Kaggle Project - Team Fat Tails

Introduction

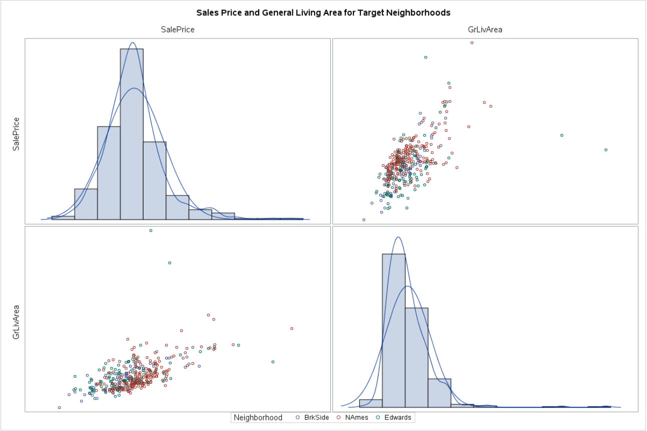
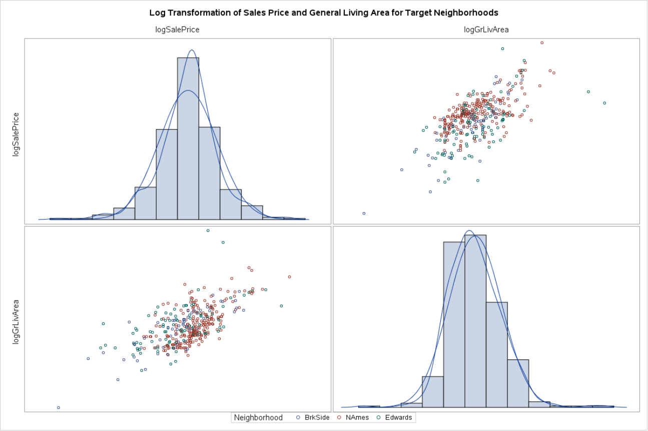
Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. However, it is essential to review the data because it proves that there are many other influences in price negotiations than the number of bedrooms or a white-picket fence.

Data Synopsis

The Ames House dataset was compiled by Dean De Cock and contains 79 explanatory variables describing almost every aspect of residual home in Ames Iowa from 2006 to 2010. The data set contains 2930 observations involved in assessing home values.

Data summary for North Ames, Edwards, and Brookside neighborhoods:

Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
Id	383	0	10	1460	744	729	744
MSSubClass	383	0	20	190	45	30	40
GrLivArea	383	0	334	5642	1302	1200	503
SalePrice	383	0	39300	345000	138063	135500	39000
logSalePrice	383	0	11	13	12	12	0
logGrLivArea	383	0	6	9	7	7	0

No Transformation	Log Transformation
	

- More data definitions

Analysis Question 1

Restatement of Problem

Century 21 has commissioned Nixon, Friedrich, and Bourzikas to perform a study to derive insights regarding homes prices in Ames. Century focuses on three neighborhoods in Ames: "North Ames", "Edwards", and "Brookside". They would like to get an estimate of how the Sales Price of the house is related to the square footage of the living area of the house. Additionally, they would like to understand the relationship between sales price and the living area square footage, as well as investigating any relationship between sales price and that home's neighborhood.

Build and Fit the Model

In order to build and fit a model, an analysis must be performed to identify features of the dataset that are statistically significant in their relation to, and prediction of, the sales price.

When one of the predictor variables impacts how another predictor variable is related to the dependent variable. A multiple linear regression model in which the mean of the LogLivingArea depends linearly on the important of the

LogSalesPrice and all three Neighborhoods, allowing for different slopes and intercepts, is as follow:

In Assessing the Fit, the coefficient is interpreted by the following models utilizing the base formula: • Ames^SalesPrice = β0 + β1*BrkSide + β1*Edwards + β3:*NAmes + β4 (LogLivingArea*BrkSide) + β5(LogLivingArea*Edwards) o β0: The intercept in this model provides an estimate 8.49 of the logGrLivArwea (reference NAmes) with a logGrLivArwea of zero. Of course, this is extrapolation and does not have a clear, practical meaning. o β1: This is the adjustment of the intercept for a Neighborhood BrkSide with respect to a NAmes Neighborhood. For a Living room of zero, the Neighborhood BrkSide has an estimated Sale Price Increases of -5. 16 (2^-2.58 back transformation) dollars per square foot less than the NAmes Livingroom. o β1 This is the adjustment of the intercept for a Neighborhood Edwards with respect to a NAmes Neighborhood. For a Living room of zero, the Neighborhood Edwards has an estimated Sale Price Increases of -1.40 (2^-0.49 back transformation) dollars per square foot less than the NAmes Livingroom. o β3: For each 1 unit increase in the Living Room of a NAmes, the estimated Sale Price increases 2^0.47 units o β4: For each 1 unit increase in the Living Room Size of BrkSide, the estimated Sale Price increases 8.16 (2^0.35 Back transformed) dollars per square foot from the change with the NAmes. o β5: For each 1 unit increase in the Living Room Size of Edwards, the estimated Sale Price increases 1.04 (2^0.05 Back transformed) dollars per square foot from the change with the NAmes.

Interrogate the Data

In reviewing the data, an analysis was performed using QQ Plots and Histograms, the linearity of the data is not in question due to the sample size, the data is right skewed and is not normally distributed as depicted, the data does not have equal standard deviations, and the data is independent of each other.

Because the assumptions in the data do not support evidence that will allow the study to continue due to data, transformation of the data was perfromed using the Log of the Sales Price and Log of the Grang Living Area. Upon this transforamtion, the linearity of the data is not in question, that is not strong evidence against normalizty of residuals looking at the histogram and QQ plot, the standard deviasion appear to be equel, and the data is indpependent. Addtionaly, there is a constant variance after the trasnformation occurred.

Additionaly, the it is assumped that the data is independent due to each house being unique to each neighnborhood.

After the transformation, the data was interrogated and a review of the studentized residuals and Cooks D was performed by running a fit diagnostic through our Proc Reg code. The review of Studentized residual identified one outliers that was related to a very large grand living room square footage and two outliers were related homes that have Sales price over 700,000 representing less than 0.13%. While these data points are low leverage with big residuals, Cooks D only show a mile problem. Due to the sample size, the Homes remained in the data set because these do not appear to affect the data.

