THE TRUE PRICE FOR YOUR HOUSE

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ABSTRACT

If you ever try to buy a 1,500 square feet house in San Francisco, California and then look for a similar house in Stillwater, Oklahoma, you would see a stark difference in the price of the house. Obviously, location plays a huge factor in the real estate prices. If you limit the location to a city, do you think the cost of two 1,500 square feet houses in San Francisco or Chicago would be the same? There are a lot of factors that go into the final sale price of the house, such as the condition of the house, proximity to schools and parks, proximity to public transport, etc.

This paper tries to understand the underlying factors that go into creating the price of each house. The goal of this paper is to build a predictive model that can identify and capture the variance in the data as accurately as possible in order to use this data to predict future house prices in Ames, Iowa. Implications exist for other locations by taking into consideration the geographic and demographic differences and their impacts. Initially, a decision tree model was used to identify variable importance. After this, various predictive modeling techniques were used in SAS Enterprise Miner to identify the best fitting model that would help predict the house price. Comparison of different models shows that the Ensemble model has performed the best with the least average squared error.

INTRODUCTION

When buying a house, we look at a lot of features, its square feet area, no. of bedrooms, bathrooms, frontyards & backyards, location, and ultimately its price. As it happens, the price itself is dependent on many factors.

This dataset provides many salient and peripheral features of a house that would give a better idea of what and how much do each of these features affect the final sale price. The dataset there are 80 explanatory variables describing every aspect of residential homes in Ames, Iowa such as Street, Neighborhood, LotShape, LandSlope, YearBuilt, FullBath, GarageCars, Fireplaces and Pool Quality for 2,930 homes.

What are we trying to answer?

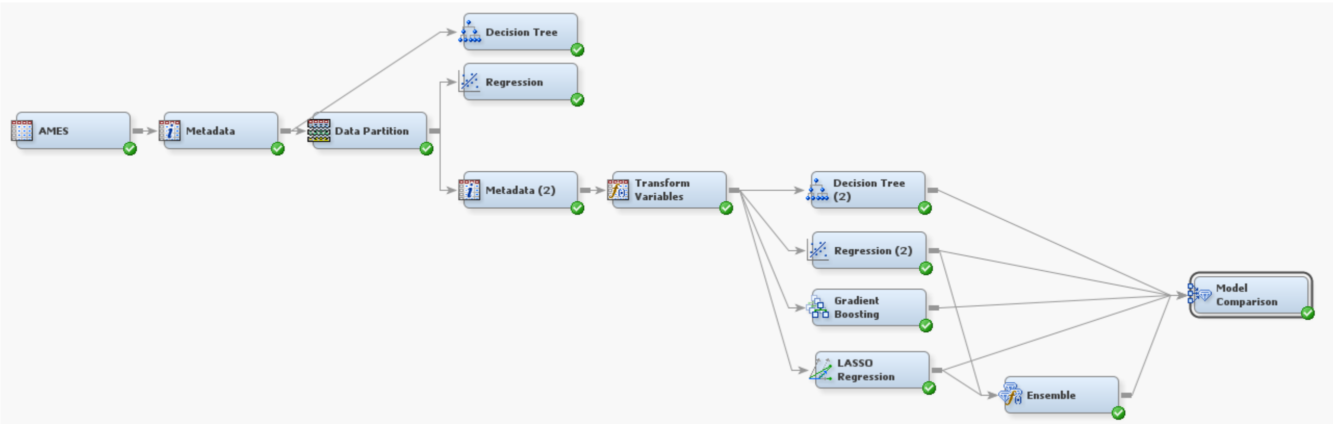
i. What are the important features and factors that impact house prices
ii. Can we build a model focusing on these important features and estimate accurately the cost of a house?

METHODOLOGY

1. Initial exploratory data analysis was done to identify outliers if any, and handle them as required. Five observations with unusual target variables were dropped from the dataset
2. Variable selection was done using decision tree model and stepwise regression to understand variable importance with respect to the target variable. Based on this, the initial set of variables that would go into the final model was reduced from 80 to 30.

