

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. However, 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

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 ...
## $ Lot_Frontage     : num [1:2930] 141 80 81 93 74 78 41 43 39 60 ...
```

```

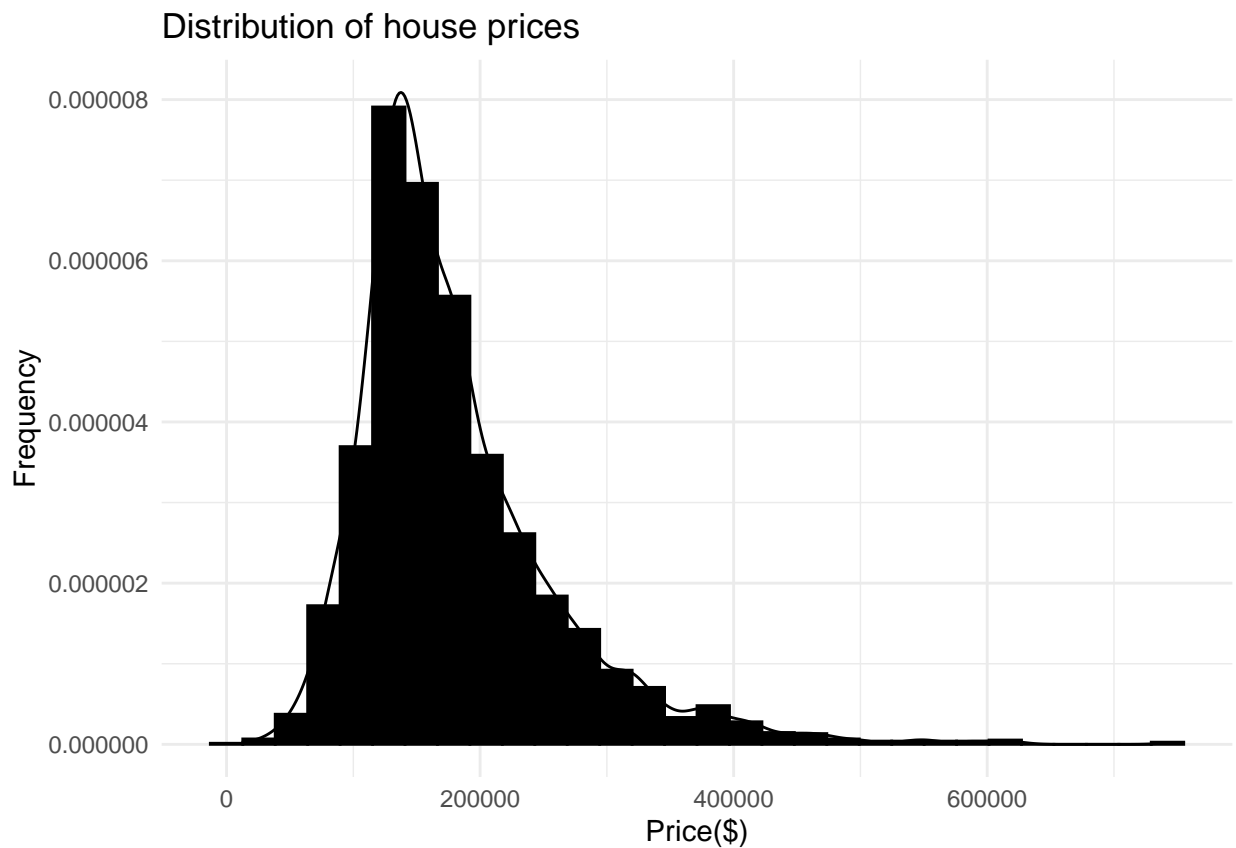
## $ Lot_Area      : int [1:2930] 31770 11622 14267 11160 13830 9978 4920 5005 5389 7500 ...
## $ Street       : Factor w/ 2 levels "Grv1","Pave": 2 2 2 2 2 2 2 2 2 ...
## $ Alley        : Factor w/ 3 levels "Gravel","No_Alley_Access",...: 2 2 2 2 2 2 2 2 2 ...
## $ Lot_Shape    : Factor w/ 4 levels "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 ...
## $ Condition_2  : Factor w/ 8 levels "Artery","Feedr",...: 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 ...
## $ Fence            : Factor w/ 5 levels "Good_Privacy",...: 5 3 5 5 3 5 5 5 5 ...
## $ Misc_Feature      : Factor w/ 6 levels "Elev","Gar2",...: 3 3 2 3 3 3 3 3 3 ...
## $ Misc_Val         : int [1:2930] 0 0 12500 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 ...
## $ Sale_Type        : Factor w/ 10 levels "COD","Con","ConLD",...: 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 ...
## $ Sale_Price       : int [1:2930] 215000 105000 172000 244000 189900 195500 213500 191500 236500 1...
## $ 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

