictors in the dataset (347), so it seems like the dimension-reduction in PLS is gaining us much.

Part II.G - Comparison

```
models = c("Lasso", "Ridge", "PCR", "PLS")
mse = c(mse_lasso, mse_ridge, mse_pcr, mse_pls)
compare = data.frame(mse, models)
ggplot(compare, aes(x=models, y=mse)) +
  geom_bar(stat="identity")+labs(x= "Models", y="MSE")
```



```
models = c("Lasso", "Ridge")
mse = c(mse_lasso, mse_ridge)
compare2 = data.frame(mse, models)
ggplot(compare2, aes(x=models, y=mse))+geom_bar(stat="identity")+labs(x= "Models", y="MSE")
```



Part II.H - Results

Based on the MSE of 4 models, we find that

- (1) PLS and PCR has comparably similar MSE, while Lasso Regression and Ridge Regression has comparably similar MSE.
- (2) Lasso and Ridge Regression's MSE much smaller than PLS and PCR's MSE.
- (3) Lasso has the lowest MSE value.

To conclude, since Lasso and Ridge Regression's MSE much smaller than PLS and PCR's MSE, it means that the useless variables in the dataset have a larger negative influence on the models. Thus, using Lasso regression model can help us to zero out the unnecessary factors and predict the SalePrice more accurately.