House Prices:

Data Cleaning, Data Visualization, Data Preprocessing & Feature Engineering

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```
# Importing data

housing <- read.csv('train.csv', sep=',')

housing[c("Id")]<-NULL
attach(housing)
```

Data Investigation

```
# Data dimensions

dim(housing)
```

```
[1] 1460   80
```

```
# Data types

types<-as.data.frame(sapply(housing,class))
types%>%group_by(sapply(housing, class))%>%summarise(count=n())
```

```
# A tibble: 2 x 2
  `sapply(housing, class)` count
  <chr>                    <int>
1 factor                      43
2 integer                     37
```

```
# missing data amount & percentages

missing<-housing%>%is.na()%>%colSums()
missing_percent<-housing%>%is.na()%>%colSums()/dim(housing)[1]


# vVariables with missing data

missing_percent[missing>0]
```

```
 LotFrontage        Alley   MasVnrType   MasVnrArea     BsmtQual     BsmtCond
0.1773972603 0.9376712329 0.0054794521 0.0054794521 0.0253424658 0.0253424658
BsmtExposure BsmtFinType1 BsmtFinType2   Electrical  FireplaceQu   GarageType
0.0260273973 0.0253424658 0.0260273973 0.0006849315 0.4726027397 0.0554794521
 GarageYrBlt GarageFinish   GarageQual   GarageCond       PoolQC        Fence
0.0554794521 0.0554794521 0.0554794521 0.0554794521 0.9952054795 0.8075342466
 MiscFeature
0.9630136986
```

```
length(missing_percent[missing>0])
```

```
[1] 19
```

```
# variables with missing data above 45%

missing_percent[missing_percent>0 & missing_percent>0.45]
```

```
      Alley FireplaceQu      PoolQC       Fence MiscFeature
  0.9376712   0.4726027   0.9952055   0.8075342   0.9630137
```

```
length(missing_percent[missing_percent>0 & missing_percent>0.45])
```

```
[1] 5
```

Observations

Our dataframe contains 80 variables, thus 1 response variable & 79 predictor variable; Of the 79 predictor variables, 43 are categorical & 36 are numerical; Of these 79 variables 19 contain missing values of which 5 have more than 45% missing

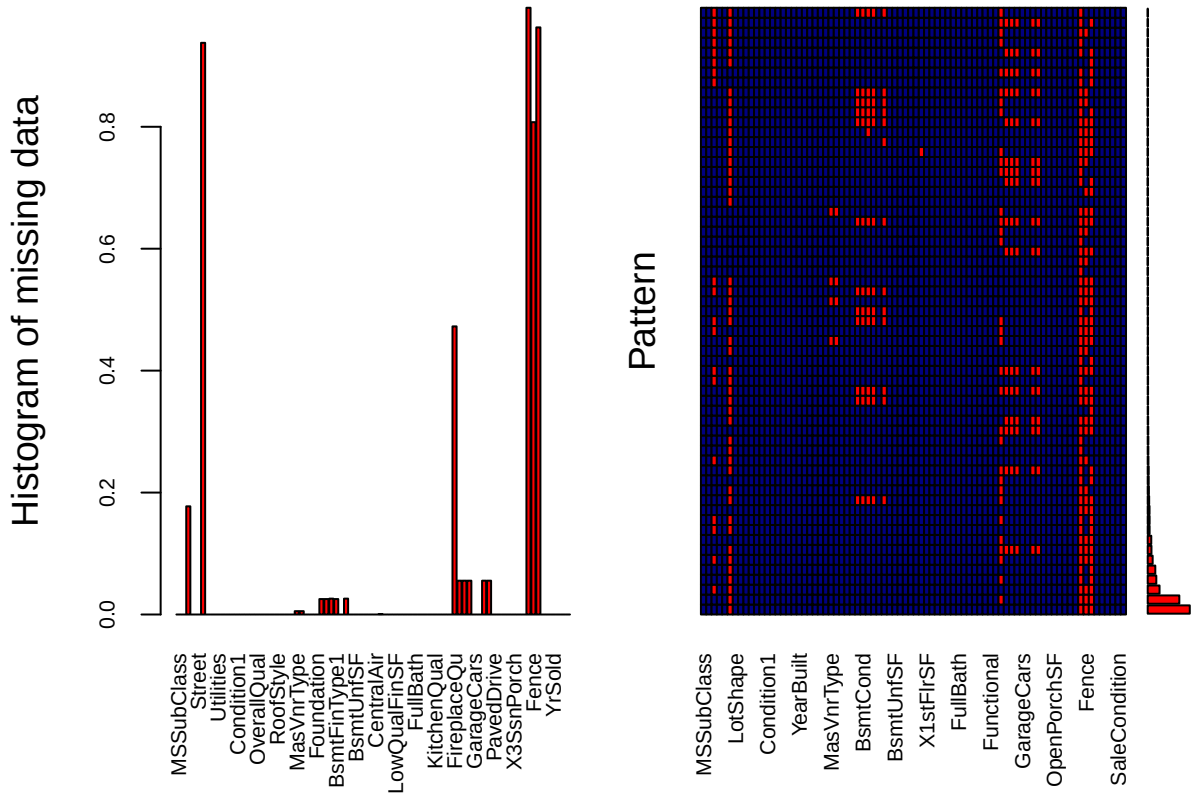
Data Cleaning

We will visualize and handle missing data; we will vizualize missing data patterns, identify sources for missing data, fill them as either factors levels or values through imputations.

Visualizing Missing Data

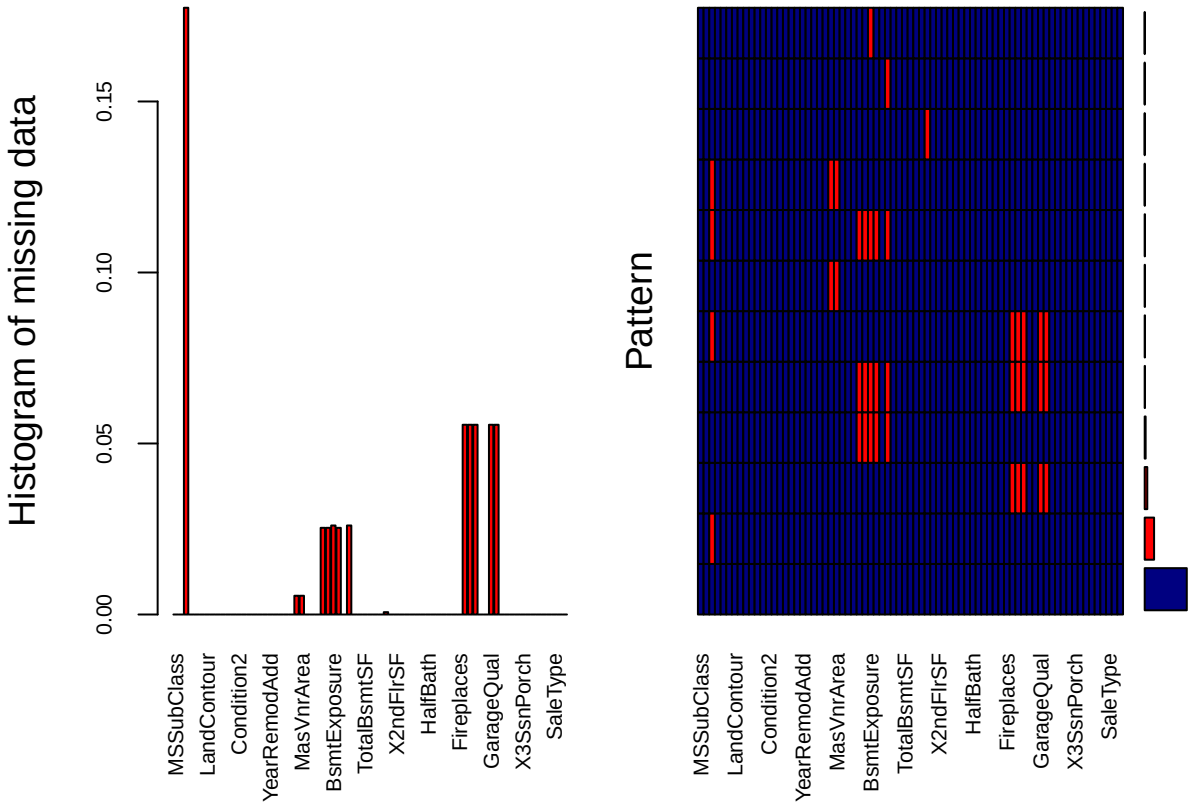
```
# Visualizing missing data

aggr(housing, col=c('navyblue','red'),
     numbers=TRUE, labels=names(housing), cex.axis=.7, gap=3, ylab=c("Histogram of missing data","Patte
```

```
Warning in plot.aggr(res, ...): not enough vertical space to display frequencies
(too many combinations)
```




```
# Removing rows with more than 45% missing data

housing[c("Alley","FireplaceQu","PoolQC","Fence","MiscFeature")]<-NULL

aggr(housing, col=c('navyblue','red'),
     numbers=TRUE, labels=names(housing), cex.axis=.7, gap=3, ylab=c("Histogram of missing data","Patte
```

