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

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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

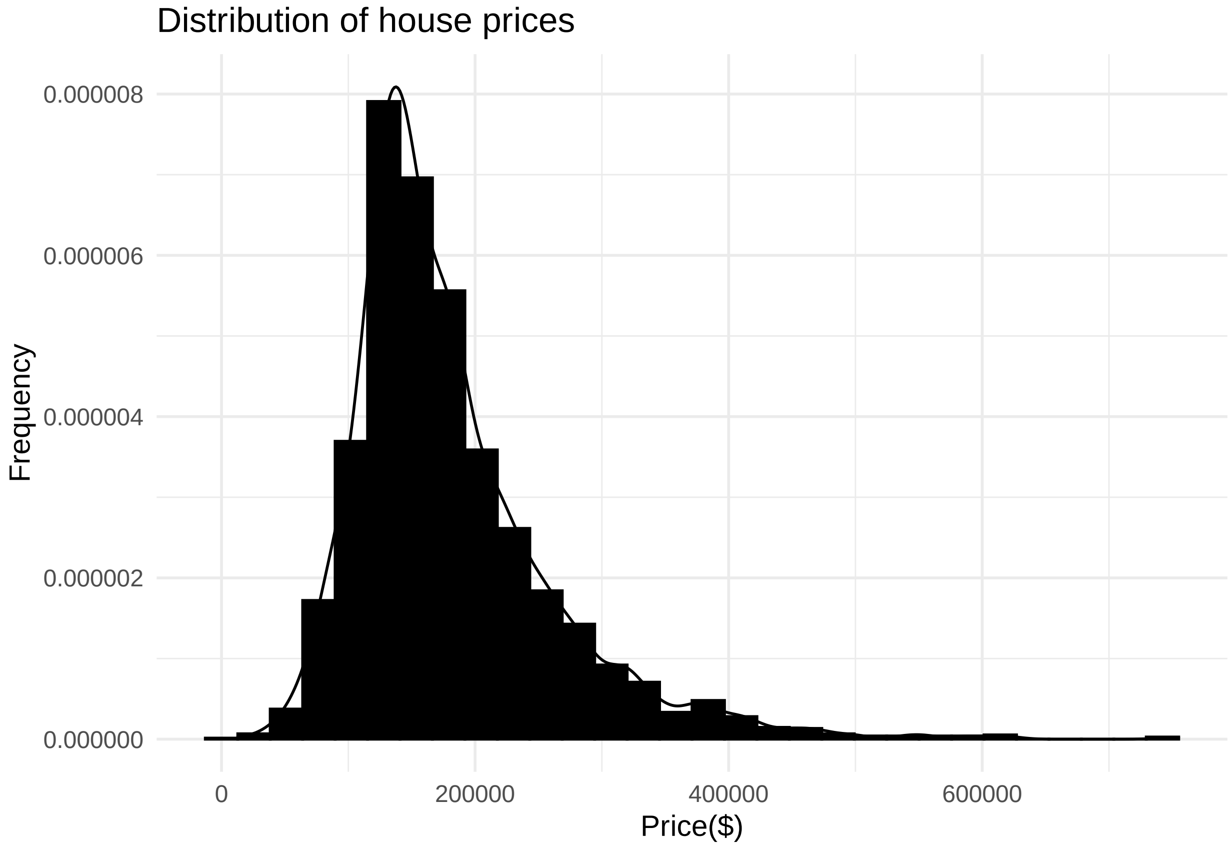
Table 1: Ames Housing Dataset dimension

x
2930
74

```
## 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

|| || || ||



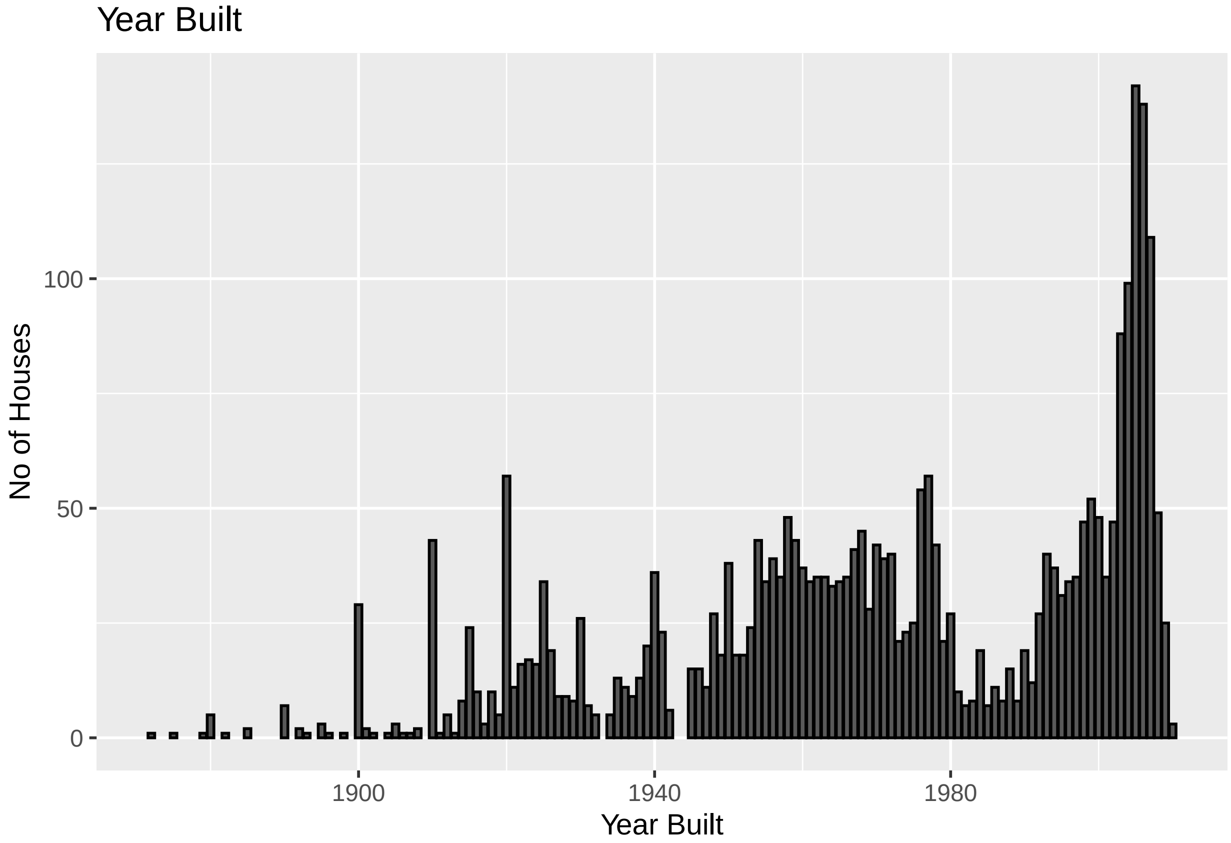
```
##
## Sale Price skewness : 1.742607
```

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

Sale Price Observation

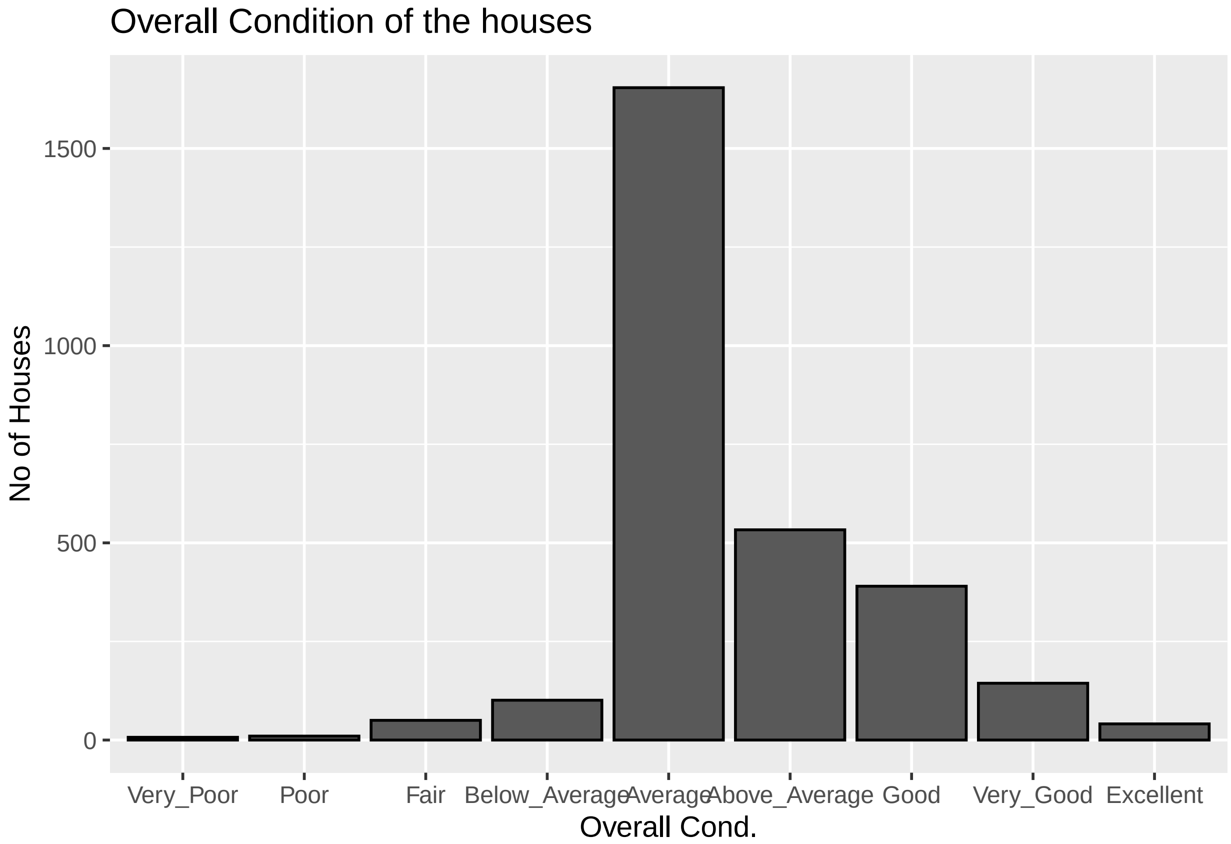
The Sale Price is right-skewed

Age of the Building



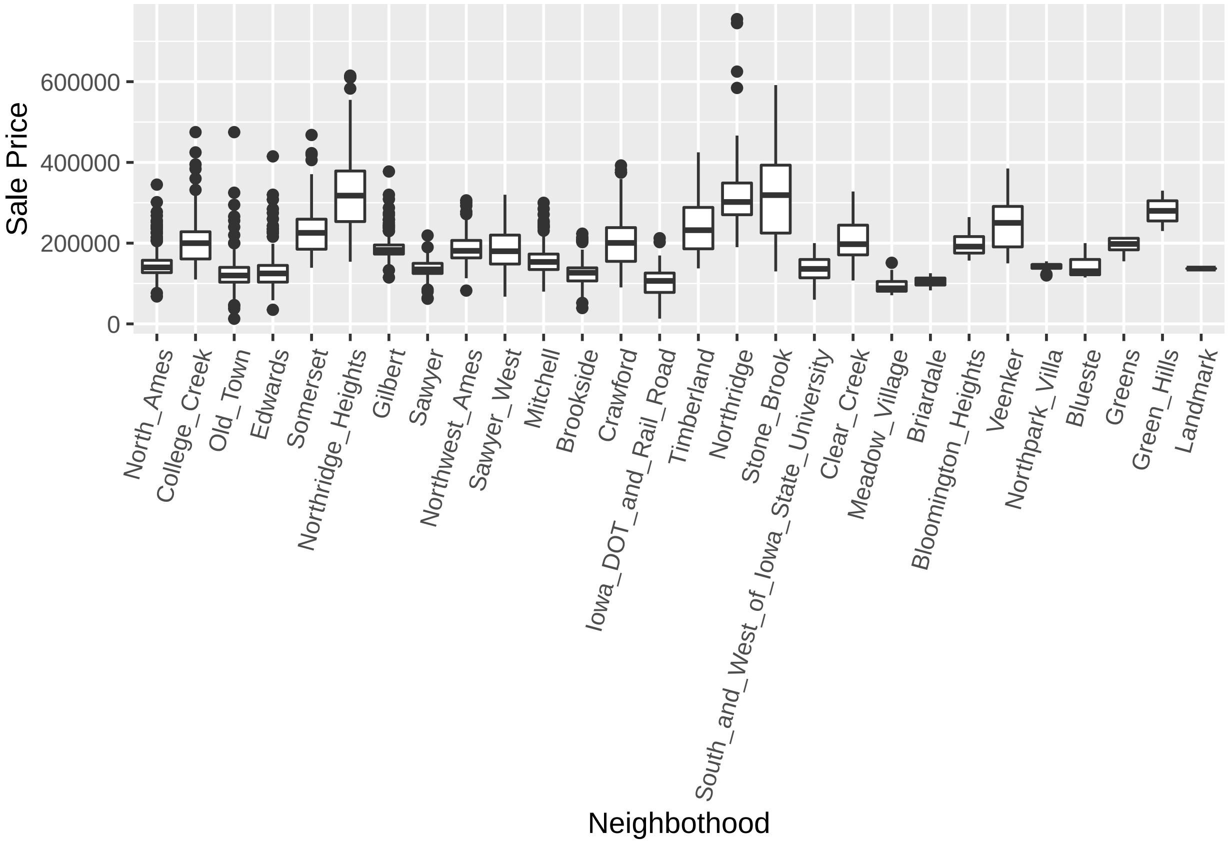
## It looks that we have more houses were built at the begining of 2000

Condition of the houses



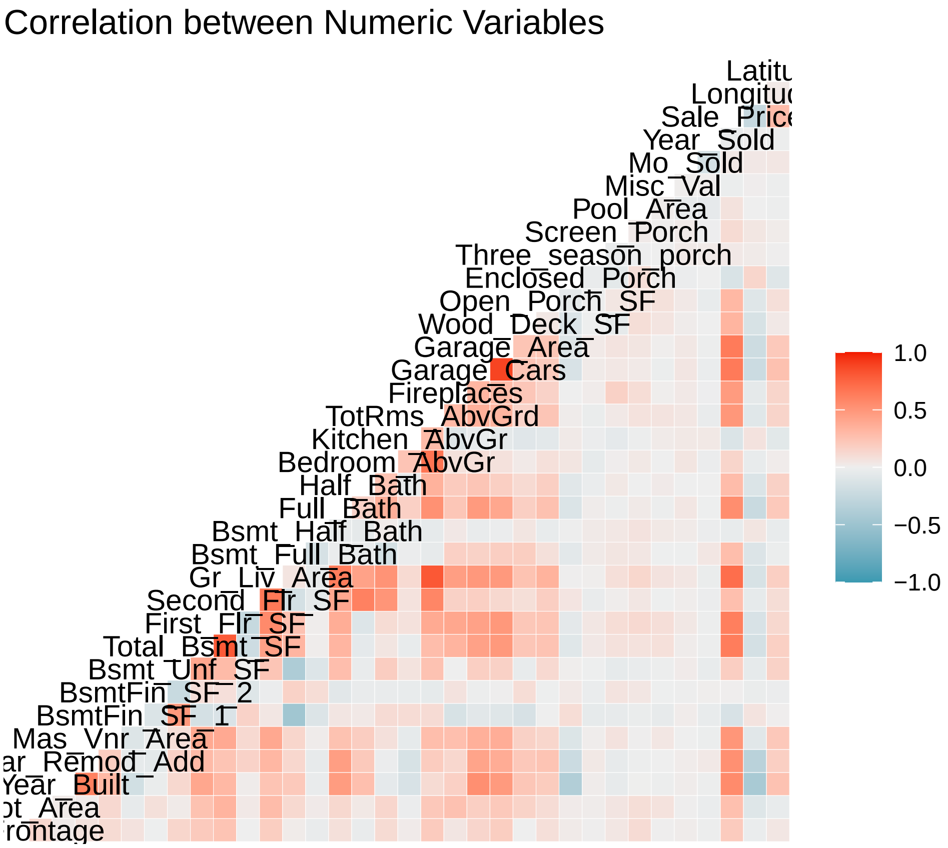