3. Transform Interval Variables
    - To account for skewness of the variables, log transformation was performed on 3 interval variables that indicated high skewness
    - Since the variables were on different scales, there could be a bias introduced in the data. In order to fix this, normalization or range standardization was performed on the interval variables.
    - The new Range for the variable was transformed with a scaled value of a variable equal to NewVar = (x - min) / (max - min), where x is current variable value, min is the minimum value for that variable, and max is the maximum value for that variable.

4. Model Comparison
   Various models were used to understand which model would explain the maximum variance with respect to the Target variable.



The idea was to identify the best model which gives the least average squared error, as it an indicator of the difference in the predicted value vs. true value of the house price. Lower ASE show indicates a better model. Shown above is the SAS Enterprise Miner diagram. Five models were used – Decision Tree, Linear Regression, LASSO Regression, Gradient Boosting and Ensemble model. We used a model comparison node to identify the model with least ASE.

RESULTS

1. Identifying Important Variables

The decision tree we have identified the variables with the highest significance w.r.t to the target variable. As we can see, Overall Quality of the House, Above Ground Living Area in Square Feet, Total Square Feet of Basement Area, Neighborhood, Year Remodeled, Garage Cars, Central Air, No. of Full Bath, etc. are important among all the other variables we have related to the sale price.

Variable Importance

Variable Name	Label	Number of Splitting Rules	Importance
OverallQual	OverallQual	5	1.0000
Neighborhood	Neighborhood	2	0.4512
GrLivArea	GrLivArea	11	0.4003
TotalBsmtSF	TotalBsmtSF	5	0.2358
_1stFlrSF		3	0.1954
BsmtFinSF1	BsmtFinSF1	5	0.1031
MSSubClass	MSSubClass	1	0.0739
GarageArea	GarageArea	3	0.0578
YearBuilt	YearBuilt	1	0.0513
KitchenQual	KitchenQual	1	0.0505
GarageType	GarageType	1	0.0420
Fireplaces	Fireplaces	1	0.0342
GarageCond	GarageCond	1	0.0309
YrsSinceRemod		1	0.0279

2. Model Comparison Results

Based on the model comparison results, we see that the Ensemble model is the model with the least average squared error. The Ensemble model creates new models by combining the predicted values for interval targets from multiple predecessor models. The new model is then used to score new data.

In this approach, multiple modeling methods were used, such as a LASSO, Regression, Decision Tree, Gradient Boosting and an Ensemble model with the input of the other 4 models, to obtain separate models from the same training data set. The output from these models is used to form the final model solution.

In this case we have seen that LASSO regression model has outperformed all the other individual models

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Average Squared Error	Valid: Root Average Squared Error	Train: Maximum Absolute Error	Train: Sum of Squared Errors	Train: Average Squared Error	Train: Root Average Squared Error
Y	LARS	LARS	LASSO ...	SalePrice	SalePrice	5.1622E8	22720.37	150689.8	7.222E11	4.1152E8	20285.89
	Ensmbl	Ensmbl	Ensemble	SalePrice	SalePrice	5.1717E8	22741.27	150224.9	7.196E11	4.1004E8	20249.45
	Reg2	Reg2	Regressi...	SalePrice	SalePrice	5.1907E8	22783.19	149760	7.188E11	4.0955E8	20237.28
	Tree2	Tree2	Decision ...	SalePrice	SalePrice	1.0079E9	31747.17	198983.6	1.303E12	7.4238E8	27246.6
	Boost	Boost	Gradient ...	SalePrice	SalePrice	1.0318E9	32122.42	248360.3	1.596E12	9.0948E8	30157.57

3. Final Selected Model Results – LASSO Regression

Fit Statistics	Statistics Label	Train	Validation
ASE	Average Squared Error	411517219.37	516215283.76
DIV	Divisor for ASE	1755.00	1170.00
MAX	Maximum Absolute Error	150689.78	160905.54
NOBS	Sum of Frequencies	1755.00	1170.00
RASE	Root Average Squared Error	20285.89	22720.37
SSE	Sum of Squared Errors	722212719994.32	603971881996.45

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value
Model	90	1.023168E13	1.136853E11	261.93
Error	1664	7.222127E11	434022067	
Corrected Total	1754	1.095389E13		

Root MSE	20833
Dependent Mean	179336
R-Square	0.9341
Adj R-Sq	0.9305
AIC	36750
AICC	36760
SBC	35491
ASE (Train)	411517219
ASE (Validate)	516215284

The RASE (root average squared error) for the model is 22 thousand. This means that on average the difference in predicted value from the actual value is 22 thousand, where the average sale price for the house is 180 thousand in the dataset.
The model also give a R-square of 93%, which is an indicator of the goodness of fit of a regression model

LIMITATIONS

As the dataset is limited to one city Ames, Iowa, we can't explore impact of geographic or demographic factors which may have an influence on house price.

