Housing Price Prediction Model using modeldata package - a subset of ames housing data

Saurav Mukherjee

2023-02-16

Introduction

I am building home price prediction model. I am using Ames Housing dataset to explore the attributes which have been identified somehow influencing the housing cost.

Initially I wanted to use the 'Ames Housing Data" - a data set describing the sale of individual residential property in Ames, Iowa from 2006 to 2010. The data set contains 2930 observations and a large number of explanatory variables (23 nominal, 23 ordinal, 14 discrete, and 20 continuous) involved in assessing home values. Howvever, I looked at a dataset which is a subset of this dataset and which is available within modeldata package created by https://modeldata.tidymodels.org/. I did some research and looked at the model - Hedonic Pricing Method to predict the house price. The Hedonic Pricing Method talks about internal characteristics as well as the external factors affecting the price of a good. Based on the idea of hedonic price modeling I am looking the is that neighborhood-specific and unit-specific characteristics help determine house prices.

##Data - Ames Housing Data

A data set from De Cock (2011) has 82 fields were recorded for 2,930 properties in Ames IA. I used a version from the package modeldata dataset name as ames which is copies from the original AmesHousing package but does not include a few quality columns that appear to be outcomes rather than predictors.

##Load required Libraries ## Load ames dataset ## Setup environments

Exploratory Data Analysis

Explore Ame Dataset - Dimension, Columns and Datatypes

Explore Sales Price Distribution

Table 1: Ames Housing Dataset dimension

x
2930
74

Table 2: Ames Housing Dataset Columns

x
MS_SubClass
MS_Zoning
Lot_Frontage
Lot_Area
Street
Alley
Lot_Shape
Land_Contour
Utilities
Lot_Config
Land_Slope
Neighborhood
Condition_1
Condition_2
Bldg_Type
House_Style
Overall_Cond
Year_Built
Year_Remod_Add
Roof_Style
Roof_Matl
Exterior_1st
Exterior_2nd
Mas_Vnr_Type
Mas_Vnr_Area
Exter_Cond
Foundation
Bsmt_Cond
Bsmt_Exposure
BsmtFin_Type_1
BsmtFin_SF_1
BsmtFin_Type_2
BsmtFin_SF_2
Bsmt_Unf_SF
Total_Bsmt_SF
Heating
Heating_QC
Central_Air
Electrical
First_Flr_SF
Second_Flr_SF
Gr_Liv_Area
Bsmt_Full_Bath
Bsmt_Half_Bath
Full_Bath
Half_Bath
Bedroom_AbvGr
Kitchen_AbvGr
TotRms_AbvGrd
Functional

