

Final Project

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Project Description

```
set.seed(123)
House_Data = read.table(url('https://raw.githubusercontent.com/zbrotherton2158/okadaStats/master/ames2008.csv'))
```

The study

questions to be answered are the following:

- What field does the data come from? This data comes from the assessors office of Ames, Iowa
- What are the goals of the study? Are there any effects of particular interest? The purpose of this data is to be able to predict the value of a house in Ames Iowa Our areas of interest are the effect of the neighborhoods, lot area, total rooms above grade, year built, and total square feet on the price of the house.
- How might these goals be answered, i.e. tests / confidence intervals? This goal could be answered by a prediction model that, given information about a house, will output a 95% confidence interval predicting the price of the house.

The data

Predictor Variable Spread

```
require(tidyverse)

## Loading required package: tidyverse

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.2      v readr      2.1.4
## v forcats    1.0.0      v stringr   1.5.0
## v ggplot2    3.4.2      v tibble    3.2.1
## v lubridate  1.9.2      v tidyr     1.3.0
## v purrr      1.0.1

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

Numerical_Count = length(select_if(House_Data, is.numeric))
Categorical_Count = length(select_if(House_Data, negate(is.numeric)))
```

Clean "none" values

```
# NOTE: Might have to revamp
# Turned Nones into 0's for respective rows

# j is the column of each selected box
for (j in 1:80){
```

```

# clear the haveNumbers in case it has values
haveNumbers = c()
# i is the row of each selected box
for (i in 1:2000) {
  # if the selected box is empty, fill it with "None"
  if (House_Data[i,j] == "") {
    House_Data[i,j] = "None"
  }
  # record whether the selected box contained a number in a list called haveNumbers
  haveNumbers = c(haveNumbers, !grepl("\\D", House_Data[i,j]))
}
# if any of the selected boxes in the column contain a number,
# replace all "None"s in the column with 0s
if (any(haveNumbers) && (j != 59)) {
  House_Data[j] = replace(House_Data[j], House_Data[j] == "None", 0)
}
}

```

Correlation Info

Numerical Correlation

```
require(corrplot)
```

```
## Loading required package: corrplot
```

```
## corrplot 0.92 loaded
```

```
require(dplyr)
```

```
Numerical_Correlations = cor(House_Data_Numerical, House_Data_Numerical$SalePrice)
```

Analysis

- How are the predictor variables spread out? Are there any noteworthy features to their spread that could be highly influential observations?

The variables are seemingly random between discrete, ordinal, nominal, and continuous types of variables. Of these, we found 26 to be numerical and 54 categorical. Within the discrete variables, variables with a spread like fireplaces where despite being numerical only have values of 1 - arbitrarily small number may have a higher effect on the price per unit increase.

- Are any of the predictor variables highly correlated?

The highest correlation numerical variables are:

- Overall Quality (~0.805)
- Gr. Living Area (~0.720)
- Year Built (~0.57)
- Full Bath (~0.561)
- Year Remodeled (~0.535)
- Rooms Above Ground (~0.504)
- Fireplace (~0.48)
- 1st Floor Square Ft. (~0.619)

- 2nd Floor Square Ft. (~ 0.295)*

The most statistically significant categorical variables are:

The models

- Which predictor variables, if any, should be included in the model a priority?

The highest correlation numerical variables and most statistically significant categorical listed under “The Data” are of the most interest and are the most prioritized in the model. (Neighborhoods, lot area, total rooms above grade, year built, and total square feet etc.)

- Are there any interactions that should be considered for inclusion in the model?
- Are there any three way interactions that should be considered?
- Are there any interactions that should NOT be considered?