|| || || ||



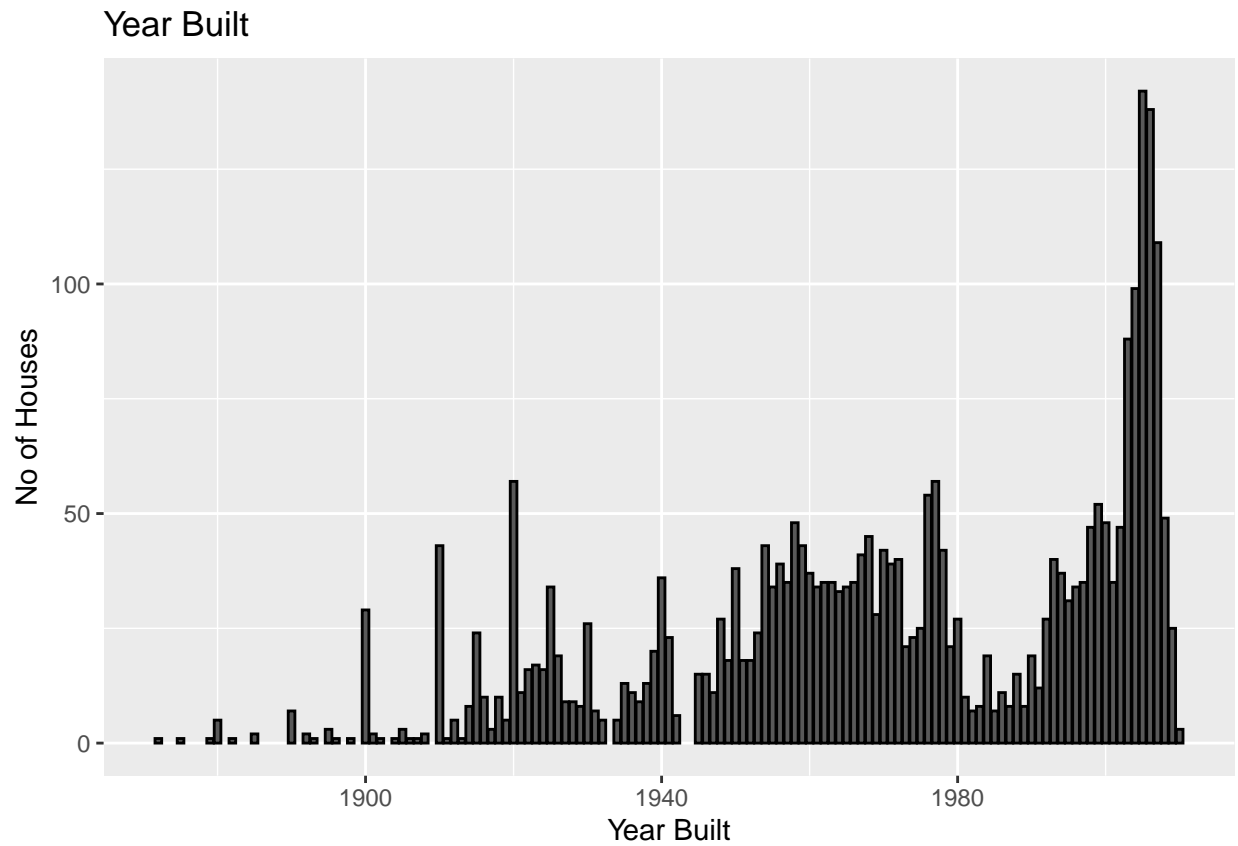
```
##
## Sale Price skewness : 1.742607

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

Sale Price Observation

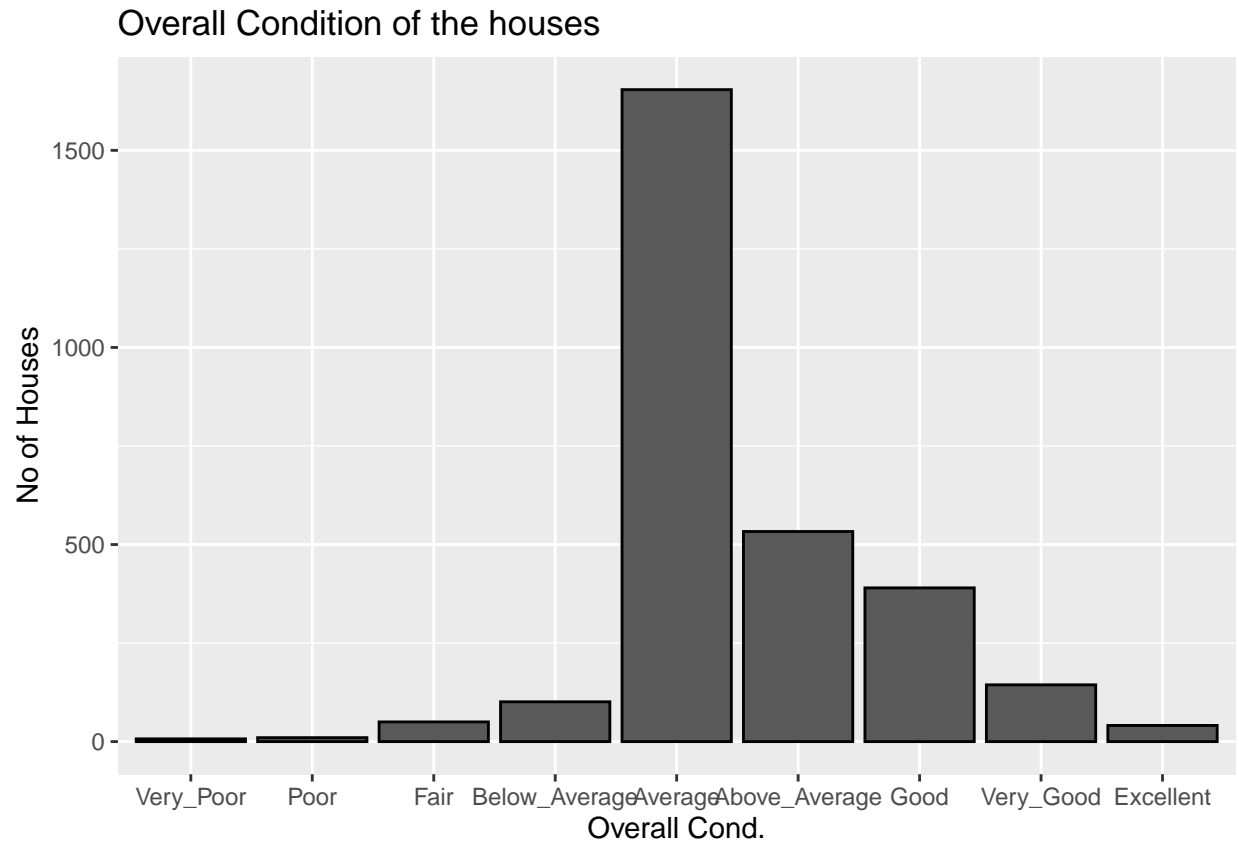
The Sale Price is right-skewed

Age of the Building



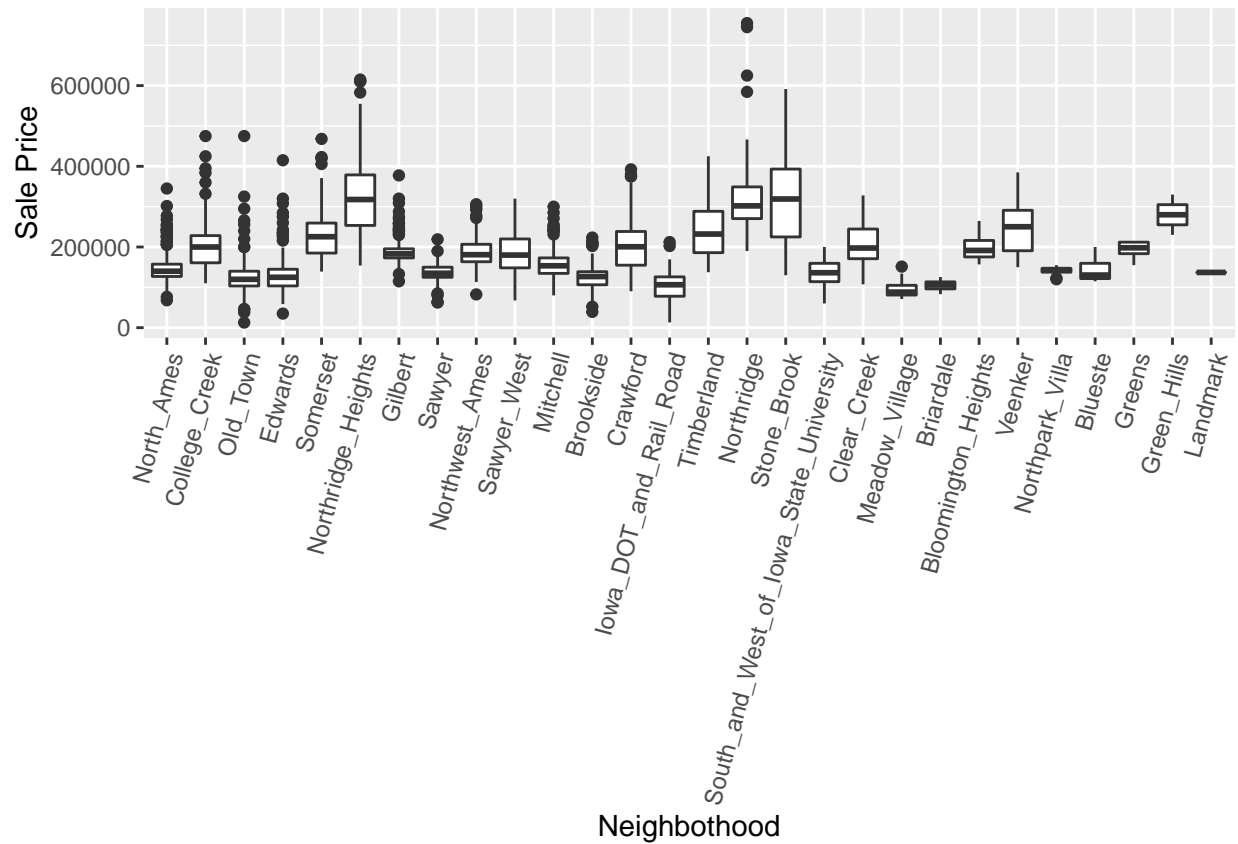
It looks that we have more houses were built at hte begining of 2000

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

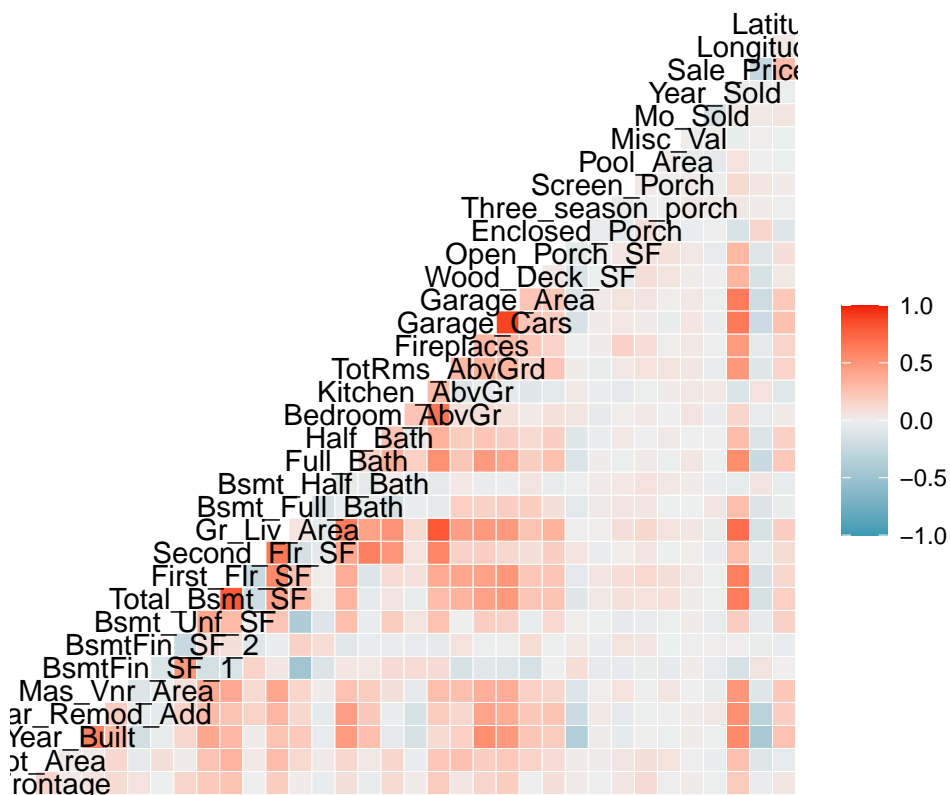


Table 2: Ames Housing Dataset - correlated numeric variables with the Sale Price