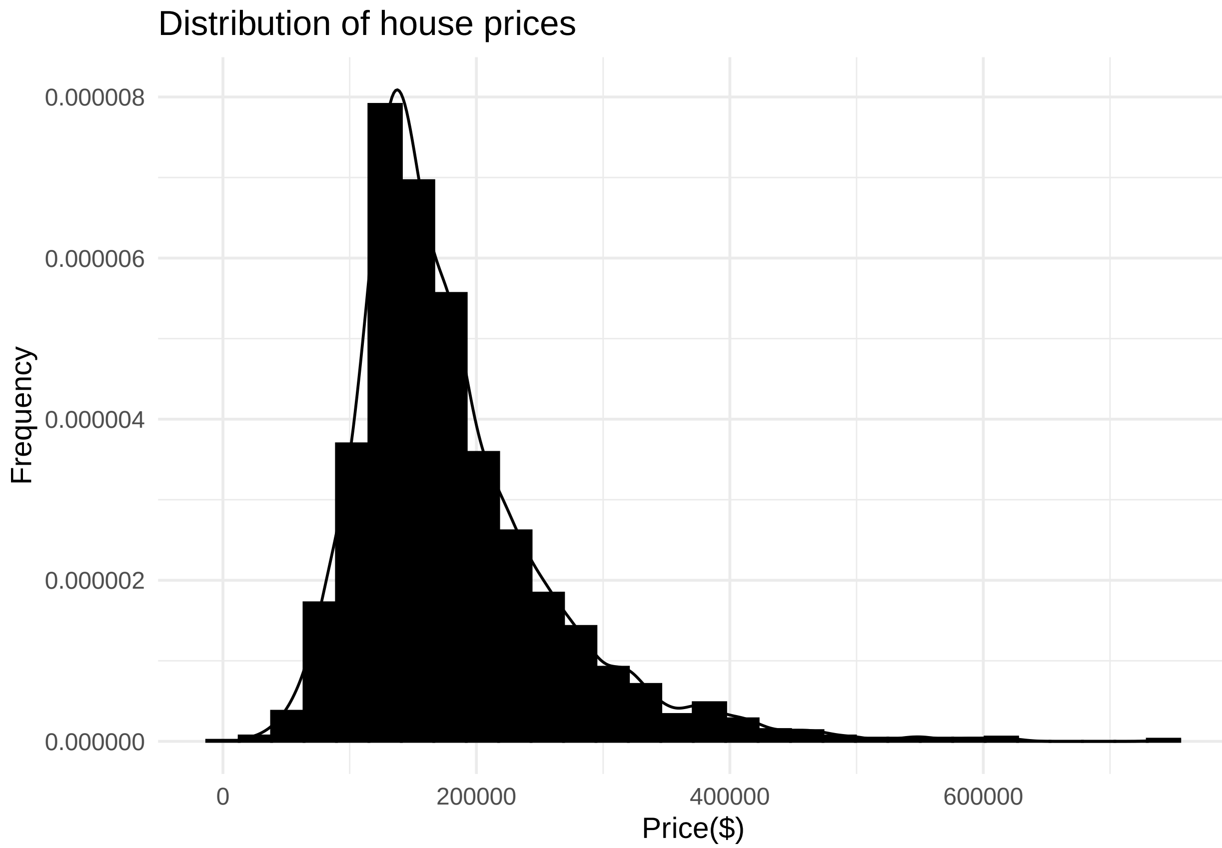
x
Fireplaces
Garage_Type
Garage_Finish
Garage_Cars
Garage_Area
Garage_Cond
Paved_Drive
Wood_Deck_SF
Open_Porch_SF
Enclosed_Porch
Three_season_porch
Screen_Porch
Pool_Area
Pool_QC
Fence
Misc_Feature
Misc_Val
Mo_Sold
Year_Sold
Sale_Type
Sale_Condition
Sale_Price
Longitude
Latitude

```
## tibble [2,930 x 74] (S3: tbl_df/tbl/data.frame)
##  $ MS_SubClass       : Factor w/ 16 levels "One_Story_1946_and_Newer_All_Styles",..: 1 1 1 1 6 6 12
##  $ MS_Zoning         : Factor w/ 7 levels "Floating_Village_Residential",..: 3 2 3 3 3 3 3 3 3 3 ...
##  $ Lot_Frontage      : num [1:2930] 141 80 81 93 74 78 41 43 39 60 ...
##  $ Lot_Area          : int [1:2930] 31770 11622 14267 11160 13830 9978 4920 5005 5389 7500 ...
##  $ Street            : Factor w/ 2 levels "Grvl","Pave": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Alley             : Factor w/ 3 levels "Gravel","No_Alley_Access",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ Lot_Shape         : Factor w/ 4 levels "Regular","Slightly_Irregular",..: 2 1 2 1 2 2 1 2 2 1 ...
##  $ Land_Contour      : Factor w/ 4 levels "Bnk","HLS","Low",..: 4 4 4 4 4 4 4 2 4 4 ...
##  $ Utilities         : Factor w/ 3 levels "AllPub","NoSeWa",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ Lot_Config        : Factor w/ 5 levels "Corner","CulDSac",..: 1 5 1 1 5 5 5 5 5 5 ...
##  $ Land_Slope        : Factor w/ 3 levels "Gtl","Mod","Sev": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Neighborhood      : Factor w/ 29 levels "North_Ames","College_Creek",..: 1 1 1 1 7 7 17 17 17 7 .
##  $ Condition_1       : Factor w/ 9 levels "Artery","Feedr",..: 3 2 3 3 3 3 3 3 3 3 ...
##  $ Condition_2       : Factor w/ 8 levels "Artery","Feedr",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ Bldg_Type         : Factor w/ 5 levels "OneFam","TwoFmCon",..: 1 1 1 1 1 1 5 5 5 1 ...
##  $ House_Style       : Factor w/ 8 levels "One_and_Half_Fin",..: 3 3 3 3 8 8 3 3 3 8 ...
##  $ Overall_Cond      : Factor w/ 10 levels "Very_Poor","Poor",..: 5 6 6 5 5 6 5 5 5 5 ...
##  $ Year_Built        : int [1:2930] 1960 1961 1958 1968 1997 1998 2001 1992 1995 1999 ...
##  $ Year_Remod_Add    : int [1:2930] 1960 1961 1958 1968 1998 1998 2001 1992 1996 1999 ...
##  $ Roof_Style        : Factor w/ 6 levels "Flat","Gable",..: 4 2 4 4 2 2 2 2 2 2 ...
##  $ Roof_Matl         : Factor w/ 8 levels "ClyTile","CompShg",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ Exterior_1st      : Factor w/ 16 levels "AsbShng","AsphShn",..: 4 14 15 4 14 14 6 7 6 14 ...
##  $ Exterior_2nd      : Factor w/ 17 levels "AsbShng","AsphShn",..: 11 15 16 4 15 15 6 7 6 15 ...
##  $ Mas_Vnr_Type      : Factor w/ 5 levels "BrkCmn","BrkFace",..: 5 4 2 4 4 2 4 4 4 4 ...
##  $ Mas_Vnr_Area      : num [1:2930] 112 0 108 0 0 20 0 0 0 0 ...
##  $ Exter_Cond        : Factor w/ 5 levels "Excellent","Fair",..: 5 5 5 5 5 5 5 5 5 5 ...
```

```
##  $ Foundation        : Factor w/ 6 levels "BrkTil","CBlock",..: 2 2 2 2 3 3 3 3 3 3 ...
##  $ Bsmt_Cond         : Factor w/ 6 levels "Excellent","Fair",..: 3 6 6 6 6 6 6 6 6 6 ...
##  $ Bsmt_Exposure     : Factor w/ 5 levels "Av","Gd","Mn",..: 2 4 4 4 4 4 3 4 4 4 ...
##  $ BsmtFin_Type_1    : Factor w/ 7 levels "ALQ","BLQ","GLQ",..: 2 6 1 1 3 3 3 1 3 7 ...
##  $ BsmtFin_SF_1      : num [1:2930] 2 6 1 1 3 3 3 1 3 7 ...
##  $ BsmtFin_Type_2    : Factor w/ 7 levels "ALQ","BLQ","GLQ",..: 7 4 7 7 7 7 7 7 7 7 ...
##  $ BsmtFin_SF_2      : num [1:2930] 0 144 0 0 0 0 0 0 0 0 ...
##  $ Bsmt_Unf_SF       : num [1:2930] 441 270 406 1045 137 ...
##  $ Total_Bsmt_SF     : num [1:2930] 1080 882 1329 2110 928 ...
##  $ Heating           : Factor w/ 6 levels "Floor","GasA",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ Heating_QC        : Factor w/ 5 levels "Excellent","Fair",..: 2 5 5 1 3 1 1 1 1 3 ...
##  $ Central_Air       : Factor w/ 2 levels "N","Y": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Electrical        : Factor w/ 6 levels "FuseA","FuseF",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ First_Flr_SF      : int [1:2930] 1656 896 1329 2110 928 926 1338 1280 1616 1028 ...
##  $ Second_Flr_SF     : int [1:2930] 0 0 0 0 701 678 0 0 0 776 ...
##  $ Gr_Liv_Area       : int [1:2930] 1656 896 1329 2110 1629 1604 1338 1280 1616 1804 ...
##  $ Bsmt_Full_Bath    : num [1:2930] 1 0 0 1 0 0 1 0 1 0 ...
##  $ Bsmt_Half_Bath    : num [1:2930] 0 0 0 0 0 0 0 0 0 0 ...
##  $ Full_Bath         : int [1:2930] 1 1 1 2 2 2 2 2 2 2 ...
##  $ Half_Bath         : int [1:2930] 0 0 1 1 1 1 0 0 0 1 ...
##  $ Bedroom_AbvGr     : int [1:2930] 3 2 3 3 3 3 2 2 2 3 ...
##  $ Kitchen_AbvGr     : int [1:2930] 1 1 1 1 1 1 1 1 1 1 ...
##  $ TotRms_AbvGrd     : int [1:2930] 7 5 6 8 6 7 6 5 5 7 ...
##  $ Functional        : Factor w/ 8 levels "Maj1","Maj2",..: 8 8 8 8 8 8 8 8 8 8 ...
##  $ Fireplaces        : int [1:2930] 2 0 0 2 1 1 0 0 1 1 ...
##  $ Garage_Type       : Factor w/ 7 levels "Attchd","Basment",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ Garage_Finish     : Factor w/ 4 levels "Fin","No_Garage",..: 1 4 4 1 1 1 1 3 3 1 ...
##  $ Garage_Cars       : num [1:2930] 2 1 1 2 2 2 2 2 2 2 ...
##  $ Garage_Area       : num [1:2930] 528 730 312 522 482 470 582 506 608 442 ...
##  $ Garage_Cond       : Factor w/ 6 levels "Excellent","Fair",..: 6 6 6 6 6 6 6 6 6 6 ...
##  $ Paved_Drive       : Factor w/ 3 levels "Dirt_Gravel",..: 2 3 3 3 3 3 3 3 3 3 ...
##  $ Wood_Deck_SF      : int [1:2930] 210 140 393 0 212 360 0 0 237 140 ...
##  $ Open_Porch_SF     : int [1:2930] 62 0 36 0 34 36 0 82 152 60 ...
##  $ Enclosed_Porch    : int [1:2930] 0 0 0 0 0 0 170 0 0 0 ...
##  $ Three_season_porch: int [1:2930] 0 0 0 0 0 0 0 0 0 0 ...
##  $ Screen_Porch      : int [1:2930] 0 120 0 0 0 0 0 144 0 0 ...
##  $ Pool_Area         : int [1:2930] 0 0 0 0 0 0 0 0 0 0 ...
##  $ Pool_QC           : Factor w/ 5 levels "Excellent","Fair",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ Fence             : Factor w/ 5 levels "Good_Privacy",..: 5 3 5 5 3 5 5 5 5 5 ...
##  $ Misc_Feature      : Factor w/ 6 levels "Elev","Gar2",..: 3 3 2 3 3 3 3 3 3 3 ...
##  $ Misc_Val          : int [1:2930] 0 0 12500 0 0 0 0 0 0 0 ...
##  $ Mo_Sold           : int [1:2930] 5 6 6 4 3 6 4 1 3 6 ...
##  $ Year_Sold         : int [1:2930] 2010 2010 2010 2010 2010 2010 2010 2010 2010 2010 ...
##  $ Sale_Type         : Factor w/ 10 levels "COD","Con","ConLD",..: 10 10 10 10 10 10 10 10 10 10 ...
##  $ Sale_Condition    : Factor w/ 6 levels "Abnorml","AdjLand",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ Sale_Price        : int [1:2930] 215000 105000 172000 244000 189900 195500 213500 191500 236500 18
##  $ Longitude         : num [1:2930] -93.6 -93.6 -93.6 -93.6 -93.6 ...
##  $ Latitude          : num [1:2930] 42.1 42.1 42.1 42.1 42.1 ...
```