## House condition - most of the houses are of average condition

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

Table 2: 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
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

	x
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

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

Table 3: 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
Exterior_1st	0.0550217
Exterior_2nd	0.0535448
Mas_Vnr_Type	-0.0763142
Exter_Cond	0.1206939
Foundation	0.4579558
Bsmt_Cond	0.1095363

	x
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

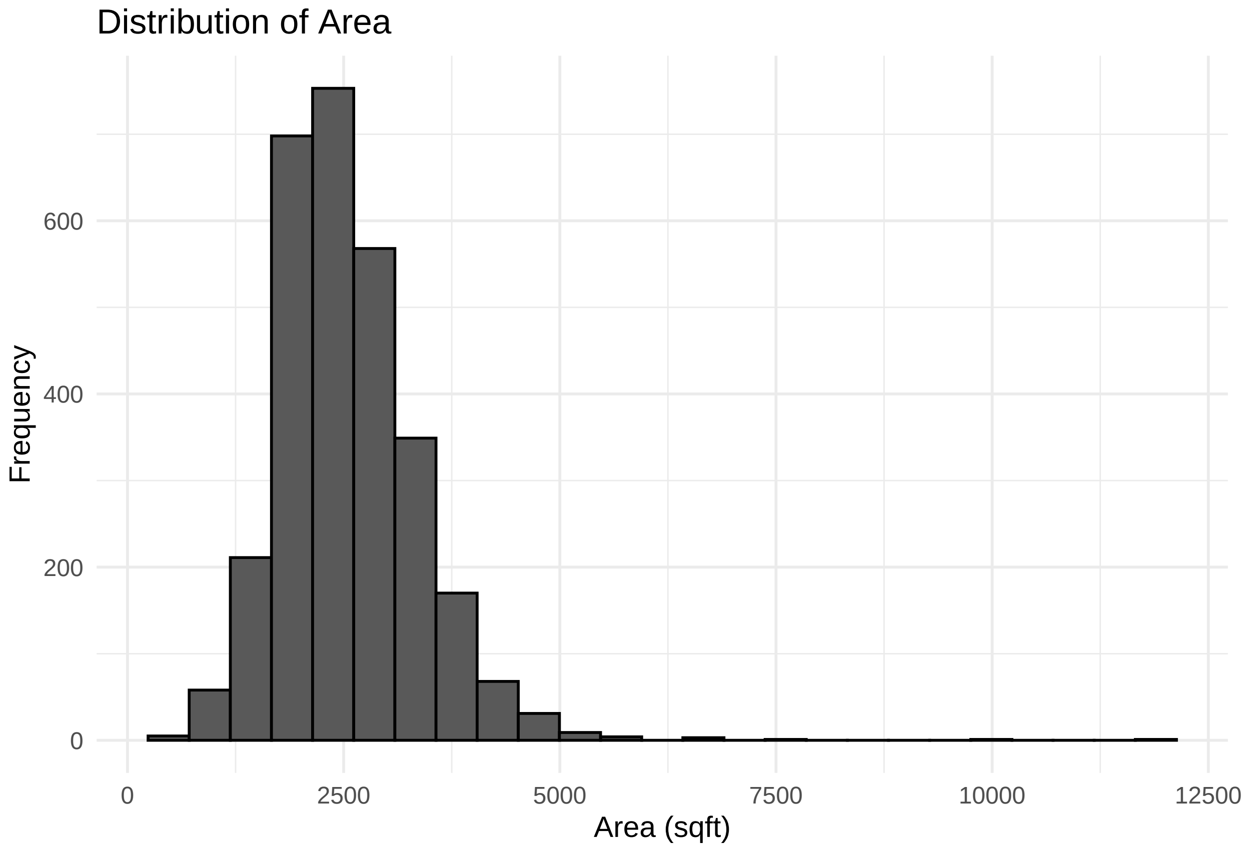
Created a variable house_Age = year_Sold - year_Build

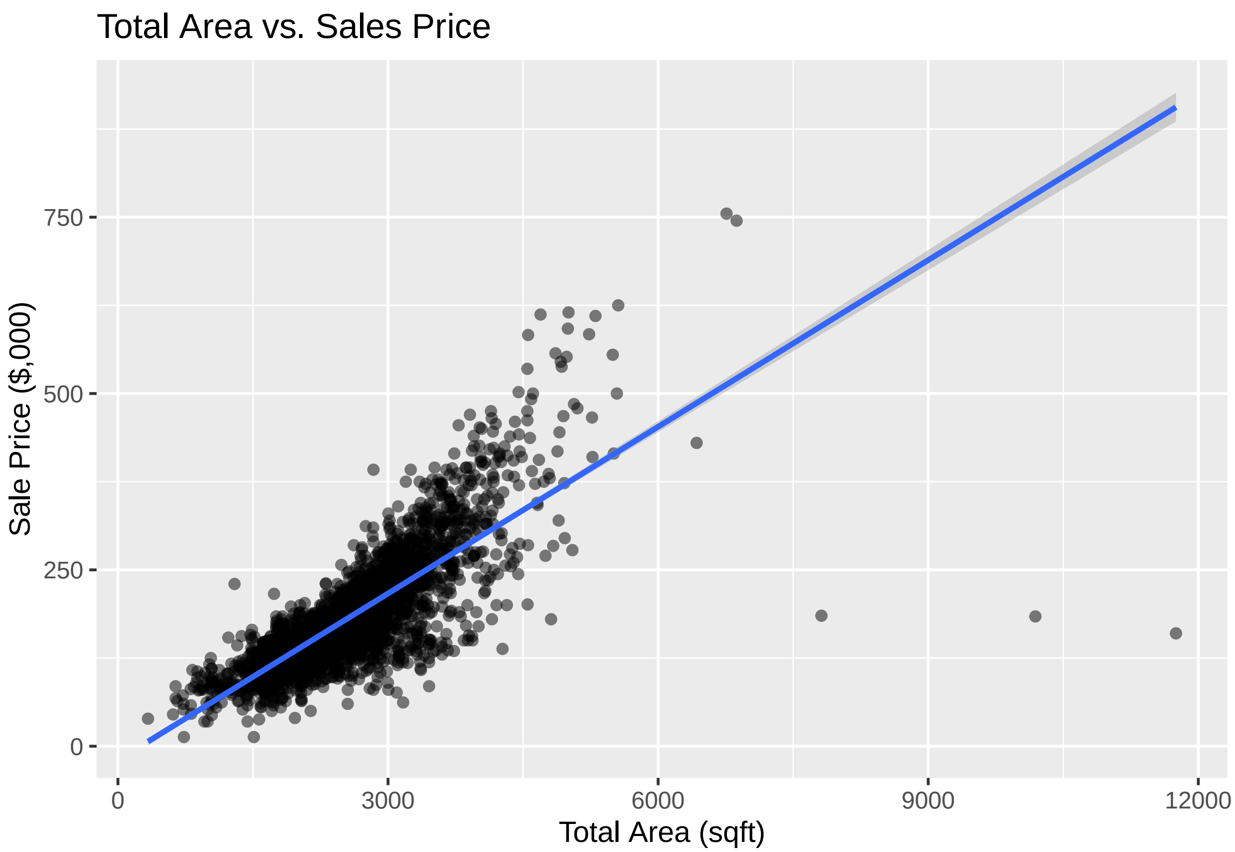
```
##
## Corelation between Total Area and Sale Price : 0.7931272
```