Collinearity

Additionally, there is no collinearity in the data because Neighborhood and Grand Living are correlated with the Sales Price, if using differently each neighborhood variable as independent data. Since these variables are correlated with each other and the response variables, it is not difficult to parse out how each will impact the response variable independently.

R2

With only an R^2 .421 and an adjusted R^2 of .418, the fit of of the model of predicting sales price by Nieghborhood and Grand Living Room square foot, is not a good model. It is recommended that additianla variables should be used to calculate a more accute Sales Price.

Check Assumptions

Homogeneity of Variances

Normality

Residual Diagnostics

Outlier Analysis

Model Comparison

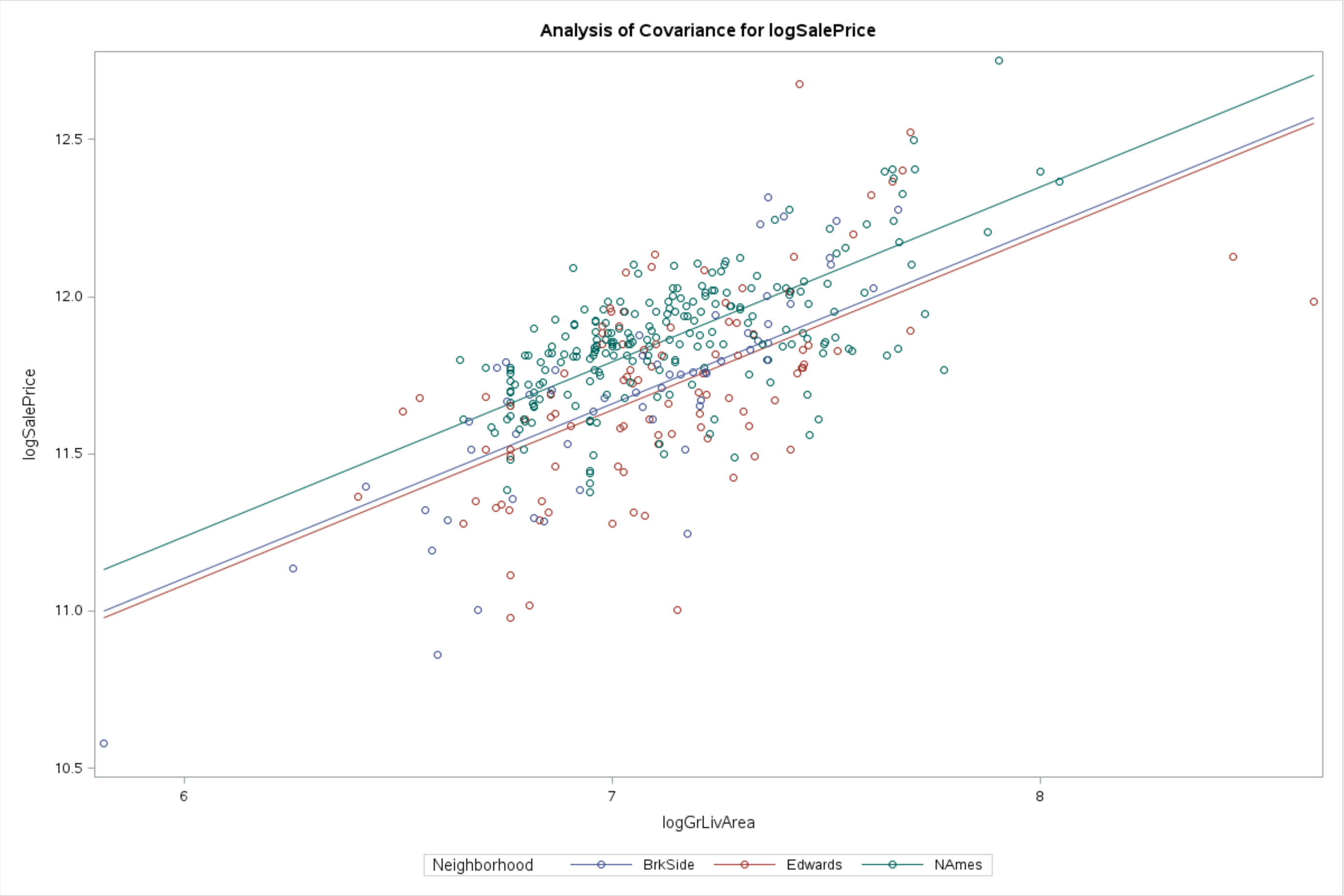
After reviewing the models after and before the transformation, the R-Square is (0.51, 0.45, respectively) with a RMSE of (0.19, 28552.30, respectively) and a Coefficient Variance of (1.63, 20.68, respectively) ensuring the better fit is with the transformed data.

No Interactions

Number of Observations Used	383

R-Square	Coeff Var	Root MSE	logSalePrice Mean
0.489705	1.66218	0.196118	11.79887

Parameter	Estimate	Standard Error	t Value	Pr > t	LCL	UCL
Intercept	7.90214954	0.23133976	34.16	<.0001	7.447279361	8.357019719
logGrLivArea	0.555788385	0.03236859	17.17	<.0001	0.492143867	0.619432902
Neighborhood BrkSide	-0.132788629	0.02906111	-4.57	<.0001	-0.189929827	-0.075647431
Neighborhood Edwards	-0.153226231	0.02357095	-6.5	<.0001	-0.199572446	-0.106880015
Neighborhood NAmes	0	.	.	.	.	.