Model Draft

```
#factorize these?
model = lm(SalePrice ~
  #Numerical
  Overall.Qual +
  Gr.Liv.Area +
  Year.Built +
  Year.Remod.Add +
  Full.Bath +
  #Categorical
  Neighborhood +
  Condition.1 +
  Condition.2 +
  Bldg.Type +
  House.Style +
  Roof.Matl +
  Exter.Qual +
  BsmtFin.Type.1 +
  Kitchen.Qual +
  Fireplace.Qu +
  Garage.Type +
  Pool.QC
, House_Data)
summary(model)

##
## Call:
## lm(formula = SalePrice ~ Overall.Qual + Gr.Liv.Area + Year.Built +
##     Year.Remod.Add + Full.Bath + Neighborhood + Condition.1 +
##     Condition.2 + Bldg.Type + House.Style + Roof.Matl + Exter.Qual +
##     BsmtFin.Type.1 + Kitchen.Qual + Fireplace.Qu + Garage.Type +
##     Pool.QC, data = House_Data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -175321  -11880       247   11314  168763
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

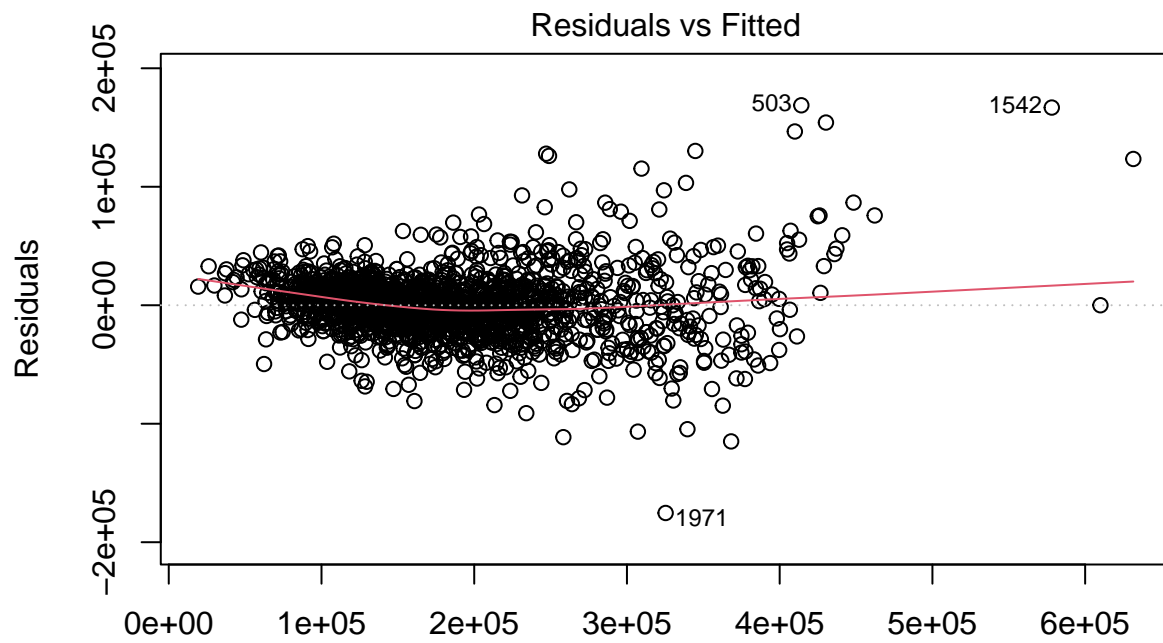
## (Intercept)	-1.563e+06	1.335e+05	-11.710	< 2e-16	***
## Overall.Qual	1.112e+04	8.454e+02	13.157	< 2e-16	***
## Gr.Liv.Area	7.224e+01	2.535e+00	28.496	< 2e-16	***
## Year.Built	3.917e+02	5.012e+01	7.815	9.00e-15	***
## Year.Remod.Add	2.151e+02	4.376e+01	4.914	9.67e-07	***
## Full.Bath	-3.675e+02	1.710e+03	-0.215	0.829912	
## NeighborhoodBlueste	1.828e+04	1.189e+04	1.537	0.124461	
## NeighborhoodBrDale	1.143e+04	1.115e+04	1.025	0.305435	
## NeighborhoodBrkSide	3.614e+03	8.636e+03	0.418	0.675639	
## NeighborhoodClearCr	8.601e+03	8.941e+03	0.962	0.336186	
## NeighborhoodCollgCr	-1.040e+03	7.565e+03	-0.137	0.890723	
## NeighborhoodCrawfor	2.429e+04	8.226e+03	2.953	0.003186	**
## NeighborhoodEdwards	-6.826e+03	8.023e+03	-0.851	0.395019	
## NeighborhoodGilbert	-5.213e+03	7.926e+03	-0.658	0.510865	
## NeighborhoodGreens	3.069e+04	1.390e+04	2.208	0.027372	*
## NeighborhoodGrnHill	1.349e+05	2.675e+04	5.043	5.01e-07	***
## NeighborhoodIDOTRR	-4.556e+03	8.758e+03	-0.520	0.602974	
## NeighborhoodMeadowV	4.262e+03	9.213e+03	0.463	0.643677	
## NeighborhoodMitchel	-1.726e+02	8.160e+03	-0.021	0.983122	
## NeighborhoodNonemes	-4.933e+03	7.817e+03	-0.631	0.528044	
## NeighborhoodNoRidge	4.258e+04	8.275e+03	5.145	2.94e-07	***
## NeighborhoodNPkVill	7.279e+03	1.035e+04	0.703	0.481867	
## NeighborhoodNridgHt	2.902e+04	7.732e+03	3.754	0.000180	***
## NeighborhoodNWAmes	-7.734e+03	8.056e+03	-0.960	0.337142	
## NeighborhoodOldTown	-4.345e+03	8.381e+03	-0.518	0.604218	
## NeighborhoodSawyer	-2.401e+03	8.111e+03	-0.296	0.767243	
## NeighborhoodSawyerW	-5.168e+03	7.917e+03	-0.653	0.514036	
## NeighborhoodSomerst	1.342e+04	7.525e+03	1.783	0.074778	.
## NeighborhoodStoneBr	4.447e+04	8.291e+03	5.363	9.16e-08	***
## NeighborhoodSWISU	-6.571e+03	9.406e+03	-0.699	0.484919	
## NeighborhoodTimber	1.022e+04	8.186e+03	1.248	0.212157	
## NeighborhoodVeenker	7.593e+03	9.925e+03	0.765	0.444311	
## Condition.1Feedr	5.204e+03	4.385e+03	1.187	0.235511	
## Condition.1Norm	1.155e+04	3.584e+03	3.223	0.001290	**
## Condition.1PosA	1.742e+04	8.351e+03	2.086	0.037107	*
## Condition.1PosN	1.337e+04	6.768e+03	1.976	0.048323	*
## Condition.1RR Ae	-5.366e+03	7.140e+03	-0.752	0.452413	
## Condition.1RR An	1.182e+04	6.178e+03	1.914	0.055823	.
## Condition.1RR Ne	4.854e+03	1.226e+04	0.396	0.692291	
## Condition.1RR Nn	4.248e+03	1.008e+04	0.422	0.673398	
## Condition.2Feedr	1.217e+04	1.775e+04	0.686	0.493015	
## Condition.2Norm	1.639e+04	1.544e+04	1.061	0.288823	
## Condition.2PosA	1.678e+05	3.118e+04	5.382	8.29e-08	***
## Condition.2PosN	1.557e+04	2.246e+04	0.693	0.488230	
## Condition.2RR An	1.492e+04	3.055e+04	0.489	0.625222	
## Condition.2RR Nn	3.422e+04	2.412e+04	1.418	0.156228	
## Bldg.Type2fmCon	-6.220e+03	4.261e+03	-1.460	0.144512	
## Bldg.TypeDuplex	-2.404e+04	3.698e+03	-6.502	1.01e-10	***
## Bldg.TypeTwnhs	-3.702e+04	4.662e+03	-7.942	3.37e-15	***
## Bldg.TypeTwnhsE	-2.537e+04	2.883e+03	-8.800	< 2e-16	***
## House.Style1.5Unf	1.735e+04	7.340e+03	2.364	0.018184	*
## House.Style1Story	1.516e+04	2.452e+03	6.184	7.61e-10	***
## House.Style2.5Fin	-3.887e+04	1.617e+04	-2.404	0.016317	*
## House.Style2.5Unf	-1.400e+04	7.326e+03	-1.911	0.056180	.