Table: Ames Housing Dataset

|| || || ||

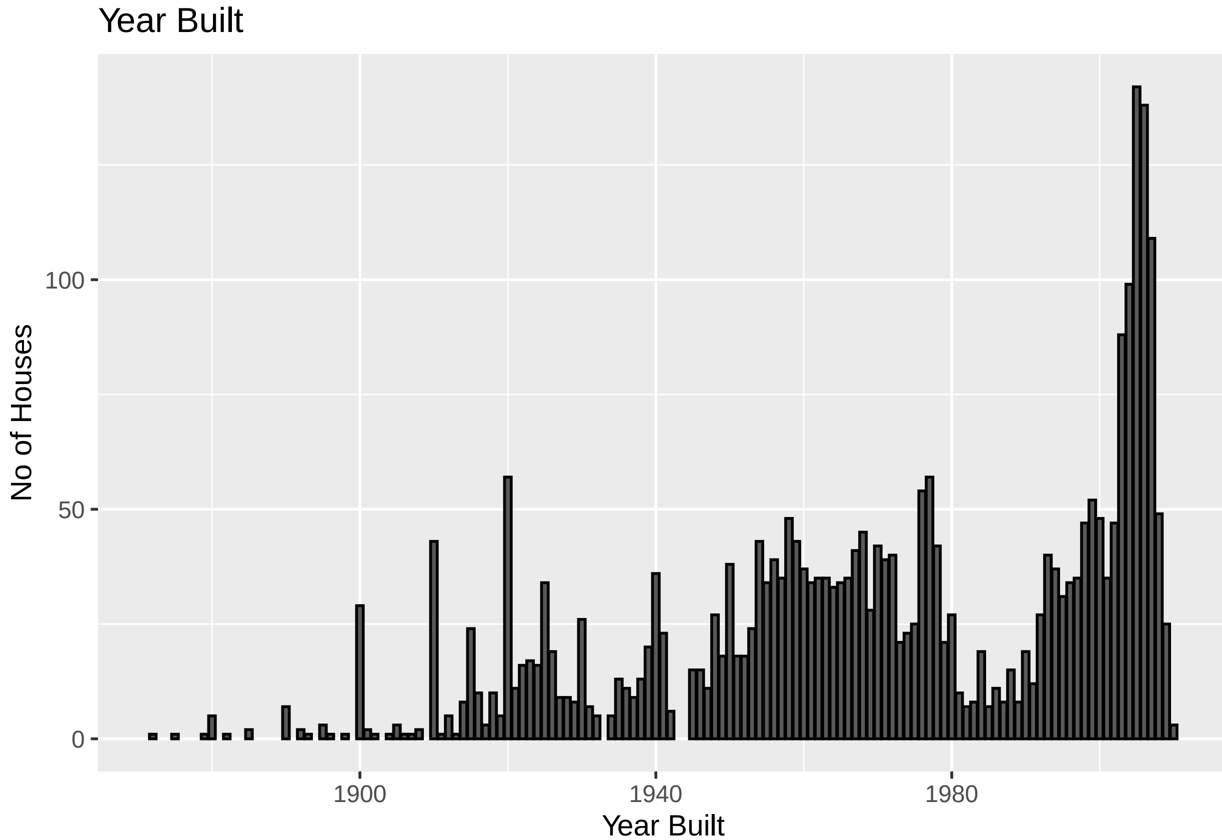


Sale Price Observation The Sale Price is right-skewed

```
##
## Sale Price skewness : 1.742607
```

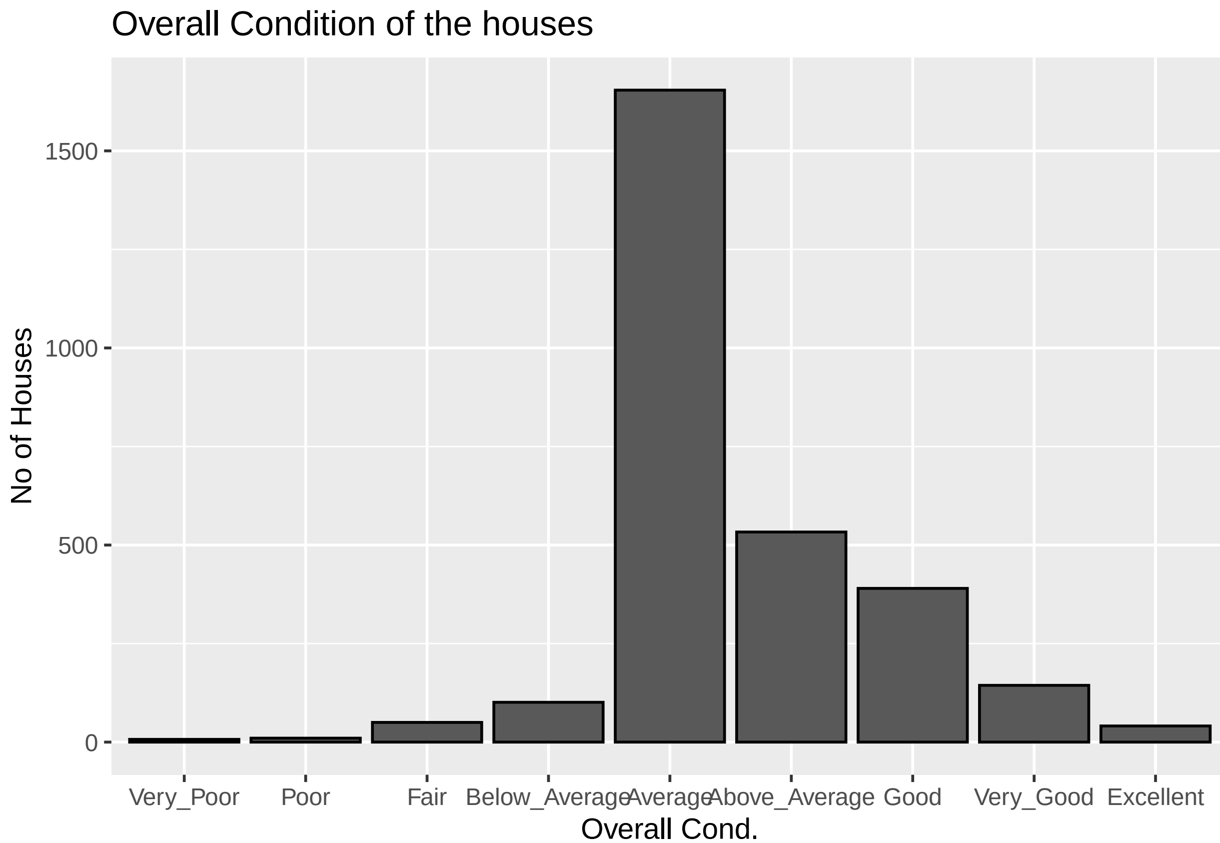
```
##
## Sale Price kurtosis : 8.108122
```

Age of the Building



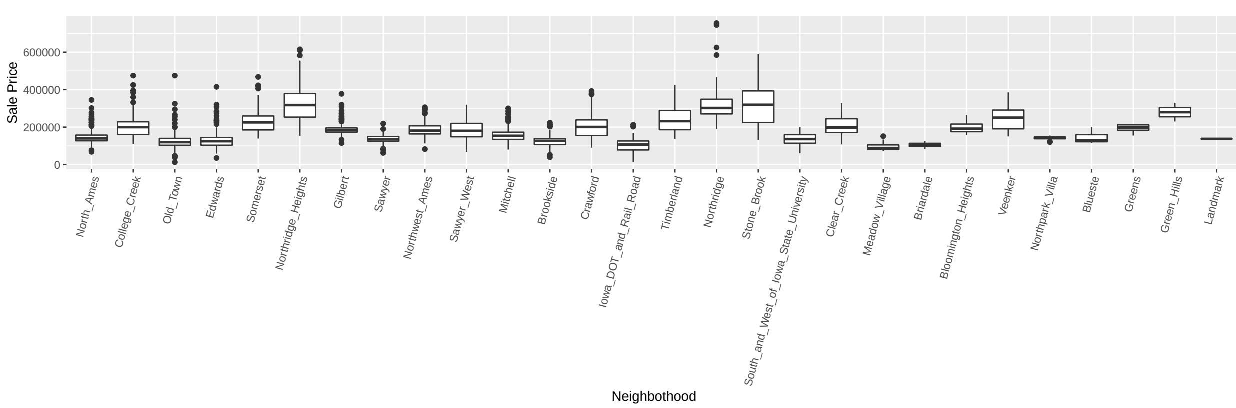
It looks that we have more houses were built at the begining of 2000