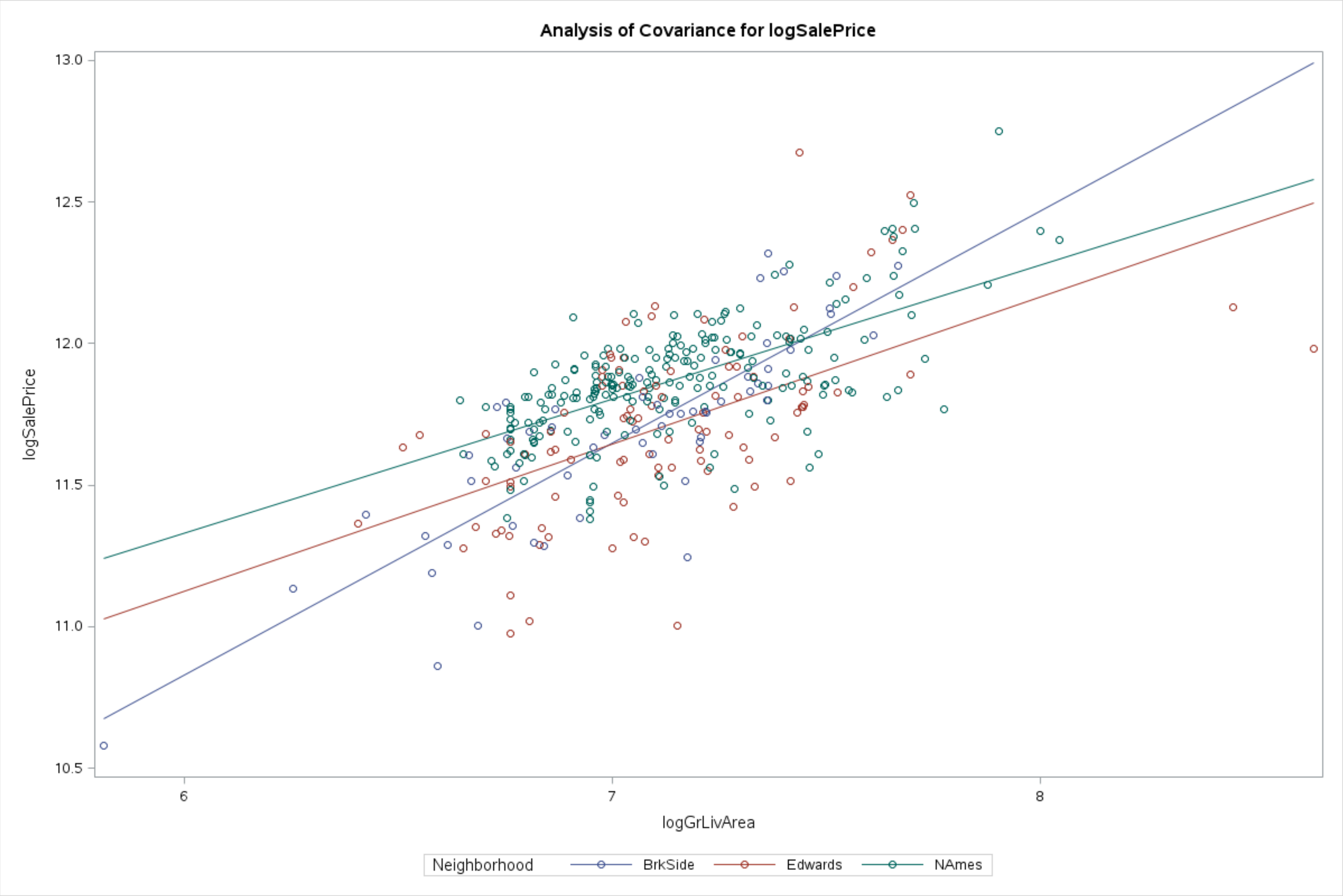


With Interactions

Number of Observations Used	383

R-Square	Coeff Var	Root MSE	logSalePrice Mean
0.512092	1.629617	0.192276	11.79887

Parameter	Estimate	Standard Error	t Value	Pr > t	LCL	UCL
Intercept	8.492727641	0.32441709	26.18	<.0001	7.854833978	9.130621305
logGrLivArea	0.473023602	0.04542895	10.41	<.0001	0.383697733	0.562349471
Neighborhood BrkSide	-2.579806905	0.59988132	-4.3	<.0001	-3.759339383	-1.400274428
Neighborhood Edwards	-0.486220461	0.51750833	-0.94	0.3481	-1.503784863	0.531343941
Neighborhood NAmes	0	.	.	.	.	.
logGrLivA*Neighborho BrkSide	0.346624454	0.08482008	4.09	<.0001	0.179844737	0.513404171
logGrLivA*Neighborho Edwards	0.046643642	0.07248011	0.64	0.5203	-0.09587228	0.189159563
logGrLivA*Neighborho NAmes	0	.	.	.	.	.



Adj R2

Parameters & Equations

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    - Estimates
    - Interpretation
    - Confidence Intervals
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Variables: SalesPrice = SP LivingArea = LA

General Formula:

$$ \hat\mu { {log(SP)} } ,=, \beta_0, +,\beta_1,Brookside, +,\beta_2,Edwards, +,\beta_3,Ames, +,\beta_4(log(LA),Brookside) +\beta_{5},(log(LA),Edwards) $$

Ames (North):

$$ \hat\mu { {log(SP_{Ames})} } ,=, \beta_0, +,\beta_1,Brookside, +,\beta_2,Edwards, +,\beta_3,Ames, +,\beta_4(log(LA),Brookside) +\beta_{5},(log(LA),Edwards) $$

Brookside:

$$ \hat\mu { {log(SP_{Brookside})} } ,=, \beta_0, +,\beta_1,Brookside, +,\beta_2,Edwards, +,\beta_3,Ames, +,\beta_4(log(LA),Brookside) +\beta_{5},(log(LA),Edwards) $$

Edwards:

$$ \hat\mu { {log(SP_{Edwards})} } ,=, \beta_0, +,\beta_1,Brookside, +,\beta_2,Edwards, +,\beta_3,Ames, +,\beta_4(log(LA),Brookside) +\beta_{5},(log(LA),Edwards) $$

Conclusion

To interpret the model, a change in Living Room Square Feet is a doubled increase. For the neighborhood with approximately the same mass, it is estimate that a 10-fold increase in the Living Area Square feet is associated with a XX which is a 83.2% increase in the median Sales Price of the neighborhood. (P value < 0.001). At a 95% confidence intervals for the increase in sales price of XX = CI which equates to an estimated increase between X% and X%.

Analysis Question 2

Restate Problem

Our objective is to build the most predictive model for sale prices of homes in Ames, Iowa using only the tools learned through week 14 of MSDS 6371. We are to produce and compare four models: forward selection, backward elimination, stepwise selection, and a custom model. Models are to be evaluated on adjusted R^2, CV PRESS, and Kaggle score. We want the model that does the best job predicting future prices (that is, best Kaggle score wins).

Model Selection

Backward elimination, forward selection, stepwise selection, and custom models were built for this question. All models were built using log-log transformed data (log of SalePrice and log of GrLivArea). Forward selection and stepwise selection had comparable Kaggle scores. Based on interpretability, the Forward Selection Model was chosen.

Check Assumptions

Based on the lack of overwhelming evidence to support the assumptions, a number of transformations were considered and a decision was made to use a log-log transformation as the basis of the most predictive model.