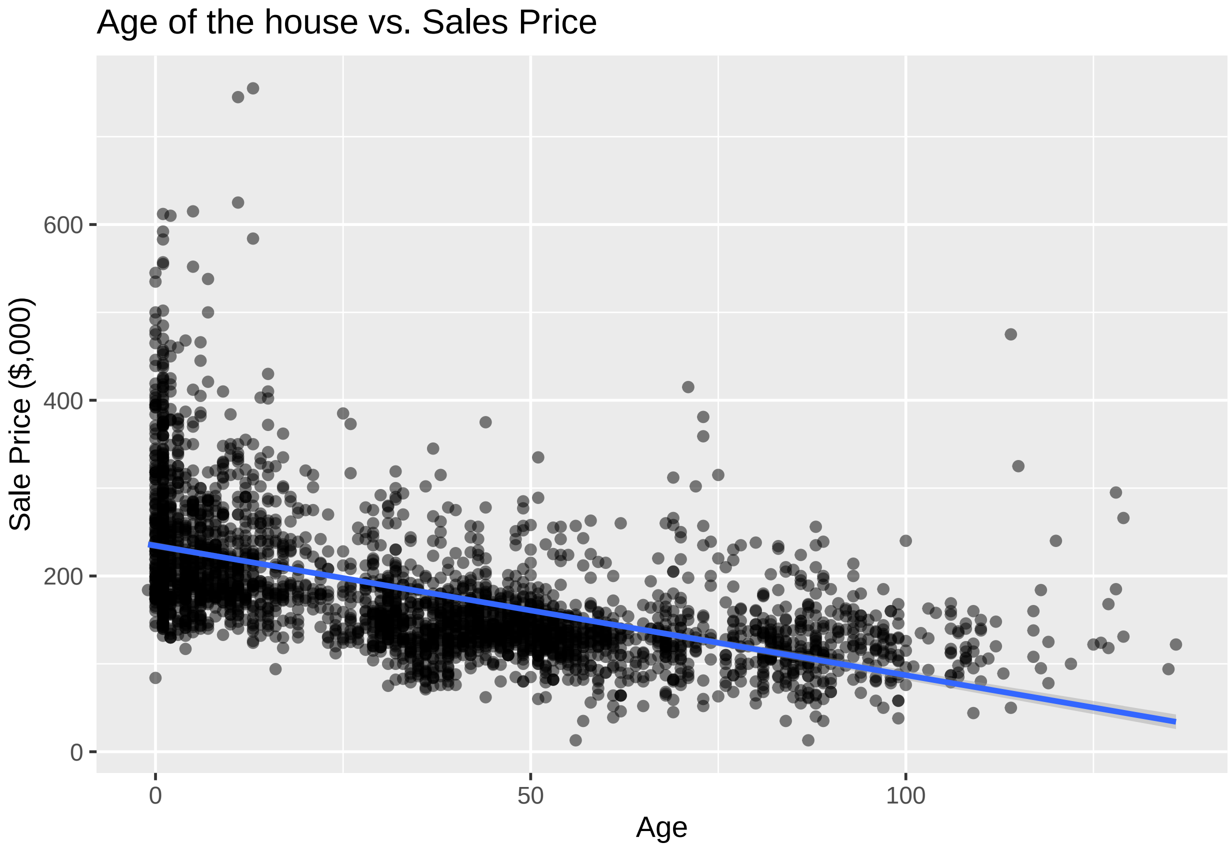
```
##
## Corelation between Total Bathroom and Sale Price : 0.636175
```

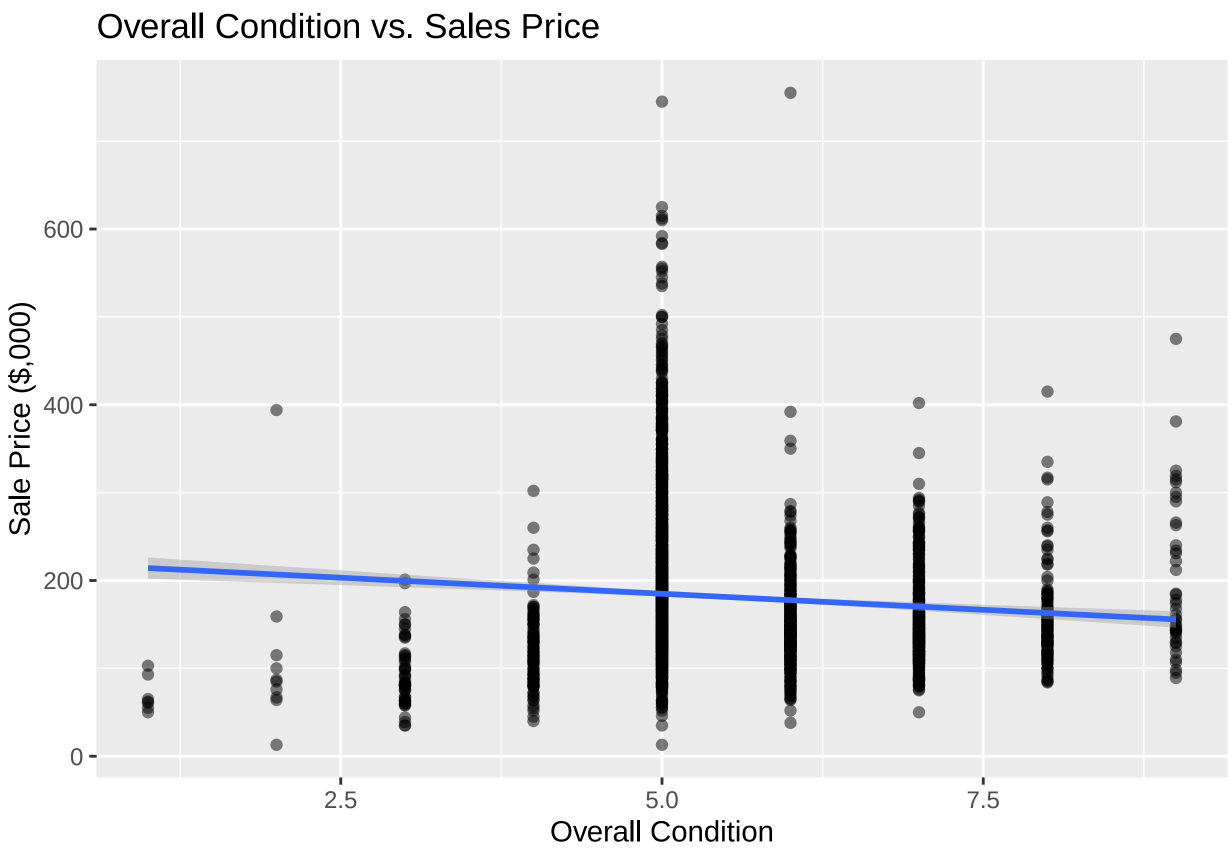
```
##
## Corelation between Age of House and Sale Price : -0.5589068
```

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


Distribution of Area
Frequency
600
400
200
0
0
2500
5000
7500
10000
12500
Area (sqft)


Total Area vs. Sales Price
Sale Price ($,000)
750
500
250
0
0
3000
6000
9000
12000
Total Area (sqft)


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

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

Create Test Set and Training set for building Linear Models

test set will be 20% of housing_data data

Table 4: Ames Housing Dataset dimension

x
2930
16

Table 5: Ames Housing Dataset