Condition of the houses



House condition - most of the houses are of average condition

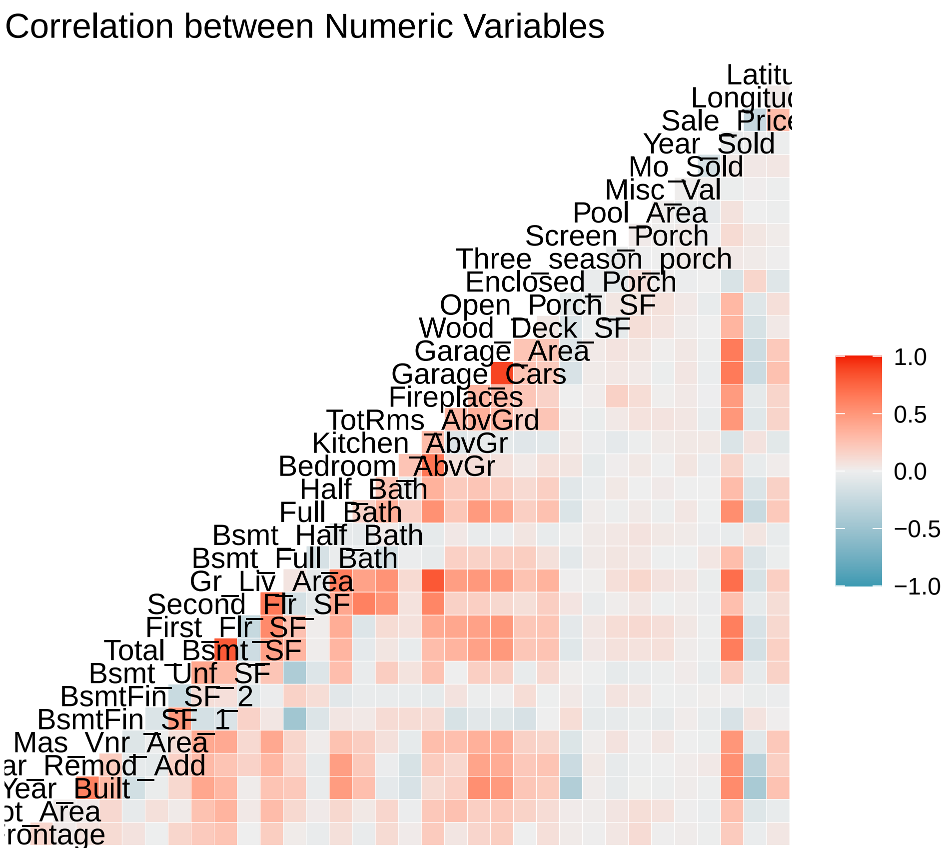
Neighborhood and House Price



House Price varies with the neighborhood with few outliers by neighborhood. Also, the median house price by neighborhood is roughly between 200,000 and 400,000. It seems Neighborhood would have some impact on housing price.

Correlation between Sale Price and other variables

Correlation between numeric variables



There are some high correlations between variables mostly positive but with some negative. I did further analysis and added pairwise correlation between other numeric variables and sales price.

Correlation of Sales Price with other numeric variables

Table 3: Ames Housing Dataset - correlated numeric variables with the Sale Price

	x
Lot_Frontage	0.2018745
Lot_Area	0.2665492
Year_Built	0.5584261
Year_Remod_Add	0.5329738
Mas_Vnr_Area	0.5021960
BsmtFin_SF_1	-0.1349055
BsmtFin_SF_2	0.0060176
Bsmt_Unf_SF	0.1833076
Total_Bsmt_SF	0.6325288
First_Flr_SF	0.6216761
Second_Flr_SF	0.2693734

	x
Gr_Liv_Area	0.7067799
Bsmt_Full_Bath	0.2758227
Bsmt_Half_Bath	-0.0358166
Full_Bath	0.5456039
Half_Bath	0.2850560
Bedroom_AbvGr	0.1439134
Kitchen_AbvGr	-0.1198137
TotRms_AbvGrd	0.4954744
Fireplaces	0.4745581
Garage_Cars	0.6475616
Garage_Area	0.6401383
Wood_Deck_SF	0.3271432
Open_Porch_SF	0.3129505
Enclosed_Porch	-0.1287874
Three_season_porch	0.0322246
Screen_Porch	0.1121512
Pool_Area	0.0684032
Misc_Val	-0.0156915
Mo_Sold	0.0352588
Year_Sold	-0.0305691
Sale_Price	1.0000000
Longitude	-0.2513973
Latitude	0.2908914

Thus, I identified variables which has higher correlations (correlation > 0.5 and < - 0.2)

I also looked at some non-numeric variables and their relatins with the Sale Price

Correlation of Sales Price with non-numeric variables

Table 4: Ames Housing Dataset - correlated non-numeric variables with the Sale Price

	x
MS_SubClass	-0.0347748
MS_Zoning	-0.3064225
Street	0.0595193
Alley	0.1088436
Lot_Shape	0.3026647
Land_Contour	-0.0693388
Utilities	-0.0310365
Lot_Config	-0.0587875
Land_Slope	0.0685534
Neighborhood	0.1575002
Condition_1	0.1590773
Condition_2	0.1048063
Bldg_Type	-0.0952280
House_Style	0.2310546
Overall_Cond	-0.1635790
Roof_Style	0.2546450
Roof_Matl	0.0720760

	x
Exterior_1st	0.0550217
Exterior_2nd	0.0535448
Mas_Vnr_Type	-0.0763142
Exter_Cond	0.1206939
Foundation	0.4579558
Bsmt_Cond	0.1095363
Bsmt_Exposure	-0.3519094
BsmtFin_Type_1	-0.0975925
BsmtFin_Type_2	0.1074020
Heating	-0.0728977
Heating_QC	-0.4426972
Central_Air	0.2645064
Electrical	0.2378218
Functional	0.1192451
Garage_Type	-0.4061833
Garage_Finish	-0.4494826
Garage_Cond	0.2750657
Paved_Drive	0.2749134
Pool_QC	-0.0919699
Fence	0.1745827
Misc_Feature	-0.0574683
Sale_Type	-0.1845079
Sale_Condition	0.3330831

Looking at the non-numeric variable, I identified few variables which are highly correlated -

MS_Zoning, Lot_Shape, Foundation, Sale_Condition , Garage_Finish, House_Style, Heating_QC,

#Feature Engineering and additional visualizations

Created a variable total_area = First_Flr_SF + Second_Flr_SF + Total_Bsmt_SF

Created a variable total_Bathroom = Full_Bath + Bsmt_Full_Bath + 0.5* Half_Bath+ 0.5 * Bsmt_Half_Bath

Created a variable sales_price_T = sale_Price_T

Created a variable orarall_Condition_n a numeric representation of overall_Condition

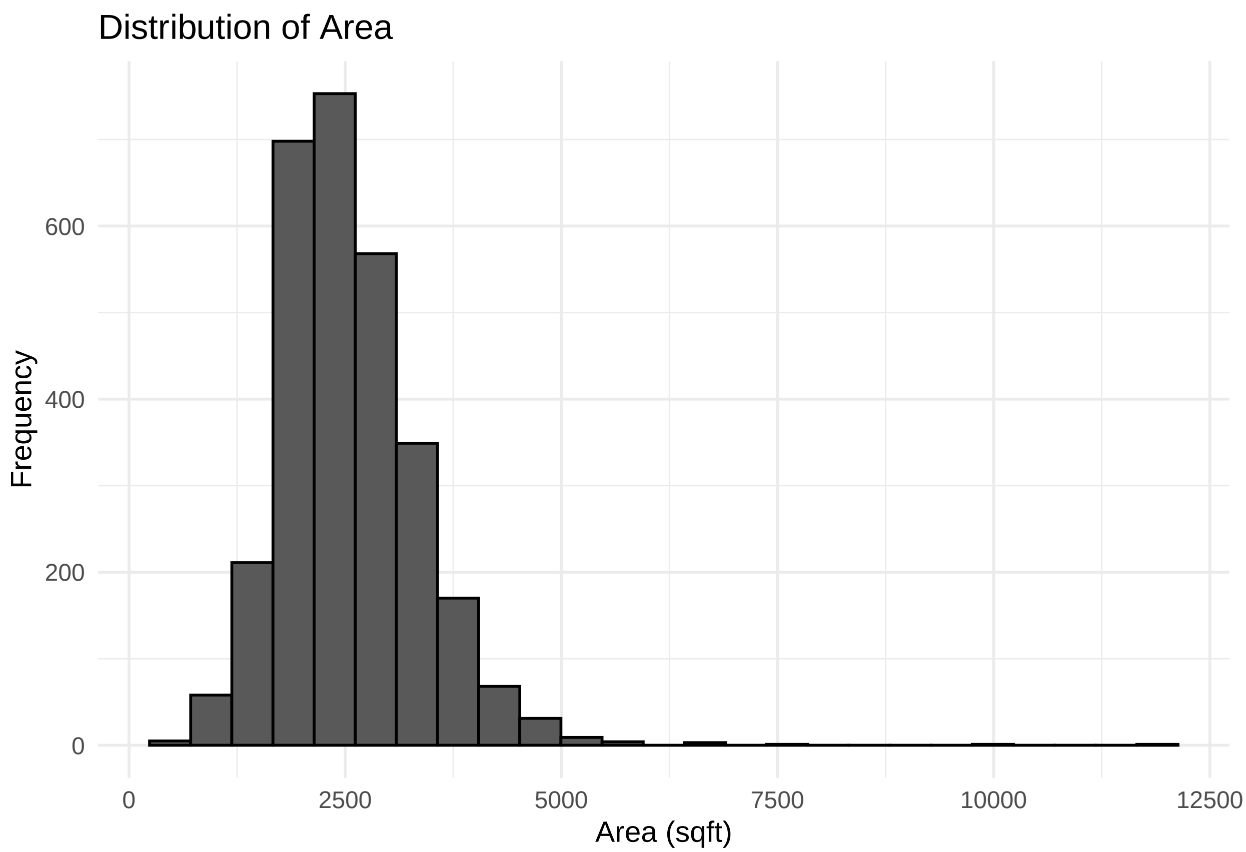
Created a variable house_Age = year_Sold - year_Build

```
##
## Corelation between Total Area and Sale Price : 0.7931272
```