```

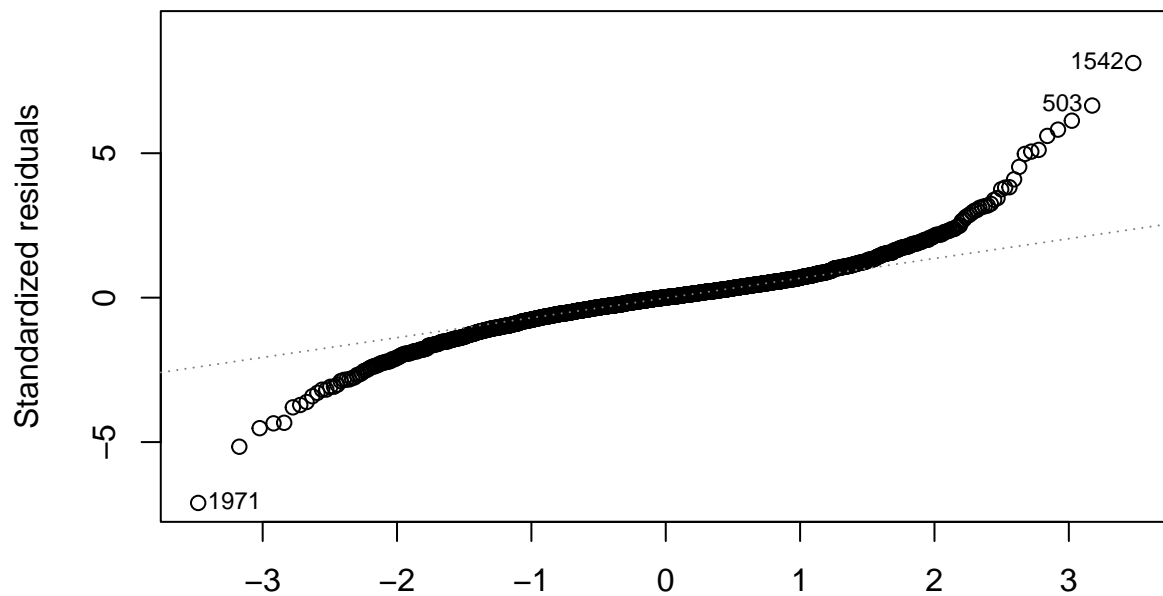
## House.Style2Story -5.745e+03 2.470e+03 -2.326 0.020144 *
## House.StyleSFoyer 2.236e+04 4.353e+03 5.136 3.09e-07 ***
## House.StyleSLvl 1.872e+03 3.841e+03 0.488 0.625944
## Roof.MatlCompShg 4.675e+05 3.163e+04 14.780 < 2e-16 ***
## Roof.MatlMembran 5.216e+05 4.123e+04 12.651 < 2e-16 ***
## Roof.MatlMetal 5.042e+05 4.166e+04 12.104 < 2e-16 ***
## Roof.MatlTar&Grv 4.679e+05 3.180e+04 14.714 < 2e-16 ***
## Roof.MatlWdShake 4.536e+05 3.312e+04 13.697 < 2e-16 ***
## Roof.MatlWdShngl 5.400e+05 3.346e+04 16.138 < 2e-16 ***
## Exter.QualFa -3.895e+04 7.725e+03 -5.042 5.05e-07 ***
## Exter.QualGd -3.860e+04 4.236e+03 -9.113 < 2e-16 ***
## Exter.QualTA -4.044e+04 4.727e+03 -8.556 < 2e-16 ***
## BsmtFin.Type.1BLQ -2.936e+03 2.483e+03 -1.182 0.237187
## BsmtFin.Type.1GLQ 3.455e+03 2.198e+03 1.572 0.116114
## BsmtFin.Type.1LwQ -9.276e+03 3.093e+03 -2.999 0.002742 **
## BsmtFin.Type.1None -1.951e+04 4.268e+03 -4.570 5.19e-06 ***
## BsmtFin.Type.1Rec -8.032e+03 2.495e+03 -3.220 0.001305 **
## BsmtFin.Type.1Unf -1.395e+04 2.086e+03 -6.688 2.96e-11 ***
## Kitchen.QualFa -3.949e+04 5.175e+03 -7.631 3.65e-14 ***
## Kitchen.QualGd -3.662e+04 3.096e+03 -11.828 < 2e-16 ***
## Kitchen.QualTA -3.797e+04 3.460e+03 -10.974 < 2e-16 ***
## Fireplace.QuFa -5.531e+03 6.758e+03 -0.818 0.413178
## Fireplace.QuGd -3.105e+03 5.555e+03 -0.559 0.576219
## Fireplace.QuNone -9.656e+03 5.722e+03 -1.688 0.091642 .
## Fireplace.QuPo -6.238e+03 7.274e+03 -0.858 0.391209
## Fireplace.QuTA -7.968e+03 5.671e+03 -1.405 0.160124
## Garage.TypeAttchd 7.678e+03 6.923e+03 1.109 0.267526
## Garage.TypeBasment 1.014e+03 8.647e+03 0.117 0.906682
## Garage.TypeBuiltIn 7.441e+03 7.417e+03 1.003 0.315854
## Garage.TypeCarPort 5.188e+03 1.010e+04 0.514 0.607637
## Garage.TypeDetchd 9.093e+03 6.977e+03 1.303 0.192633
## Garage.TypeNone 2.550e+03 7.335e+03 0.348 0.728089
## Pool.QCFa -5.726e+04 2.421e+04 -2.365 0.018134 *
## Pool.QCGd -3.024e+04 2.188e+04 -1.382 0.167134
## Pool.QCNone -5.314e+04 1.547e+04 -3.435 0.000605 ***
## Pool.QCTA -3.119e+04 2.419e+04 -1.289 0.197416
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 25770 on 1910 degrees of freedom
## Multiple R-squared: 0.8969, Adjusted R-squared: 0.8921
## F-statistic: 186.8 on 89 and 1910 DF, p-value: < 2.2e-16
plot(model)