```
Warning in plot.aggr(res, ...): not enough horizontal space to display
frequencies
```



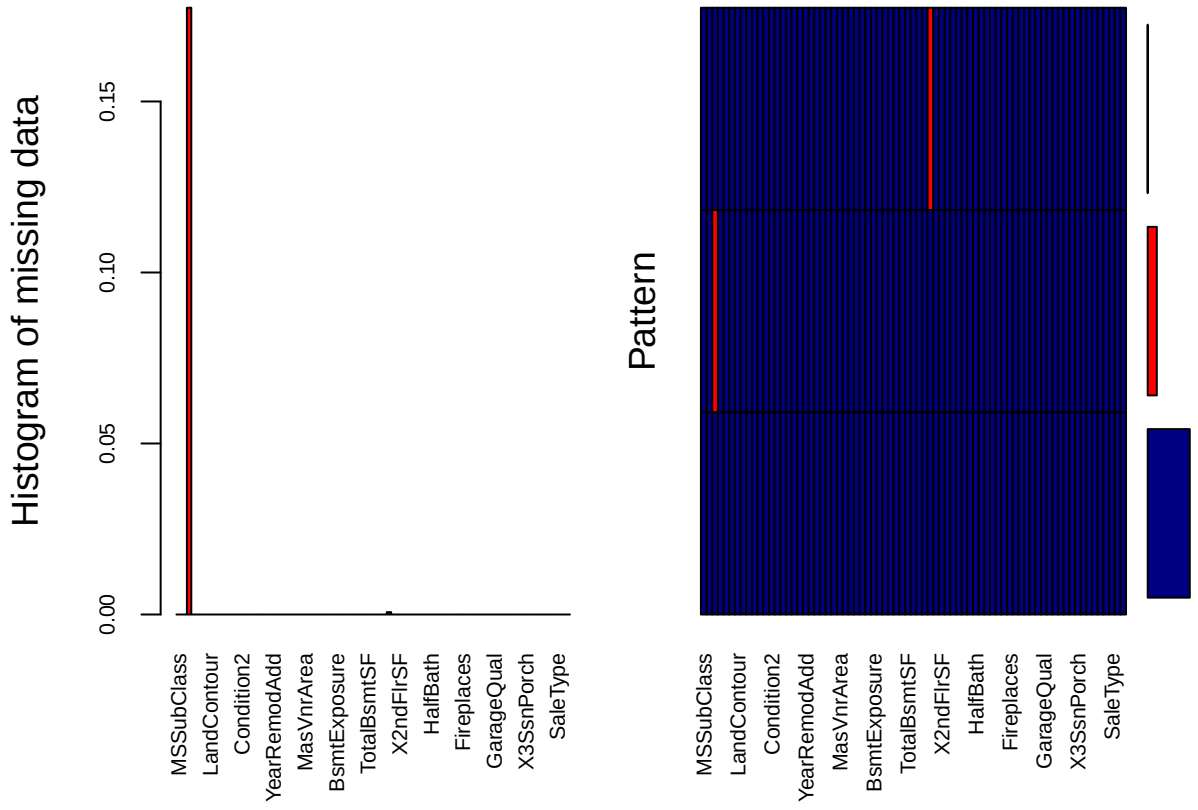
Many of the data seem to be missing in patterns, this can indicate that the data is not missing but part of a factor level that was not accounted for seperately

Replacing NA with "None"

```
# Adding levels to NA that should be category "None"

levels(housing$GarageType)<-c(levels(housing$GarageType),"None")
levels(housing$GarageFinish)<-c(levels(housing$GarageFinish),"None")
levels(housing$GarageQual)<-c(levels(housing$GarageQual),"None")
levels(housing$GarageCond)<-c(levels(housing$GarageCond),"None")


levels(housing$BsmtQual)<-c(levels(housing$BsmtQual),"None")
levels(housing$BsmtCond)<-c(levels(housing$BsmtCond),"None")
levels(housing$BsmtExposure)<-c(levels(housing$BsmtExposure),"None")
levels(housing$BsmtFinType1)<-c(levels(housing$BsmtFinType1),"None")
levels(housing$BsmtFinType2)<-c(levels(housing$BsmtFinType2),"None")

# Filling NA values with "None"
```

```
aggr(housing, col=c('navyblue','red'),
     numbers=TRUE, labels=names(housing), cex.axis=.7, gap=3, ylab=c("Histogram of missing data","Patte
```

```
Warning in plot.aggr(res, ...): not enough horizontal space to display
frequencies
```




```
missing<-housing%>%is.na()%>%colSums()
missing[missing>0]
```

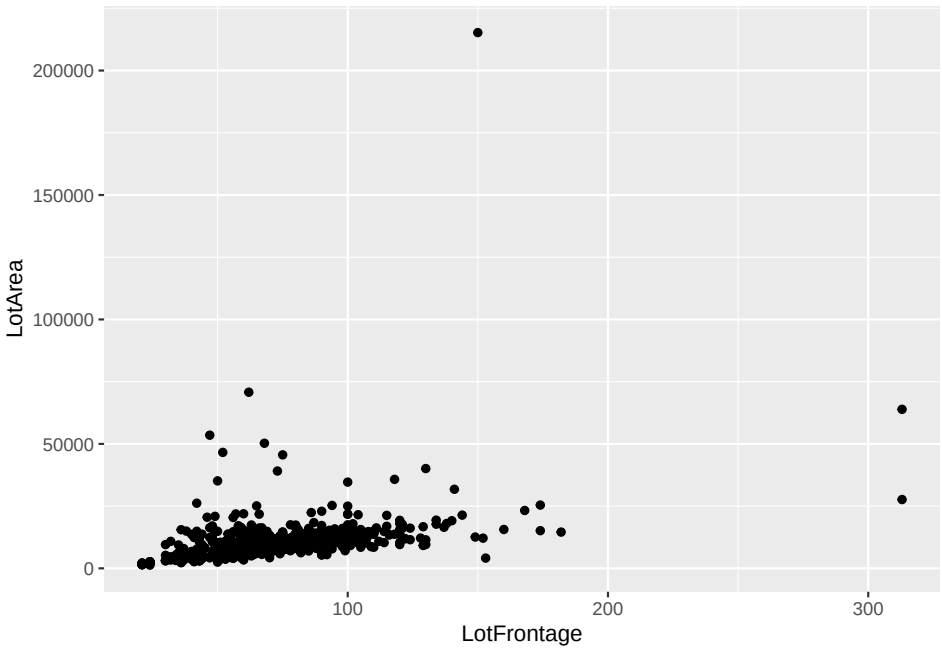
```
LotFrontage  Electrical
        259           1
```

Data Imputation

The remainder of the missing values need to be imputed, we have a numerical variable in which we will use other numerical variables to perform a mutliple linear regression model based imutation, the other categorical variable will be imputed with hot deck imputation

```
# Hot Deck Imputation

housing<-hotdeck(housing,variable=c("Electrical"))
housing$Electrical_imp<-NULL


# Model Based Multiple Regression Imputation

regression_imputation<-housing[c("LotFrontage","LotArea","X1stFlrSF","X2ndFlrSF","OverallCond","Overall
regression_imputation<-regression_imputation%>%mutate(imputed=is.na(LotFrontage))

ggplot(data=regression_imputation,aes(x=LotFrontage,y=LotArea))+geom_point(colour="black")
```