Sale_Price_T	total_Area	Gr_Liv_Area	house_Age	total_Bathroom	Garage_Cars	Garage_Area	Year_Remod_Add	Mas_Vnr_Area	MS_Zoning	Lot_Shape	Foundation	Sale_Condition	Garage_Finish	House_Style	Heating_QC
215	2736	1656	50	2.0	2	528	1960	112	Residential_Low_Density	Slightly_Irregular	CBlock	Normal	Fin	One_Story	Fair
105	1778	896	49	1.0	1	730	1961	0	Residential_High_Density	Regular	CBlock	Normal	Unf	One_Story	Typical

Sale_Price	total_Area	Gr_Liv_Area	House_Age	total_Bathroom	Garage_Cars	Garage_Area	Year_Remod_Add	Mas_Vnr_Area	MS_Zoning	Lot_Shape	Foundation	Sale_Condition	Garage_Finish	House_Style	Heating_QC
172	2658	1329	52	1.5	1	312	1958	108	Residential_Low_Density	Slightly_Irregular	CBlock	Normal	Unf	One_Story	Typical
244	4220	2110	42	3.5	2	522	1968	0	Residential_Low_Density	Regular	CBlock	Normal	Fin	One_Story	Excellent
190	2557	1629	13	2.5	2	482	1998	0	Residential_Low_Density	Slightly_Irregular	PConc	Normal	Fin	Two_Story	Good
196	2530	1604	12	2.5	2	470	1998	20	Residential_Low_Density	Slightly_Irregular	PConc	Normal	Fin	Two_Story	Excellent

Table 6: 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	MS_Zoning	Lot_Shape	Foundation	Sale_Condition	Garage_Finish	House_Style	Heating_QC
	Min. : 13.0	Min. : 334	Min. : 334	Min. : -1.00	Min. :1.000	Min. :0.000	Min. : 0.0	Min. :1950	Min. : 0.0	Floating_Village_Residential: 139	Regular :1859	BrkTil : 311	Abnorml: 190	Fin : 728	One_Story :1481	Excellent:1495
	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	Residential_High_Density : 27	Slightly_Irregular : 979	CBlock :1124	AdjLand: 12	No_Garage: 159	Two_Story : 873	Fair : 92