## Warning: not plotting observations with leverage one:
## 142, 664, 1234, 1302, 1546, 1729

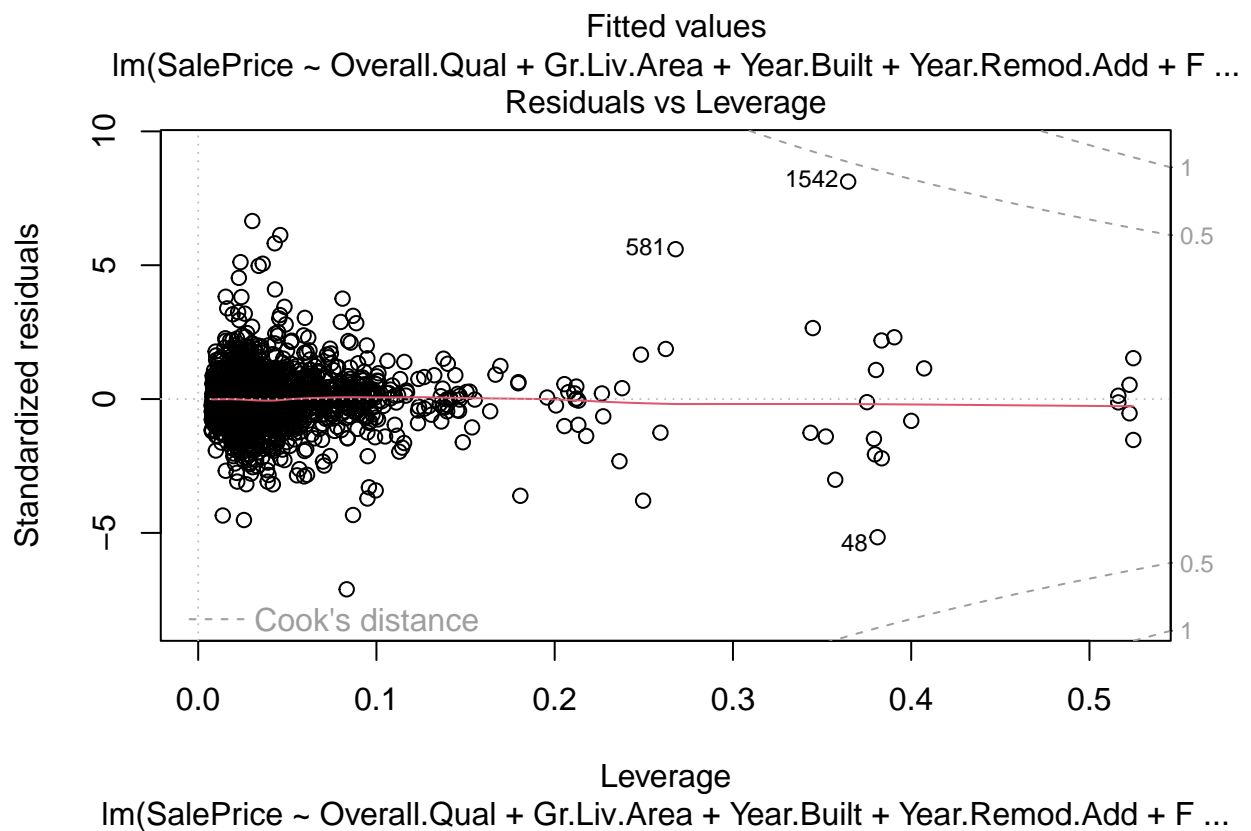
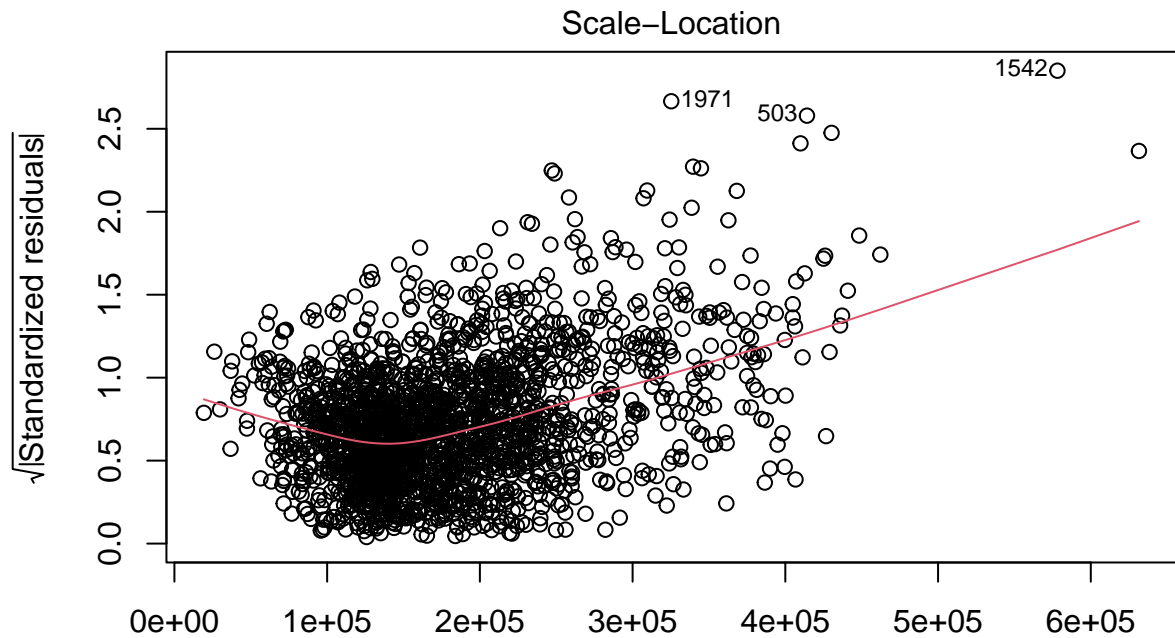
```



Fitted values
 $\text{lm}(\text{SalePrice} \sim \text{Overall.Qual} + \text{Gr.Liv.Area} + \text{Year.Built} + \text{Year.Remod.Add} + \text{F} \dots)$
 Q-Q Residuals



Theoretical Quantiles
 $\text{lm}(\text{SalePrice} \sim \text{Overall.Qual} + \text{Gr.Liv.Area} + \text{Year.Built} + \text{Year.Remod.Add} + \text{F} \dots)$



```
#to investigate numerical variables
House_Data_Numerical = data.frame(select_if(House_Data, is.numeric))