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

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

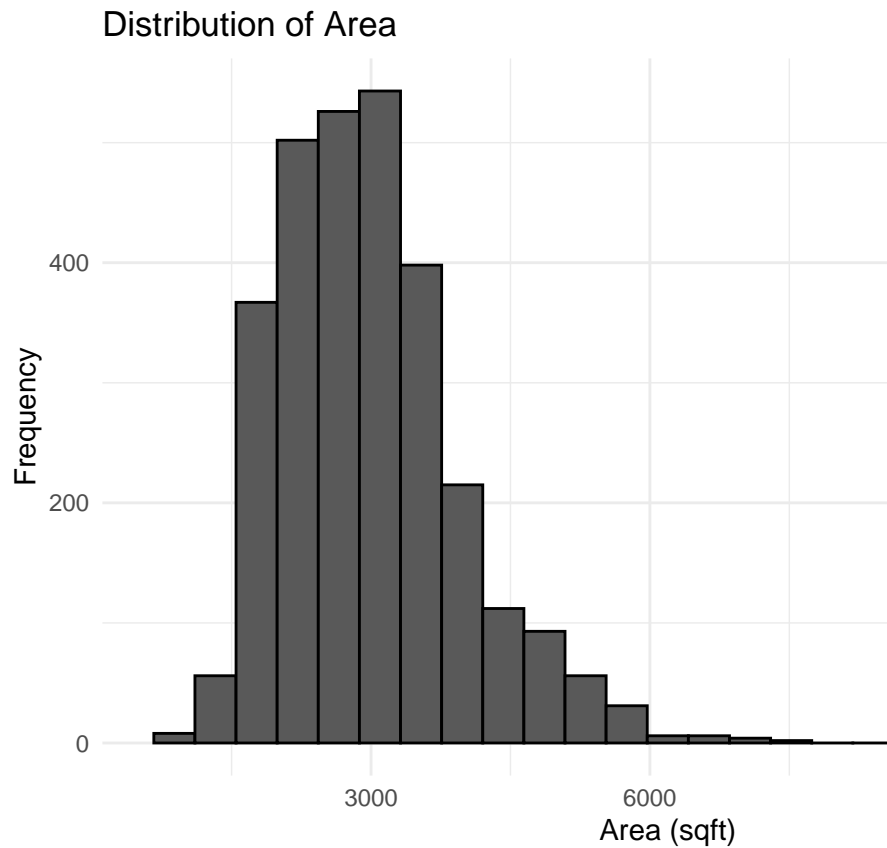
Table 3: Ames Housing Dataset - correlated non-numeric variables with the Sale Price

	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

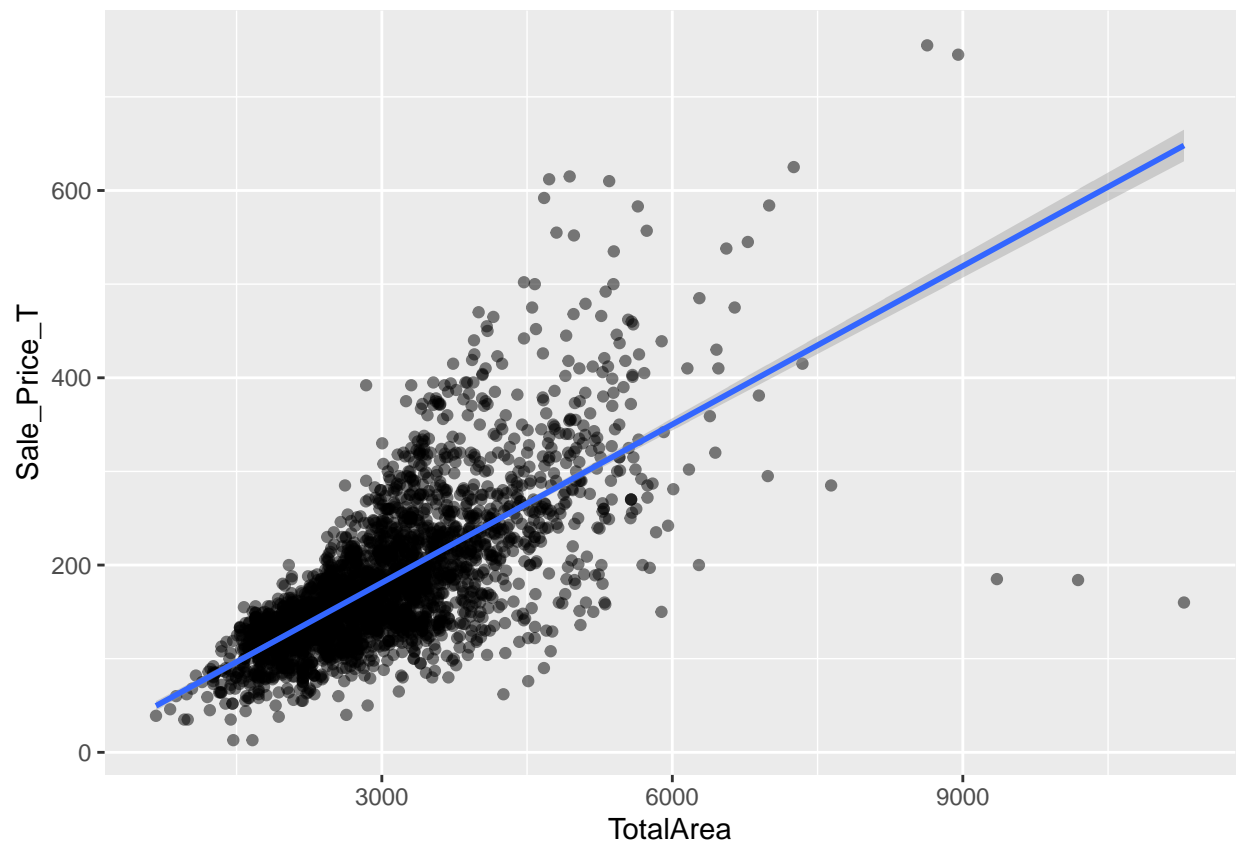
	x
Bsmt_Exposure	-0.3519094
BsmtFin_Type_1	-0.0975925
BsmtFin_Type_2	0.1074020
Heating	-0.0728977
Heating_QC	-0.4426972
Central_Air	0.2645064
Electrical	0.2378218