	Median :160.0	Median : 2450	Median :1442	Median : 34.00	Median :2.000	Median :2.000	Median : 480.0	Median :1993	Median : 0.0	Residential_Low_Density :2273	Moderately_Irregular: 76	PConc :1310	Alloca : 24	RFn : 812	One_and_Half_Fin: 314	Good : 476
	Mean :180.8	Mean : 2546	Mean :1500	Mean : 36.43	Mean :2.218	Mean :1.766	Mean : 472.7	Mean :1984	Mean : 101.1	Residential_Medium_Density : 462	Irregular : 16	Slab : 49	Family : 46	Unf :1231	SLvl : 128	Poor : 3
	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	A_agr : 2	NA	Stone : 11	Normal :2413	NA	SFoyer : 83	Typical : 864
	Max. :755.0	Max. :11752	Max. :5642	Max. :136.00	Max. :7.000	Max. :5.000	Max. :1488.0	Max. :2010	Max. :1600.0	C_all : 25	NA	Wood : 5	Partial: 245	NA	Two_and_Half_Unf: 24	NA
	NA	NA	NA	NA	NA	NA	NA	NA	NA	I_all : 2	NA	NA	NA	NA	(Other) : 27	NA

Recommendation System Model - develop, train and test

Build Linear Models

```
##
## 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
```

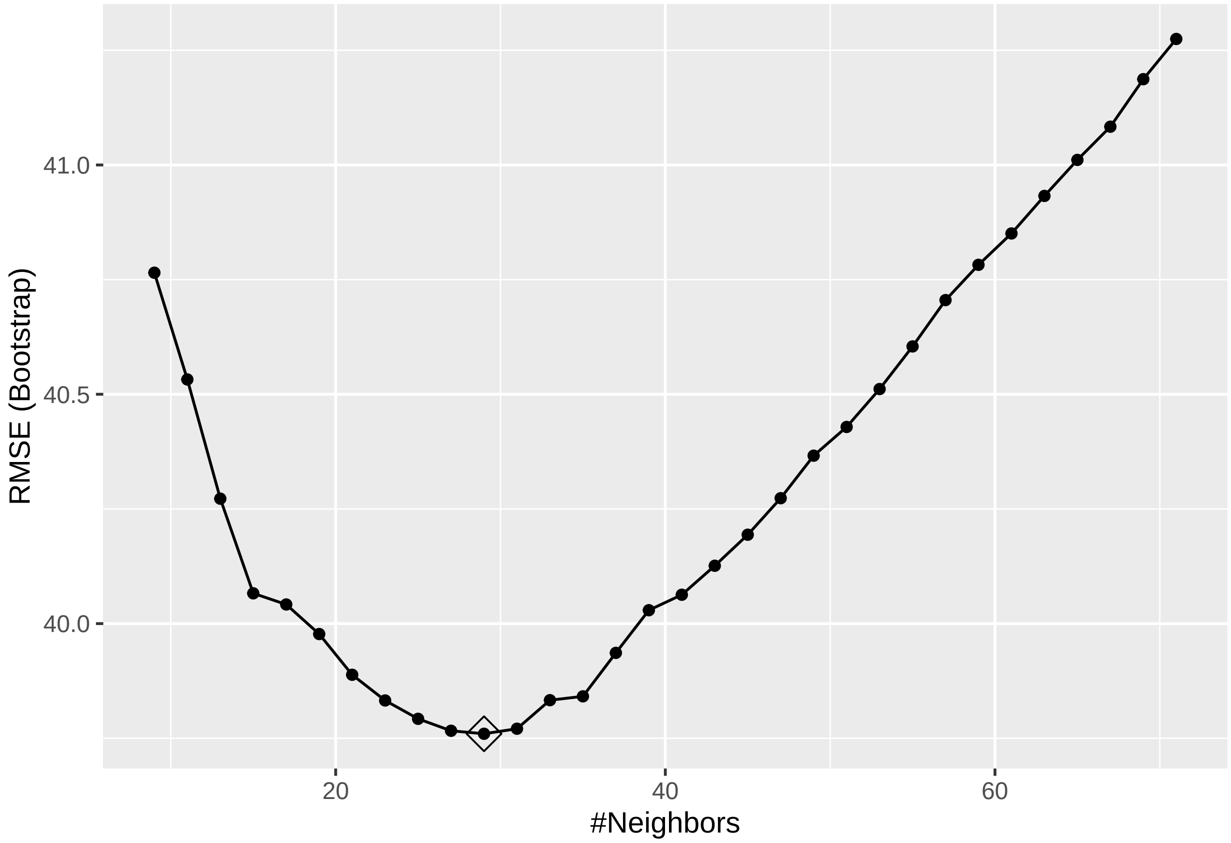
method	RMSE
Just the average in ,000	75.25000
Total Area and Total Bathroom Effect Model in in ,000	42.63694
Model based on Numeric attributes of the dataset in ,000	37.21290

Non-linear Models

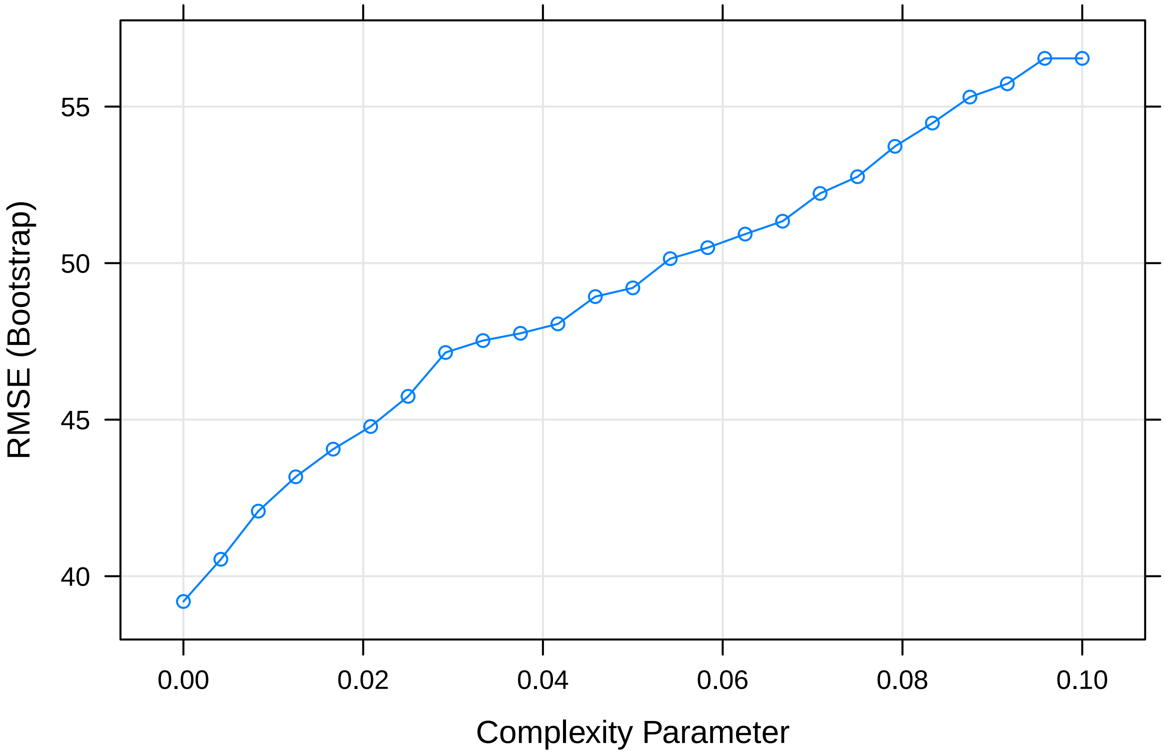
I took the optimum lamda for which the RMSE was the lowest. I built the model and ran the model against the final holdout set to validate the model performance

Train the final model

```
##             Length Class      Mode
## learn        2     -none-     list
## k            1     -none-     numeric
## theDots      0     -none-     list
## xNames      41     -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



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
Knn Model in ,000	32.92832

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
Model based on Numeric attributes of the dataset in ,000	37.21290

method	RMSE
Knn Model in ,000	36.67178
Knn Model in ,000	32.92832

Conclusion

I have used linear model with regularization to build this recommendation system. I came to a reasonable level of accuracy. Linear model is relatively simple to start with but not the best and we realized that during our study. We need more sophisticated models to enhance the accuracy - may be the random forest would be better suited for this prediction.

Reference -

Introduction to Data Science

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