CONCLUSION

Intuitively we would expect lot square footage, and number of bedrooms would have a direct relation to Sale Price, but by having a better understanding of all the hidden factors that have an impact on House Price, we would be able to run targeted marketing campaigns at better prices by highlighting these features. However, in the final model it is seen that Neighborhood where a house is located, MSSubClass (type of dwelling such as 1-Story, 2-Story, Duplex), Lot size in square feet, No. of Bedrooms Above Ground, Basement Exposure (which refers to walkout or garden level walls), No. of Cars in Garage, Exterior covering on house, Kitchen Quality, Condition1 (proximity to various locations/streets) significantly affect the valuation of the home.

CITATIONS AND ACKNOWLEDGMENTS

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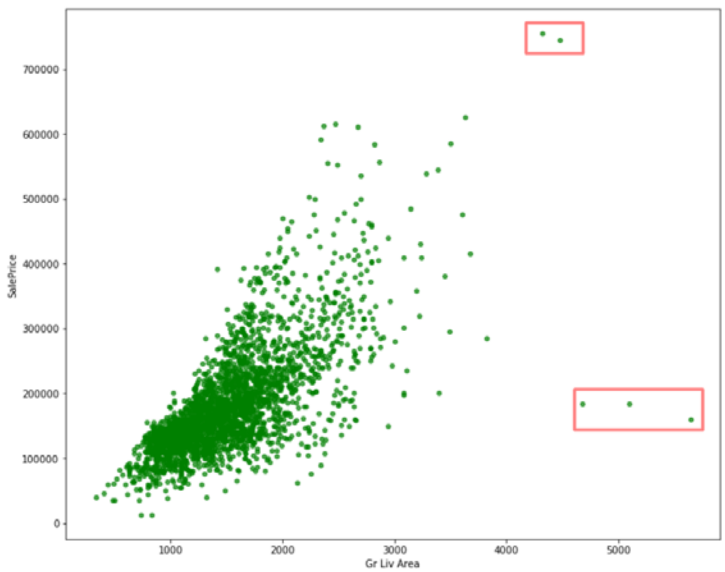
APPENDIX

APPENDIX A:

DESCRIPTIVE STATISTICS:

i. Identifying Outliers

By deep-diving into the data, we notice there are five clear outliers. The two outliers in the top have very high sale price and above ground living area (square feet), whereas there are a few other outliers with very high above ground living area, but relatively low sale price. In order to not let these observations impact the overall model, they are excluded from the dataset for further analysis.



ii. Variable Importance

Using a decision tree we see that the following variables are important with respect to the target variables

Variable Importance

Variable Name	Label	Number of Splitting Rules	Importance
OverallQual	OverallQual	5	1.0000
Neighborhood	Neighborhood	2	0.4512
GrLivArea	GrLivArea	11	0.4003
TotalBsmtSF	TotalBsmtSF	5	0.2358
_1stFlrSF		3	0.1954
BsmtFinSF1	BsmtFinSF1	5	0.1031
MSSubClass	MSSubClass	1	0.0739
GarageArea	GarageArea	3	0.0578
YearBuilt	YearBuilt	1	0.0513
KitchenQual	KitchenQual	1	0.0505
GarageType	GarageType	1	0.0420
Fireplaces	Fireplaces	1	0.0342
GarageCond	GarageCond	1	0.0309
YrsSinceRemod		1	0.0279

The stepwise regression model has selected the following variables in the final model