```
Warning: Removed 259 rows containing missing values (geom_point).
```

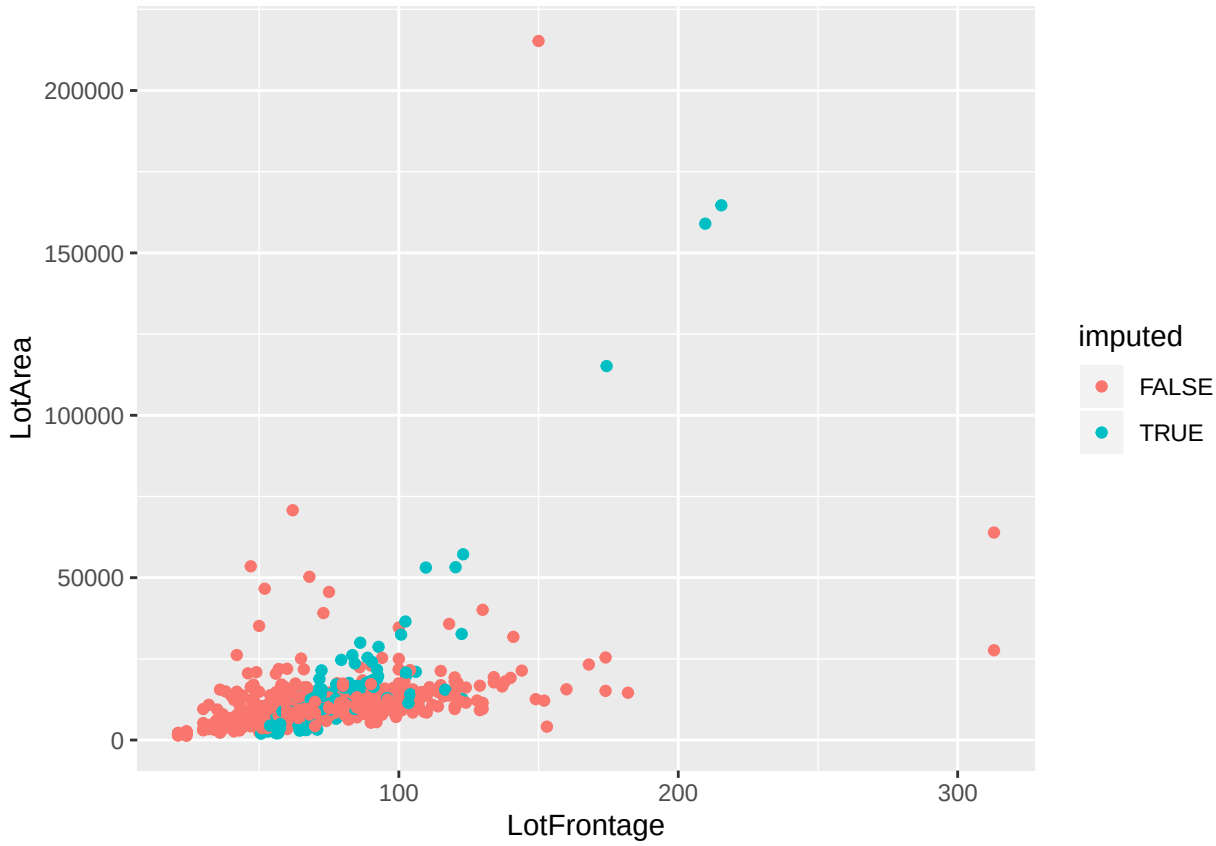



```
regression_imputation<-impute_lm(regression_imputation,LotFrontage~LotArea+X1stFlrSF+X2ndFlrSF+OverallC
```

Evaluating Imputation

We will asses the quality of our imputed data with a scatterplot

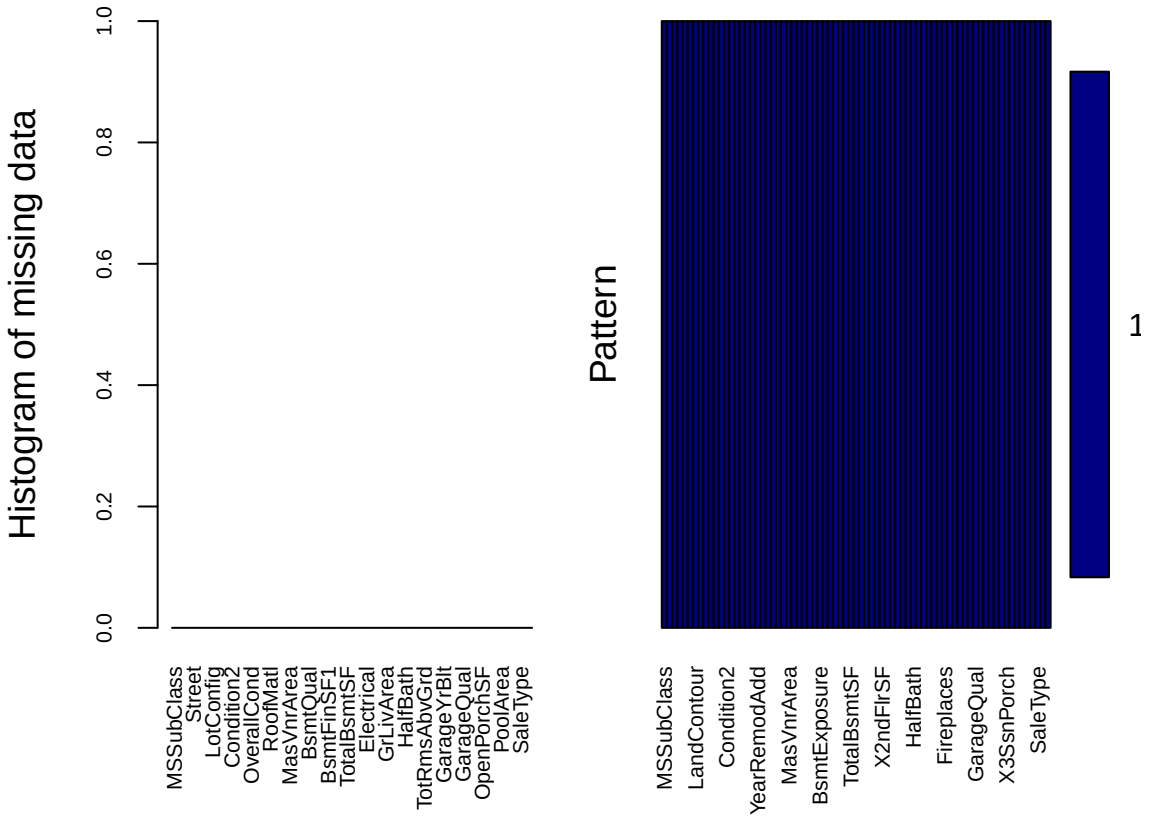
```
# Evaluating our imputation
ggplot(data=regression_imputation,aes(x=LotFrontage,y=LotArea,colour=imputed))+geom_point()
```




```
housing$LotFrontage<-regression_imputation$LotFrontage
```

Final Result

```
aggr(housing, col=c('navyblue','red'),
     numbers=TRUE, labels=names(housing), cex.axis=.7, gap=3, ylab=c("Histogram of missing data","Patte
```

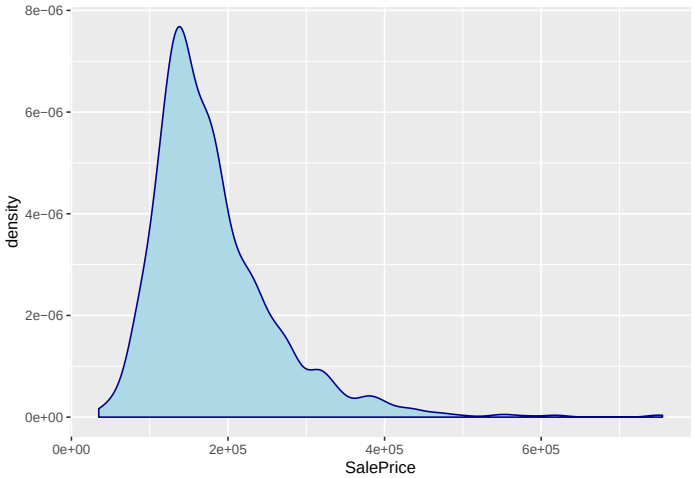


We have cleaned our dataset and it is now ready for analysis, we will start with data vizualizations to understand the nature of our data

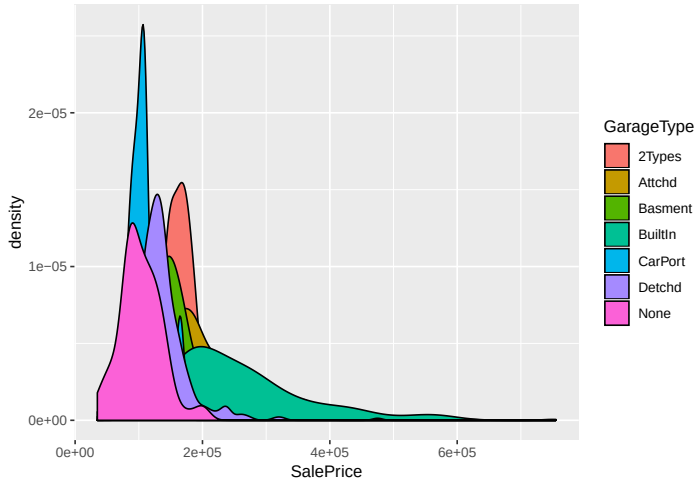
Data Visualization

Since we have many categorical variables, we will group our response variable by categorical variable groups to identify & visualize particular patterns and difference in distribution shapes according to these variables

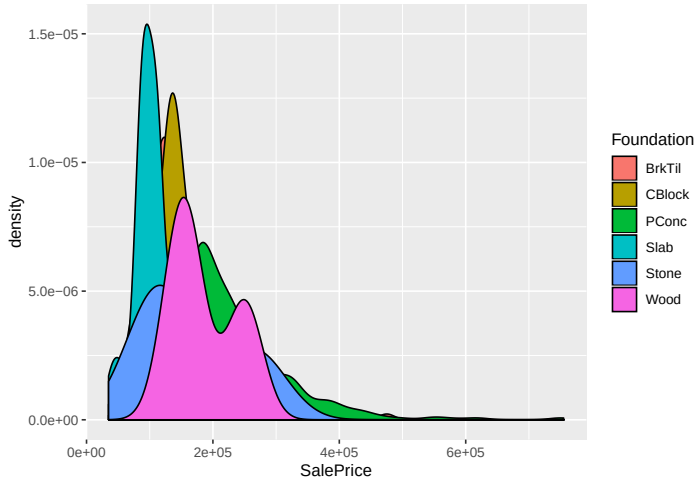
```
# Distribution of Sales Price