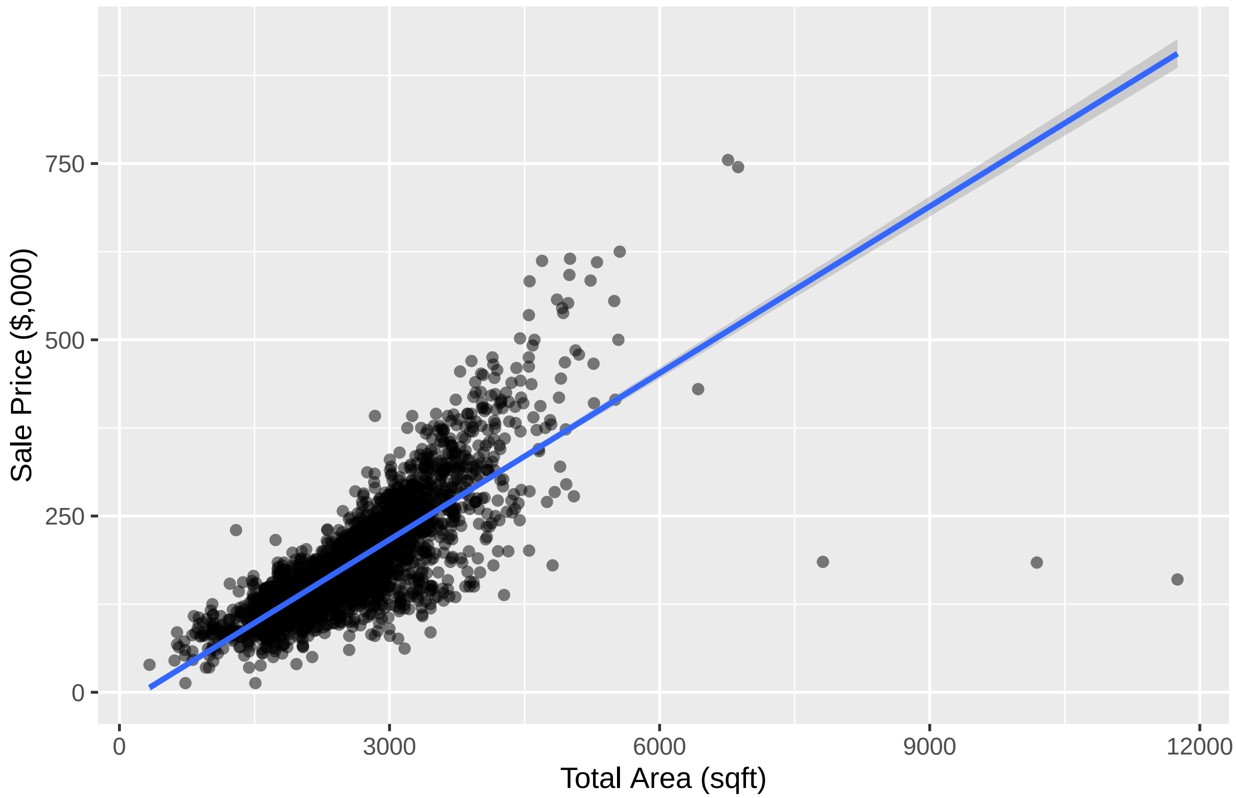
```
##
## Corelation between Total Bathroom and Sale Price : 0.636175
```

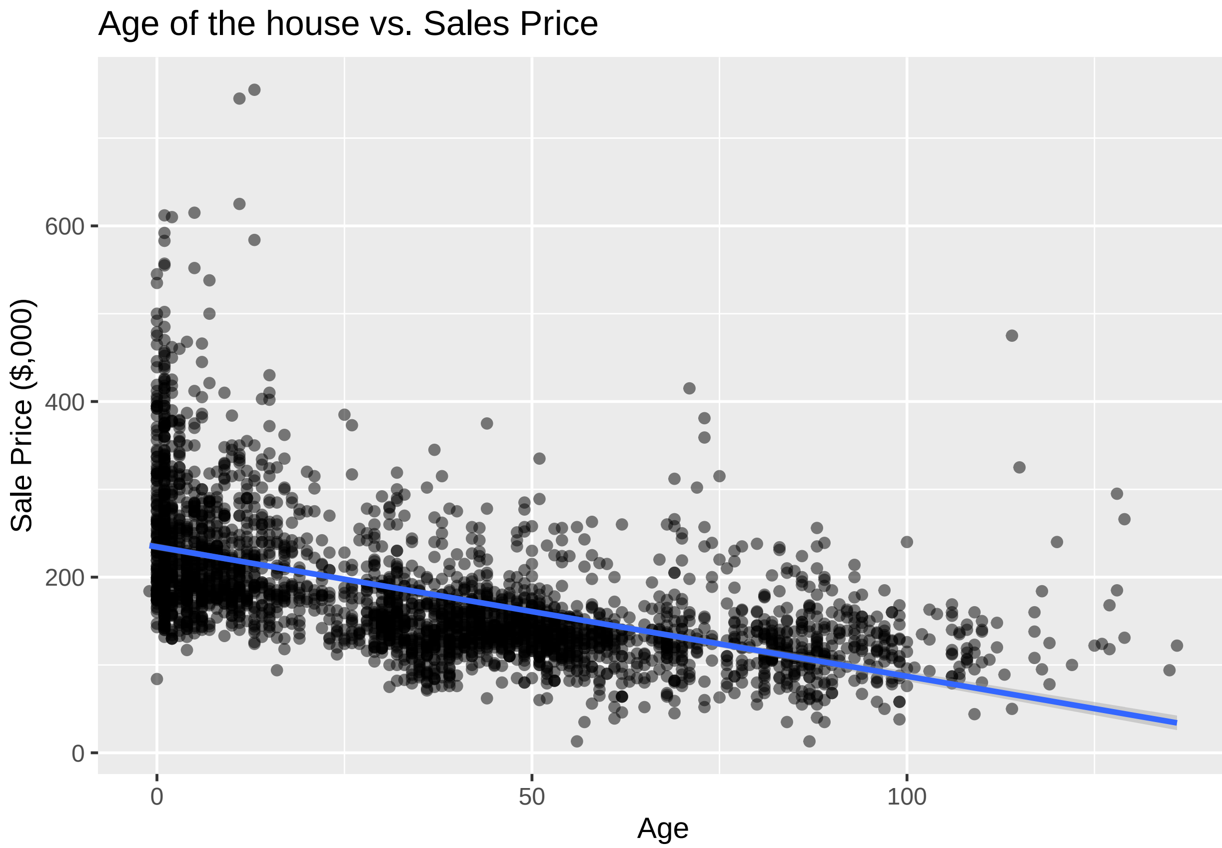
```
##
## Corelation between Age of House and Sale Price : -0.5589068
```