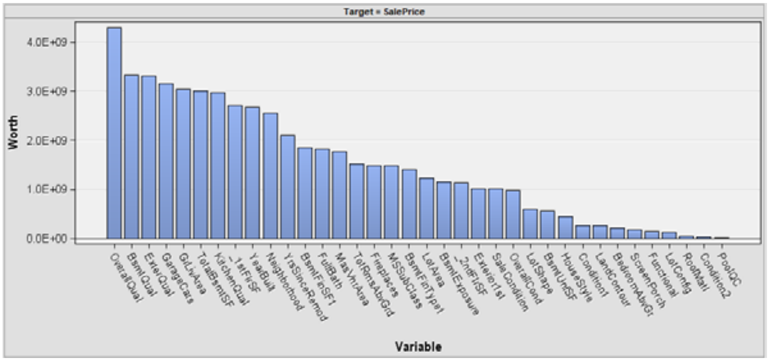
Type 3 Analysis of Effects

Effect	DF	Sum of Squares	F Value	Pr > F
BedroomAbvGr	1	4164627485	10.53	0.0012
BsmtExposure	4	2.50937E10	15.87	<.0001
BsmtFinSF1	1	1872481689	4.74	0.0297
BsmtFinType1	6	5782932931	2.44	0.0238
BsmtQual	4	1.14973E10	7.27	<.0001
BsmtUnfSF	1	7871494926	19.91	<.0001
Condition1	8	1.4569E10	4.61	<.0001
Condition2	5	9.01766E10	45.61	<.0001
ExterQual	3	7326759526	6.18	0.0004
Exterior1st	13	2.04456E10	3.98	<.0001
Fireplaces	1	2816088534	7.12	0.0077
FullBath	1	2375343366	6.01	0.0144
Functional	6	1.29684E10	5.47	<.0001
GarageCars	1	1.50819E10	38.14	<.0001
GrLivArea	1	7.00118E10	177.06	<.0001
HouseStyle	7	9535381652	3.45	0.0012
KitchenQual	4	1.06803E10	6.75	<.0001
LandContour	3	7683565491	6.48	0.0002
LotArea	1	1.26301E10	31.94	<.0001
LotConfig	4	7862059542	4.97	0.0006
LotShape	3	4052512839	3.42	0.0168
MSSubClass	14	6.46712E10	11.68	<.0001
MasVnrArea	1	3642338633	9.21	0.0024
Neighborhood	26	1.14409E11	11.13	<.0001
OverallCond	8	4.60392E10	14.55	<.0001
OverallQual	9	6.63667E10	18.65	<.0001
PoolQC	4	2.53726E10	16.04	<.0001
RoofMatl	5	2.84234E10	14.38	<.0001
SaleCondition	5	1.53259E10	7.75	<.0001
ScreenPorch	1	3268869655	8.27	0.0041
TotalBsmtSF	1	2.64183E10	66.81	<.0001
YearBuilt	1	2.40669E10	60.87	<.0001
YrsSinceRemod	1	3739047147	9.46	0.0021
_2ndFlrSF	1	9420186337	23.82	<.0001

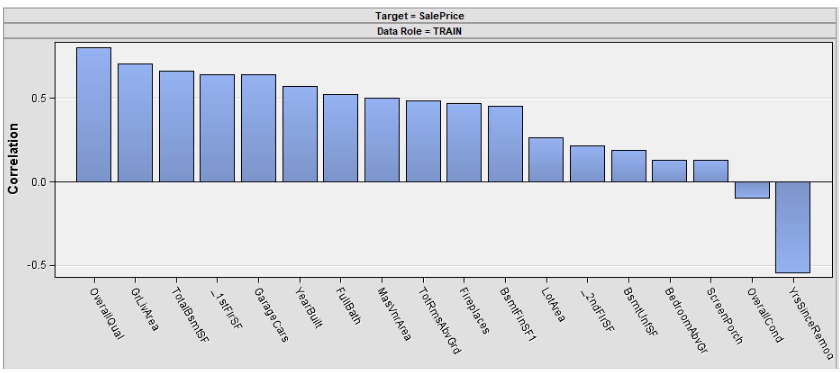
All the variables selected by the regression model and decision tree model are used to build the first cut model. Using the variables as the first step, I will start looking at the multi collinearity, VIF (variance inflation factor), correlation with Target.

iii. Analysis of Shortlisted Variables

Variable importance of the selected variables is shown below:



Top Correlated Variables with Target:



Few of the variables have high skewness, which will be transformed using log transformation:

Data Role=TRAIN

Variable	Role	Mean	Standard Deviation	Non Missing	Missing	Minimum	Median	Maximum	Skewness	Kurtosis
BedroomAbvGr	INPUT	2.82963	0.823701	1755	0	0	3	6	0.165382	1.397393
BsmtFinSF1	INPUT	425.812	437.2287	1755	0	0	347	2188	0.832834	-0.06946
BsmtUnfSF	INPUT	554.9151	435.5794	1755	0	0	475	2336	0.88315	0.388132
Fireplaces	INPUT	0.593732	0.643063	1755	0	0	1	4	0.748482	0.204974
FullBath	INPUT	1.564672	0.550427	1755	0	0	2	4	0.153328	-0.47021
GarageCars	INPUT	1.752137	0.770456	1755	0	0	2	5	-0.21724	0.362095
GrLivArea	INPUT	1487.297	473.0059	1755	0	334	1436	3820	0.856993	1.084792
LotArea	INPUT	10097.17	8388.569	1755	0	1300	9240	215245	13.36868	275.6905
MasVnrArea	INPUT	99.22336	176.9705	1755	0	0	0	1600	2.6486	9.84412
OverallCond	INPUT	5.562393	1.125003	1755	0	1	5	9	0.657198	1.380661
OverallQual	INPUT	6.067236	1.438608	1755	0	1	6	10	0.144403	0.011371
ScreenPorch	INPUT	15.97835	56.32005	1755	0	0	0	576	4.093494	19.92647
TotRmsAbvGrd	INPUT	6.403989	1.551578	1755	0	2	6	12	0.70592	0.872008
TotalBsmtSF	INPUT	1035.23	426.3422	1755	0	0	975	3200	0.375016	1.118566
YearBuilt	INPUT	1970.688	30.67313	1755	0	1875	1973	2010	-0.58876	-0.56617
YrsSinceRemod	INPUT	23.5698	20.91101	1755	0	0	15	60	0.457381	-1.32191
_1stFlrSF	INPUT	1149.524	381.9696	1755	0	334	1079	3820	1.024794	2.219401
_2ndFlrSF	INPUT	333.2838	418.5716	1755	0	0	0	1862	0.806307	-0.61584
SalePrice	TARGET	179335.8	79025.89	1755	0	12789	160000	611657	1.56179	3.519302

Class variables with more than 90% of the observations having one value will not explain much variance in the model and hence are dropped from the model

Data Role=TRAIN

Data Role	Variable Name	Role	Number of Levels	Missing	Mode	Mode Percentage	Mode2	Mode2 Percentage
TRAIN	BsmtExposure	INPUT	5	0	No	64.67	Av	13.50
TRAIN	BsmtFinType1	INPUT	7	0	Unf	29.91	GLQ	29.23
TRAIN	BsmtQual	INPUT	6	0	TA	43.19	Gd	41.42
TRAIN	Condition1	INPUT	9	0	Norm	86.10	Feedr	5.70
TRAIN	Condition2	INPUT	7	0	Norm	99.15	Artery	0.28
TRAIN	ExterQual	INPUT	4	0	TA	61.25	Gd	33.68
TRAIN	Exterior1st	INPUT	16	0	VinylSd	35.38	MetalSd	15.61
TRAIN	Functional	INPUT	8	0	Typ	92.31	Min2	2.68
TRAIN	HouseStyle	INPUT	8	0	1Story	50.14	2Story	29.29
TRAIN	KitchenQual	INPUT	5	0	TA	51.05	Gd	39.37
TRAIN	LandContour	INPUT	4	0	Lvl	89.57	Bnk	4.16
TRAIN	LotConfig	INPUT	5	0	Inside	73.45	Corner	16.92
TRAIN	LotShape	INPUT	4	0	Reg	64.39	IR1	32.42
TRAIN	MSSubClass	INPUT	16	0	020	35.61	060	18.29
TRAIN	Neighborhood	INPUT	28	0	NAmes	13.56	OldTown	9.17
TRAIN	PoolQC	INPUT	4	0	NA	99.60	TA	0.17
TRAIN	RoofMatl	INPUT	5	0	CompShg	99.15	Tar&Grv	0.46
TRAIN	SaleCondition	INPUT	6	0	Normal	83.08	Partial	8.55

iv. GLM regression model

The GLM Procedure

Dependent Variable: SalePrice SalePrice

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	162	1.7166461E13	105965808685	192.13	<.0001
Error	2767	1.5260761E12	551527323.22		
Corrected Total	2929	1.8692537E13			