Linearity

We know from the previous question that SalePrice is linearly correlated with some of the explanatory variables (size, for example), but it is unlikely to be correlated with all of them.

Heteroscedacity

There is some visual evidence against constant variance. With the large number of observations, visual inspection becomes more challenging.

Check Normality

A histogram of saleprice across all neighborhoods shows evidence of right skewness.

Independence

Although, homeowners are free to price their homes as they wish and buyers can make whatever offer they choose, there is no way to say with much certainty that home prices are truly independent.

Residual Diagnostics

Outlier Analysis

Two observations had CooksD values significantly higher than other observations.

And no observations appeared to be particularly high leverage so we can proceed without the need to removing any observations prior to modelling.

Comparing Competing Models

Predictive Models	Adjusted R2	CV PRESS	Kaggle Score
Forward	.8501	31.18449	.14880
Backward	.9350	31.67571	.21225
Stepwise	.9206	19.14915	.14880
CUSTOM			

Best model: Forward selection

The “best” model in this situation is one that has a high degree of predictable power and is easy to interpret. That model is the forward selection model.

At five explanatory variables, the forward selection model is relatively small. It includes coefficients for OverallCond, OverallQual, BsmtFinSF1, Neighborhood and logliv. In other words, it predicts that the price of a home is a function of its location, size, and overall condition.

Each neighborhood has a coefficient that acts as a multiplier for a % increase or decrease in the mean SalePrice relative to the Veenker Neighborhood (reference level selected by SAS).

The equation for this model is the following:

$$ \hat\mu { {log(SalePrice)} } ,=, \beta_0, +,\beta_1,OverallQual, +,\beta_2,OverallCond, +,\beta_3,BsmtFinSF1, +,\beta_4,log(GrLivArea) +\beta_{5},Neighborhood $$

What this means in real world terms is that a 10% increase in the above ground living area should result in an ~4.4% increase in price ($1.1^{\beta_4} = 1.1^{0.455} = 1.044$) due to log transforming the SalePrice and the GrLivArea variable.

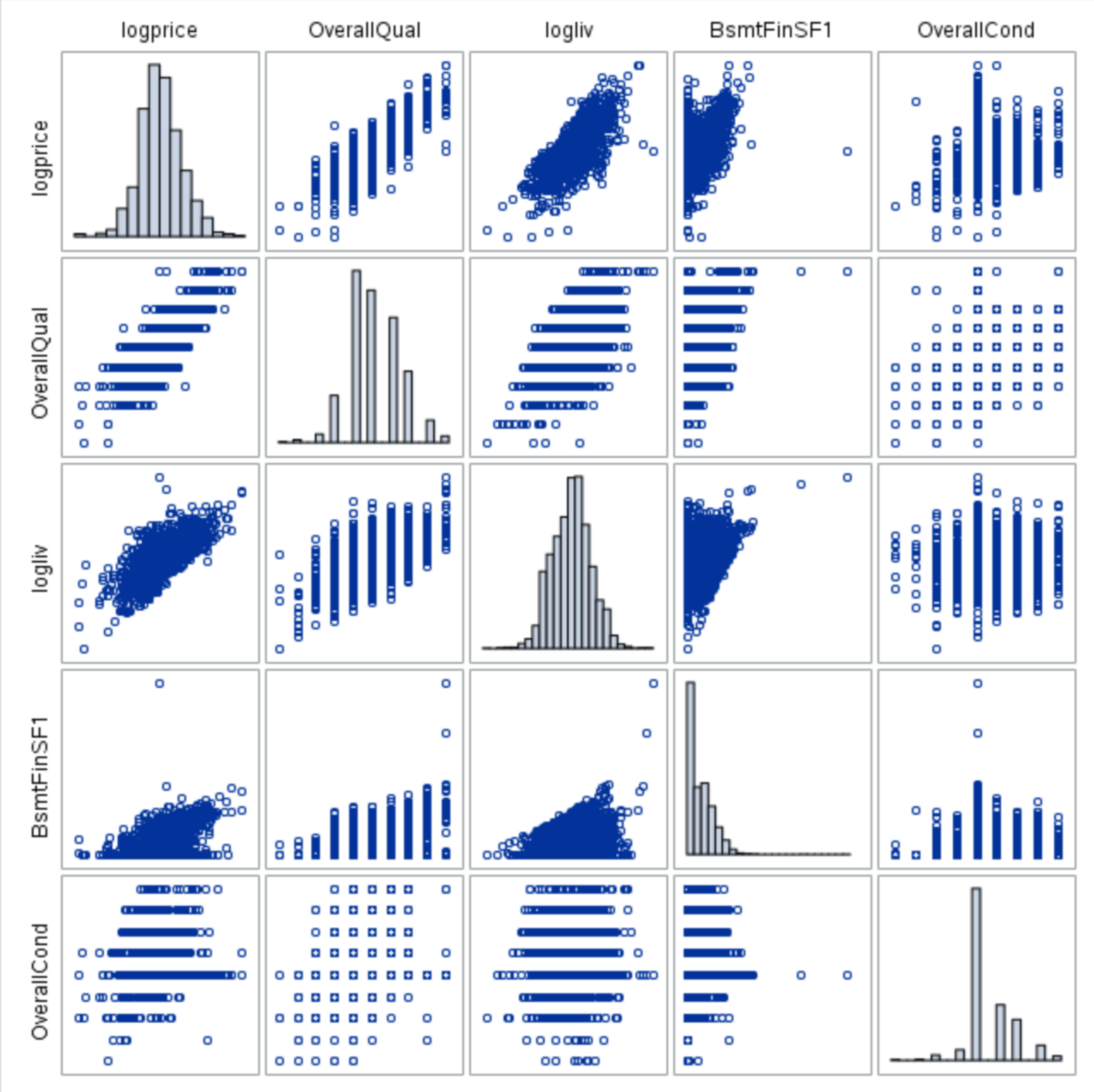
The selection of Neighborhood impacts the mean selling price by the relative percentage of e^{β_5}. The mean price for Neighborhoods with negative coefficients goes down relative to the Veenker reference neighborhood.