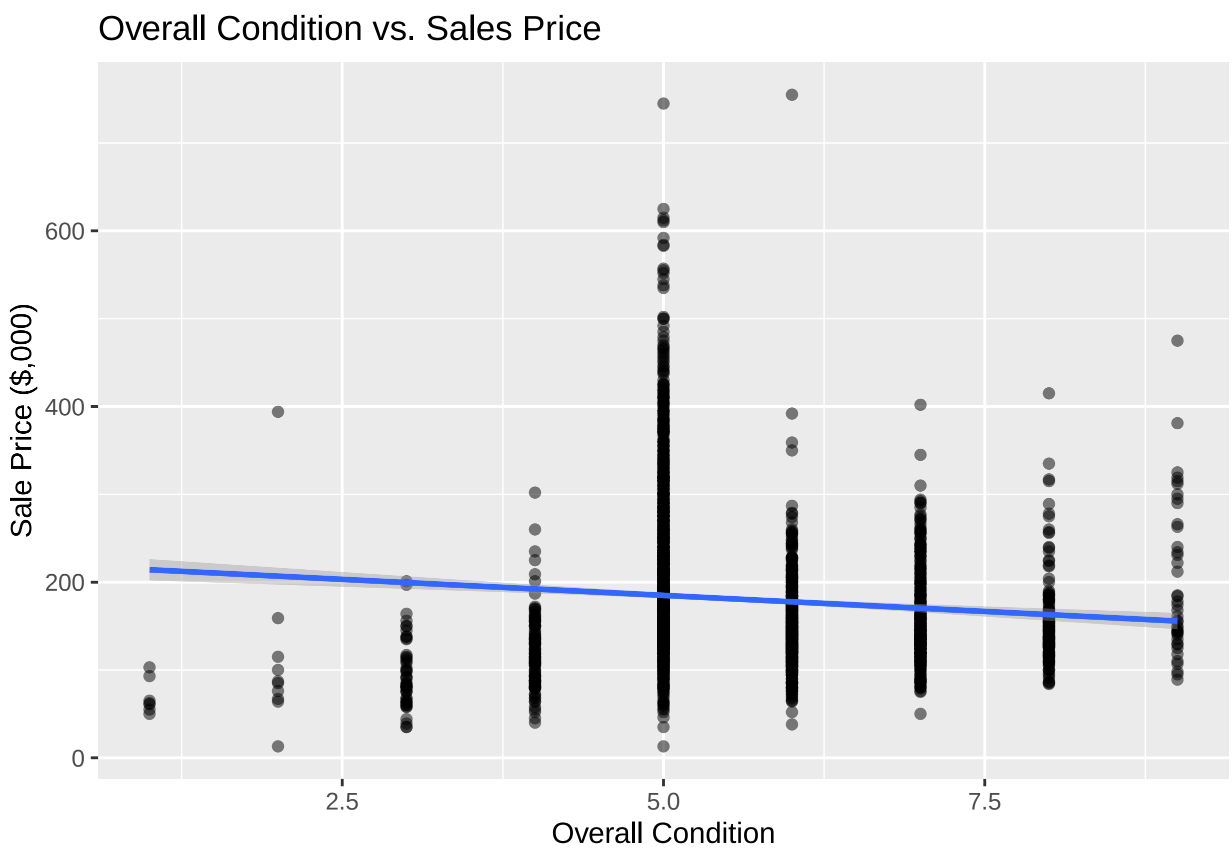
```
##
## Corelation between Overall Condition and Sale Price : -0.1016969
```



Total Area vs. Sales Price




Age of the house vs. Sales Price
Sale Price ($,000)
600
400
200
0
0
50
100
Age



Looking at the negative correlation between overall condition of the house and sales price I felt that there is something incorrect about the data. I excluded the overall condition from the final parameter set # Create Final Set with Parameters ## Numeric - Sale_Price_T,total_Area, Gr_Liv_Area, house_Age, total_Bathroom ,Garage_Cars,Garage_Area, Year_Remod_Add, Mas_Vnr_Area, ## Non-Numeric - House Attributes - Lot_Shape, Foundation, Sale_Condition , Garage_Finish, House_Style, Heating_QC, External Attributes - MS_Zoning, Neighborhood

```
ames <- ames %>% select (Sale_Price_T,total_Area, Gr_Liv_Area, house_Age, total_Bathroom ,Garage_Cars,Ga
                         Year_Remod_Add, Mas_Vnr_Area,  Lot_Shape, Foundation, Sale_Condition , Garage_
```

Create Test Set and Training set for building Linear Models

test set will be 20% of housing_data data

Table 5: Ames Housing Dataset dimension

x
2930
17

Table 6: Ames Housing Dataset

Sale_Price	Total_Area	Gr_Liv_Area	House_Age	Total_Bathroom	Garage_Cars	Garage_Area	Year_Remod_Add	Mas_Vnr_Area	Lot_Shape	Foundation	Sale_Condition	Garage_Finish	House_Style	Heating_QC	MS_Zoning	Neighborhood
215	2736	1656	50	2.0	2	528	1960	112	Slightly_Irregular	CBlock	Normal	Fin	One_Story	Fair	Residential_Low_Density	North_Ames
105	1778	896	49	1.0	1	730	1961	0	Regular	CBlock	Normal	Unf	One_Story	Typical	Residential_High_Density	North_Ames
172	2658	1329	52	1.5	1	312	1958	108	Slightly_Irregular	CBlock	Normal	Unf	One_Story	Typical	Residential_Low_Density	North_Ames
244	4220	2110	42	3.5	2	522	1968	0	Regular	CBlock	Normal	Fin	One_Story	Excellent	Residential_Low_Density	North_Ames
190	2557	1629	13	2.5	2	482	1998	0	Slightly_Irregular	PConc	Normal	Fin	Two_Story	Good	Residential_Low_Density	Gilbert
196	2530	1604	12	2.5	2	470	1998	20	Slightly_Irregular	PConc	Normal	Fin	Two_Story	Excellent	Residential_Low_Density	Gilbert

Table 7: Ames Housing Dataset Summary

Sale_Price	total_Area	Gr_Liv_Area	House_Age	total_Bathroom	Garage_Cars	Garage_Area	Year_Remod_Add	Mas_Vnr_Area	Lot_Shape	Foundation	Sale_Condition	Garage_Finish	House_Style	Heating_QC	MS_Zoning	Neighborhood
Min. : 13.0	Min. : 334	Min. : 334	Min. : -1.00	Min. :1.000	Min. :0.000	Min. : 0.0	Min. :1950	Min. : 0.0	Regular :1859	BrkTil: 311	Abnorml: 190	Fin : 728	One_Story :1481	Excellent:1495	Floating_Village_Residential: 139	North_Ames : 443
1st Qu.:130.0	1st Qu.: 2000	1st Qu.:1126	1st Qu.: 7.00	1st Qu.:1.500	1st Qu.:1.000	1st Qu.: 320.0	1st Qu.:1965	1st Qu.: 0.0	Slightly_Irregular: 979	CBlock:1244	AdjLand: 12	No_Garage: 159	Two_Story : 873	Fair : 92	Residential_High_Density : 27	College_Creek : 267
Median :160.0	Median : 2450	Median :1442	Median : 34.00	Median :2.000	Median :2.000	Median : 480.0	Median :1993	Median : 0.0	Moderately_Irregular: 76	PConc :1310	Alloca : 24	RFn : 812	One_and_Half_Fin: 314	Good : 476	Residential_Low_Density :2273	Old_Town : 239
Mean :180.8	Mean : 2546	Mean :1500	Mean : 36.43	Mean :2.218	Mean :1.766	Mean : 472.7	Mean :1984	Mean : 101.1	Irregular : 16	Slab : 49	Family : 46	Unf :1231	SLvl : 128	Poor : 3	Residential_Medium_Density: 462	Edwards : 194
3rd Qu.:214.0	3rd Qu.: 2990	3rd Qu.:1743	3rd Qu.: 54.00	3rd Qu.:2.500	3rd Qu.:2.000	3rd Qu.: 576.0	3rd Qu.:2004	3rd Qu.: 162.8	NA	Stone : 11	Normal :2413	NA	SFoyer : 83	Typical : 864	A_agr : 2	Somerset : 182
Max. :755.0	Max. :11752	Max. :5642	Max. :136.00	Max. :7.000	Max. :5.000	Max. :1488.0	Max. :2010	Max. :1600.0	NA	Wood : 5	Partial: 245	NA	Two_and_Half_Unf: 24	NA	C_all : 25	Northridge_Heights: 166
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	(Other) : 27	NA	I_all : 2	(Other) :1439