print(cor(House_Data_Numerical, House_Data_Numerical$SalePrice))
```

```
##           [,1]
## MS.SubClass -0.07520213
```

```
## Lot.Area      0.24399035
## Overall.Qual  0.80454673
## Overall.Cond  -0.12019006
## Year.Built    0.57171649
## Year.Remod.Add 0.53496165
## X1st.Flr.SF   0.61912063
## X2nd.Flr.SF   0.29593043
## Low.Qual.Fin.SF -0.05105615
## Gr.Liv.Area   0.72092212
## Full.Bath      0.56122804
## Half.Bath      0.28746758
## Bedroom.AbvGr 0.15392465
## Kitchen.AbvGr -0.12968211
## TotRms.AbvGrd 0.50427974
## Fireplaces    0.48079444
## Wood.Deck.SF  0.32936851
## Open.Porch.SF 0.31620588
## Enclosed.Porch -0.12835243
## X3Ssn.Porch   0.03014930
## Screen.Porch  0.09847254
## Pool.Area     0.08364937
## Misc.Val      -0.01175391
## Mo.Sold       0.03268045
## Yr.Sold       -0.02830382
## SalePrice     1.00000000
```

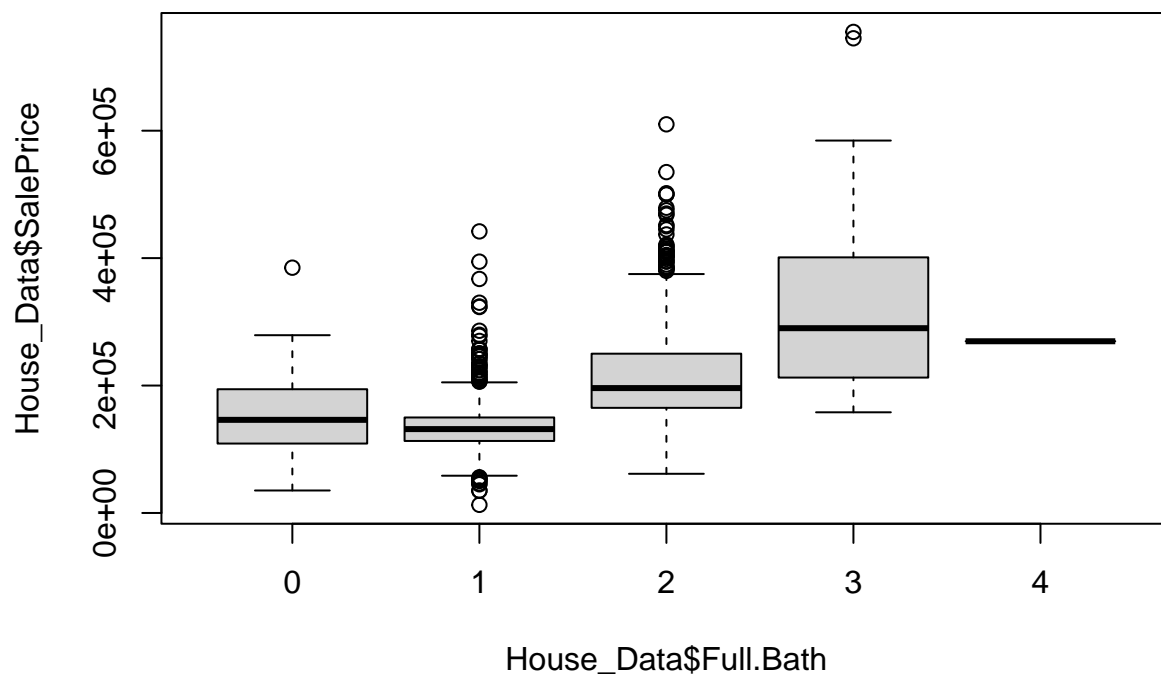
#to investigate categories

```
library(tidyverse)
```

```
House_Data_Categorical = data.frame(select_if(House_Data, negate(is.numeric)))
```

```
House_Data_Categorical$SalePrice = House_Data$SalePrice
```

```
boxplot(House_Data$SalePrice ~ House_Data$Full.Bath)
```




```
supply(lapply(House_Data_Categorical, unique), length)
```

```
##      MS.Zoning  Lot.Frontage      Street      Alley      Lot.Shape
##           7           121           2           3           4
##  Land.Contour    Utilities    Lot.Config    Land.Slope  Neighborhood
##           4           1           5           3           27
##  Condition.1    Condition.2    Bldg.Type    House.Style    Roof.Style
##           9           7           5           8           6
##    Roof.Matl  Exterior.1st  Exterior.2nd  Mas.Vnr.Type  Mas.Vnr.Area
##           7           14           16           5           362
##  Exter.Qual    Exter.Cond    Foundation    Bsmt.Qual    Bsmt.Cond
##           4           4           6           6           6
##  Bsmt.Exposure  BsmtFin.Type.1  BsmtFin.SF.1  BsmtFin.Type.2  BsmtFin.SF.2
##           5           7           816           7           211
##  Bsmt.Unf.SF  Total.Bsmt.SF      Heating    Heating.QC    Central.Air
##          927           870           6           5           2
##  Electrical  Bsmt.Full.Bath  Bsmt.Half.Bath  Kitchen.Qual    Functional
##           4           4           3           4           7
##  Fireplace.Qu  Garage.Type    Garage.Yr.Blt  Garage.Finish    Garage.Cars
##           6           7           101           4           6
##  Garage.Area    Garage.Qual    Garage.Cond    Paved.Drive    Pool.QC
##          530           6           6           3           5
##      Fence  Misc.Feature    Sale.Type  Sale.Condition    SalePrice
##           5           5           10           6           812
```

```
investigative_lm = lm(SalePrice ~ ., data = subset(House_Data_Categorical,
select = -c(Utilities, Lot.Frontage, Mas.Vnr.Area, BsmtFin.SF.1, BsmtFin.SF.2, Bsmt.Unf.SF, Total.Bsmt.SF, Garage.Yr.Blt,
summary(investigative_lm)
```