R-Square	Coeff Var	Root MSE	SalePrice Mean
0.918359	12.98956	23484.62	180796.1

Source	DF	Type III SS	Mean Square	F Value	Pr > F
BedroomAbvGr	1	3207037637.5	3207037637.5	5.81	0.0160
BsmtExposure	4	52167511587	13041877897	23.65	<.0001
BsmtFinSF1	1	634927749.79	634927749.79	1.15	0.2834
BsmtFinType1	5	6346400042.6	1269280008.5	2.30	0.0425
BsmtQual	4	47970107178	11992526794	21.74	<.0001
BsmtUnfSF	1	12317338079	12317338079	22.33	<.0001
Condition1	8	24784365847	3098045730.9	5.62	<.0001
Condition2	7	52026687589	7432383941.3	13.48	<.0001
ExterQual	3	30821191163	10273730388	18.63	<.0001
Exterior1st	15	35331643500	2355442900	4.27	<.0001
Fireplaces	1	16081519103	16081519103	29.16	<.0001
FullBath	1	4346547649.3	4346547649.3	7.88	0.0050
Functional	7	16287068541	2326724077.3	4.22	0.0001
GarageCars	1	6217687759.9	6217687759.9	11.27	0.0008
GrLivArea	1	5106976421.1	5106976421.1	9.26	0.0024
HouseStyle	7	7480601210.4	1068657315.8	1.94	0.0599
KitchenQual	4	50557307738	12639326935	22.92	<.0001
LandContour	3	13754138237	4584712745.5	8.31	<.0001
LotArea	1	15641164235	15641164235	28.36	<.0001
LotConfig	4	6886221581.4	1721555395.3	3.12	0.0142
LotShape	3	4382135980.8	1460711993.6	2.65	0.0474
MSSubClass	15	130491550840	8699436722.7	15.77	<.0001
MasVnrArea	1	8856146633.3	8856146633.3	16.06	<.0001
Neighborhood	27	290601616886	10763022848	19.51	<.0001
OverallCond	1	64734359206	64734359206	117.37	<.0001
OverallQual	1	51902397799	51902397799	94.11	<.0001
PoolQC	4	41221573495	10305393374	18.69	<.0001
RoofMatl	7	222342741647	31763248807	57.59	<.0001
SaleCondition	5	26000807453	5200161490.6	9.43	<.0001
ScreenPorch	1	16349711138	16349711138	29.64	<.0001
TotalBsmtSF	1	29645534960	29645534960	53.75	<.0001
YearBuilt	1	30487351058	30487351058	55.28	<.0001
YrsSinceRemod	1	3295731549.5	3295731549.5	5.98	0.0146
_2ndFlrSF	1	3244215640	3244215640	5.88	0.0154
_1stFlrSF	1	308349813.79	308349813.79	0.56	0.4547
GarageArea	1	5779233118.4	5779233118.4	10.48	0.0012
GarageType	6	2891421713.8	481903618.96	0.87	0.5132
GarageCond	5	942720921.84	188544184.37	0.34	0.8877

v. Mean Price Vs. Overall Condition and Overall Quality

Mean Sale price varies significantly based on Overall Condition & Overall quality of the house on Sale.

The MEANS Procedure

Analysis Variable : SalePrice SalePrice						
Overall Cond	N Obs	N	Mean	Std Dev	Minimum	Maximum
1	7	7	69981.29	20092.94	50000.00	103000.00
2	10	10	116062.10	104753.95	12789.00	394432.00
3	50	50	95994.00	38804.49	35000.00	200624.00
4	101	101	120923.87	44730.35	40000.00	301600.00
5	1654	1654	206027.03	87026.46	13100.00	745000.00
6	533	533	150377.89	50557.79	37900.00	755000.00
7	390	390	153001.96	49042.57	50138.00	402000.00
8	144	144	154775.52	51784.62	84500.00	415000.00
9	41	41	199765.85	88072.39	88750.00	475000.00