House Price Prediction Model - develop, train and test

#Average House Price

Build Linear Models

I started with linear model and some selected set of parameters/attributes and evaluated the performaces of the models use RMSE. In the first Linear Model we used “Age of the House” and “Total Bathroom” I enhanced the model and added “Age of the House”, Garage_Cars + Garage_Area + Year_Remod_Add + Mas_Vnr_Area

```
##
## Naive RMSE in ,000 : 75.25
```

```
##
## Call:
## lm(formula = Sale_Price_T ~ total_Area + total_Bathroom, data = .)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -665.48  -20.32    0.26   19.33  262.67
##
## Coefficients:
##                  Estimate Std. Error t value            Pr(>|t|)
## (Intercept)    -36.153333   3.350986  -10.79 <0.0000000000000002 ***
## total_Area       0.064023   0.001504   42.57 <0.0000000000000002 ***
## total_Bathroom  24.275518   1.511957   16.06 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 46.98 on 2340 degrees of freedom
## Multiple R-squared:  0.6639, Adjusted R-squared:  0.6636
## F-statistic:  2311 on 2 and 2340 DF,  p-value: < 0.00000000000000022
```

method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694

```
## [1] 37.2129
```

```
## # A tibble: 8 x 7
##   term             estimate std.error statistic   p.value   conf.low  conf.high
##   <chr>               <dbl>     <dbl>     <dbl>     <dbl>      <dbl>      <dbl>
## 1 (Intercept)    -1191.      89.8        -13.3  5.23e- 39 -1367.     -1015.
## 2 total_Area         0.0482   0.00132     36.4  7.89e-240     0.0456     0.0508
## 3 total_Bathroom     8.91     1.27         7.04 2.42e- 12     6.43      11.4
## 4 house_Age         -0.259    0.0344      -7.52 7.12e- 14    -0.326     -0.191
## 5 Garage_Cars       10.7      2.21         4.85 1.28e-  6     6.38      15.0
## 6 Garage_Area        0.0299   0.00765      3.91 9.63e-  5     0.0149     0.0448
## 7 Year_Remod_Add     0.605    0.0453      13.3  1.66e- 39     0.516      0.694
## 8 Mas_Vnr_Area       0.0526   0.00471     11.2  1.87e- 28     0.0434     0.0619
```

```
##
## Call:
## lm(formula = Sale_Price_T ~ total_Area + total_Bathroom + house_Age +
##     Garage_Cars + Garage_Area + Year_Remod_Add + Mas_Vnr_Area,
##     data = .)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -575.71  -18.74   -2.99   16.13  303.73
##
## Coefficients:
##                    Estimate   Std. Error t value             Pr(>|t|)
## (Intercept)    -1190.960356    89.821434 -13.259 < 0.0000000000000002 ***
```

```
## total_Area         0.048175     0.001323  36.424 < 0.0000000000000002 ***
## total_Bathroom     8.911990     1.266223   7.038   0.0000000000024160 ***
## house_Age         -0.258834     0.034409  -7.522   0.0000000000000712 ***
## Garage_Cars       10.711467     2.207507   4.852   0.0000012844482347 ***
## Garage_Area        0.029857     0.007646   3.905   0.0000962703710742 ***
## Year_Remod_Add     0.604965     0.045316  13.350 < 0.0000000000000002 ***
## Mas_Vnr_Area       0.052626     0.004706  11.182 < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.37 on 2922 degrees of freedom
## Multiple R-squared:  0.7578, Adjusted R-squared:  0.7572
## F-statistic:  1306 on 7 and 2922 DF,  p-value: < 0.00000000000000022
```

method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694
Model based on Numeric attributes of the dataset in ,000	37.21290

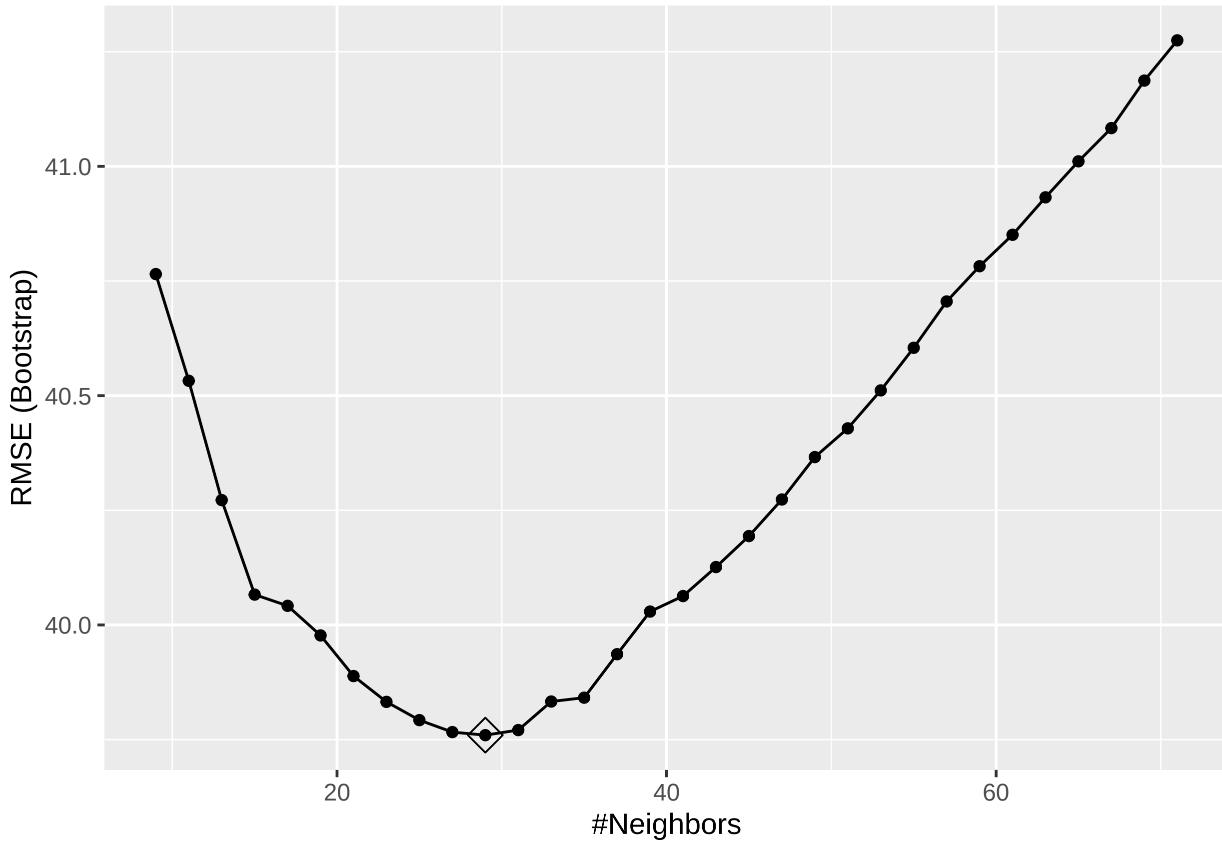
With linear model and with a set of attributes I was able to tune the model and reduce RMSE.

Non-linear Models

I wanted to further tune the model and enhance the accuracy. I planned to use "kNN", "Classification and regression trees (CART)" and Random Forrest. I added the non-linear parameters with the linear ones. Some of the non-linear ones are attributes of the house and some are external External attributes - Zoning and Neighborhood