```
##
## Call:
## lm(formula = SalePrice ~ ., data = subset(House_Data_Categorical,
##      select = -c(Utilities, Lot.Frontage, Mas.Vnr.Area, BsmtFin.SF.1,
##      BsmtFin.SF.2, Bsmt.Unf.SF, Total.Bsmt.SF, Garage.Yr.Blt,
##      Garage.Area)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -144541  -14322    -562   12866  194373
##
## Coefficients: (4 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   102212.56  101049.52   1.012 0.311911
## MS.ZoningC (all)  -70026.08   53994.08  -1.297 0.194828
## MS.ZoningFV      -38154.37   52605.88  -0.725 0.468372
## MS.ZoningI (all) -61524.07   62500.84  -0.984 0.325067
## MS.ZoningRH     -17745.71   53589.37  -0.331 0.740576
## MS.ZoningRL     -32848.29   52297.62  -0.628 0.530018
## MS.ZoningRM     -39135.55   52732.20  -0.742 0.458091
## StreetPave      30577.58   12334.38   2.479 0.013266 *
## AlleyNone       2242.23    4129.22   0.543 0.587188
## AlleyPave       9613.18    6480.05   1.484 0.138119
## Lot.ShapeIR2    7184.25    4428.17   1.622 0.104897
## Lot.ShapeIR3    26411.54    8961.83   2.947 0.003250 **
```

## Lot.ShapeReg	-1532.60	1701.81	-0.901	0.367938	
## Land.ContourHLS	-2867.03	5439.59	-0.527	0.598213	
## Land.ContourLow	-4397.28	7080.96	-0.621	0.534680	
## Land.ContourLvl	3408.24	4013.35	0.849	0.395870	
## Lot.ConfigCulDSac	4155.25	3394.35	1.224	0.221053	
## Lot.ConfigFR2	-12429.56	4402.24	-2.823	0.004804	**
## Lot.ConfigFR3	1975.85	8475.34	0.233	0.815688	
## Lot.ConfigInside	-742.31	1886.27	-0.394	0.693972	
## Land.SlopeMod	9290.98	4249.42	2.186	0.028916	*
## Land.SlopeSev	5658.60	10604.63	0.534	0.593687	
## NeighborhoodBlueste	2788.41	14594.74	0.191	0.848504	
## NeighborhoodBrDale	17977.72	13610.67	1.321	0.186721	
## NeighborhoodBrkSide	3185.40	10724.36	0.297	0.766482	
## NeighborhoodClearCr	23704.93	10970.60	2.161	0.030847	*
## NeighborhoodCollgCr	6020.35	8966.76	0.671	0.502049	
## NeighborhoodCrawfor	37284.29	9872.93	3.776	0.000164	***
## NeighborhoodEdwards	-5932.40	9529.90	-0.623	0.533691	
## NeighborhoodGilbert	-5951.83	9427.24	-0.631	0.527898	
## NeighborhoodGreens	25179.35	16724.32	1.506	0.132361	
## NeighborhoodGrnHill	178580.75	30844.06	5.790	8.32e-09	***
## NeighborhoodIDOTRR	8013.96	11418.60	0.702	0.482876	
## NeighborhoodMeadowV	-17518.38	12082.35	-1.450	0.147260	
## NeighborhoodMitchel	-147.48	9818.11	-0.015	0.988017	
## NeighborhoodNonemes	-3076.94	9421.15	-0.327	0.744010	
## NeighborhoodNoRidge	68087.42	9706.60	7.015	3.27e-12	***
## NeighborhoodNPkVill	35445.77	19543.50	1.814	0.069896	.
## NeighborhoodNridgHt	33772.89	9162.80	3.686	0.000235	***
## NeighborhoodNWAmes	12253.53	9743.10	1.258	0.208680	
## NeighborhoodOldTown	-586.23	10656.03	-0.055	0.956133	
## NeighborhoodSawyer	-3339.80	9711.03	-0.344	0.730948	
## NeighborhoodSawyerW	5637.89	9465.84	0.596	0.551516	
## NeighborhoodSomerst	30007.56	10285.40	2.917	0.003573	**
## NeighborhoodStoneBr	60176.28	10012.79	6.010	2.25e-09	***
## NeighborhoodSWISU	-2593.34	11225.24	-0.231	0.817320	
## NeighborhoodTimber	11275.52	9620.83	1.172	0.241359	
## NeighborhoodVeenker	27901.75	12226.09	2.282	0.022599	*
## Condition.1Feedr	1482.41	5211.84	0.284	0.776113	
## Condition.1Norm	13234.59	4268.58	3.100	0.001963	**
## Condition.1PosA	33193.38	9634.87	3.445	0.000584	***
## Condition.1PosN	16952.90	7916.63	2.141	0.032376	*
## Condition.1RR Ae	2961.98	8404.43	0.352	0.724557	
## Condition.1RR An	3440.72	7302.91	0.471	0.637597	
## Condition.1RR Ne	2978.83	14480.67	0.206	0.837040	
## Condition.1RR Nn	-861.61	11820.56	-0.073	0.941901	
## Condition.2Feedr	-10258.31	20496.05	-0.501	0.616784	
## Condition.2Norm	-20107.93	18055.32	-1.114	0.265566	
## Condition.2PosA	148180.65	36261.41	4.086	4.58e-05	***
## Condition.2PosN	-15973.62	25935.24	-0.616	0.538037	
## Condition.2RR An	-7814.35	35020.46	-0.223	0.823455	
## Condition.2RR Nn	-13907.84	28129.12	-0.494	0.621065	
## Bldg.Type2fmCon	-6532.26	5176.24	-1.262	0.207126	
## Bldg.TypeDuplex	3706.68	4522.89	0.820	0.412589	
## Bldg.TypeTwnhs	-42601.30	5801.08	-7.344	3.16e-13	***
## Bldg.TypeTwnhsE	-34080.03	3731.01	-9.134	< 2e-16	***

## House.Style1.5Unf	-9375.22	9065.75	-1.034	0.301214	
## House.Style1Story	-14093.61	2781.17	-5.068	4.45e-07	***
## House.Style2.5Fin	65513.41	18233.80	3.593	0.000336	***
## House.Style2.5Unf	12540.77	9230.79	1.359	0.174453	
## House.Style2Story	1522.01	2942.51	0.517	0.605048	
## House.StyleSFoyer	-32238.74	5376.80	-5.996	2.45e-09	***
## House.StyleSLvl	-21085.77	4604.82	-4.579	5.00e-06	***
## Roof.StyleGable	31046.78	15874.58	1.956	0.050652	.
## Roof.StyleGambrel	42793.53	17871.68	2.394	0.016747	*
## Roof.StyleHip	39773.70	15972.45	2.490	0.012860	*
## Roof.StyleMansard	24593.05	23406.18	1.051	0.293537	
## Roof.StyleShed	-47819.07	38691.74	-1.236	0.216661	
## Roof.MatlCompShg	291617.12	38284.46	7.617	4.20e-14	***
## Roof.MatlMembran	323216.58	53671.20	6.022	2.09e-09	***
## Roof.MatlMetal	286483.50	52932.46	5.412	7.08e-08	***
## Roof.MatlTar&Grv	308147.75	41379.16	7.447	1.49e-13	***
## Roof.MatlWdShake	304350.03	40755.51	7.468	1.28e-13	***
## Roof.MatlWdShngl	398305.77	40968.01	9.722	< 2e-16	***
## Exterior.1stAsphShn	2122.09	33814.75	0.063	0.949968	
## Exterior.1stBrkComm	30124.37	20436.64	1.474	0.140650	
## Exterior.1stBrkFace	36058.92	11786.10	3.059	0.002251	**
## Exterior.1stCBlock	-25020.94	41390.84	-0.605	0.545586	
## Exterior.1stCemntBd	64254.75	24479.00	2.625	0.008742	**
## Exterior.1stHdBoard	4824.93	11614.07	0.415	0.677871	
## Exterior.1stMetalSd	-2535.91	14809.80	-0.171	0.864061	
## Exterior.1stPlywood	17232.67	11331.43	1.521	0.128493	
## Exterior.1stStone	22893.52	36986.71	0.619	0.536018	
## Exterior.1stStucco	8300.40	13531.61	0.613	0.539686	
## Exterior.1stVinylSd	282.73	13111.39	0.022	0.982798	
## Exterior.1stWd Sdng	4227.83	11172.45	0.378	0.705168	
## Exterior.1stWdShing	-6596.56	12537.85	-0.526	0.598863	
## Exterior.2ndAsphShn	8496.93	26396.47	0.322	0.747569	
## Exterior.2ndBrk Cmn	-15276.71	20792.90	-0.735	0.462615	
## Exterior.2ndBrkFace	-6805.11	12995.67	-0.524	0.600591	
## Exterior.2ndCBlock	21606.10	26876.81	0.804	0.421567	
## Exterior.2ndCmentBd	-39244.16	24796.76	-1.583	0.113684	
## Exterior.2ndHdBoard	4763.94	11905.14	0.400	0.689088	
## Exterior.2ndImStucc	13405.43	15601.93	0.859	0.390338	
## Exterior.2ndMetalSd	14940.04	15084.16	0.990	0.322092	
## Exterior.2ndOther	-6972.15	32652.27	-0.214	0.830940	
## Exterior.2ndPlywood	