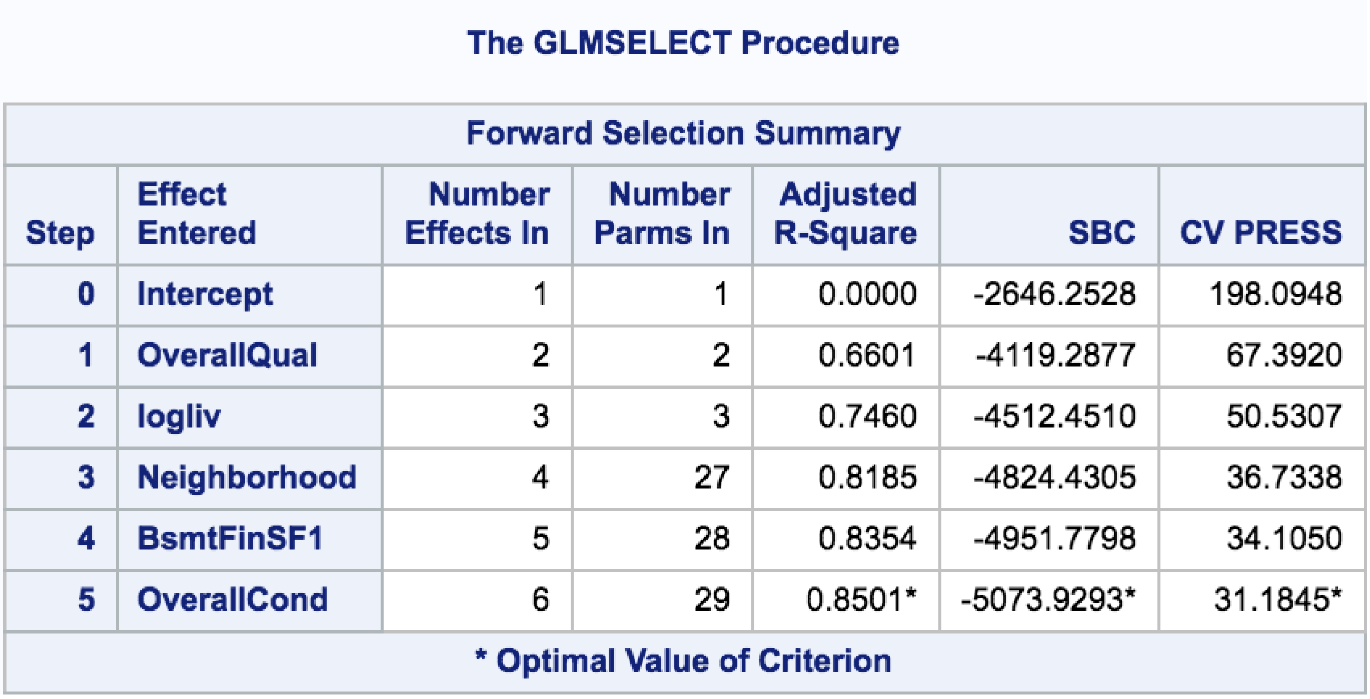
For each unit increase in the OverallQual score, the mean selling price will increase by approx. 10% ($e^{\beta_1} = e^{0.0956} = 1.10$).

For each unit increase in OverallCond score, the mean selling price will increase by approx. 4.9% ($e^{\beta_2} = e^{0.0477} = 1.0488$).

For each unit increase in BsmtFinSF1, the mean selling price will increase by approx. 0.0012% ($e^{\beta_3} = e^{0.000118} = 1.000118007$).

Visually we can see that $\log$(GrLivArea) is the strongest predictor of price followed by OverallQual. This makes sense conceptually. It’s reasonable to assume people will pay more for a big, nice home.


logprice
OverallQual
logliv
BsmtFinSF1
OverallCond
logprice
OverallQual
logliv
BsmtFinSF1
OverallCond