ggplot(housing,aes(x=SalePrice))+geom_density(color="darkblue", fill="lightblue")
```



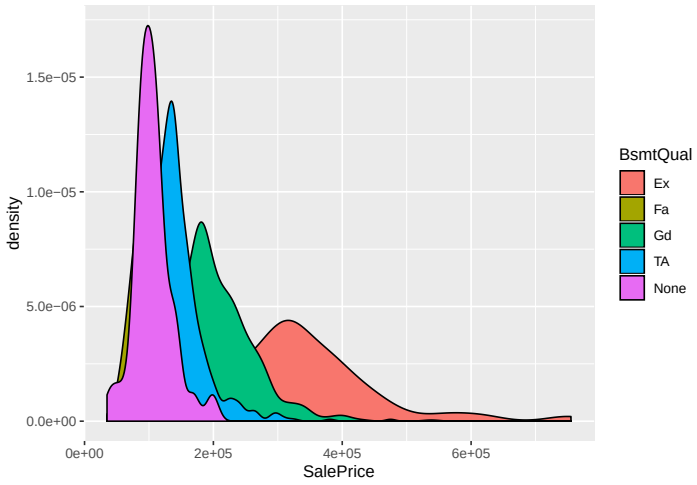
```r
# Distribution of Sales Price for GarageTypes
ggplot(housing, aes(x=SalePrice,fill=GarageType)) +   geom_density()
```



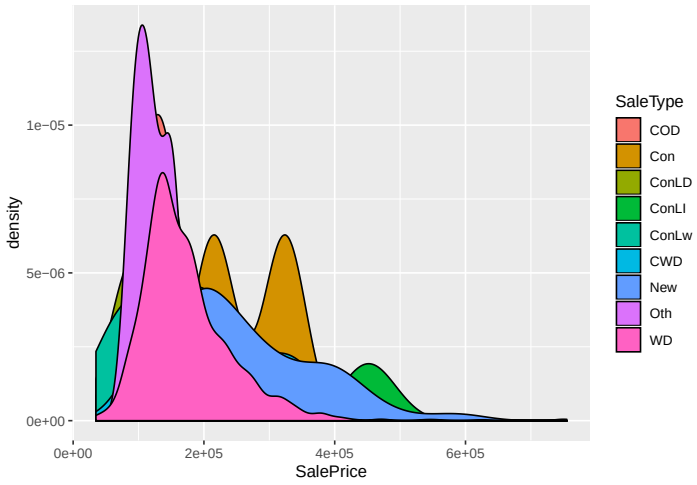

```r
# Distribution of Sales Price for Foundations
ggplot(housing, aes(x=SalePrice,fill=Foundation)) +   geom_density()
```




```r
# Distribution of Sales Price for BsmtQuals
ggplot(housing, aes(x=SalePrice,fill=BsmtQual)) +   geom_density()
```

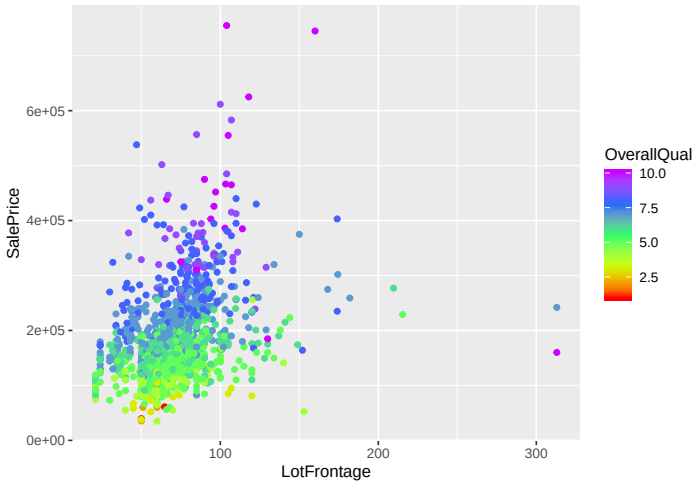



```
# Distribution of Sales Price for SaleTypes
ggplot(housing, aes(x=SalePrice,fill=SaleType)) +   geom_density()
```

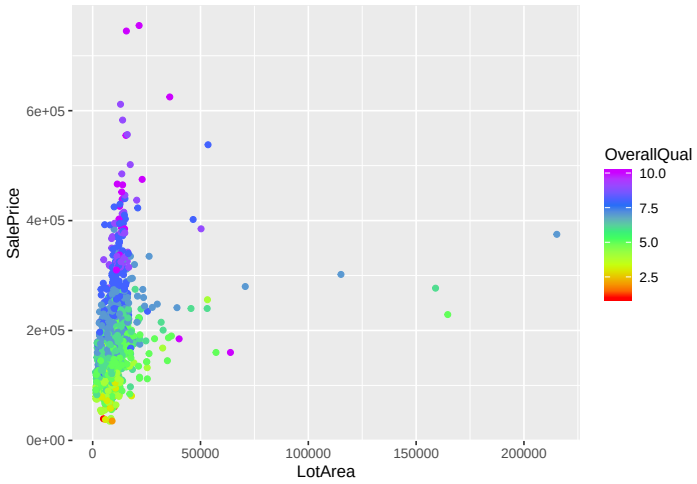


We will now look at patterns and trends in Sales Price with respect to numerical predictors, we will group colors by other numerical or categorial variables to identify & visualize further patterns

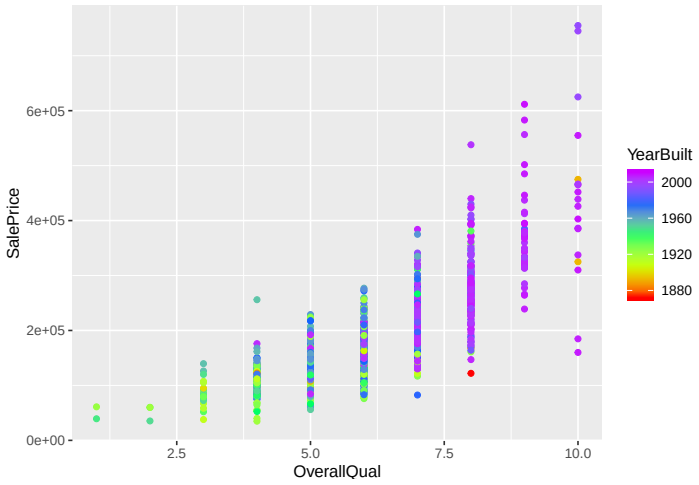
```
# LotFrontage vs SalePrice, colored by Overall Quality

ggplot(data=housing, aes(x = LotFrontage,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



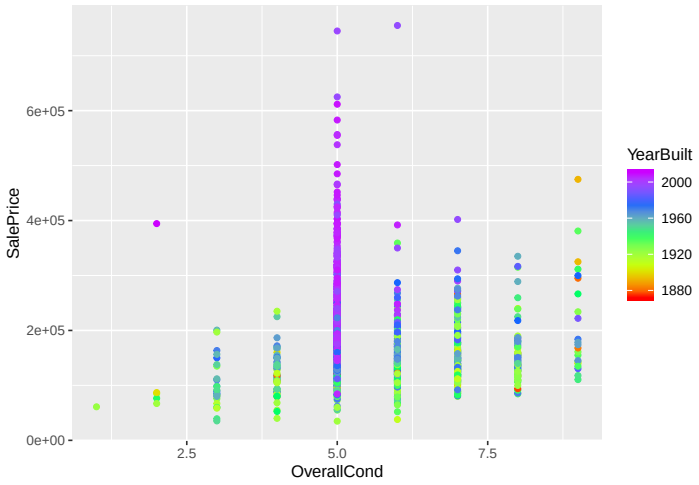

```
# LotArea vs SalePrice, colored by Overall Quality

ggplot(data=housing, aes(x = LotArea,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



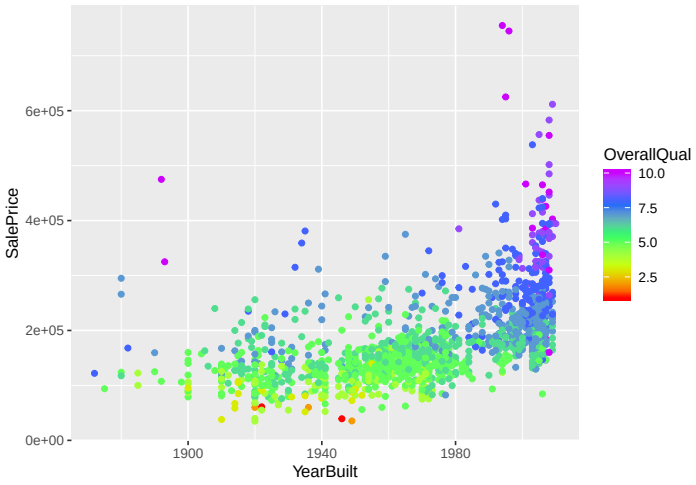