The MEANS Procedure

Analysis Variable : SalePrice SalePrice						
Overall Qual	N Obs	N	Mean	Std Dev	Minimum	Maximum
1	4	4	48725.00	29341.94	13100.00	81500.00
2	13	13	52325.31	17562.96	12789.00	82000.00
3	40	40	83185.98	23569.80	37900.00	139600.00
4	226	226	106485.10	29224.94	34900.00	256000.00
5	825	825	134752.52	27690.60	55993.00	301600.00
6	732	732	162130.32	37201.30	76000.00	415000.00
7	602	602	205025.76	43166.27	82500.00	383970.00
8	350	350	270913.59	61326.21	122000.00	538000.00
9	107	107	368336.77	79201.27	150000.00	611657.00
10	31	31	450217.32	141975.97	160000.00	755000.00

vi. ANOVA for SalePrice with Neighborhood

ANOVA to check if the proximity to certain neighborhoods have a significant impact on sale price. It was observed that neighborhoods have a statistically significant impact on sale price of the house.

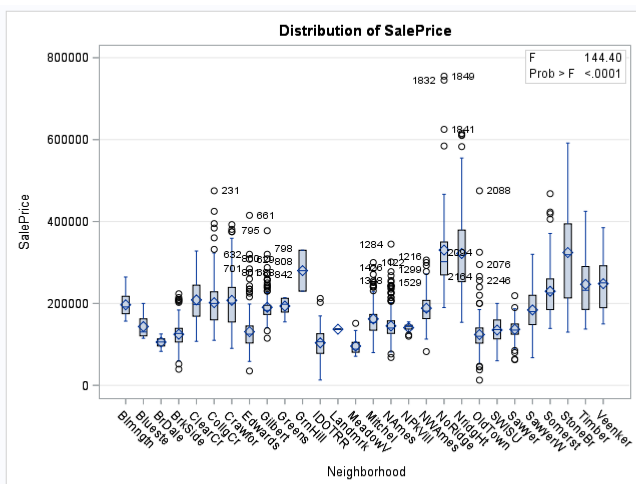
The ANOVA Procedure

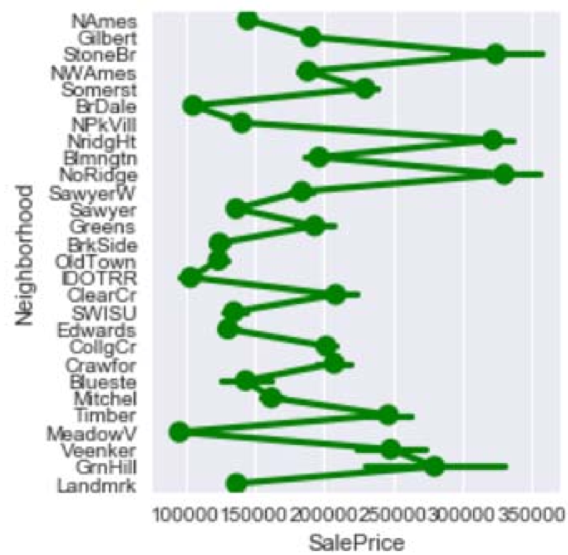
Dependent Variable: SalePrice SalePrice

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	27	1.0716005E13	396889056324	144.40	<.0001
Error	2902	7.9765326E12	2748632870.3		
Corrected Total	2929	1.8692537E13			

R-Square	Coeff Var	Root MSE	SalePrice Mean
0.573277	28.99809	52427.41	180796.1

Source	DF	Anova SS	Mean Square	F Value	Pr > F
Neighborhood	27	1.0716005E13	396889056324	144.40	<.0001





vii. ANOVA for SalePrice with Condition1 and Condition2

Condition1 and Condition2 both refer to proximity to certain streets, railways bus stations etc. Average sale price significantly depends on the condition of the residential home, e.g. (Artery) adjacent to arterial street, (Feedr) adjacent to feeder street, (PosA) adjacent to postive off-site feature --park, greenbelt, etc., (PosN) near postive off-site feature --park, greenbelt, etc. Two-way ANOVA shows that Condition 1 and Condition 2 have a significant relationship with SalePrice, however the interaction Condition1*Condition2 do not have a significant relationship.