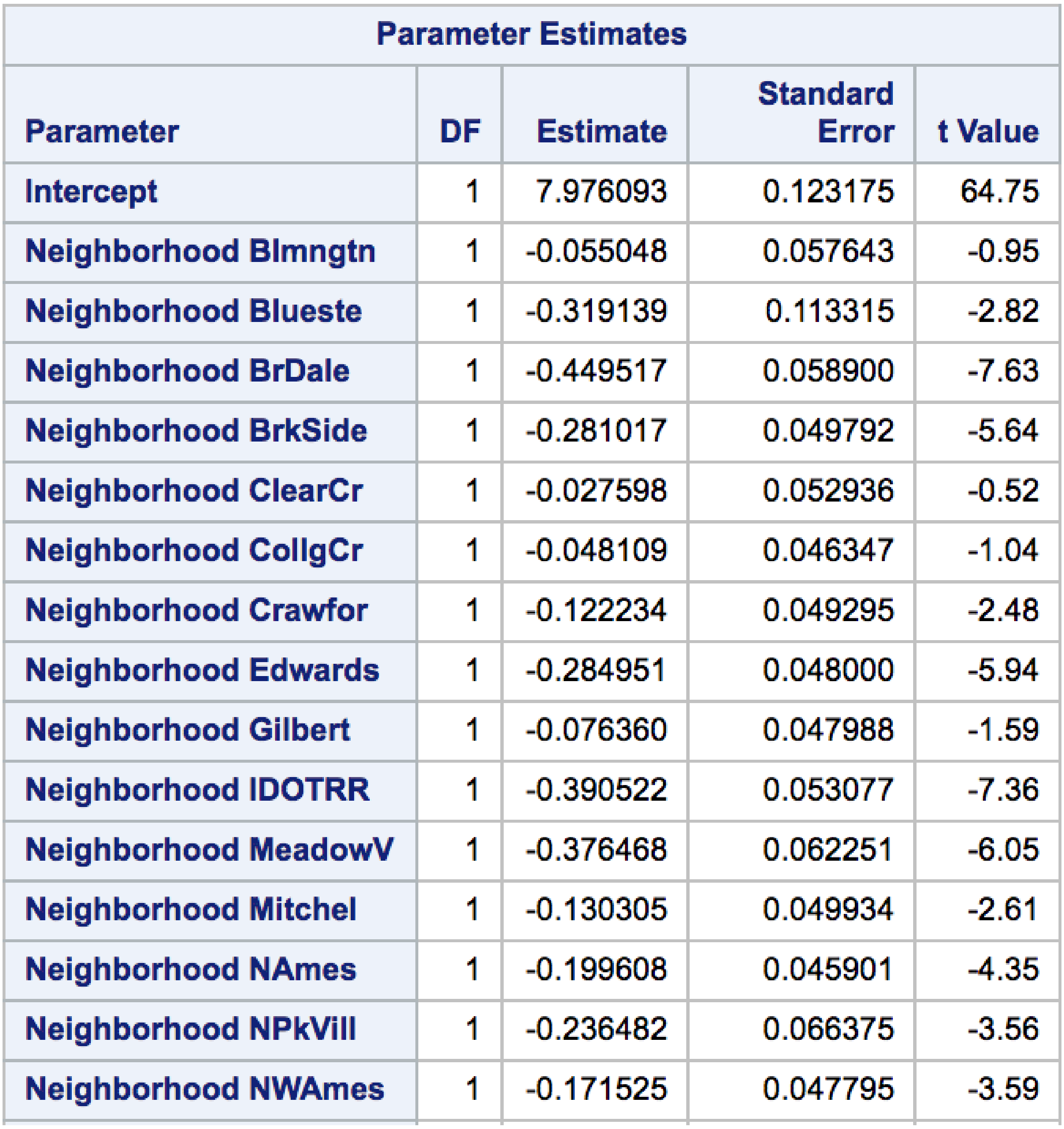


The GLMSELECT Procedure

Forward Selection Summary

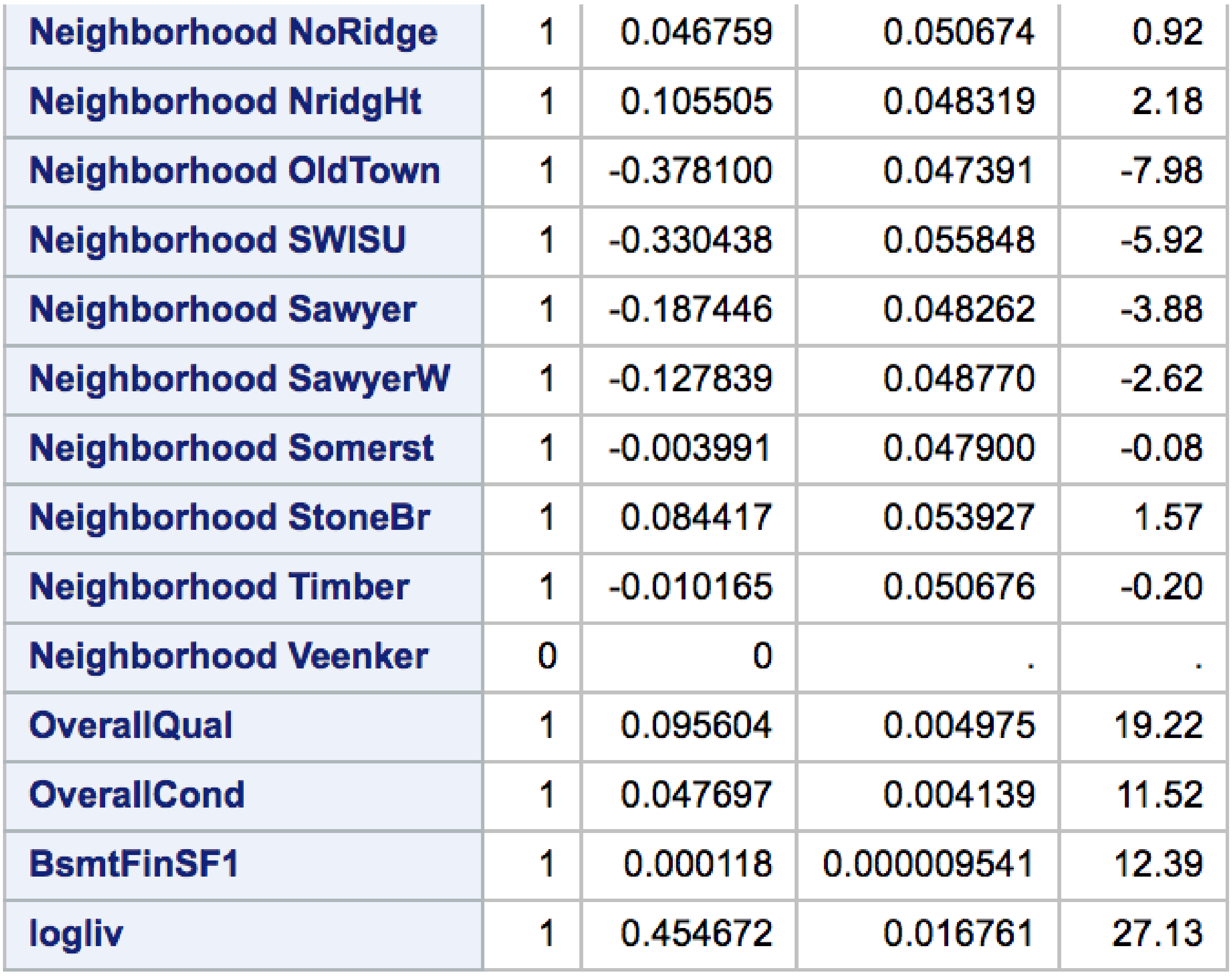
Step	Effect Entered	Number Effects In	Number Parms In	Adjusted R-Square	SBC	CV PRESS
0	Intercept	1	1	0.0000	-2646.2528	198.0948
1	OverallQual	2	2	0.6601	-4119.2877	67.3920
2	logliv	3	3	0.7460	-4512.4510	50.5307
3	Neighborhood	4	27	0.8185	-4824.4305	36.7338
4	BsmtFinSF1	5	28	0.8354	-4951.7798	34.1050
5	OverallCond	6	29	0.8501*	-5073.9293*	31.1845*

* Optimal Value of Criterion



Parameter Estimates

Parameter	DF	Estimate	Standard Error	t Value
Intercept	1	7.976093	0.123175	64.75
Neighborhood Blmngtn	1	-0.055048	0.057643	-0.95
Neighborhood Blueste	1	-0.319139	0.113315	-2.82
Neighborhood BrDale	1	-0.449517	0.058900	-7.63
Neighborhood BrkSide	1	-0.281017	0.049792	-5.64
Neighborhood ClearCr	1	-0.027598	0.052936	-0.52
Neighborhood CollgCr	1	-0.048109	0.046347	-1.04
Neighborhood Crawfor	1	-0.122234	0.049295	-2.48
Neighborhood Edwards	1	-0.284951	0.048000	-5.94
Neighborhood Gilbert	1	-0.076360	0.047988	-1.59
Neighborhood IDOTRR	1	-0.390522	0.053077	-7.36
Neighborhood MeadowV	1	-0.376468	0.062251	-6.05
Neighborhood Mitchel	1	-0.130305	0.049934	-2.61
Neighborhood NAmes	1	-0.199608	0.045901	-4.35
Neighborhood NPkVill	1	-0.236482	0.066375	-3.56
Neighborhood NWAmes	1	-0.171525	0.047795	-3.59