```
# OverallQual vs SalePrice, colored by Year Built

ggplot(data=housing, aes(x = OverallQual,y=SalePrice,colour=YearBuilt)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



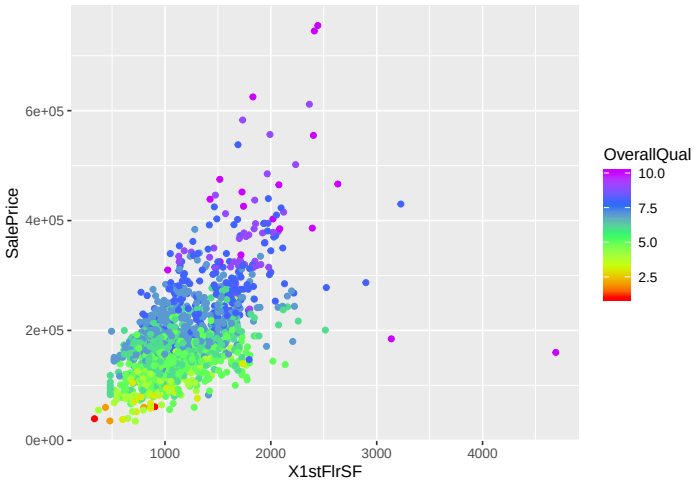

```
# OverallCond vs SalePrice, colored by Year Built

ggplot(data=housing, aes(x = OverallCond,y=SalePrice,colour=YearBuilt)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



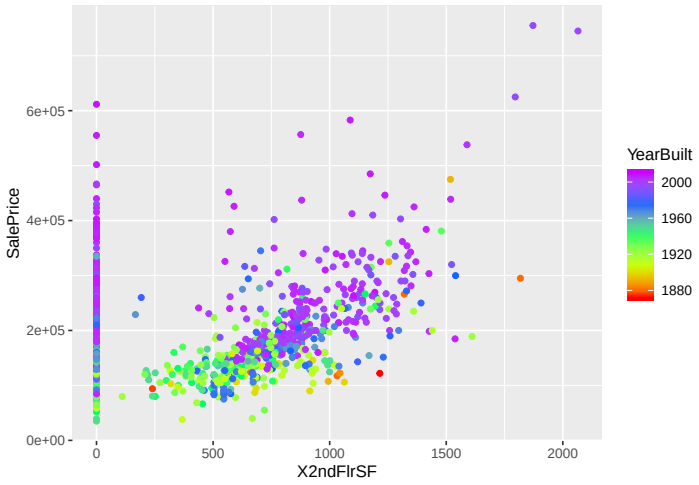

```
# Year Built vs SalePrice, colored by Overall Quality

ggplot(data=housing, aes(x = YearBuilt,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



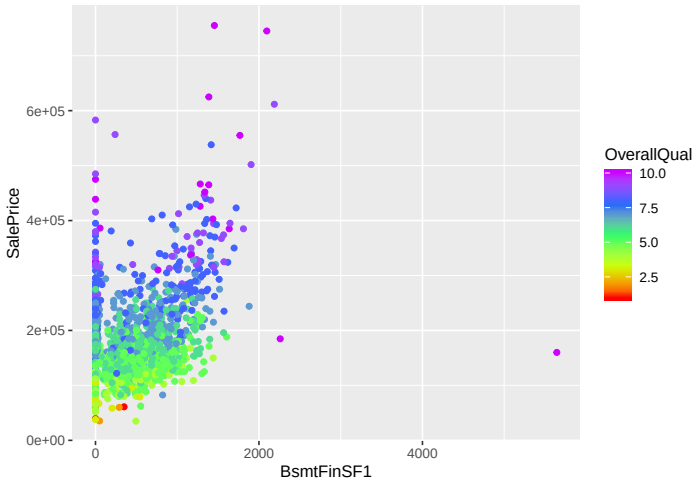

```
# X1stFlrSF vs SalePrice, colored by OverallQual

ggplot(data=housing, aes(x = X1stFlrSF,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```




```
# X2ndFlrSF vs SalePrice, colored by Year Built

ggplot(data=housing, aes(x = X2ndFlrSF,y=SalePrice,color=YearBuilt)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```

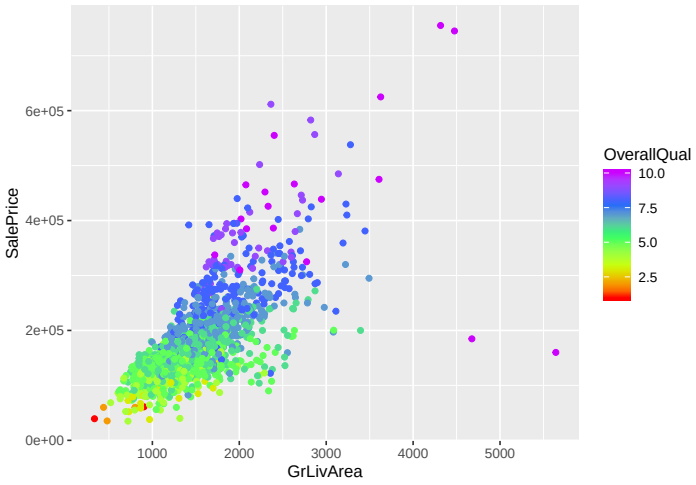



```
# BsmtFinSF1 vs SalePrice, colored by Overall Quality

ggplot(data=housing, aes(x = BsmtFinSF1,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```

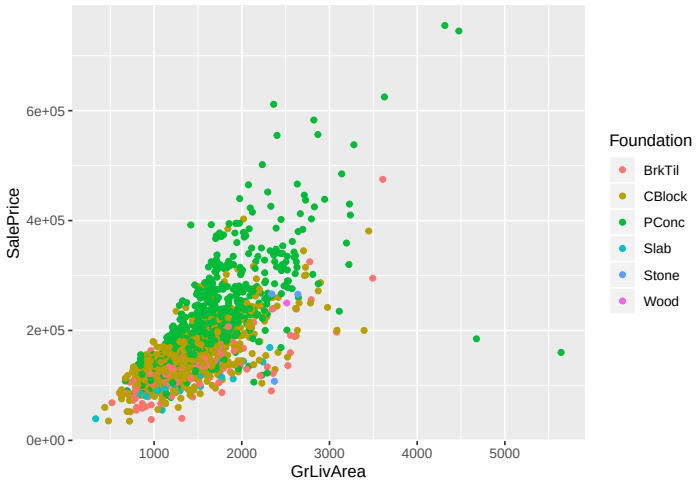



```
# TotalBsmtSF vs SalePrice, colored by Overall Quality

ggplot(data=housing, aes(x = TotalBsmtSF,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```

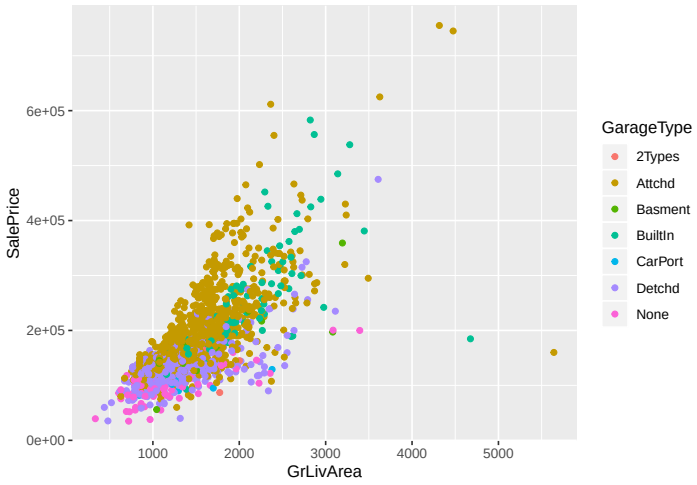

```
# GrLivArea vs SalePrice, colored by Overall Quality

ggplot(data=housing, aes(x = GrLivArea,y=SalePrice,colour=OverallQual)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



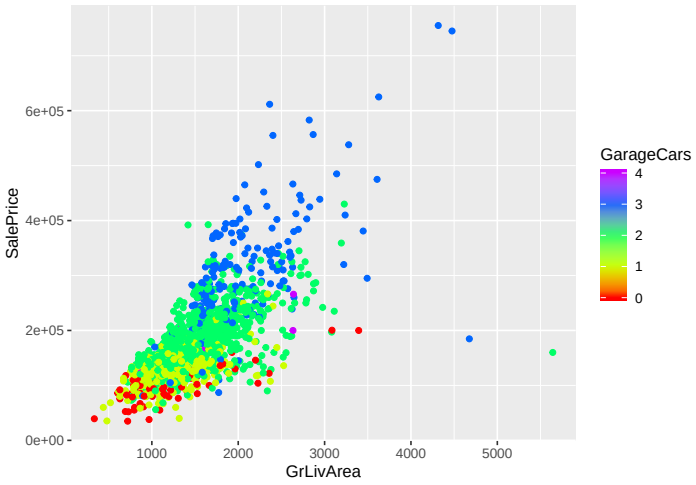