-2752.58	11340.08	-0.243	0.808243	
## Exterior.2ndStone	-23969.45	21154.72	-1.133	0.257345	
## Exterior.2ndStucco	-6111.62	13500.36	-0.453	0.650820	
## Exterior.2ndVinylSd	11065.56	13179.19	0.840	0.401233	
## Exterior.2ndWd Sdng	5408.17	11452.92	0.472	0.636836	
## Exterior.2ndWd Shng	9885.27	12412.42	0.796	0.425906	
## Mas.Vnr.TypeBrkFace	-1830.69	8189.07	-0.224	0.823131	
## Mas.Vnr.TypeCBlock	51131.23	48170.98	1.061	0.288629	
## Mas.Vnr.TypeNone	-7119.98	8108.83	-0.878	0.380034	
## Mas.Vnr.TypeStone	1673.16	8522.55	0.196	0.844381	
## Exter.QualFa	-40456.73	9910.51	-4.082	4.66e-05	***
## Exter.QualGd	-31067.19	4982.65	-6.235	5.64e-10	***
## Exter.QualTA	-40208.55	5535.56	-7.264	5.62e-13	***
## Exter.CondFa	-2944.14	12352.40	-0.238	0.811641	

## Exter.CondGd	5917.84	11157.30	0.530	0.595901	
## Exter.CondTA	2136.43	10990.99	0.194	0.845900	
## FoundationCBlock	2419.57	3185.69	0.760	0.447648	
## FoundationPConc	5378.59	3461.78	1.554	0.120433	
## FoundationSlab	7301.32	10045.83	0.727	0.467444	
## FoundationStone	2660.00	12666.27	0.210	0.833687	
## FoundationWood	467.26	15489.64	0.030	0.975938	
## Bsmt.QualFa	-45219.32	6305.02	-7.172	1.08e-12	***
## Bsmt.QualGd	-28962.66	3564.80	-8.125	8.34e-16	***
## Bsmt.QualNone	-75661.72	41329.46	-1.831	0.067314	.
## Bsmt.QualPo	-19943.89	34000.29	-0.587	0.557561	
## Bsmt.QualTA	-36519.97	4343.06	-8.409	< 2e-16	***
## Bsmt.CondFa	-8836.65	18456.14	-0.479	0.632146	
## Bsmt.CondGd	-6137.91	18339.06	-0.335	0.737898	
## Bsmt.CondNone	NA	NA	NA	NA	
## Bsmt.CondPo	-23919.49	29010.61	-0.825	0.409762	
## Bsmt.CondTA	-5310.28	18034.00	-0.294	0.768441	
## Bsmt.ExposureGd	22083.62	3074.91	7.182	1.01e-12	***
## Bsmt.ExposureMn	-4716.21	3182.27	-1.482	0.138512	
## Bsmt.ExposureNo	-7811.00	2379.86	-3.282	0.001050	**
## Bsmt.ExposureNone	-16393.13	20709.61	-0.792	0.428717	
## BsmtFin.Type.1BLQ	-1501.57	2960.84	-0.507	0.612117	
## BsmtFin.Type.1GLQ	4677.70	2625.31	1.782	0.074959	.
## BsmtFin.Type.1LwQ	850.35	3806.73	0.223	0.823264	
## BsmtFin.Type.1None	NA	NA	NA	NA	
## BsmtFin.Type.1Rec	-1782.76	3004.65	-0.593	0.553033	
## BsmtFin.Type.1Unf	-6296.59	2678.74	-2.351	0.018854	*
## BsmtFin.Type.2BLQ	-6565.09	6641.78	-0.988	0.323066	
## BsmtFin.Type.2GLQ	5646.08	8204.56	0.688	0.491440	
## BsmtFin.Type.2LwQ	-3126.87	6410.16	-0.488	0.625753	
## BsmtFin.Type.2None	19222.90	29660.80	0.648	0.517010	
## BsmtFin.Type.2Rec	-4176.83	6370.39	-0.656	0.512126	
## BsmtFin.Type.2Unf	-692.52	5244.37	-0.132	0.894960	
## HeatingGasA	4908.42	31241.48	0.157	0.875174	
## HeatingGasW	30402.98	32112.62	0.947	0.343890	
## HeatingGrav	8378.25	35263.26	0.238	0.812225	
## HeatingOthW	11152.35	38330.80	0.291	0.771124	
## HeatingWall	8735.62	36573.95	0.239	0.811251	
## Heating.QCFa	-10389.25	4794.07	-2.167	0.030360	*
## Heating.QCGd	-4437.86	2193.17	-2.023	0.043173	*
## Heating.QCPo	-33260.43	32261.48	-1.031	0.302699	
## Heating.QCTA	-5320.87	2118.90	-2.511	0.012122	*
## Central.AirY	5992.27	3857.07	1.554	0.120464	
## ElectricalFuseF	-5531.13	6140.91	-0.901	0.367870	
## ElectricalFuseP	10225.67	16374.92	0.624	0.532399	
## ElectricalSBkr	1278.93	3082.43	0.415	0.678260	
## Bsmt.Full.Bath1	5493.12	1926.78	2.851	0.004410	**
## Bsmt.Full.Bath2	22576.13	7913.88	2.853	0.004385	**
## Bsmt.Full.Bath3	17777.72	30832.87	0.577	0.564294	
## Bsmt.Half.Bath1	736.33	3099.27	0.238	0.812233	
## Bsmt.Half.Bath2	-22425.58	17653.38	-1.270	0.204135	
## Kitchen.QualFa	-53747.49	6173.63	-8.706	< 2e-16	***
## Kitchen.QualGd	-37760.70	3752.71	-10.062	< 2e-16	***
## Kitchen.QualTA	-47255.24	4086.65	-11.563	< 2e-16	***

## FunctionalMaj2	-28224.18	16579.36	-1.702	0.088862	.
## FunctionalMin1	-7843.98	10194.70	-0.769	0.441749	
## FunctionalMin2	-2637.98	10268.87	-0.257	0.797293	
## FunctionalMod	301.42	11431.09	0.026	0.978967	
## FunctionalSev	-18326.27	24471.73	-0.749	0.454032	
## FunctionalTyp	-2727.07	9135.36	-0.299	0.765343	
## Fireplace.QuFa	-28035.62	7726.83	-3.628	0.000293	***
## Fireplace.QuGd	-15810.49	6312.48	-2.505	0.012347	*
## Fireplace.QuNone	-30216.46	6452.70	-4.683	3.05e-06	***
## Fireplace.QuPo	-26809.06	8303.08	-3.229	0.001266	**
## Fireplace.QuTA	-13804.89	6445.39	-2.142	0.032344	*
## Garage.TypeAttchd	23008.59	8472.20	2.716	0.006677	**
## Garage.TypeBasment	16944.07	10481.80	1.617	0.106160	
## Garage.TypeBuiltIn	30115.79	8968.24	3.358	0.000802	***
## Garage.TypeCarPort	-1321.76	12190.44	-0.108	0.913670	
## Garage.TypeDetchd	12280.31	8488.10	1.447	0.148139	
## Garage.TypeNone	9824.28	32306.31	0.304	0.761089	
## Garage.FinishNone	21191.83	42481.12	0.499	0.617945	
## Garage.FinishRFn	-2201.73	2074.14	-1.062	0.288600	
## Garage.FinishUnf	-2339.46	2501.70	-0.935	0.349840	
## Garage.Cars1	27389.57	44198.94	0.620	0.535543	
## Garage.Cars2	39732.53	44256.96	0.898	0.369431	
## Garage.Cars3	69102.26	44350.79	1.558	0.119392	
## Garage.Cars4	62022.63	45428.57	1.365	0.172339	
## Garage.Cars5	45451.15	53755.20	0.846	0.397934	
## Garage.QualFa	-92662.47	42663.76	-2.172	0.029994	*
## Garage.QualGd	-65367.92	41670.26	-1.569	0.116898	
## Garage.QualNone	NA	NA	NA	NA	
## Garage.QualPo	-139571.20	49501.87	-2.820	0.004863	**
## Garage.QualTA	-89749.50	42488.10	-2.112	0.034797	*
## Garage.CondFa	75179.53	31123.19	2.416	0.015812	*
## Garage.CondGd	66318.36	31852.17	2.082	0.037480	*
## Garage.CondNone	NA	NA	NA	NA	
## Garage.CondPo	89491.77	33343.91	2.684	0.007345	**
## Garage.CondTA	83576.90	30709.42	2.722	0.006562	**
## Paved.DriveP	3243.95	5547.38	0.585	0.558776	
## Paved.DriveY	6509.84	3364.37	1.935	0.053158	.
## Pool.QCFa	-165945.95	35308.16	-4.700	2.80e-06	***
## Pool.QCGd	-111285.06	26114.70	-4.261	2.14e-05	***
## Pool.QCNone	-177794.63	18563.66	-9.578	< 2e-16	***
## Pool.QCTA	-122124.69	28331.05	-4.311	1.72e-05	***
## FenceGdWo	665.44	5062.48	0.131	0.895437	
## FenceMnPrv	2111.26	4168.61	0.506	0.612592	
## FenceMnWw	2566.99	12100.27	0.212	0.832020	
## FenceNone	94.93	3798.33	0.025	0.980064	
## Misc.FeatureNone	-7091.01	20770.55	-0.341	0.732845	
## Misc.FeatureOthr	26954.62	30428.45	0.886	0.375826	
## Misc.FeatureShed	-5100.57	21098.60	-0.242	0.809003	
## Misc.FeatureTenC	30924.24	47106.90	0.656	0.511608	
## Sale.TypeCon	40974.32	21980.29	1.864	0.062468	.
## Sale.TypeConLD	9530.50	9340.65	1.020	0.307714	
## Sale.TypeConLI	-4847.61	10918.71	-0.444	0.657117	
## Sale.TypeConLw	-2557.13	15947.47	-0.160	0.872626	
## Sale.TypeCWD	12531.18	11343.76	1.105	0.269450	