Functional	0.1192451
Garage_Type	-0.4061833
Garage_Finish	-0.4494826
Garage_Cond	0.2750657
Paved_Drive	0.2749134
Pool_QC	-0.0919699
Fence	0.1745827
Misc_Feature	-0.0574683
Sale_Type	-0.1845079
Sale_Condition	0.3330831

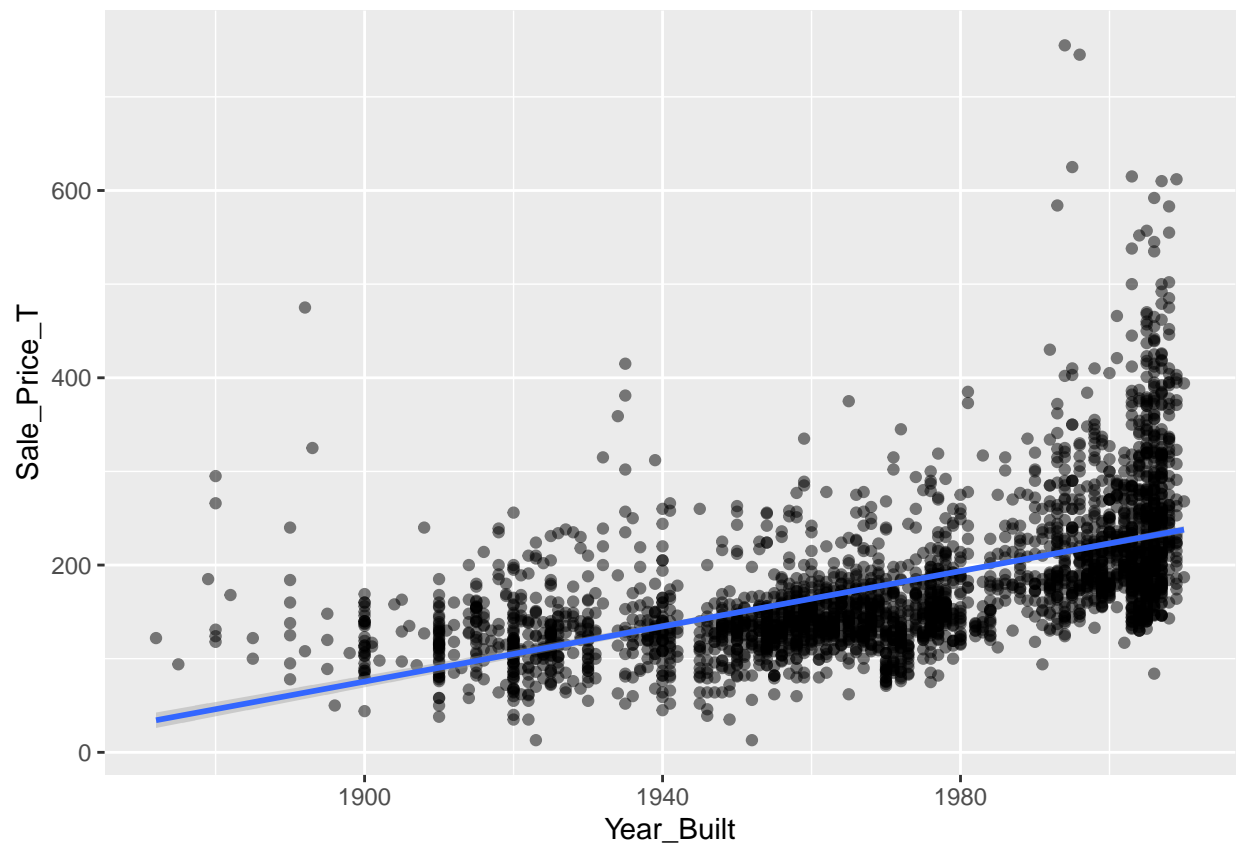
Looking at the non-numeric variable, I identified few variables which are highly correlated -

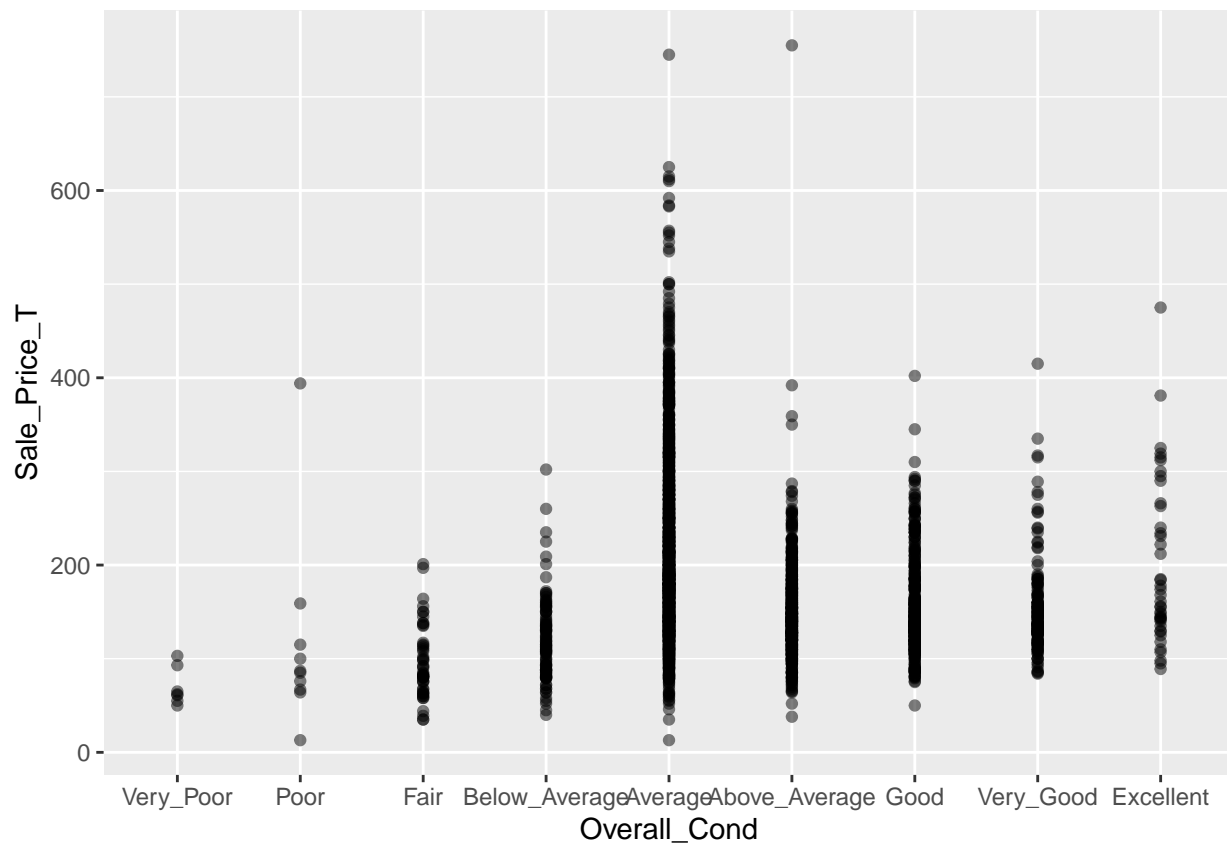
MS_Zoning, Lot_Shape, Foundation, Sale_Condition , Garage_Finish, House_Style, Heating_QC,



#Data Wrangling and Some more visualizations