```
# GrLivArea vs SalePrice, colored by Foundation

ggplot(data=housing, aes(x = GrLivArea,y=SalePrice,colour=Foundation)) +

    geom_point()
```




```
# GrLivArea vs SalePrice, colored by GarageType

ggplot(data=housing, aes(x = GrLivArea,y=SalePrice,colour=GarageType)) +

    geom_point()
```




```
# GrLivArea vs SalePrice, colored by GarageCars

ggplot(data=housing, aes(x = GrLivArea,y=SalePrice,colour=GarageCars)) +

    geom_point()+scale_color_gradientn(colours = rainbow(5))
```



Observations

Now that we have visualized our data & identified predictor variables that show particular trends and patterns with our response variable, we will select features and preprocess our data for building predictive models

Feature Engineering & Data Preprocessing

Since our dataset contains an abundance of categorical data, which are inadequeate for many models we will be building ie Multiple Linear Regression, Deep Neural Networks. We will encode these categorical variables with One Hot Encoding

```
# encoding categorical variables in our dataset

encoder <- onehot(housing)
```

```
Warning: Variables excluded for having levels > max_levels:
NeighborhoodVariables excluded for having levels > max_levels:
Exterior1stVariables excluded for having levels > max_levels: Exterior2nd
```

```
preprocessed <- as.data.frame(predict(encoder, housing))
```

We will look at particular variables of interest, specifically those that help explain variability in our response variable as indicated by the linear regression function. Once identified we will save a new prepocessed dataset that contain only key properly encoded categorical & key numerical variables variables

```
summary(lm(data=preprocessed,SalePrice~.))
```

```
Call:
lm(formula = SalePrice ~ ., data = preprocessed)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-205693  -10946     378   10821  205693

Coefficients: (42 not defined because of singularities)
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -2.228e+04  1.094e+06  -0.020 0.983759
MSSubClass             -1.594e+01  8.572e+01  -0.186 0.852500
`MSZoning=C (all)`     -1.723e+04  9.383e+03  -1.836 0.066598 .
`MSZoning=FV`           9.418e+03  4.182e+03   2.252 0.024503 *
`MSZoning=RH`           4.580e+03  6.902e+03   0.664 0.507128
`MSZoning=RL`           5.702e+03  2.498e+03   2.282 0.022630 *
`MSZoning=RM`                  NA         NA      NA       NA
LotFrontage             6.143e+01  4.684e+01   1.311 0.189931
LotArea                 6.788e-01  1.152e-01   5.892 4.88e-09 ***
`Street=Grvl`          -3.086e+04  1.262e+04  -2.445 0.014637 *
`Street=Pave`                  NA         NA      NA       NA
`LotShape=IR1`         -5.098e+02  1.647e+03  -0.310 0.756986
`LotShape=IR2`          3.234e+03  4.550e+03   0.711 0.477398
`LotShape=IR3`         -6.647e+02  9.377e+03  -0.071 0.943494
`LotShape=Reg`                 NA         NA      NA       NA
`LandContour=Bnk`      -4.759e+03  3.796e+03  -1.254 0.210242
`LandContour=HLS`       5.373e+03  4.074e+03   1.319 0.187395
`LandContour=Low`      -1.502e+04  5.828e+03  -2.577 0.010074 *
`LandContour=Lvl`              NA         NA      NA       NA
`Utilities=AllPub`      2.891e+04  2.737e+04   1.056 0.291103
`Utilities=NoSeWa`             NA         NA      NA       NA
`LotConfig=Corner`      6.338e+02  1.890e+03   0.335 0.737470
`LotConfig=CulDSac`     9.594e+03  3.123e+03   3.072 0.002169 **
`LotConfig=FR2`        -5.432e+03  3.911e+03  -1.389 0.165158
`LotConfig=FR3`        -6.897e+03  1.321e+04  -0.522 0.601594
`LotConfig=Inside`             NA         NA      NA       NA
`LandSlope=Gtl`         4.675e+04  1.196e+04   3.909 9.77e-05 ***
`LandSlope=Mod`         5.558e+04  1.188e+04   4.680 3.18e-06 ***
`LandSlope=Sev`                NA         NA      NA       NA
`Condition1=Artery`    -7.212e+03  1.298e+04  -0.555 0.578666
`Condition1=Feedr`      2.096e+03  1.270e+04   0.165 0.868906
`Condition1=Norm`       1.186e+04  1.234e+04   0.961 0.336747
`Condition1=PosA`      -4.615e+02  1.560e+04  -0.030 0.976399
`Condition1=PosN`       5.308e+03  1.384e+04   0.383 0.701414
`Condition1=RRAe`      -1.368e+04  1.489e+04  -0.919 0.358334
`Condition1=RRAn`       5.800e+03  1.315e+04   0.441 0.659159
`Condition1=RRNe`      -7.178e+03  2.148e+04  -0.334 0.738271
`Condition1=RRNn`              NA         NA      NA       NA
`Condition2=Artery`     3.787e+03  2.859e+04   0.132 0.894639
`Condition2=Feedr`     -5.450e+03  2.231e+04  -0.244 0.807054
`Condition2=Norm`      -8.248e+03  1.883e+04  -0.438 0.661440
`Condition2=PosA`       1.945e+04  3.929e+04   0.495 0.620724
`Condition2=PosN`      -2.680e+05  2.713e+04  -9.878  < 2e-16 ***
`Condition2=RRAe`      -1.267e+05  4.657e+04  -2.720 0.006623 **
`Condition2=RRAn`      -2.267e+04  3.124e+04  -0.726 0.468099
`Condition2=RRNn`              NA         NA      NA       NA
`BldgType=1Fam`         5.762e+03  9.092e+03   0.634 0.526356
`BldgType=2fmCon`      -7.888e+02  7.479e+03  -0.105 0.916023
`BldgType=Duplex`      -1.255e+03  8.738e+03  -0.144 0.885828
`BldgType=Twnhs`       -8.951e+02  4.907e+03  -0.182 0.855285
```