Neighborhood NoRidge	1	0.046759	0.050674	0.92
Neighborhood NridgHt	1	0.105505	0.048319	2.18
Neighborhood OldTown	1	-0.378100	0.047391	-7.98
Neighborhood SWISU	1	-0.330438	0.055848	-5.92
Neighborhood Sawyer	1	-0.187446	0.048262	-3.88
Neighborhood SawyerW	1	-0.127839	0.048770	-2.62
Neighborhood Somerst	1	-0.003991	0.047900	-0.08
Neighborhood StoneBr	1	0.084417	0.053927	1.57
Neighborhood Timber	1	-0.010165	0.050676	-0.20
Neighborhood Veenker	0	0	.	.
OverallQual	1	0.095604	0.004975	19.22
OverallCond	1	0.047697	0.004139	11.52
BsmtFinSF1	1	0.000118	0.000009541	12.39
logliv	1	0.454672	0.016761	27.13

Conclusion

Appendix A

SAS Program

main.sas

@import "main.sas"

dataimport.sas

@import "dataimport.sas"

procmeans.sas

@import "procmeans.sas"

analysis1_model_interactions.sas

@import "analysis1_model_interactions.sas"

analysis1_model1_nointeractions.sas

@import "analysis1_model_interactions.sas"

Appendix B

train_cleansed_vtarget_ntarget by Neighborhood

Neighborhood	N Obs	Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
BrkSide	58	Id	58	0	10	1444	735	696	746
		MSSubClass	58	0	20	190	50	50	20
		GrLivArea	58	0	334	2134	1203	1211	638
		SalePrice	58	0	39300	223500	124834	124300	41500
		logSalePrice	58	0	11	12	12	12	0
		logGrLivArea	58	0	6	8	7	7	1
Edwards	100	Id	100	0	40	1460	763	732	720
		MSSubClass	100	0	20	190	57	50	55
		GrLivArea	100	0	605	5642	1340	1200	499
		SalePrice	100	0	58500	320000	128220	121750	44450
		logSalePrice	100	0	11	13	12	12	0
		logGrLivArea	100	0	6	9	7	7	0
NAmes	225	Id	225	0	15	1459	738	761	737
		MSSubClass	225	0	20	190	39	20	40
		GrLivArea	225	0	767	3112	1310	1200	439
		SalePrice	225	0	87500	345000	145847	140000	30500
		logSalePrice	225	0	11	13	12	12	0
		logGrLivArea	225	0	7	8	7	7	0

combined_cleansed_vall_ntarget

Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
Id	745	0	10	2873	1454	1425	1470
MSSubClass	745	0	20	190	44	30	40
LotArea	745	0	2522	63887	9675	9020	3117
OverallQual	745	0	1	10	5	5	1
OverallCond	745	0	1	9	6	6	2
YearBuilt	745	0	1900	2009	1955	1957	16
YearRemodAdd	745	0	1950	2010	1971	1964	39
MasVnrArea	744	1	0	1224	69	0	91
BsmtFinSF1	744	1	0	5644	424	399	652
BsmtFinSF2	744	1	0	1164	65	0	0

Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
BsmtUnfSF	744	1	0	1866	466	414	529
TotalBsmtSF	744	1	0	6110	955	952	356
FirstFlrSF	745	0	334	5095	1120	1054	345
SecondFlrSF	745	0	0	1836	172	0	328
LowQualFinSF	745	0	0	512	4	0	0
GrLivArea	745	0	334	5642	1296	1200	454
BsmtFullBath	743	2	0	3	0	0	1
BsmtHalfBath	743	2	0	2	0	0	0
FullBath	745	0	0	3	1	1	0
HalfBath	745	0	0	2	0	0	0
BedroomAbvGr	745	0	1	6	3	3	1
KitchenAbvGr	745	0	0	2	1	1	0
TotRmsAbvGrd	745	0	2	15	6	6	2
Fireplaces	745	0	0	3	0	0	1
GarageYrBlt	686	59	1910	2009	1962	1960	16
GarageCars	745	0	0	5	1	1	1
GarageArea	745	0	0	1418	385	364	226
WoodDeckSF	745	0	0	736	62	0	104
OpenPorchSF	745	0	0	484	30	0	40
EnclosedPorch	745	0	0	552	25	0	0
ThreeSsnPorch	745	0	0	407	3	0	0
ScreenPorch	745	0	0	576	22	0	0
PoolArea	745	0	0	738	3	0	0
MiscVal	745	0	0	17000	109	0	0
MoSold	745	0	1	12	6	6	4
YrSold	745	0	2006	2010	2008	2008	2
SalePrice	383	362	39300	345000	138063	135500	39000
logSalePrice	383	362	11	13	12	12	0
logGrLivArea	745	0	6	9	7	7	0
total_area	744	1	334	13170	2636	2554	804
remodel_age	745	0	8	68	47	54	39

combined_cleansed_vall_ntarget by Neighborhood

Neighborhood	N Obs	Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
BrkSide	108	Id	108	0	10	2796	1378	1394	1503
		MSSubClass	108	0	20	190	49	50	20
		LotArea	108	0	3500	21384	6960	6168	1342
		OverallQual	108	0	1	7	5	5	1
		OverallCond	108	0	2	9	6	6	2
		YearBuilt	108	0	1900	1970	1932	1930	15
		YearRemodAdd	108	0	1950	2008	1968	1950	45
		MasVnrArea	108	0	0	444	11	0	0
		BsmtFinSF1	107	1	0	1309	201	68	336
		BsmtFinSF2	107	1	0	606	20	0	0
		BsmtUnfSF	107	1	0	1078	543	524	537
		TotalBsmtSF	107	1	0	1324	764	788	277
		FirstFlrSF	108	0	334	1445	899	901	235
		SecondFlrSF	108	0	0	908	331	399	583
		LowQualFinSF	108	0	0	360	5	0	0
		GrLivArea	108	0	334	2134	1235	1231	559
		BsmtFullBath	107	1	0	2	0	0	0
		BsmtHalfBath	107	1	0	1	0	0	0
		FullBath	108	0	1	2	1	1	0
		HalfBath	108	0	0	1	0	0	0
		BedroomAbvGr	108	0	1	5	3	3	1
		KitchenAbvGr	108	0	1	2	1	1	0
		TotRmsAbvGrd	108	0	2	10	6	6	1
		Fireplaces	108	0	0	2	0	0	1
		GarageYrBlt	96	12	1916	2004	1948	1940	37
		GarageCars	108	0	0	5	1	1	1
		GarageArea	108	0	0	1184	314	280	224
		WoodDeckSF	108	0	0	509	46	0	42
		OpenPorchSF	108	0	0	365	25	0	18
		EnclosedPorch	108	0	0	268	39	0	70
		ThreeSsnPorch	108	0	0	150	3	0	0