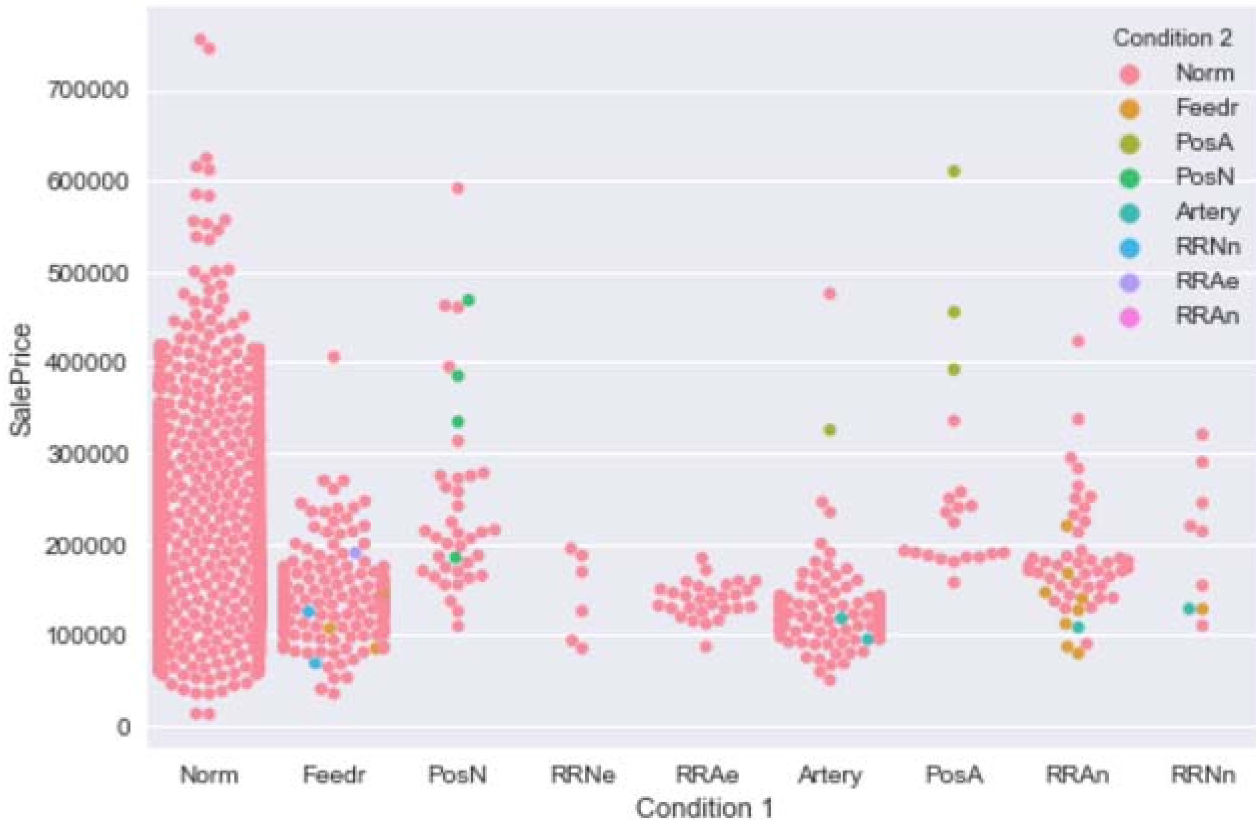
The GLM Procedure

Dependent Variable: SalePrice SalePrice

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	1.1508771E12	76725141199	12.75	<.0001
Error	2914	1.754166E13	6019787231.4		
Corrected Total	2929	1.8692537E13			

R-Square	Coeff Var	Root MSE	SalePrice Mean
0.061569	42.91426	77587.29	180796.1

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Condition 1	8	201269056419	25158632052	4.17	<.0001
Condition 2	7	180913713469	25844816210	4.29	<.0001
Condition*Condition	6	14660669047	2443444841.1	0.41	0.8759


Condition 2
Norm
Feedr
PosA
PosN
Artery
RRNn
RRAe
RRAn
SalePrice
700000
600000
500000
400000
300000
200000
100000
0
Norm
Feedr
PosN
RRNe
RRAe
Artery
PosA
RRAn
RRNn
Condition 1