```
`BldgType=TwnhsE`              NA         NA      NA       NA
`HouseStyle=1.5Fin`     -1.391e+03  5.665e+03  -0.245 0.806126
`HouseStyle=1.5Unf`      1.475e+04  9.199e+03   1.603 0.109142
`HouseStyle=1Story`      7.405e+03  6.238e+03   1.187 0.235400
`HouseStyle=2.5Fin`     -2.851e+04  1.407e+04  -2.027 0.042864 *
`HouseStyle=2.5Unf`     -1.408e+04  1.045e+04  -1.348 0.178030
`HouseStyle=2Story`     -7.192e+03  5.436e+03  -1.323 0.186063
`HouseStyle=SFoyer`     -1.169e+03  5.700e+03  -0.205 0.837573
`HouseStyle=SLvl`              NA         NA      NA       NA
OverallQual              8.308e+03  1.017e+03   8.167 7.54e-16 ***
OverallCond              6.308e+03  9.083e+02   6.945 6.02e-12 ***
YearBuilt                2.752e+02  7.192e+01   3.826 0.000137 ***
YearRemodAdd             4.867e+01  5.739e+01   0.848 0.396605
`RoofStyle=Flat`        -8.272e+04  3.601e+04  -2.297 0.021775 *
`RoofStyle=Gable`       -7.876e+04  3.093e+04  -2.546 0.011013 *
`RoofStyle=Gambrel`     -7.490e+04  3.204e+04  -2.338 0.019556 *
`RoofStyle=Hip`         -7.863e+04  3.095e+04  -2.540 0.011188 *
`RoofStyle=Mansard`     -7.171e+04  3.089e+04  -2.322 0.020398 *
`RoofStyle=Shed`               NA         NA      NA       NA
`RoofMatl=ClyTile`      -7.867e+05  3.553e+04 -22.141  < 2e-16 ***
`RoofMatl=CompShg`      -4.492e+04  1.197e+04  -3.753 0.000183 ***
`RoofMatl=Membran`       3.971e+04  3.675e+04   1.080 0.280125
`RoofMatl=Metal`         1.828e+04  3.600e+04   0.508 0.611645
`RoofMatl=Roll`         -6.256e+04  2.903e+04  -2.155 0.031352 *
`RoofMatl=Tar&Grv`      -5.340e+04  2.239e+04  -2.385 0.017232 *
`RoofMatl=WdShake`      -6.396e+04  1.830e+04  -3.495 0.000491 ***
`RoofMatl=WdShngl`             NA         NA      NA       NA
`MasVnrType=BrkCmn`     -1.166e+04  7.504e+03  -1.554 0.120512
`MasVnrType=BrkFace`    -7.004e+03  2.849e+03  -2.458 0.014094 *
`MasVnrType=None`        1.210e+03  3.107e+03   0.389 0.697021
`MasVnrType=Stone`             NA         NA      NA       NA
MasVnrArea               3.159e+01  5.837e+00   5.412 7.44e-08 ***
`ExterQual=Ex`           2.879e+04  5.465e+03   5.267 1.63e-07 ***
`ExterQual=Fa`           1.418e+04  9.239e+03   1.534 0.125159
`ExterQual=Gd`           6.219e+03  2.491e+03   2.496 0.012684 *
`ExterQual=TA`                 NA         NA      NA       NA
`ExterCond=Ex`           1.514e+03  1.828e+04   0.083 0.933987
`ExterCond=Fa`           6.251e+03  5.905e+03   1.058 0.290030
`ExterCond=Gd`          -2.474e+03  2.476e+03  -0.999 0.317991
`ExterCond=Po`           1.657e+04  2.685e+04   0.617 0.537268
`ExterCond=TA`                 NA         NA      NA       NA
`Foundation=BrkTil`      4.048e+04  1.552e+04   2.609 0.009185 **
`Foundation=CBlock`      4.107e+04  1.527e+04   2.690 0.007241 **
`Foundation=PConc`       4.519e+04  1.515e+04   2.982 0.002917 **
`Foundation=Slab`        3.520e+04  1.795e+04   1.961 0.050069 .
`Foundation=Stone`       4.041e+04  1.920e+04   2.105 0.035467 *
`Foundation=Wood`              NA         NA      NA       NA
`BsmtQual=Ex`           -1.994e+04  3.846e+04  -0.519 0.604119
`BsmtQual=Fa`           -3.616e+04  3.833e+04  -0.943 0.345630
`BsmtQual=Gd`           -3.965e+04  3.825e+04  -1.037 0.300136
`BsmtQual=TA`           -3.881e+04  3.817e+04  -1.017 0.309463
`BsmtQual=None`                NA         NA      NA       NA
`BsmtCond=Fa`           -3.271e+03  4.459e+03  -0.734 0.463360
`BsmtCond=Gd`           -3.328e+03  3.409e+03  -0.976 0.329160
```

`BsmtCond=Po`	6.798e+04	3.129e+04	2.172	0.030026	*
`BsmtCond=TA`	NA	NA	NA	NA	
`BsmtCond=None`	NA	NA	NA	NA	
`BsmtExposure=Av`	1.197e+04	2.472e+04	0.484	0.628410	
`BsmtExposure=Gd`	2.249e+04	2.480e+04	0.907	0.364735	
`BsmtExposure=Mn`	7.246e+03	2.478e+04	0.292	0.770042	
`BsmtExposure=No`	6.488e+03	2.466e+04	0.263	0.792530	
`BsmtExposure=None`	NA	NA	NA	NA	
`BsmtFinType1=ALQ`	-4.428e+03	2.996e+03	-1.478	0.139733	
`BsmtFinType1=BLQ`	-1.869e+03	3.269e+03	-0.572	0.567597	
`BsmtFinType1=GLQ`	3.100e+03	2.861e+03	1.084	0.278774	
`BsmtFinType1=LwQ`	-6.132e+03	3.932e+03	-1.560	0.119117	
`BsmtFinType1=Rec`	-3.938e+03	3.298e+03	-1.194	0.232694	
`BsmtFinType1=Unf`	NA	NA	NA	NA	
`BsmtFinType1=None`	NA	NA	NA	NA	
BsmtFinSF1	4.416e+01	5.431e+00	8.131	1.00e-15	***
`BsmtFinType2=ALQ`	1.831e+04	2.658e+04	0.689	0.490973	
`BsmtFinType2=BLQ`	5.601e+03	2.630e+04	0.213	0.831374	
`BsmtFinType2=GLQ`	1.286e+04	2.708e+04	0.475	0.634949	
`BsmtFinType2=LwQ`	2.788e+03	2.629e+04	0.106	0.915546	
`BsmtFinType2=Rec`	1.062e+04	2.623e+04	0.405	0.685555	
`BsmtFinType2=Unf`	1.287e+04	2.619e+04	0.491	0.623329	
`BsmtFinType2=None`	NA	NA	NA	NA	
BsmtFinSF2	3.996e+01	9.388e+00	4.257	2.22e-05	***
BsmtUnfSF	2.266e+01	4.900e+00	4.625	4.13e-06	***
TotalBsmtSF	NA	NA	NA	NA	
`Heating=Floor`	-8.115e+03	3.065e+04	-0.265	0.791274	
`Heating=GasA`	-1.353e+04	1.470e+04	-0.921	0.357259	
`Heating=GasW`	-1.787e+04	1.585e+04	-1.127	0.259764	
`Heating=Grav`	-2.184e+04	1.816e+04	-1.203	0.229223	
`Heating=OthW`	-4.912e+04	2.420e+04	-2.029	0.042626	*
`Heating=Wall`	NA	NA	NA	NA	
`HeatingQC=Ex`	3.164e+03	2.106e+03	1.502	0.133263	
`HeatingQC=Fa`	6.543e+03	4.640e+03	1.410	0.158745	
`HeatingQC=Gd`	2.936e+02	2.223e+03	0.132	0.894936	
`HeatingQC=Po`	1.725e+03	2.805e+04	0.062	0.950965	
`HeatingQC=TA`	NA	NA	NA	NA	
`CentralAir=N`	2.153e+02	3.977e+03	0.054	0.956843	
`CentralAir=Y`	NA	NA	NA	NA	
`Electrical=FuseA`	2.651e+03	3.059e+03	0.867	0.386369	
`Electrical=FuseF`	8.794e+02	5.687e+03	0.155	0.877136	
`Electrical=FuseP`	-4.452e+03	1.883e+04	-0.236	0.813167	
`Electrical=Mix`	-5.714e+04	4.698e+04	-1.216	0.224165	
`Electrical=SBrkr`	NA	NA	NA	NA	
X1stFlrSF	5.213e+01	5.658e+00	9.214	< 2e-16	***
X2ndFlrSF	7.300e+01	5.549e+00	13.155	< 2e-16	***
LowQualFinSF	9.303e+00	1.910e+01	0.487	0.626309	
GrLivArea	NA	NA	NA	NA	
BsmtFullBath	-8.394e+02	2.060e+03	-0.407	0.683789	
BsmtHalfBath	-3.280e+03	3.118e+03	-1.052	0.293021	
FullBath	1.679e+03	2.222e+03	0.756	0.450073	
HalfBath	7.561e+02	2.153e+03	0.351	0.725574	
BedroomAbvGr	-4.660e+03	1.391e+03	-3.351	0.000830	***
KitchenAbvGr	-1.802e+04	5.836e+03	-3.087	0.002064	**

```
`KitchenQual=Ex`         2.459e+04  4.023e+03   6.111 1.31e-09 ***
`KitchenQual=Fa`         4.810e+03  5.031e+03   0.956 0.339294
`KitchenQual=Gd`        -1.590e+03  2.224e+03  -0.715 0.474924
`KitchenQual=TA`                NA         NA      NA       NA
TotRmsAbvGrd             1.270e+03  9.638e+02   1.318 0.187816
`Functional=Maj1`       -2.818e+04  7.635e+03  -3.690 0.000233 ***
`Functional=Maj2`       -1.870e+04  1.298e+04  -1.441 0.149714
`Functional=Min1`       -1.111e+04  4.901e+03  -2.267 0.023559 *
`Functional=Min2`       -1.053e+04  4.749e+03  -2.218 0.026745 *
`Functional=Mod`        -2.327e+04  7.516e+03  -3.096 0.002007 **
`Functional=Sev`        -6.907e+04  2.984e+04  -2.315 0.020790 *
`Functional=Typ`                NA         NA      NA       NA
Fireplaces               2.919e+03  1.358e+03   2.150 0.031742 *
`GarageType=2Types`      1.068e+05  1.232e+05   0.867 0.386369
`GarageType=Attchd`      1.223e+05  1.231e+05   0.993 0.320662
`GarageType=Basment`     1.266e+05  1.229e+05   1.031 0.302854
`GarageType=BuiltIn`     1.241e+05  1.232e+05   1.007 0.314089
`GarageType=CarPort`     1.277e+05  1.238e+05   1.032 0.302471
`GarageType=Detchd`      1.270e+05  1.232e+05   1.031 0.302762
`GarageType=None`               NA         NA      NA       NA
GarageYrBlt             -6.868e+01  6.309e+01  -1.089 0.276564
`GarageFinish=Fin`      -5.762e+02  2.442e+03  -0.236 0.813486
`GarageFinish=RFn`      -2.474e+03  2.223e+03  -1.113 0.266000
`GarageFinish=Unf`              NA         NA      NA       NA
`GarageFinish=None`             NA         NA      NA       NA
GarageCars               3.760e+03  2.339e+03   1.608 0.108175
GarageArea               2.382e+01  7.992e+00   2.981 0.002931 **
`GarageQual=Ex`          1.028e+05  3.131e+04   3.282 0.001058 **
`GarageQual=Fa`         -4.535e+03  5.079e+03  -0.893 0.372131
`GarageQual=Gd`          4.747e+03  7.984e+03   0.595 0.552207
`GarageQual=Po`         -1.315e+04  2.542e+04  -0.517 0.604966
`GarageQual=TA`                 NA         NA      NA       NA
`GarageQual=None`               NA         NA      NA       NA
`GarageCond=Ex`         -9.866e+04  3.607e+04  -2.735 0.006319 **
`GarageCond=Fa`         -2.237e+03  5.620e+03  -0.398 0.690700
`GarageCond=Gd`         -3.340e+03  9.392e+03  -0.356 0.722188
`GarageCond=Po`          3.590e+02  1.462e+04   0.025 0.980413
`GarageCond=TA`                 NA         NA      NA       NA
`GarageCond=None`               NA         NA      NA       NA
`PavedDrive=N`          -1.199e+03  3.569e+03  -0.336 0.736920
`PavedDrive=P`          -4.538e+03  5.098e+03  -0.890 0.373580
`PavedDrive=Y`                  NA         NA      NA       NA
WoodDeckSF               1.251e+01  6.056e+00   2.065 0.039118 *
OpenPorchSF             -9.592e+00  1.185e+01  -0.810 0.418245
EnclosedPorch            1.044e+01  1.282e+01   0.814 0.415576
X3SsnPorch               2.954e+01  2.359e+01   1.252 0.210715
ScreenPorch              2.393e+01  1.289e+01   1.857 0.063590 .
PoolArea                 6.898e+01  1.912e+01   3.607 0.000321 ***
MiscVal                 -1.622e-01  1.506e+00  -0.108 0.914256
MoSold                  -1.934e+02  2.570e+02  -0.753 0.451799
YrSold                  -3.101e+02  5.386e+02  -0.576 0.564924
`SaleType=COD`          -4.864e+03  4.367e+03  -1.114 0.265552
`SaleType=Con`           3.468e+04  1.768e+04   1.961 0.050043 .
`SaleType=ConLD`         8.762e+03  9.314e+03   0.941 0.347019
```