Neighborhood	N Obs	Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
		ScreenPorch	108	0	0	259	14	0	0
		PoolArea	108	0	0	0	0	0	0
		MiscVal	108	0	0	2000	41	0	0
		MoSold	108	0	1	12	6	6	3
		YrSold	108	0	2006	2010	2008	2008	2
		SalePrice	58	50	39300	223500	124834	124300	41500
		logSalePrice	58	50	11	12	12	12	0
		logGrLivArea	108	0	6	8	7	7	0
		total_area	107	1	334	3491	2316	2321	776
		remodel_age	108	0	10	68	50	68	45
Edwards	194	Id	194	0	40	2873	1515	1437	1473
		MSSubClass	194	0	20	190	55	50	60
		LotArea	194	0	2522	63887	10356	9345	3281
		OverallQual	194	0	1	10	5	5	2
		OverallCond	194	0	1	9	6	5	1
		YearBuilt	194	0	1900	2009	1957	1954	31
		YearRemodAdd	194	0	1950	2010	1974	1968	47
		MasVnrArea	193	1	0	1224	50	0	48
		BsmtFinSF1	194	0	0	5644	410	289	609
		BsmtFinSF2	194	0	0	1164	47	0	0
		BsmtUnfSF	194	0	0	1678	429	392	606
		TotalBsmtSF	194	0	0	6110	885	864	434
		FirstFlrSF	194	0	495	5095	1115	1056	331
		SecondFlrSF	194	0	0	1836	218	0	462
		LowQualFinSF	194	0	0	450	4	0	0
		GrLivArea	194	0	498	5642	1338	1196	429
		BsmtFullBath	193	1	0	3	0	0	1
		BsmtHalfBath	193	1	0	2	0	0	0
		FullBath	194	0	0	3	1	1	1
		HalfBath	194	0	0	2	0	0	0
		BedroomAbvGr	194	0	1	6	3	3	1

Neighborhood	N Obs	Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
		KitchenAbvGr	194	0	0	2	1	1	0
		TotRmsAbvGrd	194	0	3	15	6	6	2
		Fireplaces	194	0	0	3	0	0	1
		GarageYrBlt	157	37	1910	2009	1966	1958	29
		GarageCars	194	0	0	3	1	1	1
		GarageArea	194	0	0	1418	336	321	268
		WoodDeckSF	194	0	0	736	71	0	120
		OpenPorchSF	194	0	0	484	34	0	40
		EnclosedPorch	194	0	0	286	25	0	0
		ThreeSsnPorch	194	0	0	180	1	0	0
		ScreenPorch	194	0	0	576	17	0	0
		PoolArea	194	0	0	738	6	0	0
		MiscVal	194	0	0	17000	123	0	0
		MoSold	194	0	1	12	6	6	3
		YrSold	194	0	2006	2010	2008	2008	2
		SalePrice	100	94	58500	320000	128220	121750	44450
		logSalePrice	100	94	11	13	12	12	0
		logGrLivArea	194	0	6	9	7	7	0
		total_area	194	0	880	13170	2559	2439	948
		remodel_age	194	0	8	68	44	50	47
NAmes	443	Id	443	0	15	2772	1446	1436	1345
		MSSubClass	443	0	20	190	38	20	30
		LotArea	443	0	4058	39384	10040	9500	2786
		OverallQual	443	0	3	8	5	5	1
		OverallCond	443	0	3	9	6	6	2
		YearBuilt	443	0	1918	2003	1960	1959	10
		YearRemodAdd	443	0	1950	2009	1971	1964	26
		MasVnrArea	443	0	0	1115	92	0	151
		BsmtFinSF1	443	0	0	1880	484	500	521
		BsmtFinSF2	443	0	0	1029	84	0	0
		BsmtUnfSF	443	0	0	1866	463	398	444

Neighborhood	N Obs	Variable	N	N Miss	Minimum	Maximum	Mean	Median	Quartile Range
		TotalBsmtSF	443	0	0	2223	1031	1031	341
		FirstFlrSF	443	0	576	2223	1175	1107	385
		SecondFlrSF	443	0	0	1778	113	0	0
		LowQualFinSF	443	0	0	512	4	0	0
		GrLivArea	443	0	715	3112	1292	1200	452
		BsmtFullBath	443	0	0	2	0	0	1
		BsmtHalfBath	443	0	0	1	0	0	0
		FullBath	443	0	1	3	1	1	0
		HalfBath	443	0	0	2	0	0	0
		BedroomAbvGr	443	0	1	6	3	3	1
		KitchenAbvGr	443	0	1	2	1	1	0
		TotRmsAbvGrd	443	0	4	12	6	6	1
		Fireplaces	443	0	0	3	1	0	1
		GarageYrBlt	433	10	1918	2008	1964	1961	12
		GarageCars	443	0	0	4	2	2	1
		GarageArea	443	0	0	1200	423	418	223
		WoodDeckSF	443	0	0	657	63	0	108
		OpenPorchSF	443	0	0	319	30	0	40
		EnclosedPorch	443	0	0	552	21	0	0
		ThreeSsnPorch	443	0	0	407	4	0	0
		ScreenPorch	443	0	0	385	26	0	0
		PoolArea	443	0	0	512	2	0	0
		MiscVal	443	0	0	15500	119	0	0
		MoSold	443	0	1	12	6	6	3
		YrSold	443	0	2006	2010	2008	2008	2
		SalePrice	225	218	87500	345000	145847	140000	30500
		logSalePrice	225	218	11	13	12	12	0
		logGrLivArea	443	0	7	8	7	7	0
		total_area	443	0	1176	5267	2747	2662	789
		remodel_age	443	0	9	68	47	54	26

Appendix X

@import "../data/data_description.md"

Appendix XX

Downloading from the Kaggle API

Using Code Blocks in Markdown

Using SAS in Markdown Code Blocks