```
## 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

$$\begin{array}{r} \hline x \\ \hline 2930 \\ 16 \end{array}$$

Table 5: Ames Housing Dataset

Sale	Price	Year	Overall	Category	Category	Total	Average	Bedrooms	Bathrooms	Size	Location	Shops	Found	Salon	Condition	House	Style	QC
215	3312	1960	Average	2	528	1080	1960	112	Residential	Slightly	Older	Normal	Fin		One	Stainy		
105	1792	1961	Above_Average	3	730	882	1961	0	Residential	Regular	Older	Normal	Unf		One	Spot	Typical	
172	2658	1958	Above_Average	3	312	1329	1958	108	Residential	Slightly	Older	Normal	Unf		One	Spot	Typical	
244	4220	1968	Average	2	522	2110	1968	0	Residential	Regular	Older	Normal	Fin		One	Stainy	Excellent	
190	3258	1997	Average	2	482	928	1998	0	Residential	Slightly	Older	Normal	Fin		Two	Spot	Good	
196	3208	1998	Above_Average	2	470	926	1998	20	Residential	Slightly	Older	Normal	Fin		Two	Stainy	Excellent	

Table 6: Ames Housing Dataset Summary

Sale_Price	Year_Built	Overall_Cond	Garage_Cars	Garage_Area	Total_Bsmt_SF	Year_Remod_Add	Mas_Vnr_Area	MS_Zoning	Lot_Shape	Foundation	Sale_Condition	Garage_Finish	House_Style	Heating_QC
Min. : 130000	Min. : 1872	Average : 1654	Min. : 0.000	Min. : 0	Min. : 1950	Min. : 0.0	Min. : 0.0	Floating_Village : 139	Irregular : 1859	Basic : 311	Normal : 190	Fin : 728	One_Story : 1481	Excellent : 1495
1st Qu. : 130000	1st Qu. : 1872	Above_Average : 1654	1st Qu. : 0.000	1st Qu. : 0	1st Qu. : 1950	1st Qu. : 0.0	1st Qu. : 0.0	Residential : 27	Slightly_Regular : 979	Basic : 12	Normal : 159	Fin : 873	Two_Story : 92	Fair : 92
Median : 160000	Median : 1973	Good : 1654	Median : 0.000	Median : 0	Median : 1993	Median : 0.0	Median : 0.0	Residential : 2273	Moderately_Regular : 76	Basic : 1310	Normal : 24	Fin : 812	One_and_a_half_Story : 314	Good : 476
Mean : 180800	Mean : 1971	Very_Good : 1654	Mean : 1.766	Mean : 1051	Mean : 1984	Mean : 101.1	Mean : 101.1	Residential : 462	Irregular : 16	Basic : 49	Normal : 46	Fin : 1231	SLvl : 128	Poor : 3
3rd Qu. : 210000	3rd Qu. : 2001	Below_Average : 1654	3rd Qu. : 2.000	3rd Qu. : 1300	3rd Qu. : 2004	3rd Qu. : 162.8	3rd Qu. : 162.8	A_agr : 2	NA : NA	Stone : 11	Normal : 2413	Fin : 83	SFoyer : 864	Typical : 864
Max. : 755000	Max. : 2010	Fair : 1654	Max. : 5.000	Max. : 1488	Max. : 2010	Max. : 1600	Max. : 1600	C_all : 25	NA : NA	Wood : 5	Partial : 245	Fin : 24	Two_and_a_half_Story : 24	Unf : 27
NA : NA	NA : NA	(Other) : 58	NA : NA	NA : NA	NA : NA	NA : NA	NA : NA	I_all : 2	NA : NA	NA : NA	NA : NA	(Other) : 27	NA : NA	NA : NA