```
`SaleType=ConLI`          4.773e+02  1.144e+04   0.042 0.966730
`SaleType=ConLw`          4.801e+03  1.200e+04   0.400 0.689065
`SaleType=CWD`            1.738e+04  1.296e+04   1.340 0.180336
`SaleType=New`            1.680e+04  1.580e+04   1.063 0.287893
`SaleType=Oth`            4.814e+03  1.487e+04   0.324 0.746171
`SaleType=WD`                    NA         NA      NA       NA
`SaleCondition=Abnorml` -5.197e+03  1.573e+04  -0.330 0.741157
`SaleCondition=AdjLand`  7.007e+02  2.120e+04   0.033 0.973634
`SaleCondition=Alloca`   1.296e+03  1.774e+04   0.073 0.941801
`SaleCondition=Family`  -8.208e+03  1.654e+04  -0.496 0.619723
`SaleCondition=Normal`  -1.814e+02  1.557e+04  -0.012 0.990711
`SaleCondition=Partial`          NA         NA      NA       NA
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 24410 on 1278 degrees of freedom
Multiple R-squared:  0.9173,    Adjusted R-squared:  0.9056
F-statistic: 78.35 on 181 and 1278 DF,  p-value: < 2.2e-16
```

```r
ceoffs <- coef(summary(lm(data=preprocessed,SalePrice~.)))
ss_sig <- ceoffs[ceoffs[,"Pr(>|t|)"]<0.1,]

printCoefmat(ss_sig)
```

```
                      Estimate  Std. Error  t value  Pr(>|t|)
`MSZoning=C (all)`  -1.7226e+04  9.3826e+03  -1.8359 0.0665976 .
`MSZoning=FV`        9.4175e+03  4.1822e+03   2.2518 0.0245028 *
`MSZoning=RL`        5.7016e+03  2.4981e+03   2.2824 0.0226296 *
LotArea              6.7882e-01  1.1522e-01   5.8917 4.881e-09 ***
`Street=Grvl`       -3.0858e+04  1.2623e+04  -2.4446 0.0146367 *
`LandContour=Low`   -1.5020e+04  5.8283e+03  -2.5771 0.0100743 *
`LotConfig=CulDSac`  9.5939e+03  3.1227e+03   3.0723 0.0021687 **
`LandSlope=Gtl`      4.6747e+04  1.1960e+04   3.9085 9.773e-05 ***
`LandSlope=Mod`      5.5579e+04  1.1877e+04   4.6796 3.180e-06 ***
`Condition2=PosN`   -2.6800e+05  2.7131e+04  -9.8778 < 2.2e-16 ***
`Condition2=RRAe`   -1.2666e+05  4.6573e+04  -2.7197 0.0066232 **
`HouseStyle=2.5Fin` -2.8512e+04  1.4066e+04  -2.0271 0.0428643 *
OverallQual          8.3085e+03  1.0174e+03   8.1666 7.543e-16 ***
OverallCond          6.3081e+03  9.0833e+02   6.9447 6.021e-12 ***
YearBuilt            2.7516e+02  7.1922e+01   3.8258 0.0001366 ***
`RoofStyle=Flat`    -8.2724e+04  3.6013e+04  -2.2971 0.0217752 *
`RoofStyle=Gable`   -7.8756e+04  3.0933e+04  -2.5460 0.0110130 *
`RoofStyle=Gambrel` -7.4900e+04  3.2040e+04  -2.3377 0.0195558 *
`RoofStyle=Hip`     -7.8633e+04  3.0952e+04  -2.5405 0.0111884 *
`RoofStyle=Mansard` -7.1710e+04  3.0885e+04  -2.3218 0.0203979 *
`RoofMatl=ClyTile`  -7.8667e+05  3.5529e+04 -22.1415 < 2.2e-16 ***
`RoofMatl=CompShg`  -4.4922e+04  1.1971e+04  -3.7527 0.0001828 ***
`RoofMatl=Roll`     -6.2558e+04  2.9030e+04  -2.1550 0.0313519 *
`RoofMatl=Tar&Grv`  -5.3403e+04  2.2393e+04  -2.3848 0.0172323 *
`RoofMatl=WdShake`  -6.3957e+04  1.8301e+04  -3.4947 0.0004908 ***
`MasVnrType=BrkFace` -7.0036e+03  2.8490e+03  -2.4582 0.0140938 *
MasVnrArea           3.1590e+01  5.8371e+00   5.4119 7.440e-08 ***
`ExterQual=Ex`       2.8785e+04  5.4655e+03   5.2667 1.628e-07 ***
`ExterQual=Gd`       6.2186e+03  2.4914e+03   2.4960 0.0126845 *
```

```
`Foundation=BrkTil`   4.0482e+04  1.5516e+04   2.6091 0.0091851 **
`Foundation=CBlock`   4.1068e+04  1.5268e+04   2.6899 0.0072406 **
`Foundation=PConc`    4.5187e+04  1.5153e+04   2.9821 0.0029169 **
`Foundation=Slab`     3.5205e+04  1.7950e+04   1.9612 0.0500692 .
`Foundation=Stone`    4.0412e+04  1.9196e+04   2.1052 0.0354671 *
`BsmtCond=Po`         6.7978e+04  3.1295e+04   2.1722 0.0300263 *
BsmtFinSF1            4.4161e+01  5.4314e+00   8.1306 1.001e-15 ***
BsmtFinSF2            3.9963e+01  9.3878e+00   4.2569 2.225e-05 ***
BsmtUnfSF             2.2660e+01  4.8998e+00   4.6247 4.132e-06 ***
`Heating=OthW`       -4.9120e+04  2.4204e+04  -2.0294 0.0426260 *
X1stFlrSF             5.2131e+01  5.6579e+00   9.2137 < 2.2e-16 ***
X2ndFlrSF             7.3001e+01  5.5493e+00  13.1550 < 2.2e-16 ***
BedroomAbvGr         -4.6599e+03  1.3908e+03  -3.3505 0.0008301 ***
KitchenAbvGr         -1.8016e+04  5.8358e+03  -3.0872 0.0020642 **
`KitchenQual=Ex`      2.4586e+04  4.0234e+03   6.1107 1.315e-09 ***
`Functional=Maj1`    -2.8177e+04  7.6351e+03  -3.6905 0.0002333 ***
`Functional=Min1`    -1.1110e+04  4.9010e+03  -2.2670 0.0235593 *
`Functional=Min2`    -1.0533e+04  4.7491e+03  -2.2178 0.0267451 *
`Functional=Mod`     -2.3265e+04  7.5157e+03  -3.0956 0.0020069 **
`Functional=Sev`     -6.9071e+04  2.9841e+04  -2.3146 0.0207900 *
Fireplaces            2.9188e+03  1.3576e+03   2.1500 0.0317420 *
GarageArea            2.3820e+01  7.9919e+00   2.9806 0.0029315 **
`GarageQual=Ex`       1.0277e+05  3.1310e+04   3.2822 0.0010580 **
`GarageCond=Ex`      -9.8661e+04  3.6070e+04  -2.7353 0.0063191 **
WoodDeckSF            1.2507e+01  6.0565e+00   2.0651 0.0391179 *
ScreenPorch           2.3934e+01  1.2891e+01   1.8567 0.0635902 .
PoolArea              6.8982e+01  1.9122e+01   3.6074 0.0003212 ***
`SaleType=Con`        3.4683e+04  1.7682e+04   1.9615 0.0500427 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
feature_engineered_preprocessed_data<-preprocessed[c("MSZoning=C (all)","MSZoning=FV","MSZoning=RL","Lo
```

Conclusions

Our dataset is properly processed & ready for modelling