```
## Sale.TypeNew          52337.82   18855.41    2.776 0.005566 **
## Sale.Type0th          30715.80   17521.08    1.753 0.079762 .
## Sale.TypeVWD          4124.24   30083.03    0.137 0.890971
## Sale.TypeWD           -876.34    4198.03   -0.209 0.834666
## Sale.ConditionAdjLand  26481.01   10896.05    2.430 0.015184 *
## Sale.ConditionAlloca  17239.00    8646.77    1.994 0.046339 *
## Sale.ConditionFamily  -1464.56    6054.18   -0.242 0.808878
## Sale.ConditionNormal   9944.26    3054.32    3.256 0.001152 **
## Sale.ConditionPartial -30822.10   18425.70   -1.673 0.094548 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 28760 on 1767 degrees of freedom
## Multiple R-squared:  0.8812, Adjusted R-squared:  0.8657
## F-statistic: 56.52 on 232 and 1767 DF,  p-value: < 2.2e-16
```

Results

- What is the final regression model for the data?
- Using the standard diagnostic tests, does the model appear to fit the data well?
- What are the final confidence intervals for the effects of interest mentioned in the study section?

Use your validation data to construct these intervals. Do these intervals seem very sensitive to the choice of model (i.e. do they vary widely for different choices of variables in the model)? • What is your estimated prediction accuracy for your model? (Evaluated on the validation set). • Compare the intervals constructed using your final selected model fit to the validation set to the same intervals constructed on the training set. Are they very different? Which do you believe more?

Appendix

Ideally, there will be comments in the file, i.e. lines beginning with “#” to clarify what each part of the code is doing.

Acknowledgements : If you consult outside sources that refer to this data set, you should cite these

as references, and describe what you used from each source. Sources include material found on the internet, journal articles and books.