Recommendation System Model - develop, train and test

Build Linear Models

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

## # A tibble: 6 x 16
##   Sale_Price_T TotalArea Year_~1 Overa~2 Garag~3 Garag~4 Total~5 Year_~6 Mas_V~7
##   <dbl>      <int>   <int> <fct>      <dbl>   <dbl>   <dbl>   <int>   <dbl>
## 1      105      1792   1961 Above_~      1      730     882    1961     0
## 2      172      2658   1958 Above_~      1      312    1329    1958    108
## 3      244      4220   1968 Average      2      522    2110    1968     0
## 4      190      3258   1997 Average      2      482     928    1998     0
## 5      196      3208   1998 Above_~      2      470     926    1998    20
## 6      236      3232   1995 Average      2      608    1595    1996     0
## # ... with 7 more variables: MS_Zoning <fct>, Lot_Shape <fct>,
## #   Foundation <fct>, Sale_Condition <fct>, Garage_Finish <fct>,
## #   House_Style <fct>, Heating_QC <fct>, and abbreviated variable names
## #   1: Year_Built, 2: Overall_Cond, 3: Garage_Cars, 4: Garage_Area,
## #   5: Total_Bsmt_SF, 6: Year_Remod_Add, 7: Mas_Vnr_Area

## [1] 54.84304
```

method	RMSE
Just the average in ,000	75.25000

method	RMSE
Area Effect Model in in ,000	54.84304

```
## [1] 37.32972
```

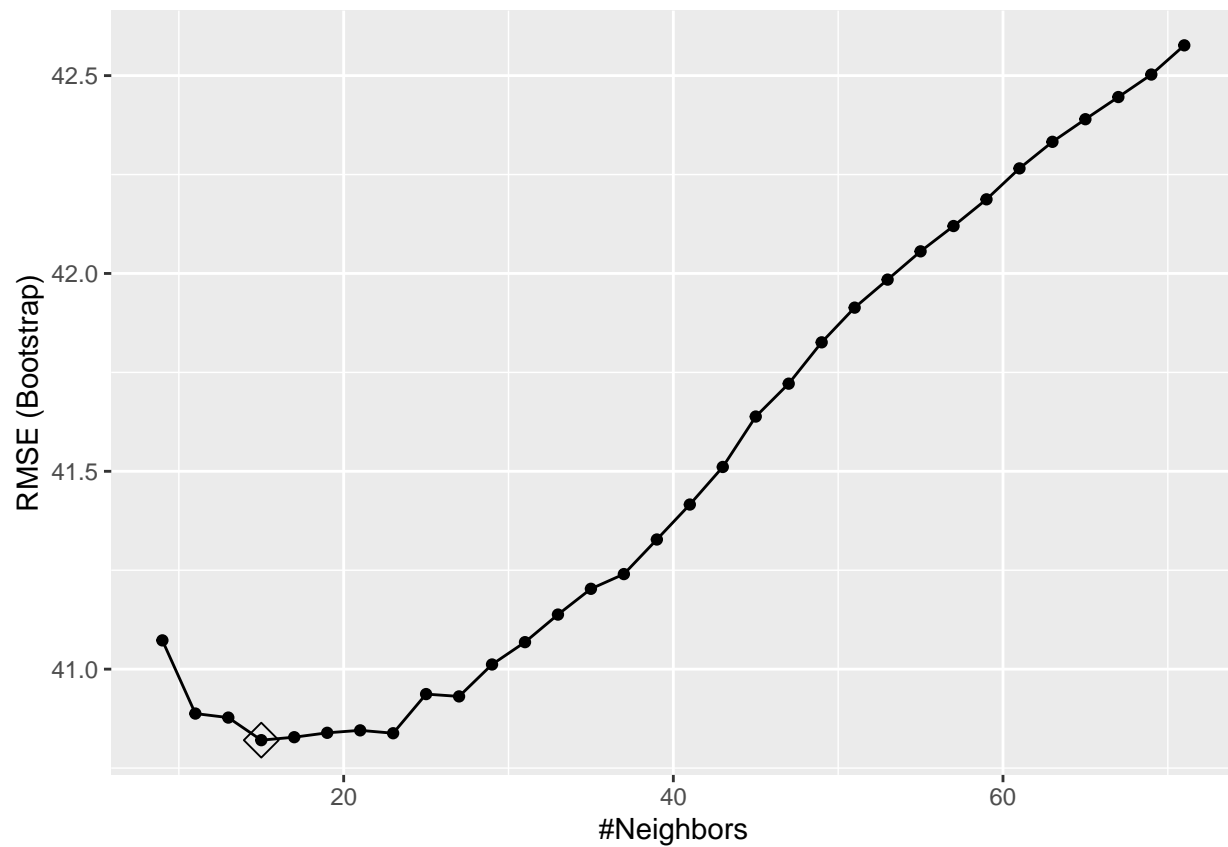
```
## # A tibble: 16 x 7
##   term                estimate std.e~1 stati~2    p.value conf.low conf.h~3
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)        -1.87e+3 8.51e+1 -22.0    5.13e- 99 -2.04e+3 -1.70e+3
## 2 TotalArea           3.16e-2 9.07e-4  34.9    5.40e-223 2.98e-2  3.34e-2
## 3 Year_Built           5.32e-1 4.18e-2  12.7    3.50e- 36 4.50e-1  6.14e-1
## 4 Overall_CondPoor     8.51e+0 1.91e+1   0.445 6.56e- 1 -2.90e+1 4.60e+1
## 5 Overall_CondFair     1.17e+1 1.57e+1   0.744 4.57e- 1 -1.91e+1 4.24e+1
## 6 Overall_CondBelow_Avera~ 1.60e+1 1.52e+1   1.05 2.93e- 1 -1.38e+1 4.58e+1
## 7 Overall_CondAverage   3.18e+1 1.48e+1   2.14 3.22e- 2 2.71e+0 6.09e+1
## 8 Overall_CondAbove_Avera~ 3.43e+1 1.48e+1   2.31 2.09e- 2 5.20e+0 6.33e+1
## 9 Overall_CondGood      4.44e+1 1.48e+1   2.99 2.81e- 3 1.53e+1 7.35e+1
## 10 Overall_CondVery_Good 4.93e+1 1.51e+1   3.27 1.11e- 3 1.97e+1 7.89e+1
## 11 Overall_CondExcellent 6.72e+1 1.60e+1   4.21 2.69e- 5 3.59e+1 9.86e+1
## 12 Garage_Cars         1.06e+1 2.19e+0   4.82 1.48e- 6 6.27e+0 1.49e+1
## 13 Garage_Area          2.79e-2 7.56e-3   3.70 2.23e- 4 1.31e-2 4.28e-2
## 14 Total_Bsmt_SF        4.10e-2 2.03e-3  20.2   3.49e- 85 3.70e-2 4.50e-2
## 15 Year_Remod_Add       3.99e-1 5.06e-2   7.87 4.85e- 15 2.99e-1 4.98e-1
## 16 Mas_Vnr_Area         5.13e-2 4.63e-3  11.1   6.09e- 28 4.22e-2 6.04e-2
## # ... with abbreviated variable names 1: std.error, 2: statistic, 3: conf.high
```

method	RMSE
Just the average in ,000	75.25000
Area Effect Model in in ,000	54.84304
Area + Year Built Effects Model in ,000	37.32972

Non-linear Models

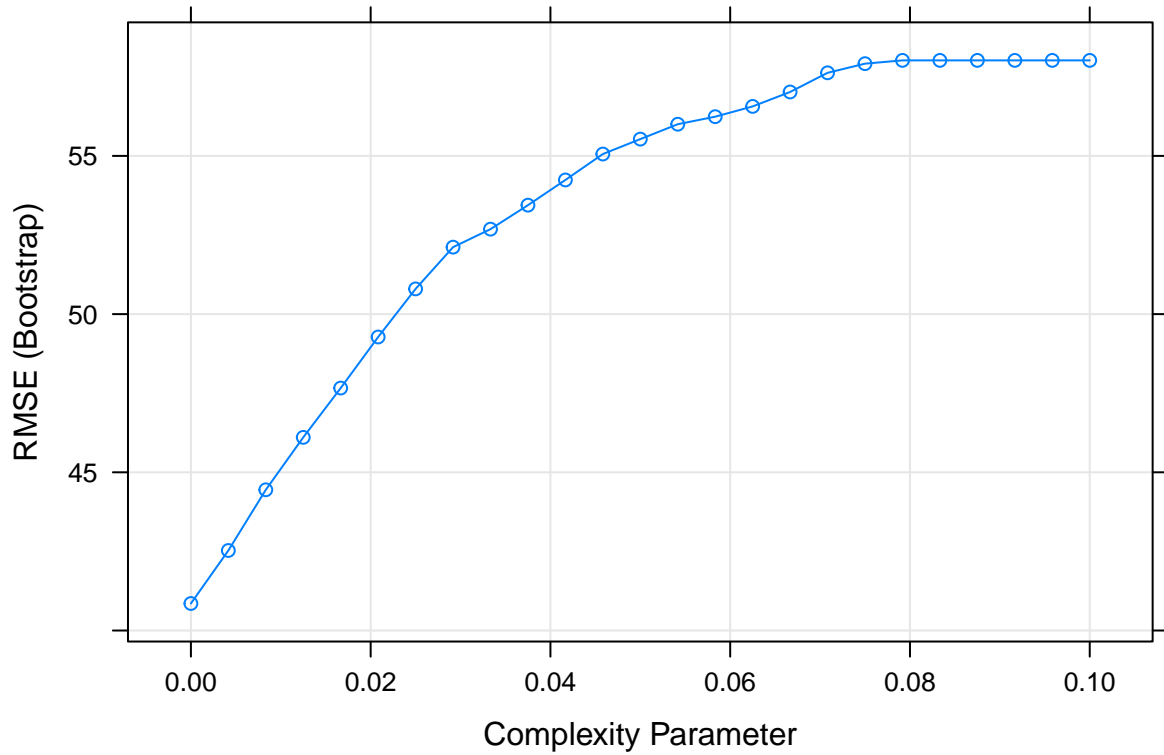
I took the optimum lamda for which the RMSE was the lowest. I built the model and ran the model against the final holdout set to validate the model performance

Train the final model



method	RMSE
Just the average in ,000	75.25000
Area Effect Model in in ,000	54.84304
Area + Year Built Effects Model in ,000	37.32972
Knn Model in ,000	37.09808