k Nearest Neighbor (kNN) Model

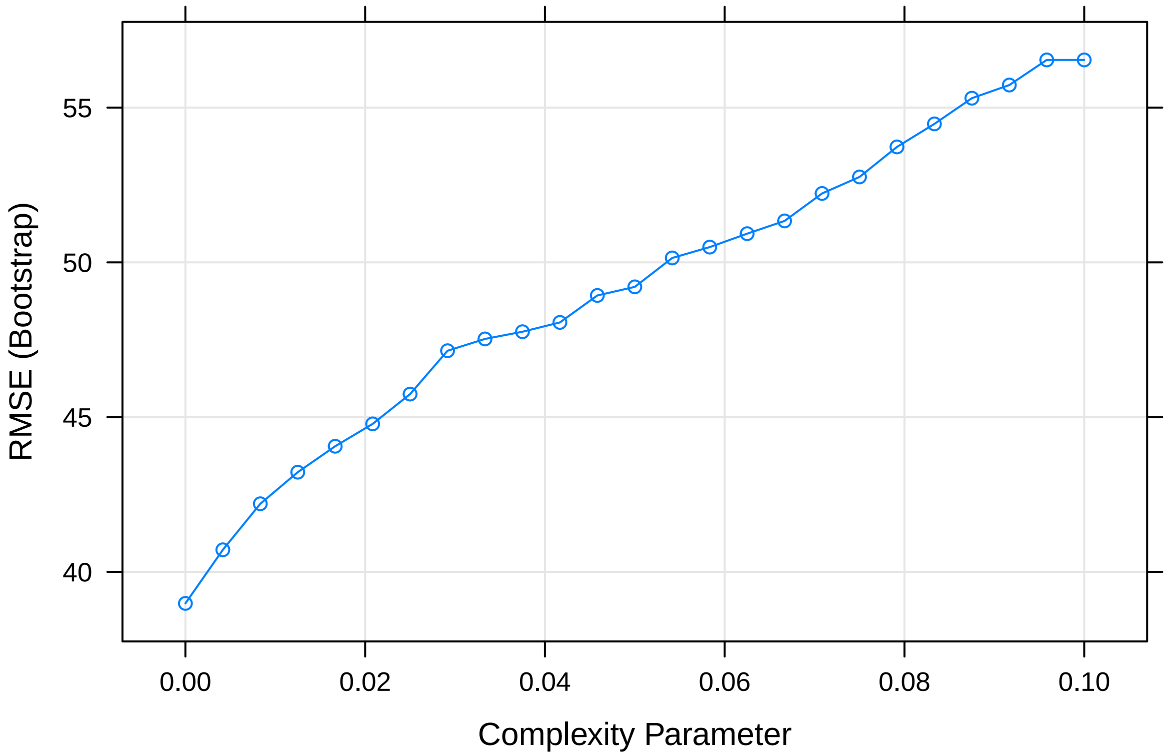
```
##             Length Class      Mode
## learn        2     -none-     list
## k            1     -none-     numeric
## theDots      0     -none-     list
## xNames      69     -none-     character
## problemType  1     -none-     character
## tuneValue    1     data.frame list
## obsLevels    1     -none-     logical
## param        0     -none-     list
```



method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694
Model based on Numeric attributes of the dataset in ,000	37.21290
Knn Model in ,000	36.67178

Next I am using Classification and regression trees (CART) model to see whether it reduces the RMSE value # Using Model - Classification and regression trees (CART)

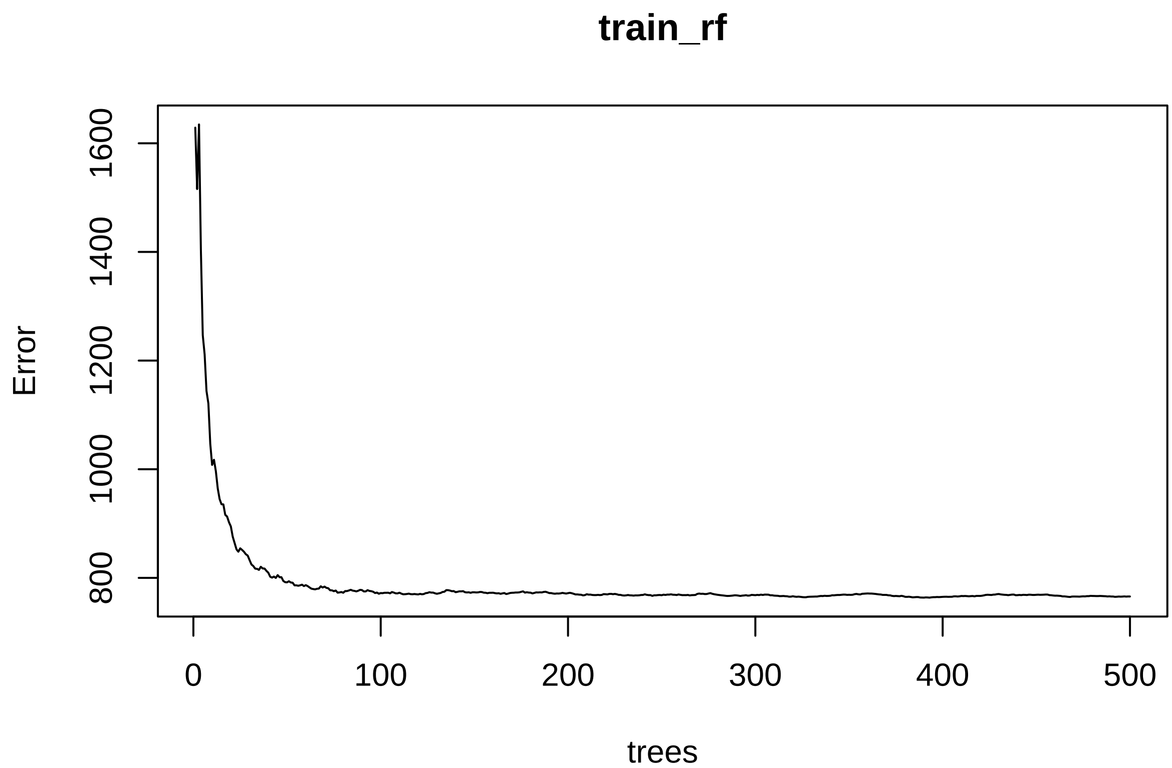
```
# fit a classification tree and plot it
train_rpart <- train(Sale_Price_T ~ .,
                     method = "rpart",
                     tuneGrid = data.frame(cp = seq(0.0, 0.1, len = 25)),
                     data = train_set)
plot(train_rpart)
```




```r
#predict(train_rpart, test_set)

y_hat <- round(predict(train_rpart, test_set))


# Calculate RMSE based on Classification and regression trees (CART)
model_rmse <- RMSE(test_set$Sale_Price_T,y_hat)

rmse_results <- bind_rows(rmse_results,
                          tibble(method="Classification and regression trees (CART) Model in ,000",
                                 RMSE = model_rmse ))
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694
Model based on Numeric attributes of the dataset in ,000	37.21290
Knn Model in ,000	36.67178
Classification and regression trees (CART) Model in ,000	33.30301

#Random Forrest -



method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694
Model based on Numeric attributes of the dataset in ,000	37.21290
Knn Model in ,000	36.67178
Classification and regression trees (CART) Model in ,000	33.30301
Random Forrest in ,000	24.75728

I got the best result when I used the Classification and regression trees (CART). I wanted to use the Confusion Matrix to calculate the accuracy for in the case of kNN and Classification and regression trees (CART). But because Sale Price is a continuous variable, I could not use Confusion Matrix function directly. When I converted Sale Price (both predicted and original) into factor, I got extremely low accuracy. After doing further research I found out that this is not a ideal situation to use Confusion Matrix to calculate the accuracy.

Final Result and improvements over time

RMSEs over Model

method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694

method	RMSE
Model based on Numeric attributes of the dataset in ,000	37.21290
Knn Model in ,000	36.67178
Classification and regression trees (CART) Model in ,000	33.30301
Random Forrest in ,000	24.75728

Conclusion

To build the House Price Prediction model I started with building Linear model with a set of numeric variables. I identified those variables by observing strong correlation with the "Sale Price" ## Parameters used in the Linear Model Sale_Price_T,total_Area, Gr_Liv_Area, house_Age, total_Bathroom ,Garage_Cars,Garage_Area, Year_Remod_Add, Mas_Vnr_Area I used RMSE to calculate the efficiency

Next to reduce th error margin , I looked at three other Models kNN, Classification and regression trees (CART) and Random Forrest. I identified some non-numeric attributes looking at their correlation with the Sale Price ## Non-Numeric - House Attributes - Lot_Shape, Foundation, Sale_Condition , Garage_Finish, House_Style, Heating_QC, External Attributes - MS_Zoning, Neighborhood

Finally with Random Forrest Model I got the lowest RMSE.

I am sure doing some additional Feature Engineering and combining more than one models I will be able to build a better House Prediction Model.

Reference -

Introduction to Data Science by Rafael A. Irizarry

https://jse.amstat.org/v19n3/decock.pdf - Ames, Iowa: Alternative to the Boston Housing Data as an End of Semester Regression Project - Dean De Cock

https://modeldata.tidymodels.org/reference/ames.html - Ames Housing Data

https://www.investopedia.com