```
## Accuracy
## 0.0239726
```



##	1	2	3	4	5	6	7	8
##	171.61538	195.41176	181.00000	205.71429	353.35714	217.57143	128.57895	444.55556
##	9	10	11	12	13	14	15	16
##	241.52941	227.50000	298.80000	173.00000	200.85714	274.00000	195.41176	119.21429
##	17	18	19	20	21	22	23	24
##	212.83333	278.46667	153.05556	144.71429	195.00000	150.35714	160.20000	165.63636
##	25	26	27	28	29	30	31	32
##	121.55556	102.15789	132.68750	160.20000	124.57895	179.45455	213.81818	73.93333
##	33	34	35	36	37	38	39	40
##	137.18182	132.66667	132.66667	73.93333	117.33333	141.12500	134.44444	274.71429
##	41	42	43	44	45	46	47	48
##	235.16667	179.47059	179.47059	114.20000	135.86667	194.20000	149.25000	320.07143
##	49	50	51	52	53	54	55	56
##	123.05556	259.11111	79.07143	126.76923	124.70000	90.00000	144.76471	239.26667
##	57	58	59	60	61	62	63	64
##	105.58333	286.12500	195.00000	259.11111	239.26667	179.93333	320.07143	201.43750
##	65	66	67	68	69	70	71	72
##	362.72727	194.20000	94.16667	73.93333	141.41667	291.92308	327.31579	259.11111
##	73	74	75	76	77	78	79	80
##	253.44444	149.57143	173.00000	235.16667	134.72727	152.33333	229.44444	224.00000
##	81	82	83	84	85	86	87	88
##	208.22222	134.71429	117.33333	126.00000	105.46667	117.20000	151.00000	146.00000
##	89	90	91	92	93	94	95	96
##	154.00000	134.44444	241.52941	320.07143	298.80000	310.11111	555.38462	225.62500
##	97	98	99	100	101	102	103	104
##	322.83333	168.66667	179.71429	205.36842	205.36842	204.76923	211.45455	193.14286

##	105	106	107	108	109	110	111	112
##	225.62500	264.00000	211.45455	224.00000	167.14286	353.35714	273.25000	320.07143
##	113	114	115	116	117	118	119	120
##	298.80000	253.00000	239.28571	255.77778	222.85714	229.44444	241.33333	173.00000
##	121	122	123	124	125	126	127	128
##	104.00000	151.00000	116.75000	353.11111	161.30000	200.85714	253.44444	168.62500
##	129	130	131	132	133	134	135	136
##	171.61538	171.61538	151.00000	236.90000	144.76471	126.76923	136.81250	160.20000
##	137	138	139	140	141	142	143	144
##	153.78571	208.22222	135.27273	156.75000	132.68750	113.50000	179.45455	146.00000
##	145	146	147	148	149	150	151	152
##	141.41667	135.27273	104.00000	109.60000	153.55556	90.90000	141.41667	175.00000
##	153	154	155	156	157	158	159	160
##	129.05556	116.86667	121.57895	116.00000	117.20000	141.12500	129.05556	101.61538
##	161	162	163	164	165	166	167	168
##	102.00000	132.66667	132.66667	179.47059	144.71429	56.81250	170.52941	92.83333
##	169	170	171	172	173	174	175	176
##	112.20000	155.10000	134.78947	168.62500	353.11111	310.11111	172.00000	149.25000
##	177	178	179	180	181	182	183	184
##	212.83333	181.00000	130.35294	239.76923	278.46667	229.44444	227.50000	182.75000
##	185	186	187	188	189	190	191	192
##	235.16667	90.90000	74.81250	112.20000	56.81250	121.57895	116.86667	156.75000
##	193	194	195	196	197	198	199	200
##	132.66667	143.90909	200.00000	105.58333	105.46667	229.44444	164.15789	200.00000
##	201	202	203	204	205	206	207	208
##	362.72727	320.07143	264.00000	327.31579	134.71429	169.71429	94.16667	135.23077
##	209	210	211	212	213	214	215	216
##	164.15789	181.00000	195.00000	212.83333	154.00000	105.46667	117.20000	154.00000
##	217	218	219	220	221	222	223	224
##	119.21429	444.55556	179.93333	177.87500	274.71429	273.25000	320.07143	310.11111
##	225	226	227	228	229	230	231	232
##	206.44444	200.00000	181.00000	180.69231	212.00000	110.30000	116.75000	229.44444
##	233	234	235	236	237	238	239	240
##	195.00000	253.44444	195.00000	153.78571	146.00000	139.00000	236.90000	174.73333
##	241	242	243	244	245	246	247	248
##	174.73333	116.75000	171.61538	160.88889	143.84211	56.81250	109.60000	181.08333
##	249	250	251	252	253	254	255	256
##	141.41667	132.68750	171.61538	145.00000	135.86667	124.57895	119.21429	128.57895
##	257	258	259	260	261	262	263	264
##	291.92308	117.33333	156.75000	129.05556	137.23529	136.81250	110.30000	134.78947
##	265	266	267	268	269	270	271	272
##	136.81250	136.81250	132.66667	116.00000	81.87500	170.52941	74.81250	129.05556
##	273	274	275	276	277	278	279	280
##	137.23529	146.00000	152.77778	152.77778	145.55556	109.60000	126.00000	56.81250
##	281	282	283	284	285	286	287	288
##	142.30769	135.86667	90.90000	126.76923	144.76471	212.00000	241.52941	327.31579
##	289	290	291	292	293	294	295	296
##	205.36842	200.00000	200.00000	164.15789	270.64706	224.00000	204.76923	241.52941
##	297	298	299	300	301	302	303	304
##	135.23077	135.23077	135.23077	97.00000	151.00000	138.00000	116.00000	176.00000
##	305	306	307	308	309	310	311	312
##	194.92308	155.10000	109.60000	175.00000	168.66667	89.30000	291.53846	152.33333
##	313	314	315	316	317	318	319	320
##	273.25000	212.00000	194.20000	278.46667	173.00000	153.00000	94.16667	123.05556

##	321	322	323	324	325	326	327	328
##	123.05556	176.00000	144.71429	239.26667	239.26667	177.87500	180.69231	185.50000
##	329	330	331	332	333	334	335	336
##	299.88889	416.57143	205.36842	154.00000	150.35714	153.78571	146.00000	135.27273
##	337	338	339	340	341	342	343	344
##	189.25000	327.31579	362.72727	362.72727	278.46667	327.31579	222.85714	286.12500
##	345	346	347	348	349	350	351	352
##	225.62500	227.50000	194.00000	172.00000	182.15385	205.36842	153.05556	201.43750
##	353	354	355	356	357	358	359	360
##	201.43750	193.14286	161.30000	193.14286	458.00000	353.35714	299.88889	323.62500
##	361	362	363	364	365	366	367	368
##	255.77778	270.64706	239.28571	286.12500	139.37500	149.25000	213.44444	135.27273
##	369	370	371	372	373	374	375	376
##	274.00000	274.00000	177.87500	175.18750	175.18750	211.11765	274.71429	179.47059
##	377	378	379	380	381	382	383	384
##	153.00000	134.71429	136.81250	121.55556	102.00000	121.12500	150.35714	236.90000
##	385	386	387	388	389	390	391	392
##	160.88889	235.16667	134.44444	170.52941	112.20000	160.88889	110.30000	168.62500
##	393	394	395	396	397	398	399	400
##	128.57895	145.00000	116.75000	181.08333	353.11111	109.60000	128.00000	134.71429
##	401	402	403	404	405	406	407	408
##	170.52941	92.83333	110.30000	134.44444	102.00000	101.61538	132.66667	194.92308
##	409	410	411	412	413	414	415	416
##	94.16667	102.00000	121.57895	135.80000	124.87500	105.58333	117.20000	74.81250
##	417	418	419	420	421	422	423	424
##	291.92308	138.00000	124.57895	153.00000	143.90909	194.92308	146.00000	143.84211
##	425	426	427	428	429	430	431	432
##	116.86667	104.00000	145.00000	278.46667	252.00000	444.55556	205.36842	241.52941
##	433	434	435	436	437	438	439	440
##	149.25000	212.83333	224.00000	142.30769	142.30769	123.05556	126.00000	212.00000
##	441	442	443	444	445	446	447	448
##	212.83333	182.75000	140.10000	208.22222	555.38462	144.71429	135.27273	116.75000
##	449	450	451	452	453	454	455	456
##	117.33333	124.57895	194.92308	155.10000	181.08333	135.23077	137.23529	137.23529
##	457	458	459	460	461	462	463	464
##	310.11111	310.11111	179.93333	139.37500	153.00000	136.81250	130.35294	105.46667
##	465	466	467	468	469	470	471	472
##	89.30000	94.16667	130.35294	179.47059	171.61538	135.23077	123.05556	136.81250
##	473	474	475	476	477	478	479	480
##	134.72727	182.15385	264.00000	175.18750	182.15385	298.80000	164.15789	211.00000
##	481	482	483	484	485	486	487	488
##	299.88889	458.00000	255.07692	154.00000	264.00000	153.00000	153.00000	278.46667
##	489	490	491	492	493	494	495	496
##	278.46667	444.55556	194.00000	189.25000	189.25000	204.76923	182.15385	278.46667
##	497	498	499	500	501	502	503	504
##	211.45455	253.00000	362.72727	310.11111	206.44444	195.41176	182.15385	121.12500
##	505	506	507	508	509	510	511	512
##	175.18750	110.30000	139.00000	104.00000	217.57143	90.00000	121.55556	112.20000
##	513	514	515	516	517	518	519	520
##	239.26667	134.71429	135.86667	145.00000	160.20000	141.41667	142.30769	121.55556
##	521	522	523	524	525	526	527	528
##	90.90000	56.81250	101.61538	136.81250	134.71429	179.47059	179.47059	89.30000
##	529	530	531	532	533	534	535	536
##	126.76923	121.57895	137.23529	145.55556	154.00000	141.12500	109.60000	105.58333

```

##      537      538      539      540      541      542      543      544
## 153.78571 112.20000 123.50000 116.00000 181.08333 122.85714 137.18182 129.05556
##      545      546      547      548      549      550      551      552
##  90.00000  74.81250 101.61538 134.71429 153.78571 134.78947 134.44444 179.37500
##      553      554      555      556      557      558      559      560
## 231.14286 143.84211 144.76471  74.81250 270.64706 239.28571 149.25000 227.50000
##      561      562      563      564      565      566      567      568
## 200.85714 118.25000 164.15789 274.71429 322.83333 135.23077 253.00000 241.52941
##      569      570      571      572      573      574      575      576
## 154.00000 255.07692 105.46667 155.10000 156.75000 208.22222 181.08333 217.57143
##      577      578      579      580      581      582      583      584
##  56.81250  89.30000 235.16667 175.00000 396.29412 195.00000 118.25000 105.46667
##      585      586      587
##  73.93333 144.71429 241.71429

```

method	RMSE
Just the average in ,000	75.25000
Area Effect Model in in ,000	54.84304
Area + Year Built Effects Model in ,000	37.32972
Knn Model in ,000	37.09808
Knn Model in ,000	37.66704

```

## Accuracy
## 0.01718213

```

Final Result and improvements over time

RMSEs over Model Accuracies of the Models

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 <https://modeldata.tidymodels.org/reference/ames.html> - Ames Housing Data
<https://www.investopedia.com>